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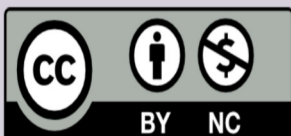
## Publicaciones Científicas

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# An Approach to the Modeling and Simulation of Intra-Hospital Diseases

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- ORIGINAL ARTICLE -

# An Approach to the Modeling and Simulation of Intra-Hospital Diseases

## Un Acercamiento a la Modelización y Simulación de Enfermedades Intra-Hospitalarias

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### Abstract

This publication presents an approach to a simulator to recreate a large number of scenarios and to make agile decisions in the planning of a real emergency room system. A modeling and simulation focused on the point prevalence of intrahospital infections in an emergency room and how it is affected by different factors related to hospital management. To carry out the simulator modeling, the Agent-based Modeling and Simulation (ABMS) paradigm was used. Thus, different intervening agents in the emergency room environment — patients and doctors, among others— were classified. The user belonging to the health system has different data to configure the simulation, such as the number of patients, the number of available beds, etc.

Based on the tests carried out and the measurements obtained, it is concluded that the disease propagation model relative to the time and contact area of the patients has greater precision than the purely statistical model of the intensive care unit.

**Keywords:** Simulation Health Systems ABMS.

### Resumen

En esta publicación se presenta una versión preliminar de un simulador inicial para recrear una gran cantidad de escenarios y tomar decisiones ágiles en la planificación de un sistema real de sala de emergencias. Una modelización y simulación centrada en la prevalencia puntual de infecciones intrahospitalarias en una sala de emergencias y cómo se ve afectada por diferentes factores relacionados con la gestión hospitalaria. Para realizar el modelado del simulador se utilizó el paradigma de Modelado y Simulación Basado en Agentes (ABMS). Así, se clasificaron diferentes agentes intervinientes en el entorno de urgencias —pacientes y médicos, entre otros—. El usuario perteneciente al sistema de salud dispone de diferentes parámetros para configurar la simulación, como el número de pacientes, el número de camas disponibles, etc. En base a las

pruebas realizadas y las mediciones obtenidas, se concluye que el modelo de propagación de la enfermedad relativo al tiempo y área de contacto de los pacientes tiene mayor precisión que el modelo puramente estadístico de la unidad de cuidados intensivos.

**Palabras claves:** Simulación Sistemas de Salud ABMS.

### 1 Introduction

This analysis stems from the present needs in health services with a focus on hospital emergency services, where great complexity is observed.

The growing demand for emergency medical care, mostly due to the progressive growth of aging, increased life expectancy and greater number of chronic diseases, the management of emergency departments is increasingly important. Particularly, the increasing number of patients entering into the service is one of the most important problems worldwide, requiring a substantial amount of human and material resources, which are often limited. The management and coordination of these resources becomes a critical point [1] [2].

As a consequence of this increase of patients, the service saturation is produced [3]. Several previous simulation works were made in order to approach the management of emergency rooms [4] [5].

In addition to this, the loss of medical care effectiveness in saturation scenarios, it also produces an increase in intrahospital diseases propagation. According to data published by the European Center for Disease Prevention and Control [6], about 7.1% of patients acquire at least one intrahospital infection during their stay. In response to this, some simulations works oriented to analyze and predict the emergency rooms intrahospital propagation were developed [5]. Based on them, this work is focused on analyze and test a more complex propagation model, dependant of distance between patients, and the time of stay in the room, explained in next sections. According to

this problem, a simulator was developed as a tool to recreate a large number of scenarios and make agile decisions in the planning of a real emergency room system.

This simulator focused on the point prevalence of intrahospital infections in an emergency room and how it is affected by different factors related to hospital management.

To carry out the simulator modeling, the Agent-based Modeling and Simulation (ABMS) [7] paradigm was used. There are similar works done with the Netlogo framework [5][8]. In this publication, the framework used is Repast Symphony [9], a specialized tool in ABMS, which is more powerful than Netlogo, regarding the modeling and implementation of agents. Furthermore, in the present work, a spatiality and time-dependent disease propagation model—more complex than the models of previous purely statistical works—is implemented and studied. Thus, different intervening agents in the emergency room environment—patients and doctors, among others—were classified.

The behavior adopted by the agents is fundamental in this process, since the spread of the intrahospital infection will be modeled by interactions between these agents. For example, one of the most important sources of infection are waiting rooms, which are likely to be overcrowded. The most effective way to calibrate the simulator is through the greater or lesser interaction of agents, and thereby adjusting the rate of transmission of the disease.

The user belonging to the health system has different data to configure the simulation, such as the number of patients, the number of available beds, etc. When performing different runs or executions, you can obtain results by analyzing different possible bottlenecks, configuring the number of available clinicians, the number of receptionists in charge of admission, triage, among others. In this way, decisions can be made regarding the allocation of resources and personnel to speed up the hospital stay of patients and avoid contagions as a result of their interactions.

The developed simulator can be included in future projects, given its possible scalability for more complex emergency rooms where a large number of statistics can be produced and thus reliable and fast results can be obtained.

This work is organized as follows: in section 2 the data collection. Then, in section 3 the model of the emergency room and the spread of diseases is presented. Next to it, section 4 contains the validation, calibration and verification of the system. In section 5, the simulator results are shown. Finally, in section 6, the conclusions and future works are developed.

## 2 Data collection

The data in the health area has restrictions because of being sensitive or private. Therefore, the amount of

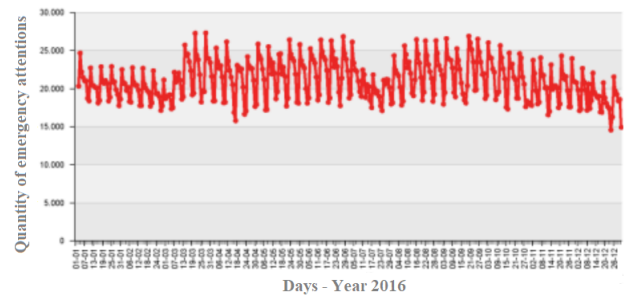


Figure 1: Income of patients provided by the DEIS in the year 2016.

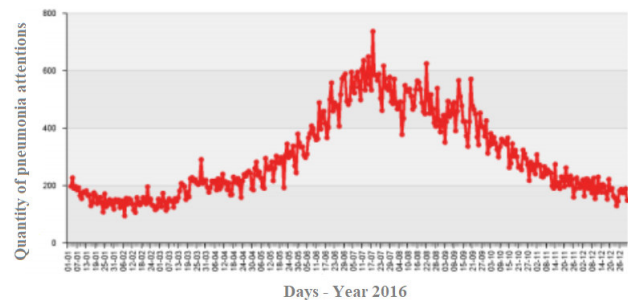


Figure 2: Income of patients with pneumonia provided by the DEIS in the year 2016.

data and all the desired metrics are not obtained. Due to this problem, a data pool from various sources was built, to fill in the missing information.

The data pool is divided in two groups. The first one is related to the emergency room and the health care, containing the necessary data for the modeling and design of the emergency room. The second one, linked to an intrahospital disease, has the data of an specific illness.

In this work, the second group contains data for the pneumonia, due to its great presence in the emergency rooms. If the study of another disease is required, the system will be re-calibrated with the data related with this hypothetical illness, as long as, it fits with the contagion model proposed below.

As an example, some of the most important distributions used are shown below. The income of patients by year to the emergency room is observed in the Fig. 1, this data is provided by the Department of statistics and information of health of Chile (DEIS) [10].

Also, another important data given by the DEIS is the income of patients with pneumonia, in the year 2016. It can be observed in the Fig. 2.

The distribution used for internal assignments of medical care is shown in the Table 1. This data was constructed based on the "Estudio de las prevalencias de infecciones nosocomiales en España" (EPINE)[11].

Table 1: Distribution of patients by area, provided by the EPINE for the year 2016.

Area	Patients	Percentage(%)
Surgery	12691	29,2939085
Consulting rooms	19260	44,4567551
Pediatrics	2224	5,1335318
Intensive care	3064	7,0724557
Obstetrics/gynecology	3288	7,5895021
Geriatrics	820	1,892759
Psychiatry	1976	4,5610876
Total	43323	100,00

### 3 System Modeling

#### 3.1 Emergency room

In order to develop the simulation, a theoretical emergency room model was built. In first place, a functional analysis was made with the data available [12] [13]. The result was an admission area next to a Triage and a waiting room. Behind them, the clinical consulting rooms can be found.

Along the waiting room, different specialties consulting rooms are available. The decision of which specialties would be included in the system was taken with regard to the data collection [14].

At this point, a restriction to the system is necessary. In this work, the model will be bound only to single services, in other words, a patient will make use of one specialty service in the same visit.

The consulting rooms will include the services related to medical specialties and the intensive care room will attend its own admissions.

After studying the data, five specialties were chosen for the emergency model, apart from the consulting rooms and the intensive care room. The criterion considered the five most important specialties in terms of quantity of patient admissions. Therefore, the resulting specialties were: surgery, pediatrics, obstetrics / gynecology, geriatrics and psychiatry. Based on the collected data [11], and the previously imposed restrictions, the distribution of patients is obtained considering both specialty and the hospital attention model.

The intensive care unit needs to be attached to the emergency room model in order to observe the evolution of this critical area for the contagion of intrahospital diseases, and to study the behavior of the punctual prevalence and mortality in this room.

Based on the data, inpatient rooms are usually the rooms that are farther from the consulting rooms and the waiting room. Thus, a decision was made to add the intensive care room at the far end of the admission area.

Based on what has been analyzed in the structures of the observed health centers [12] [13], together with the criterion explained above, the functional distribution is to be constructed as follows. First of all, next

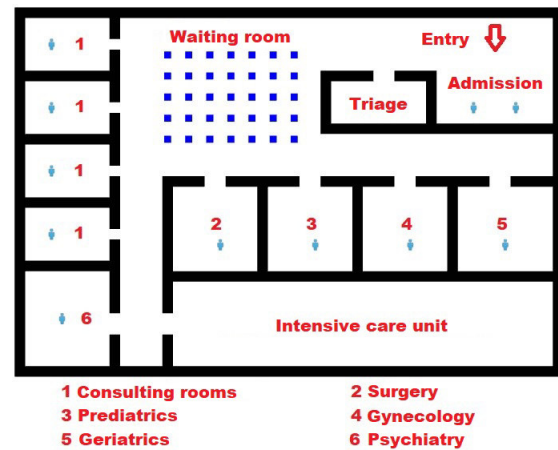


Figure 3: Structural model of the emergency room of the developed simulator.

to the entrance of the emergency room, the admission area with the corresponding receptionists is found. Adjacent to the admission area, the triage and waiting room are found.

Then, next to the waiting room the consulting rooms are found. These will be the closest to the waiting room while the other specialties will be distributed in the remaining space, with the intensive care unit as the farthest specialty from the admission area. With all the observations considered, the emergency room model in Fig. 3 is proposed.

##### 3.1.1 Triage

A triage room was modeled with the following characteristics. In the first place, there are different cases in the admission process. There are patients who can go through triage, and others who are directly distributed to their corresponding care unit. By the worst-case criterion, the model imposed as a restriction that all patients will pass through this room, without exception.

In triage patients queue as they check in on a first-come-first-serve basis. Once in the queue, they wait until they are attended.

Regarding the triage stages, based on the data collected [15], four functional stages are observed: reception, assessment, classification and distribution. Of these four stages, only the first three present personnel in charge. That is, once the classification is finished, the distribution stage is carried out by the same personnel of the classification stage. The patient is informed of the steps to be taken and the distribution runs its course in the emergency room with no staff in charge. Therefore, only the personnel corresponding to the first three stages of triage will be taken into account, and the fourth will be included within the system's flow of patients.

For the model of each triage stage, the Box agent was modeled. It used the client-server paradigm and is

responsible for unqueuing the patients from the aforementioned queue.

In a real triage system, the stages work as a pipeline, moving patients from one stage to another until the process is complete. In this case, the model was simplified, and each Box has the task of carrying out the complete care service of the triage and not just one stage. That is, the patients will not move between Boxes, including all the time corresponding to the three stages. As a consequence, it is necessary to run three boxes in parallel, thus allowing three parallel care services with the necessary duration, thus obtaining similar results in terms of care services as with the serial pipeline model. Although the number of boxes will be set at three, this number will be left as an input parameter allowing user configuration. In this way it will allow to re-create scenarios of increase or decrease of personnel.

According to the data obtained [16], the maximum duration of attention service in triage is fifteen minutes. By the worst-case criterion, this care service time will be the same for all patients undergoing triage. Once the attention is finished, it should be possible to determine both the next room of the patient and its priority. To determine the next attention service, the distribution according to specialty explained above is used. When the patient is assigned to a certain area, he queues, with the exception of the intensive care unit, where care service is immediately executed. When the process is completed, a triage level is assigned for the patient, depending on the severity of their situation.

Based on the obtained data [16], the values with the percentages that are used as a decision criterion in terms of probabilities for each level are constructed. The patient queue in their corresponding care unit, depending on the level of urgency assigned. Those of level 1 will be the highest priority and those of level 5 the lowest priority, together with their maximum waiting time. When two or more patients are found with the same priority, the queue is arranged according to in the order of arrival.

### 3.1.2 Intensive care unit

An intensive care unit was modeled, which behaves differently from the other rooms. The highest interest in this work lies in the waiting room, as the internal traffic of people in intensive care was considered insignificant.

As regards hospital care, the behavior of patients is connected with the selection of a bed and their hospitalization time from beginning to end. If beds are not available, the patient must be withdrawn and is counted as a rejected patient due to lack of resources.

Based on the collected data [10], the percentages of patients are calculated according to the hospitalization days used for the model implementation.

## 3.2 Disease spread

A correct model of disease spread requires the consideration of multiple factors. It consists of two types of contagion: the direct and the indirect [17].

In the first place, direct contagion depends on the number of interactions that people have, as well as their duration. In addition, the distance factor is derived from the previous, to consider if an interaction occurred or not.

To represent flexibility regarding the number of interactions and their duration, the interactions were limited to having a duration of one tick of the system clock. There-fore, to recreate interactions whose duration must be several ticks, it is necessary to execute multiple interactions, one per tick.

Assuming the hypothetical case in which a clock tick is one minute, it is required to recreate an interaction of 15-minute duration, so the result will be the execution of an interaction 15 times, with intervals of one minute between them. Given this example, in the case of an interaction of 14 minutes 59 seconds, the inter-action referred to one minute will be executed 14 times, and it will represent an inter-action of 14 minutes. As a consequence, 59 seconds of interaction would be lost.

Therefore, it is concluded that for this model, it is essential to take into account that the choice of the tick of the system will affect the precision of the model. It can also be concluded that the higher the precision of the model, the more computing re-sources are required.

Because of the previous conclusion, the tick was set in ten seconds. This choice was made following a practical criteria, the smaller tick possible for the hardware available. In this case, 50 runs of simulation has a duration of five to six hours, depending the parameters entered. Up to this point, it was decided that more time to get results would be unpractical in the day to day work.

When analyzing the area factor, if direct contact transmission is taken into account, the distance is practically a few centimeters. If the droplet transmission mechanism is included, it will involve a higher area.

This mechanism has a greater scope than direct contact. According to the collected data [18], the recommended minimum distance with an infected person is one meter to avoid contagion by droplets. It is also clarified that with this distance there is a probability of contagion, depending on the disease and the given situation. That said, the following restriction will apply. A distance of two meters will be applied as the upper bound, that is, twice the recommended one. For a two-meter distance, it will be assumed that the possible contagion is negligible and will not be taken into account.

In addition, depending on the distance to the infected person, the probability of being infected varies. The closer a healthy patient is to an infected one, the more likely the healthy patient is to become infected.

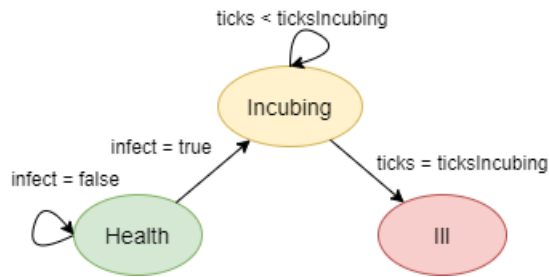


Figure 4: Moore's state machine 'State of health'.

Another restriction will be added: within two meters, the probability of infection will be uniform.

Transmission by air and vectors is not included in the model, since they are considered negligible with respect to the other types of contagion. Up to this point, interpersonal interaction was taken into account, but the model regarding indirect infections has not yet been explained. Objects will be included in the model, as they will have the capacity to become contaminated and infect patients.

Although it is an indirect contagion, the development of this contagion is by contact. Therefore, it was decided that contagion by indirect contact will have the same probability as contagion by direct contact. In indirect contact, an interaction will only be considered when a person directly touches the object. The chance of infection will be a calibration parameter of the system. In this way, depending on the disease studied, this probability can be adapted to achieve the necessary behavior and thus obtain results.

The desired behavior for contagions was explained. However, there is still the problem of representing this behavior in multiple patients, objects and other people that can be included. The strategy to be used to solve this problem is to use state machines to recreate said behavior. Thus, when designing a state machine, the same model of contagion replicated in multiple people can be obtained. Two Moore state machines were designed to represent contagions. The first is the Moore state machine 'State of health' shown in Fig. 4.

- **Healthy:** a state in which the person is capable of contracting a disease but cannot spread it.
- **Incubating:** a state in which the person contracted an in-hospital disease but shows no symptoms yet, being in an early stage of said disease. The patient can infect other people and contaminate objects.
- **Sick:** a state in which the person contracted an in-hospital disease and shows symptoms and can therefore start treatment. The patient can infect other people and contaminate other objects.

Another state machine that intervenes in this process is the 'Object' machine, which will be the main responsible for indirect contagions and contamination of objects.

The Object machine consists of two states:

- **Clean State:** the object is not infected; it can be infected by a person but does not have the ability to infect anyone.

- **Infected State:** the object was contaminated by a person, therefore, it has the ability to infect people who come in contact with it.

Any person who has the "State of health" state machine may be a participant in the disease spread process, as well as any element that has the "Object" machine. Both machines have the ability to communicate with others 'Health status' or 'Object' states machines.

Communication skills represent the interactions that influence contagion. The machines will be aligned to the tick of the system, representing the duration of the interactions through an interaction per tick. In addition, the machines allow multiple interactions at the same tick of the clock, that is, a person can be interacting with more than one infected patient or object at the same time, depending on the situation.

### 3.2.1 Disease spread in the intensive care unit

In the case of the intensive care unit, the developed model does not cover its internal movement. Therefore, the model presented is not the best in terms of interactions, duration and specific areas.

Indirect contact contagion does not undergo model modifications in this room. Despite the absence of movement, there are interactions between patients and objects, more specifically with the beds.

Direct contact and by droplets will be reduced to a purely statistical model, as the necessary data is not available to use the previous model within the intensive care room. It was decided that the infection criterion will be that each healthy patient in the intensive care room has a chance of infection proportional to the number of infected patients in the room. From this previous analysis, equation 1 was proposed.

$$P = n * ICUInfectionChance \quad (1)$$

A new calibration parameter can be observed, 'ICU Infection Chance'. As it is a new model with a different behavior, it should be calibrated in parallel with the general model of the emergency room, to obtain results with the minimum possible error.

The state machine presented in Fig. 5 will continue to be valid including this model in its execution. That is, the machine will use the model explained in the previous section as long as it is outside the intensive care unit. Once the machine detects that it has entered the intensive care unit, it will start using the model explained in this section.

Analysis of the spread of disease is very important in this room for two factors. First, the punctual prevalence in intensive care units is usually much higher than other areas, due to long hospitalization times.

Secondly, the number of deaths resulting from the intrahospital spread of diseases can be studied. In other

words, the seriously ill in this room, upon contracting an intrahospital disease, significantly increase their mortality rate.

To carry out this analysis, the simulator will have a user-configurable input, which will be the mortality for a given disease. In this way, it is possible to study the evolution of the number of deaths derived from hospital diseases with respect to other factors, for example, hospital administration factors such as the number of available doctors.

### 3.3 Agent modeling

For the complete modeling of the system, multiple agents were designed with different objectives, among them are doctors, specialists, receptionists, patients, cleaning personnel, beds and chairs. These agents are the ones who carry out the main tasks involving disease spread and take part in the hospital attention process.

The patient agent is the only mobile agent in the system, a vital factor for the disease spread model.

This agent has the 'State of health' state machine incorporated into its model. In other words, it will have the necessary behavior to interact with other agents that have this machine or the 'Object' machine.

It will proceed to focus on the model of hospital care of the patient, basically, it is what will determine their movement throughout the emergency room and their waiting time. To model this behavior, the 'Patient' state machine in Fig. 5 was designed.

In this model, the machine states are synchronized with the system tick. For each tick, each patient has a task to do. Besides, through his health care, this agent can decide between different possibilities, in a non deterministic way. To achieve this, the patients, and all the agents involved in the system, have probabilistic distributions to follow, provided by the data collection.

Therefore, the patient can be assigned to different health cares, to be rejected for lack resources, to die in the intensive care unit, to get ill by an intrahospital disease, among other possibilities.

The states corresponding to the 'Patient' state machine in Fig. 5 are explained below:

- Initial: the initial state in which the patient enters the hospital.
- Reception: upon entering this state, the patient goes to the Reception room. There, the admission is made, which lasts one minute. This was decided by imposing a restriction to obtain an upper bound. When the admission ends, the patient is released by the receptionist and the Waiting Triage state is set.
- Triage: upon entering this state, the patient goes to the Triage room. Once there, the first diagnosis is made and his next destination is chosen. This diagnosis is carried out in fifteen minutes. In addition, it receives a priority level. The next state will be Waiting (one of its variants), or it goes directly to the Hospitalization state, as appropriate.

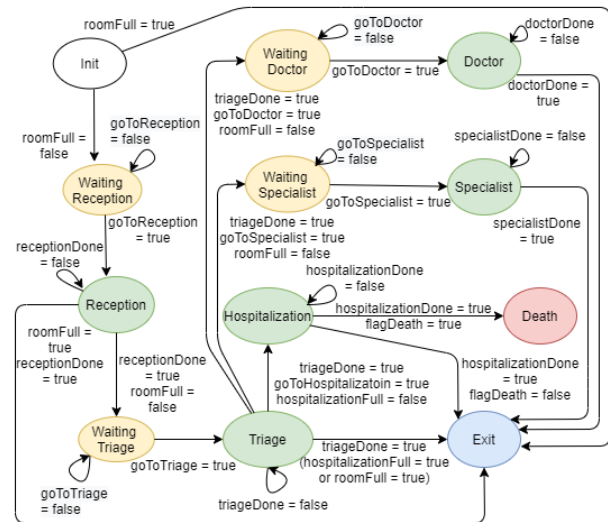


Figure 5: Moore's state machine 'Patient'.

- Doctor: in this state, the patient was selected by the Doctor agent to be treated, said patient will go to the office that was assigned. The attention lasts for 15 minutes. When the attention ends, it goes to the Exit state.

- Specialist: once this state has started, it means that the patient was summoned by the specialist who was assigned in the Triage. He goes to the corresponding room and remains there performing the attention for 15 minutes. At the end of it, the Exit state is set by the patient.

- Hospitalization: in this state, the patient goes directly to the hospitalization room. In the event that the room is full, that is, there are no beds available, the patient is rejected due to lack of resources and the Exit state is set. The length of stay of the patient is decided in terms of probability using the data collected [10]. During that time the patient will be occupying a bed, once that time is over, the hospitalization is over. There are two possible outcomes, the first is to continue towards the Exit state, in which the patient withdraws upon discharge. The second possible outcome is the death of the patient. The particular case in which the patient was hospitalized and later contracted an in-hospital disease is analyzed. In this case, the patient has a chance of dying. If indeed the patient dies, the Dead state is set.

- Dead: in this state, the patient will count the metrics that correspond to his death and the agent will be eliminated.

- Exit: in this state the agent leaves the room in which he was attended, and goes directly to the exit. Once it gets there, the count of the metrics for this agent is made and then the agent is removed.

- Waiting: it is a state where the patient goes to the waiting room, chooses a seat randomly, where he remains until he is selected by a member of the staff to continue his attention. It was decided to separate this

state into several states, one for each part of the care service. In this way, it seeks to know more precisely in which part of the attention the patient is and what is the resource for which he is waiting, as well as the waiting times.

The patient selects the corresponding Waiting state and queues in the queue associated with the required care, waiting to be summoned.

As an example, the state transition diagram of the state Triage is shown in Table 2, being the state with more transitions available in the model.

#### 4 Validation, calibration and verification

In order to validate the system, the spiral development model was used. Therefore, for each iteration the model design, implementation, results and data collection are refined.

To calibrate the system, the input parameters "Infection chance" and "Infection chance in intensive care" are used. These two are modified to achieve the desired annual punctual prevalence outputs and, consequently, the rest of the results derived from it. In this process, data from the year 2016 is used, within the data set collected [11] [10].

The other input parameters remain static within the calibration process. To decide their values, the data collection is consulted. They can be observed in the Table 3 and Table 4. In the Table 5, the description of these parameters is shown.

In the Table 6, the averages of the outputs obtained during the calibration process are shown. These values are averages of 50 runs of simulation, being the annual punctual prevalence the most important in the process.

Finally, the verification process was similar to the calibration process, using the data corresponding to the year 2017, belonging to the data set collected [11] [10].

#### 5 Results

To obtain the results, similarly to the calibration process, 50 simulation runs were executed for each data input configuration to minimize statistical error.

Before obtaining results, the system was calibrated and verified with the collected data, obtaining a reliable system. As a case of study, the simulator was calibrated focused on the pneumonia, a classic intrahospital illness. Calibration is used as a base case, in terms of configured inputs and obtained results, which was also performed by means of 50 runs. Then one or more parameters are varied in order to study the evolution of the system. For reasons of space and ease of reading, this paper will include different graphs made from the tables generated by the outputs.

In order to study the saturation points, the experimentation criteria is focused on varying the input

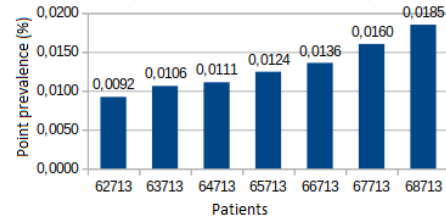


Figure 6: Averages of the results varying the patients admitted during one year.

parameters to excite the system, and analyze the scenarios where the saturation is maximum. When the saturation points are found, contingency plans for the saturation scenarios can be studied and tested if the current model let them. In future works, more saturation scenarios and contingency plans can be added to the model to achieve more complexity and reduce error.

In the first place, the behavior of the system was studied before the variation of patient entry. The base case of 65,713 patients was taken, then this entry varied at the rate of a thousand patients. The averages of the runs for each entry can be seen in Fig. 6.

In Fig. 6, an increase in prevalence can be observed as the number of patients admitted within a year increases. Regarding the specific prevalence in the intensive care unit, it is observed that it remains constant, this is due to the fact that the emergency room is already saturated and rejects the extra patients who may need it. Similarly, deaths remain constant as the number of patients evolves.

Regarding the origin of the infections, it can be observed that the percentage of patients infected by the staff decreases. Although in absolute terms the infections by the staff increase, the increase is slower than the infections by the patients and the objects. This shows that as patients increase, the waiting room begins to have more relevance in infections.

The rest of the indicators analyzed remain relatively constant with respect to the variation in the number of patients.

The behavior of the system is studied by varying the number of clinical doctors who are available to provide care. The averages of the corresponding results can be observed in Fig. 7.

In Fig. 7, an increase in point prevalence is observed as the number of clinical doctors available for attention decreases. In the range between 4 and 2 doctors, growth is slow, but an exponential jump is noted when going to 1 available doctor.

The prevalence for 2 doctors is 1.24% and with one doctor it jumps to 23.77%. As for the point prevalence in intensive care, it increases slightly from 3.39% to 3.74%, also having an increase in deaths from 20.58 to 29 deaths.

To study the origin of the exponential jump seen, it

Table 2: State transition diagram of the state Triage.

<i>x/State = Triage</i>								
triageDone	F	T	T	T	T	T	T	T
roomFull	X	X	T	T	T	F	F	F
hospitalizationFull	X	T	X	X	X	F	X	X
goToDoctor	X	X	T	F	F	X	T	F
goToSpecialist	X	X	F	T	F	X	F	T
goToHospitalization	X	T	F	F	T	T	F	F
Next State	Triage	Exit	Exit	Exit	Exit	Hospitalization	Doctor	Specialist

Table 3: Inputs for hospital care configuration

<i>Hospitalcare</i>	
First day	1
Num beds	90
Cleaning staff period (hs)	24
Num boxes	3
Num days	365
Num doctors	2
Num patients	65713
Num receptionists	1

Table 4: Inputs for intrahospital pneumonia

<i>Pneumonia</i>	
Immunity chance (%)	81
Intensive care mortality (%)	25.5
Max incubating time (hs)	144
Min incubating time (hs)	24

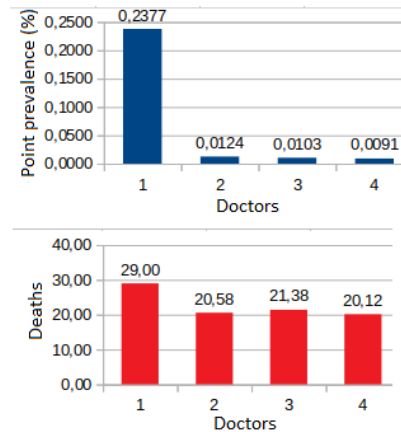


Figure 7: Averages of the results varying the number of general doctors available.

can be analyzed from the point of view of the origin of contagions. Although all types of infections increase in absolute terms considerably, the one that increased the most above the others is indirect contagion through objects, representing 65.79% of total infections.

The rest of the indicators remain relatively constant, with a slight increase in rejections in the waiting room due to its saturation.

Then, the attention capacity of the triage is studied by changing the number of boxes that are available. The results are reflected in Fig. 8.

Fig. 8 shows the evolution of the indicators regarding the number of boxes available in the triage. In the range between 3 and 6 boxes, there is a constant point prevalence, similarly with the point prevalence in intensive care and with deaths in this room. The rest of the indicators are also constant in this range.

Going from 3 boxes to 2, there is a slight increase in the point prevalence from 1.24% to 1.37%. The prevalence in intensive care went from 3.39% to 3.44%, with an apparently constant behavior and deaths which similarly remain constant. No major changes are found in the rest of the indicators in this case.

When going from 2 boxes to 1 available box the

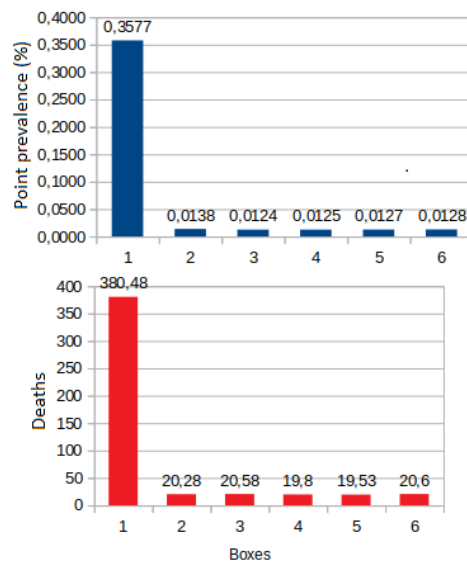


Figure 8: Averages of the results varying the number of triage boxes available in parallel.

Table 5: Descriptions of input parameters

<i>Parameter</i>	<i>Description</i>
Cleaning Staff Period	Defines the period of cleaning, the minimum is 1 clean/hour, and the maximum is 1 clean in 24 hours
First day	Defines the first day of the simulation, the day 1 is equal to the January first. According to the period of time simulated, the distribution of patients varies
Num beds	Quantity of beds available in the intensive care unit
Num boxes	Quantity of boxes available in the triage room
Num days	Quantity of days in a simulation run, the minimum is 1 and the maximum is 365
Num doctors	Quantity of clinical doctors available
Num patients	Quantity of patients in the emergency room along the period of time set, related to the quantity of days simulated
Num receptionists	Quantity of receptionist available for admission
Immunity chance	Immunity chance of the vaccine used for the illness studied, in this case the pneumococcal vaccine
Intensive care mortality	Intensive care mortality of the illness studied. In this case, the pneumonia mortality in ICU is not available in the data set, because of this, the mortality in ICU by intrahospital illness is used, being this data a media of all intrahospital diseases. In future works, this value needs to be replaced
Max incubating time	The maximum incubating time of the illness studied
Min incubating time	The minimum incubating time of the illness studied

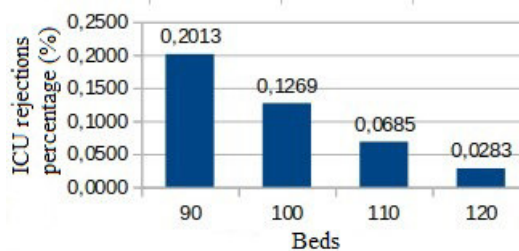


Figure 9: Averages of the results varying the number of beds available.

change is drastic, the point prevalence jumps exponentially from 1.37% to 35.77%. The prevalence of intensive care goes from 3.44% to 19.15% and absolute deaths go from 20.28 to 380.40, increasing its value approximately 19 times.

If the origin of the infections is analyzed, again in a similar way to the case of the doctors, indirect infections are the main responsible for the exponential increase, going from 15.85% of the cases with two boxes to 52.65% of the cases. cases with a box.

Regarding the rejections in the waiting room, a radical change is seen, going from 0 rejections to 4122 rejections recorded, with a rejection rate for a single available box of 6.27%, the highest registered so far.

The behavior of the system is studied varying the number of beds available. They can be found in Fig. 9.

In Fig. 9, the simulation results are observed by

varying the number of beds. Regarding the rate of refusal of patients in intensive care, it dropped from 20.12% with 90 beds to 2.82% with 120 beds. It took a 33.3% increase in the number of beds to achieve an acceptable rejection rate.

Analyzing the Bridgman formula [19] (see equation 2), an optimal bed occupancy rate of 85% was used for calibration, which was the recommended value.

$$NBeds = \frac{Discharges * AverageStay}{365 * OptimalOccupancyIndex} \quad (2)$$

A new optimal index was calculated using the value of 120 beds as a parameter and the value of 63.66% was obtained.

It proceeded to study the results of the simulation by varying the cleaning intervals of the personnel. These can be seen in Fig. 10.

In Fig. 10, it can be seen that as the cleaning frequency increases, the point prevalence falls slightly, the same happens with the point prevalence in the intensive care unit.

Likewise, in the best case, the prevalence drops to 1.09%, starting from the base of 1.24% in the case of calibration. Considering the frequency was multiplied by 24, it is not a major gain. This is because the influence of indirect contagion in this scenario is 13.51% in the base case of calibration. That is, it does not influence the total contagion too much. Likewise, the indirect contagion by objects fell from 13.51% to 0.56%. In the best case, it was practically eliminated.

Table 6: Media and standard deviation of 50 outputs for annual runs of simulation, with the calibration inputs.

<i>Output parameter</i>	$\mu$	$\sigma$
Infected patients	817.72	176.4707387
Punctual prevalence(%)	0.012443809	0.002685477
Intensive care total patients	3706.78	46.95073588
Intensive care infected patients	125.8	55.83618898
Intensive care punctual prevalence(%)	0.033981458	0.015187583
Infected patients deaths at intensive care	20.58	9.658343543
Intensive care mortality of infected patients(%)	0.249156973	0.055991907
Total infected patients by personal	157.46	154.90942
Percentage infected patients by personal(%)	0.168195537	0.154762204
Total infected objects	320.74	55.66643872
Total infected patients by objects	109.3	38.16870446
Percentage infected patients by objects(%)	0.135113751	0.044283977
Total infected patients by other patients	425.2	70.63625132
Percentage infected patients by other patients(%)	0.538341956	0.11806517
Intensive care rejected patients	935.2	85.2417738
Percentage of rejections at intensive care(%)	0.201270937	0.015790882
Waiting room rejected patients	0.28	1.132077736
Percentage of rejections at waiting room(%)	4.26095E-06	1.72276E-05
Out of time patients	1225.02	37.84996169
Percentage of out of time patients(%)	0.018641973	0.000575989

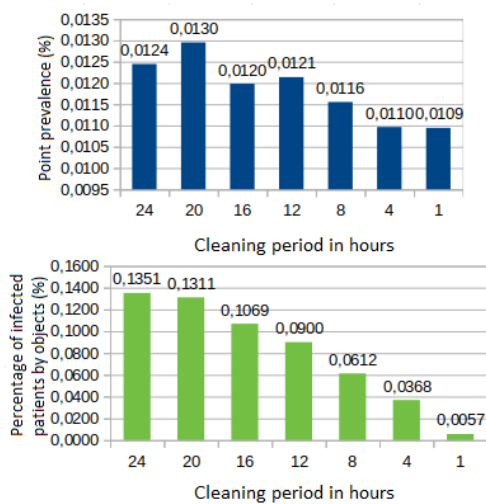


Figure 10: Averages of the results varying the interval between consecutive cleanings.

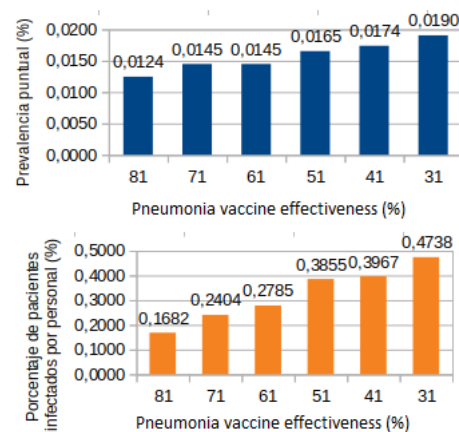


Figure 11: Averages of the results varying the effectiveness of the pneumococcal vaccine.

The rest of the indicators remain constant, a logical consequence since they are not related to this input parameter.

The study proceeds with the results corresponding to the variation in the effectiveness of the pneumococcal vaccine, being 81% the calibration value, according the data collected [20]. In the present model, this vaccine is applied only to health personnel. The associated results are in Fig. 11.

Given the results of Fig. 11, a progressive increase in the point prevalence is found as the effectiveness of the given vaccine decreases.

In the same way, the participation of personnel in contagion increases, going from 16.82% for 81% ef-

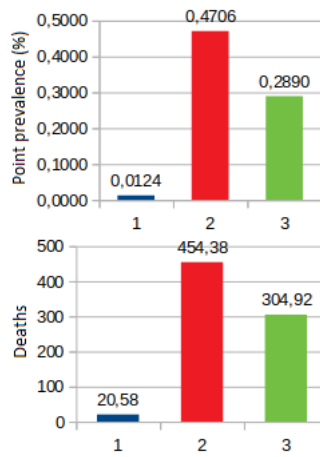


Figure 12: Average of the results in different scenarios. 1. Calibration case. 2. Worst case: 1 box y 1 doctor available. 3. Worst case with cleaning period in one hour.

fectiveness to 47.38% with 31% effectiveness. Given the model where staff are the only vaccinated, it is a logical consequence.

The rest of the indicators remain constant since it has no relation to this input parameter.

Given the scenarios studied above, it can be concluded that the greatest risks of infections are in the decrease in the number of doctors and the number of boxes, which by minimizing their number produce exponential jumps in infections. Consequently, it is necessary to recreate the worst possible case in terms of care services, setting both the doctors and boxes with the value 1. The rest of the parameters remain with the values acquired in the calibration. The results of this scenario can be seen in Fig. 12.

In Fig. 12, the data obtained for the scenario of 1 box and 1 doctor available (case 2) are observed. In this scenario, it is obtained that the point prevalence scales to 47.06%, the highest value obtained. As for absolute deaths, it reaches 454.38 deaths.

In terms of the origin of the contagion, in a similar way to the cases previously studied, when there is saturation, the indirect contagion scales to the first place, in this case with 60.31% of the infections. In addition, the rejection rate in the waiting room increased to 8.09%.

Given the worst scenario, whose main problem is indirect contagion, we proceed to study how this scenario evolves by scaling up the frequency of staff cleaning. In previous scenarios, with a frequency of one cleaning per hour, indirect contagion was practically eliminated. In Fig. 12, particularly in case 3, the results obtained for the case with 1 box, 1 doctor and the best available cleaning period are found, that is, 1-hour interval between consecutive cleaning.

In case 3, a significant decrease in the indicators can be observed when compared with case 2. The

point prevalence falls from 47.06% to 28.9%. As for the number of deaths, it fell from 454.38 to 304.92. This is due, as expected, to the control of indirect contagion, participation in the contagion falls from 60.31% to 7.42%.

## 6 Conclusions and Future works

Based on the tests carried out and the measurements obtained, it is concluded that the disease propagation model relative to the time and contact area of the patients has greater precision than the purely statistical model of the intensive care unit. The results show a difference of two orders of magnitude.

From the measurements obtained, it can be concluded that, focusing on the precision of the model, a variance for the point prevalence of 7.21 was obtained. 10-6, while the variance of the point prevalence in intensive care is 0.00023066.

Another conclusion based on the results analyzed is that the greatest risk for the spread of contagion is the loss of active personnel in the emergency room. In particular, if the staff in consulting rooms is halved, the point prevalence can climb to 23.77%.

In triage, if the staff is reduced to a third there is an increase in the point prevalence to 35.77%. Analyzing the combination of both cases, a point prevalence growth is obtained that reaches 47.06%.

Although, in terms of deaths, the mortality data in intensive care was used in this study for all intrahospital diseases and not only for pneumonia, the growth of deaths in relative terms can be analyzed.

The calibration scenario presents 20 deaths per year. The case of an available doctor presents 29, an increase of 45%. In the case of a single box in the triage, 380 deaths resulted, an increase of 1900%. Analyzing the worst case, that is, the combination of both cases, 454 deaths resulted, an increase of 2270%.

In addition, it is concluded from the analyzed results that the main cause of the exponential increase in point prevalence when there is a saturation is indirect contagion. This increased from 13.5% in the case of calibration to 60% in the case of higher saturation.

Although prevention is essential to avoid reaching this situation where the emergency room is totally saturated, the increase in cleaning personnel can be used as a contingency plan, to keep the room continuously sanitized.

In the worst case of saturation, it went from one cleaning every 24 hours to one cleaning per hour, obtaining a reduction in the participation of indirect contagion to 7.4%.

Consequently, a reduction of the point prevalence is obtained, which became 28.9%. Deaths fell from 354 to 305, a decrease of 32.82%.

Although there is a notable reduction, it must be taken into account that there are still high values of point prevalence and deaths with respect to the cali-

bration scenario. In addition, the best possible case was taken, where the cleaning frequency increased 24 times, a number somewhat excessive for real scenarios. Therefore, it is claimed that although it may be a good contingency plan, the best option remains the prevention of this situation.

During the calibration process, based on the collected data [19], the Bridgman formula was used to calculate beds for the emergency room.

Within this formula, as seen above, is the optimal occupancy rate, which according to the literature, a margin of 15% is recommended, that is, a rate of 85%.

By performing multiple simulation runs with this value, an indicator of rejection of patients in the intensive care room of 20% was obtained for the calibration scenario. Analyzing the behavior of rejections daily, it was possible to observe their concentration during winter, the season where there is a greater admission of patients, given by the distribution collected in the bibliography [10].

The margin of 15% as a theoretical value can be useful if it is assumed that the distribution of patient admission tends to be uniform. In practical cases, a notable increase in patients is obtained in winter, therefore, a higher margin is required to cover the admission of these patients.

The calibration scenario had 90 beds, a value obtained by the Bridgman formula. When simulating different numbers of beds, the value of 120 beds was obtained, which gives the emergency room a rejection rate in intensive care of 2.82%. That is, 33.3% more beds than recommended.

Using Bridgman's formula, a new optimal occupancy rate of 63.66% was calculated. It is recommended to use this value for the calculation of beds to obtain a rejection of less than 3%.

The main future work is the model extension, improving aspects such as cleaning staff, direct intervention by nurses in contagion and care. Besides, modeling contagion caused by mechanical ventilation, adding movement and direct health care to the intensive care room, among other possible extensions.

This includes the collection of homogeneous data sets, coming from hospital institutions, approximating and modeling real emergency rooms.

In addition, another important work to be carried out is related to the acceleration of the execution of the simulation with specialized tools in simulator parallelization. Based on the simulator implemented with Repast Symphony, tools such as Repast HPC [21] or Flame GPU [22] can be used to achieve an improvement in execution times.

### Competing interests

The authors have declared that no competing interests exist.

### Authors' contribution

L.M. and D.E. analyzed the tools for modelling the system and conducted the experiments. L.M. researched different public data sets about pneumonia in emergency rooms. Also, L.M. implemented the modelling with Repast and wrote the manuscript. All authors discussed the results, read and approved the final manuscript.

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