Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

PLANNING WARD AND INTENSIVE CARE UNIT BEDS FOR COVID-19 PATIENTS USING A DISCRETE EVENT SIMULATION MODEL

Daniel Garcia-Vicuña
Fermin Mallor

Smart Cities Institute
Public University of Navarre
Campus Arrosadia
Pamplona, 31006, SPAIN

Laida Esparza

Department of Critical Care Medicine
Navarre Hospital Compound
Irunlarrea-Str. 3
Pamplona, 31008, SPAIN

ABSTRACT

This paper reports the construction of a simulation model used to support the decision-making concerned with the short-term planning of the necessary hospital beds to face the COVID-19 in Navarre, Spain. The simulation model focusses on estimating the health system's transitory state. It reproduces the outbreak dynamics by using the Gompertz growth model and the patient flow through the hospital, including the possible admission in the Intensive Care Unit (ICU). The output estimates the number of the necessary ward and ICU beds to provide healthcare to all patients for the next days. The simulation model uses expert opinions at the first stages of the outbreak, but as more data are collected the necessary parameters are fitted by statistical analysis or combining both. Every day, the research team informed the regional logistic team in charge of planning the health resources. Based on these predictions the authorities plan the necessary resources.

1 INTRODUCTION

The disease COVID-19 presents an important threat to global health. Since the outbreak in China in early December 2019, the number of patients confirmed to have the disease has exceeded two and a half million and more than 190,000 people have died from COVID-19 infection (up to April 24, 2020, https://coronavirus.jhu.edu/map.html). Regularly updated information on the COVID-19 outbreak is also available on the European Centre for Disease Prevention and Control's (ECDC) website, the European Commission's (EC) website, and the World Health Organization's (WHO) website. This outbreak leads to an important increase in the demand for hospital beds, especially the Intensive Care Unit (ICU) beds, which involve highly specialized personnel and expensive technical sanitary material (the hospitalization bed is still widely used as a hospital management parameter both at strategic and operational level). An efficient prognosis of the necessary resources is needed to provide the best possible care to patients to report to public health authorities. The accuracy of the predictions allows preparing the response and helping to save lives.

The hospital is known to be a complex system evolving in a stochastic environment. The uncertainty is even higher currently because of the lack of knowledge about the spread of the disease and its consequences on patients. In this unsettle context, simulation emerges as a suitable analytical tool, since it is a powerful quantitative instrument for the analysis of complex systems, and can be used in combination with other statistical techniques. The literature contains numerous bibliographical references relating to the use of simulation models for decision making in the healthcare context. Reviews of the use of simulation models in healthcare can be found in (Brailsford et al. 2009; Günal and Pidd 2010; Katsaliaki and Mustafee 2011; Mielczarek and Uziałko-Mydlikowska 2012). The ultimate aim of these models is to reconcile resource availability with demand in order to provide high-quality healthcare to patients while keeping a reasonable

978-1-7281-9499-8/20/$31.00 ©2020 IEEE

level of human and technological resources. Problems analyzed into this framework are patient flow (Shahani et al. 2008; Kolker 2009), bed planning (Ridge et al. 1998; Zhu et al. 2012; Rodrigues et al. 2018), health service design (Mallor et al. 2016) and medical staff scheduling (Erhard et al. 2018), among others. Although discrepancies between assumptions made in mathematical simulation models and behavior of real health systems reported in the medical literature have been pointed out (Azcarate et al. 2020), there is no doubt about the usefulness of simulation models for the analysis of relevant problems in complex health systems.

Simulation models that address these problems are usually designed to reproduce the performance of the health system in its stationary state and evaluate the resource levels, the patient flow management policies, and the decision making process in the long term. The recommendations obtained from the simulation analysis are meant to be implemented in the health system and last for a certain time horizon until environment conditions change or a better solution is found. However, this stationary scenario does not prevail in the current outbreak time, the health system is under extreme stress in the middle of a rapidly changing environment. In this context, the simulation models have to focus on the transition period and being enough flexible to be combined with dynamic forecast models that predict the number of infected patients and learn about the necessary resources to deal with the disease. In this paper, the design of a simulation model that reproduces the behavior of the health system from the current state is presented. It is a discrete event simulation (DES) model that mimics the patient flow of COVID-19 patients through the health system (hospital, home hospitalization, socio-sanitary residence, etc.).

Infectious disease prediction models mainly include differential equation prediction models based on population dynamics (Grassly and Fraser 2008; Brauer and Castillo-Chavez 2012). The individuals of the population are divided into different categories, each one considered as a possible state for the individual: S (Susceptible), E (Exposed), I (Infected) and R (Remove), and the population in each state is calculated over time from the estimation of the transition rates among these states. The currently applied models include the SI model, SIS model, SIR model, and SEIR model. However, these models are complicated and require the estimation of too many factors, which demands many data that currently are not available. Therefore, growth population models suppose a simpler alternative to model the accumulated number of cases. These methods that include the logistic, Gompertz, Rosenzweig, and Richards models, have been already used to model the spread of outbreaks as A/H1N1 and Ebola (Liu et al. 2015). In particular, in our simulation model, the arrival of patients is simulated by fitting a Gompertz growth model to the accumulated number of cases registered in previous days. Parameters are estimated each time a new datum is observed.

The main contribution of this paper is the proposal of a new simulation framework to enable the prediction in the short-term (from days to one month) the need for critical resources to provide healthcare to COVID-19 patients. Our model includes a) the representation of the current state of the health system and the simulation of the system considering all patients already in the system; b) daily prediction of the number of patients that need any sort of hospitalization (home, ward, ICU); and c) flexibility to recreate scenarios based on stochastic models fitted to data (data-driven prediction), scenarios defined by expert judgement and a mixed of both. From a practical point of view, this paper also reports a successful real application of simulation to support an important decision-making process essential for the health of patients in broad regions of Spain. In addition, the simplicity of this simulation model and the lack of local assumptions about the COVID-19 behavior make it usable in any country or region.

The rest of the paper is organized as follows. Section 2 presents the DES model. The estimation of all stochastic elements: patient arrival pattern; length of stay (LoS) in ward, home, and ICU; etc. is explained in Section 3, as well as the starting of the simulation considering the current state of the health system. Results of the application of the simulation model to the Autonomous Community of Navarre (Spain) are included in Section 4. Finally, in Section 5 we discuss the possible enhancement of the simulation model and some conclusions.

2 THE DISCRETE EVENT SIMULATION MODEL

2.1 Modelling the Patient Flow

A COVID-19 patient can access the health system in different ways. Usually, when a person feels some symptoms, he/she goes to primary healthcare or the hospital emergency department, calls to an emergency phone number, he/she is scrutinized in a nursing home, etc. After the first contact is made, the person undergoes a SARS-CoV-2 test (as a *Polymerase chain reaction* (*PCR*) test) whose result can be either negative or positive. In this second case, if hospitalization is required, the person is admitted to the health care system as a COVID-19 patient and depending on the severity of the disease he/she is hospitalized in the ICU, in a hospital ward or at home (home hospitalization refers to those patients who are treated in medical-conditioning beds outside the hospital as hotels or patients' own homes).

These three situations require dedicated resources, material, and personnel, to treat the patient. Especially important are the ward beds and ICU beds. Other important resources, as nurses and physicians, can be calculated from the number of required beds. Figure 1 shows the patient flow through the health system, highlighting the different sources of the arrival of patients and the entry in the hospital of those having a positive result in the SARS-CoV-2 test. Patients can be admitted to the ICU just after being confirmed as a positive case or after some time hospitalized at home or in the hospital ward due to a health worsening. The discharge of the system is because of death, or health improvement.

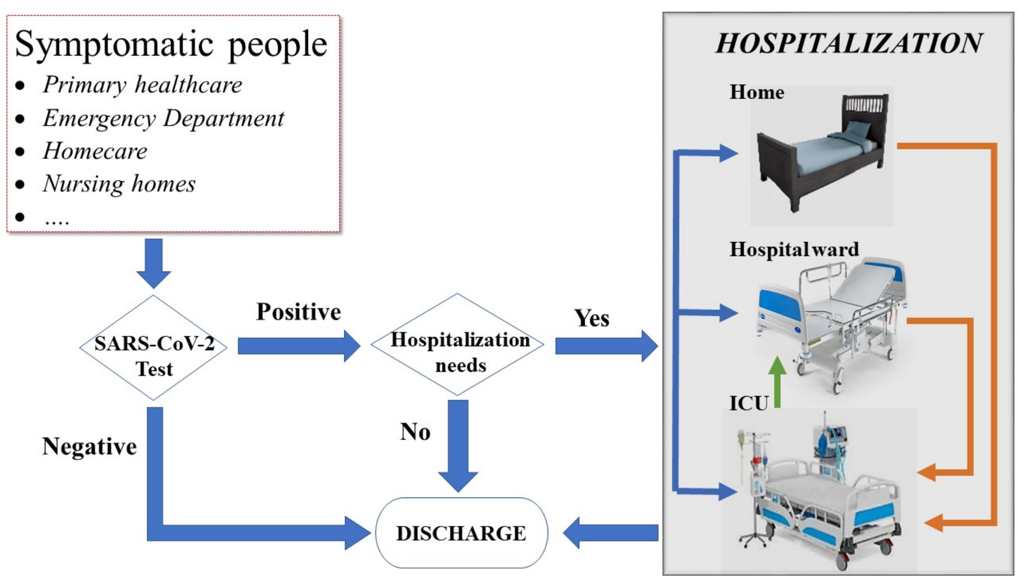

Figure 1: Representation of the COVID-19 patient flow in the health system.

2.2 Main Elements and Events Considered in the Simulation Model

DES model is defined by the set of state variables, which provide at any time a complete description of the simulated system, and the set of events, which modify the value of state variables. The simulation model represents the patient flow through the different ways of hospitalization, that is, the part into the grey box in Figure 1. Therefore, three state variables are needed: the number of patients hospitalized in each one of the three modalities (home, ward, and ICU). There are three events related to patient arrivals: the arrival of a new patient needing home, ward and ICU hospitalization, respectively, and other three events related to the end of the patient hospitalization time at home, in ward and in ICU, respectively.

2.3 Stochastic Modelling

2.3.1 Patient Arrival Pattern Modelling.

The entry to the health system represented in the DES is the time process of patients needing any of the three types of hospitalization. We fit a common model, without distinguishing the type of patient and at arrival, we assign the probability of the hospitalization type according to observed frequencies. An empirical Gompertz growth model (Zwietering et al. 1990) is fitted to the accumulated series of the total hospitalized cases. The Gompertz model is described in equation (1).

$$H(t) = H_T exp\left(-ln(H_T/H_0)\exp\left(-c(t-t_0)\right)\right) \tag{1}$$

where,

- $H(t)$ is the cumulative number of hospitalized patients until time t.
- H_T is a parameter of the growth model that represents the total number of hospitalized patients at the end of the outbreak.
- c is other parameter representing the initial rate of population growth.
- H_0 is the number of hospitalized patients at time t_0.

This growth model starts with exponential growth but gradually decreases its specific growth rate. The estimation of the parameters is done by minimizing the sum of squared errors. In practice, the fit of data can be done for example using the curve_fit() function in the optimize module of SciPy in Python or the growthrates package in R. Once the curve $H(t)$ is fitted, it is possible to estimate the number of new hospitalized patients of each of the following days. Let consider t_{i} and $t_{\mathrm{i+1}}$ two consecutive days in the future, the number of expected arrivals for the day $t_{\mathrm{i+1}}$ is calculated as $H(t_{\mathrm{i+1}}) - H(t_{\mathrm{i}})$. Then, the simulation model samples the number of hospitalized patients for that day $t_{\mathrm{i+1}}$ from a Poisson distribution with mean $H(t_{\mathrm{i+1}}) - H(t_{\mathrm{i}})$. However, at the first stages of the outbreak could not be enough data to fit the Gompertz model. In this case, several alternatives can be used, all of them based on the use of population growth models:

- Fit the growth model to cumulative positive cases registered in a greater area, for example, in the case of Navarre, Spain. Then apply two factors to transform the predicted positive cases in arrivals to hospitals in the subarea: the first one is a population factor that relates the population of both areas (e.g., Navarre has the 1.3% of Spain's population) and the second one transforms the detected cases into those requiring hospitalization (at the first stages about 40% of detected cases needed hospitalization). Denoting by f_g and f_h both geographic and hospitalization factors, and by *D(t)* the fitted Gompertz curve to the detected cases in the bigger area, then $H(t) = f_g f_h D(t)$. Given that in this first period there is a data shortage, these factors can be estimated by experts according to data published in the literature referred to the behavior of the disease in countries where it is more spread. This indirect technique could be applied also to the detected cases in the same area and then only estimate the f_h factor.
- When the hospitalization cases begin to accumulate significantly (meaning the observed cumulative cases are beginning its exponential growth) then the growth model is fitted to these data, and both parameters (f_g and f_h) are no longer necessary because they must be 1. The parameter H_T can be estimated by expert opinion, using rates observed in other countries, or directly from data.

In all cases, the curve is fitted each time a new datum is observed.

2.3.2 Stochastic Modelling of Hospital Length of Stay

The LoS in the three modalities of hospitalization is simulated from probability distributions that are estimated in different ways, depending on the amount of available data. During the first stages of the outbreak, when no data or very few exist about the LoS of patients, the simulation model uses triangular distributions where the parameters (minimum, maximum and most probable time) are fixed by an expert opinion that could be based on values reported in the literature describing the China and the Italian situation (Grasselli et al. 2020; Guan et al. 2020; Young et al. 2020; Zhou et al. 2020), two countries where the pandemic spread earlier.

After one or two weeks of admitting COVID-19 patients in the hospital, there could be enough data to fit probability distributions. One main feature of these data is their high level of censorship, given that only a small percentage of the admitted patient has been discharged. This fact motivates the need for re-estimating the distribution fitting on a daily basis by adding the new data collected. The use of probability plots facilitates the selection of the parametric probability distribution family that best fits the data.

Then, the parameters of the selected family are estimated by maximum likelihood taking into account all data collected so far (censored and non-censored data). The experience with the local data and data coming from other regions of Spain shows that Weibull and lognormal family distributions fit well the data. Specifically, by using the described methodology the LoS at the hospital, in the three modalities of hospitalization, is estimated.

Other parameters that are necessary to estimate from the data are the percentage of patients admitted to hospitalization that will need ICU and the percentage of those patients that are admitted directly to the ICU just after testing positive. For the patients that are admitted after some days of hospitalization, the time of transitioning to ICU is fitted to a probability distribution.

It is important to highlight that during the evolution of the pandemic, the therapeutic protocols have been updated, in accordance with the published medical literature, and better management has been acquired in the care of patients, both in hospitalization and in the ICUs. These events are likely to have had a representative positive effect on patients. We have objectified that the distributions obtained for the duration of the stay are different according to the study period, observing how the average duration decreases as the pandemic progresses. The same occurs with the percentage of patients requiring admission to the ICU from the hospitalization floors. To reflect this fact in the simulation, the LoS of the patients are simulated based on the day of admission, differentiating several stages of the pandemic. With this, we want to emphasize the need to review and analyze the data in parallel to the progress of the situation, in order to objectify changes in trends that can be explained by the implementation of various measures, whether governmental or health.

3 THE SIMULATOR

3.1 Input Data

The simulator is fed by an input data file obtained from the hospital electronic health record (EHR) system. The information needed for each COVID-19 patient arriving at the health system is the dates of hospital admission and discharge and the dates of ICU admission and discharge. An empty field means that the corresponding event has not happened. That is, an already discharged patient from hospital with empty fields in the ICU fields means that this patient did not need intensive healthcare. When an admission date field is not empty but the discharge date field is, then the patient is already in the health system.

The input data file records the information of all COVID-19 patients from the first day of the outbreak to the present day. Therefore, the simulator can reproduce the occupancy of the hospital and ICU from the beginning of the outbreak until the present, and at this moment it is known the number of patients in the health system (in all hospitalization modalities) and the date of admission of those patients. This information is used to start the simulation run as it is explained in the next subsection.

The simulation could also be run just by knowing the number of patients admitted at the hospital in each of the different hospitalization ways. In this case, the simulator is not able to reproduce the past and get a very accurate representation of the health system at time zero of the simulation clock, but it can be estimated.

Another input file required by the simulator is the accumulated historical series, either of positive cases or patients admitted to the hospital. This information is used to obtain the best-fitting Gompertz curve, which allows the patient arrivals pattern to be estimated.

3.2 Starting the Simulation

The simulation clock is set to zero at the time of the EHR-file's last update. Before that time, it is the past that can be reproduced by the simulator by reading the records in the EHR file, and ahead, it is the future that needs to be simulated. The transition from the past to the future is done at the moment the simulation starts, which requires to initialize the event calendar (Law 2014). There are two types of events, admission to hospital and discharge from hospital. Therefore, it is necessary to *know/simulate* the next time in the future where each one of these events is happening.

The event calendar records the discharge time of all currently hospitalized patient. These discharge times are obtained for each of these patients at simulation time zero from the fitted distributions to the LoS in each hospitalization modality. To explain the procedure, let consider the case of the hospital ward. Let T denote the random variable LoS in the hospital ward, and suppose that patient j is hospitalized in the ward since x time units ago. Then the LoS for patient j is described by the conditional distribution of variable T given that $T > x$ ($P\{T > x\} = T_x$), whose density function is $f(t)/(1 - F(t))$, where $f(t)$ and $F(t)$are the density and the distribution functions of T, respectively. Once a value t is sampled from this distribution, the discharge time for patient j is set at time $t - x$ and it is included in the event calendar. Discharge time is simulated for each patient in the health system. After that, the arrival time for the next COVID-19 patient is simulated to complete the event calendar. The fitted Gompertz curve provides the number of patients arriving each day. These arrivals can be uniformly distributed during the next 24 hours or following a non-stationary pattern when, for example, a significant decrease of arrivals occurs at night.

In the case of the ICU, in addition, it is necessary to simulate the possible transition of already hospitalized patients from the other two hospitalization ways. Let p_{H-ICU} be the estimated percentage of hospitalized patients that are transferred to the ICU. By using the EHR a probability distribution to the random variable Y, time for transferring to ICU is estimated. A patient is transferred to ICU with probability p_{H-ICU} and after x time units with probability $y_x = P\{Y > x\}$. Therefore, a patient hospitalized x time units ago will be transfer to ICU with probability $p_{H-ICU,x} = p_{H-ICU} \times y_x/T_x$. A uniform random number is compared with the value $p_{H-ICU,x}$ to determine for each hospitalized patient whether he/she will be transferred to ICU or not. If the result is to transfer the patient to ICU, then the time is sampled from the conditional distribution $(Y \mid Y > x)$.

3.3 Simulation Output

The simulator evolves the hospital by simulating arrivals and discharges of patients and recording the number of necessary beds at any time. There are two sources of randomness in this simulation model. On the one hand, the number of patients admitted to the hospital each day, and on the other hand, the LoS sampled of the patients. By repeating the simulation many times (thousands) for each day it is obtained the distribution of the number of necessary beds. The simulator calculates percentiles of the necessary beds' distribution which are reported in excel files and plotted in graphics as confidence bands. Specifically, the 5th percentile (P5), the 50th percentile (P50), and the 95th percentile (P95) are calculated.

Figure 2 presents two examples of the simulator output, one for hospitalization needs and the other for the ICU specifically. The green-colored line represents the real evolution of the occupation, and the black dot indicates the Simulation Starting Point (SSP), that is, the moment from which it is simulated.

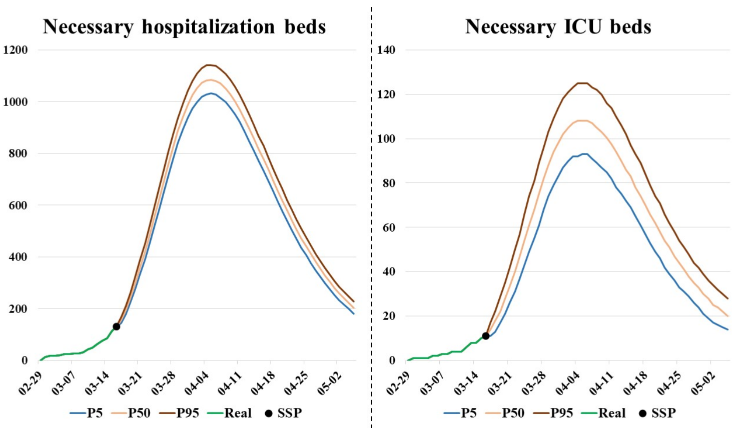

Figure 2: Number of necessary hospitalization and ICU beds respectively for the following days. From the SSP, 3 lines corresponding to the 5th, 50th, and 95th percentiles are plotted.

4 CASE STUDY. APPLICATION TO THE COMMUNITY OF NAVARRE (SPAIN)

4.1 Incidence of COVID-19 disease in Navarre

Navarre is a small Autonomous Community of the north of Spain. Its population is around 650,000 inhabitants, but it is not equally distributed throughout the community. More than half of the population gathers around the capital (Pamplona) and its surroundings, an area that represents 5% of the total surface. This is the reason why 4 out of the 6 main hospitals in Navarre are located in Pamplona. This hospital network is made up of 3 private hospitals and 3 public hospitals. In total, there are 1,820 hospital beds and 73 ICU beds available, with the possibility of increasing these quantities if necessary.

Navarre is among the five Spanish autonomous communities with a higher cumulative incidence rate of COVID-19 confirmed cases, according to the data collected by the Ministry of Health, Government of Spain. By April 16, 4,477 COVID-19 cases (6.9 per 1,000 inhabitants) had been confirmed in Navarre, and among them, 1,764 had been admitted to hospitals (2.7 per 1,000). Figure 3 shows four graphs with daily and cumulative data about positive cases and patients who have been admitted to hospitals in Navarre. It is observed that time trends peaked on March 25 and 27 and decreased after April 1 and 2.

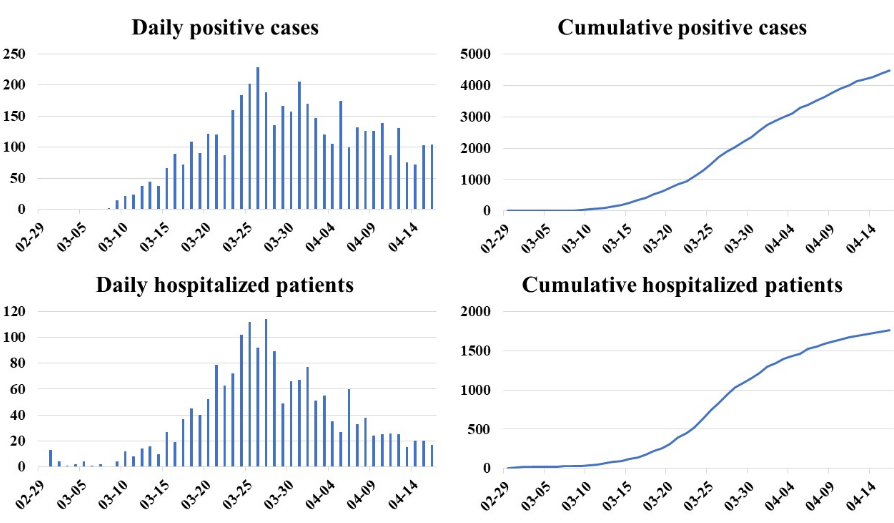

Figure 3: Daily and cumulative data of positive cases and hospitalized patients recorded in Navarre from February 29 to April 16, 2020.

4.2 Prediction of the Bed Occupancy Using the Simulation Model

4.2.1 Initial Phase of the Pandemic (2020/02/29-2020/03/26)

During the initial phase of a pandemic, the available data are scarce, both in the number of positive cases or admitted patients, as well as in the LoS observed in the hospital. Therefore, the involvement of experts is necessary to estimate these parameters. In this way, a first approach can be made to simulate the evolution of the pandemic in the following days.

Navarre was one of the first communities in Spain to be infected, so in this initial phase, the historical series of people infected with the virus is used to estimate the patient arrival pattern. With the first data collected, two different outputs can be obtained from the Gompertz growth model fit. On the one hand, the trend may lead to an exponential growth of the series, and on the other hand, the total number of infected people can be underestimated if the slope of the curve is not very steep yet.

Figure 4 shows different results after applying the Gompertz growth model fit to the cumulative positive cases in Navarre. It is observed that the fit of March 16 (2020-03-16) is obtained below the real data. However, experts decide to fix the number of total cases (parameter H_T in equation (1)), increasing the value to 6,500 (1% of the total population of Navarre). This second curve (2020-03-16 (6,500)) is more conservative in predicting arrivals, but it fits better the real cases. In addition, two more fits made on March 31 (2020-03-31) and April 4 (2020-04-04) can be seen. It is observed that as more information becomes available over time, the resulting curve becomes more similar to the real one.

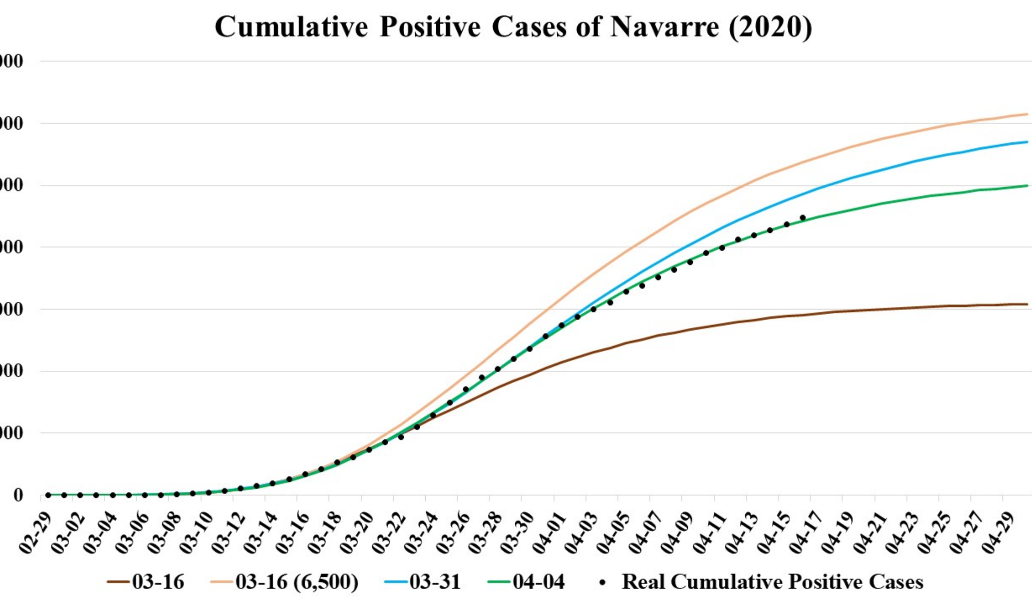

Figure 4: Cumulative positive cases of Navarre from February 29 to April 16, 2020, and different fitted curves obtained from the Gompertz growth model.

As it is mentioned in Section 2.3.2, at the initial stage of the outbreak when there is not enough data to estimate the LoS of patients, a triangular distribution is used. Experts fix the minimum, maximum, and most probable time as 10, 18, and 13 days respectively. Besides, since the arrival pattern is based on positive cases, a hospitalization factor must be applied (40% for hospitalized patients and 4% for ICU patients). Figure 5 shows both the prediction of the number of hospitalized and ICU beds occupied in Navarre simulated on March 16 for the next days. In each graph, the real evolution of bed occupancy in each area is shown in green. In both cases, the prediction obtained is conservative.

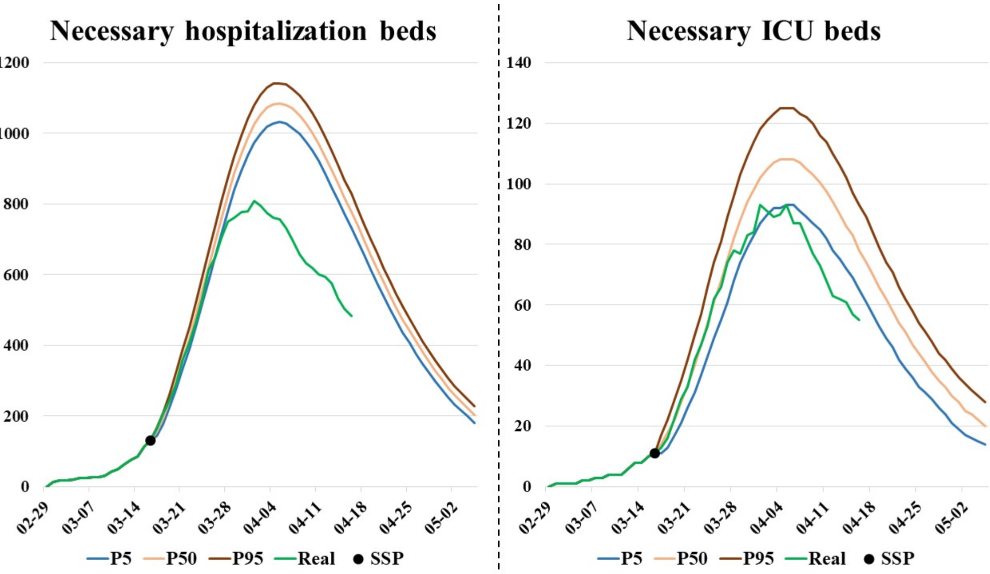

Figure 5: Comparison between the predictions made on March 16, 2020, for the number of hospitalization and ICU beds occupied in Navarre and the real occupancies.

4.2.2 Second Phase (2020/03/26-2020/04/16)

As the pandemic spreads, the amount of information increases, which makes it possible to improve the simulation model. Since March 26, the arrival pattern is calculated from the series of hospitalized patients. As with the positive cases, the first fits require setting the maximum of people finally hospitalized (parameter H_T in equation (1)), although in this case because the curve fitted by the Gompertz growth model increases exponentially. According to experts, about 2400 patients are expected to be hospitalized during the pandemic. Figure 6 shows different results after applying the Gompertz growth model fit to the cumulative hospitalized patients in Navarre. It can be seen that the curves obtained on March 26 and 29 (03-26 and 03-29) overestimate hospitalizations, so they are replaced in the simulation by those in which the maximum is set at 2,400 (03-26 (2,400) and 03-29 (2,400)).

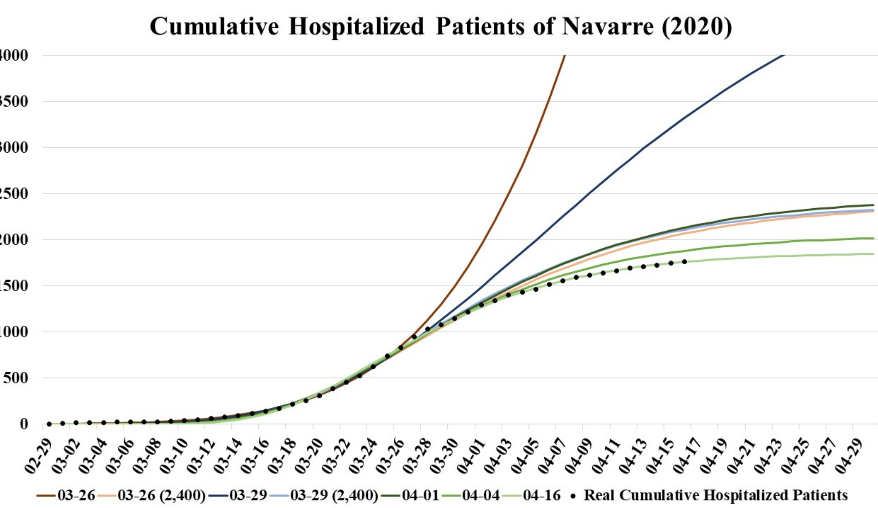

Figure 6: Cumulative hospitalized patients of Navarre from February 29 to April 16, 2020, and different fitted curves obtained from the Gompertz growth model.

Regarding the LoS of patients both in hospital and ICU, there were already enough data to estimate them every day, as it is explained in Section 2.3.2. With all this information updated day by day (see Table 1), and the curves shown in Figure 6, it is possible to simulate the evolution of the bed occupancy from a specific day. Figure 7 shows 4 simulations carried out on March 26 and 29 and April 1 and 4, comparing the results with the real evolution. As in previous results, it is observed that as the days go by, the results are more accurate because more information is available.

Table1: Weibull distributions (W) for modelling different LoS (in days) and the probabilities of a patient is admitted directly to the ICU (p_{ICU}) and of a hospitalized patient is transferred to the ICU (p_{H-ICU}).

Date	Hospital	ICU	Hospital before ICU	$\boldsymbol{p_{ICU}}$	$\boldsymbol{p_{H-ICU}}$
03-26	W (1.223, 18.470)	W (1.450; 22.707)	W (2.337, 3.802)	0.029	0.047
03-29	W (1.204, 18.489)	W (1.450; 24.663)	W (2.424, 4.016)	0.014	0.032
04-01	W (1.261, 15.421)	W (1.450; 25.423)	W (1.670; 4.410)	0.013	0.030
04-04	W (1.030, 15.000)	W (1.430; 28.677)	W (1.691; 4.445)	0.011	0.031

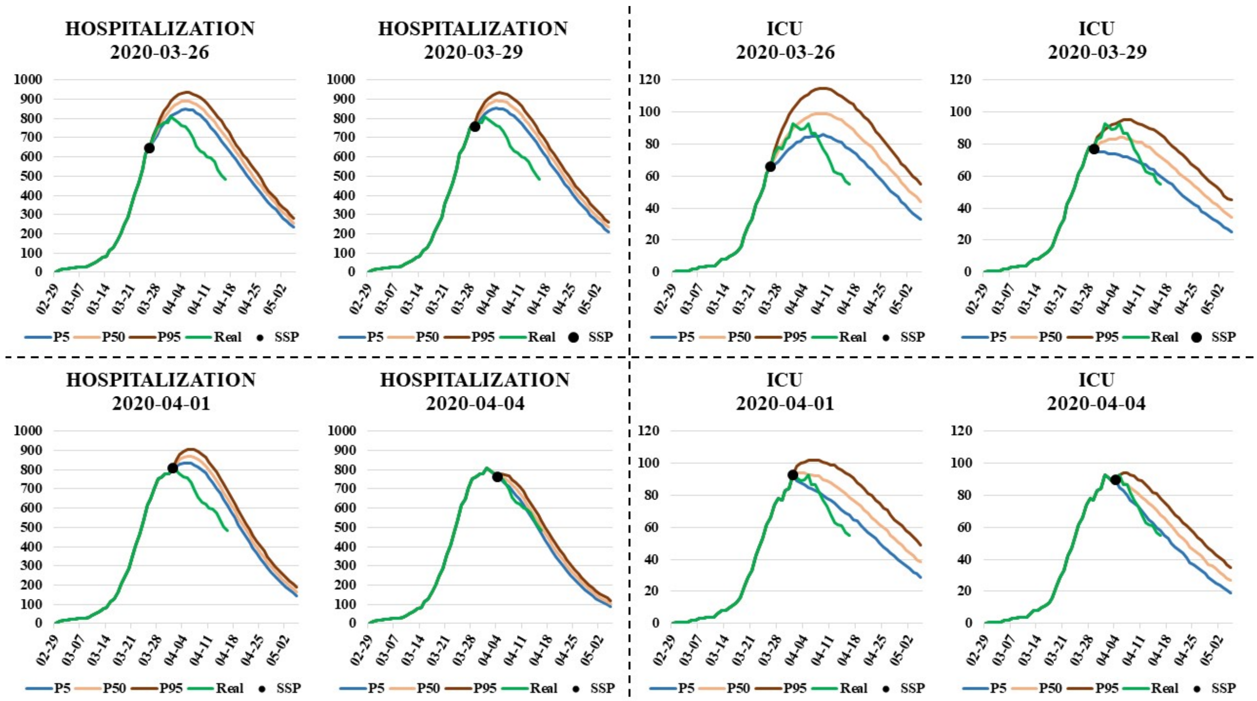

Figure 7: Comparison between the predictions made on different days for the number of hospitalization and ICU beds occupied in Navarre and the real occupancies.

5 CONCLUSIONS

Healthcare systems are overburdened due to a large demand for healthcare services from COVID-19 patients that leads to strained ICU's capacity and overworked healthcare workers (whose availability is reduced due to illness). Good predictions of the resources needed for taking care of patients are essential for planning in advance the necessary resources and reduce the pressure on the system and stress on the healthcare staff.

Normally, the provision of accurate predictions 4 or 5 days in advance is sufficient for the implementation of contingency plans and the deployment of sufficient resources to meet expected spikes in demand. In this paper, we have developed a discrete event simulation model for predicting the need for hospital beds and ICUs. The simulation model is fed by the predictions of new hospitalizations made, directly or indirectly, through a Gompertz growth model. However, there are more growth models that have been used successfully in similar contexts such as logistic, Richards, and Stannard (Zwietering et al. 1990). The simulation model will use these models together to make the predictions. The authors are working on enhancing the simulation model to include these models with which to improve predictions. Furthermore, factors affecting the LoS and consumption of different resources (age, Adjusted Morbidity Groups (AMG), and other characteristics collected by the EHR) are being studied, in order to develop a more detailed simulated model and adapted to the different patient profiles.

The structural simplicity of the simulation model makes it appropriate for general use, i.e., it can be adapted to estimate the bed needs in any geographic area. The growth model is simple enough to fit it to available data or, in the absence of it, to be estimated by educated guesses of experts.

It is worthy to mention the strength of simulation models in this context of uncertainty: their capability to run what-if scenarios that allow decision-makers to explore the consequences of different policy choices, like the location and number of additional healthcare resources needed for COVID-19 patients given the uncertainty in demand. The simulation model is data-driven, patients arrivals and LoS can be estimated from data, but it has also the flexibility of allowing the simulation from the input determined by the user to explore additional scenarios. However, the quality of predictions depends on the data quality. New social distancing policies modify the pandemic dynamic and can affect the accuracy of the medium term (two weeks) model predictions.

From a technical and methodological point of view, a distinct feature of the simulation model is its focus on the transition period of the health system instead of the stationary state as it is usual in the simulation studies or transition periods but after regeneration points. This transition period reproduced by the simulator is unique as the outbreak evolves with no regeneration points. Therefore, the accurate representation of the initial health system state plays an important role. The simulation of the remaining LoS of each patient already admitted in the hospital has shown to be a key point to project smoothly the dynamics of the health system and linking it (and mixing it) with the new dynamics obtained from the simulation of the arrivals and stays of the new incoming patients.

The success of the model presented here is due to its request by the hospital manager. The person in charge of the hospital logistics required the development of a predictive analytic tool to make more informed decisions. This involvement made possible the daily supply of complete and updated data on the current situation of the health system, including the series of new detected cases and the description at the patient level of the situation of each health facility. The logistic team also provided with informed guesses about the value of model parameters in the first stages of the outbreak to create reasonable what-if scenarios.

ACKNOWLEDGMENTS

This paper was supported by grant MTM2016-77015-R (AEI, FEDER). The authors wish to acknowledge the support received by the Navarre Hospital Compound and the Information System Department of the Government of Navarre.

REFERENCES

Azcarate, C., L. Esparza, and F. Mallor. 2020. "The Problem of the Last Bed: Contextualization and a New Simulation Framework for Analyzing Physician Decisions". *Omega* 96:102120.

Brailsford, S. C., P. R. Harper, B. Patel, and M. Pitt. 2009. "An Analysis of the Academic Literature on Simulation and Modelling in Health Care". *Journal of Simulation* 3(3):130–140.

Brauer, F., and C. Castillo-Chavez. 2012. *Mathematical Models in Population Biology and Epidemiology*. 2nd ed. New York: Springer.

Erhard, M., J. Schoenfelder, A. Fügener, and J. O. Brunner. 2018. "State of the Art in Physician Scheduling". *European Journal of Operational Research* 265(1):1–18.

Grasselli, G., A. Pesenti, and M. Cecconi. 2020. "Critical Care Utilization for the COVID-19 Outbreak in Lombardy, Italy: Early Experience and Forecast during an Emergency Response". *Journal of the American Medical Association* 323(16):1545–1546.

Grassly, N. C., and C. Fraser. 2008. "Mathematical Models of Infectious Disease Transmission". *Nature Reviews Microbiology* 6(6):477–487.
Guan, W., Z. Ni, Y. Hu, W. Liang, C. Ou, J. He, L. Liu, H. Shan, C. Lei, D. S. C. Hui, B. Du, L. Li, G. Zeng, K. Y. Yuen, R. Chen, C. Tang, T. Wang, P. Chen, J. Xiang, S. Lie, J. Wang, Z. Liang, Y. Peng, L. Wei, Y. Liu, Y. Hu, P. Peng, J. Wang, J. Liu, Z. Chen, G. Li, Z. Zheng, S. Qiu, J. Luo, C. Ye, S. Zhu, and N. Zhong. 2020. "Clinical Characteristics of Coronavirus Disease 2019 in China". *New England Journal of Medicine* 382:1708–1720.
Günal, M. M., and M. Pidd. 2010. "Discrete Event Simulation for Performance Modelling in Health Care: A Review of the Literature". *Journal of Simulation* 4(1):42–51.
Katsaliaki, K., and N. Mustafee. 2011. "Applications of Simulation within the Healthcare Context". *Journal of the Operational Research Society* 62(8):1431–1451.
Kolker, A. 2009. "Process Modeling of ICU Patient Flow: Effect of Daily Load Leveling of Elective Surgeries on ICU Diversion". *Journal of Medical Systems* 33(1):27–40.
Law, A. M. 2014. *Simulation Modeling and Analysis*. 5th ed. New York: McGraw-Hill.
Liu, W., S. Tang, and Y. Xiao. 2015. "Model Selection and Evaluation Based on Emerging Infectious Disease Data Sets Including A/H1N1 and Ebola". *Computational and Mathematical Methods in Medicine* 2015:207105.
Mallor, F., C. Azcárate, and J. Barado. 2016. "Control Problems and Management Policies in Health Systems: Application to Intensive Care Units". *Flexible Services and Manufacturing Journal* 28(1–2):62–89.
Mielczarek, B., and J. Uziałko-Mydlikowska. 2012. "Application of Computer Simulation Modeling in the Health Care Sector: A Survey". *Simulation* 88(2):197–216.
Ridge, J. C., S. K. Jones, M. S. Nielsen, and A. K. Shahani. 1998. "Capacity Planning for Intensive Care Units". *European Journal of Operational Research* 105(2):346–355.
Rodrigues, F., G. S. Zaric, and D. A. Stanford. 2018. "Discrete Event Simulation Model for Planning Level 2 "Step-down" Bed Needs Using NEMS". *Operations Research for Health Care* 17:42–54.
Shahani, A. K., S. A. Ridley, and M. S. Nielsen. 2008. "Modelling Patient Flows as an Aid to Decision Making for Critical Care Capacities and Organisation". *Anaesthesia* 63(10):1074–1080.
Young, B. E., S. W. X. Ong, S. Kalimuddin, J. G. Low, S. Y. Tan, J. Loh, O. T. Ng, K. Marimuthu, L. W. Ang, T. M. Mak, S. K. Lau, D. E. Anderson, K. S. Chan, T. Y. Tan, T. Y. Ng, L. Cui, Z. Said, L. Kurupatham, M. I. C. Chen, M. Chan, S. Vasoo, L. F. Wang, B. H. Tan, R. T. P. Lin, V. J. M. Lee, Y. S. Leo, and D. C. Lye. 2020. "Epidemiologic Features and Clinical Course of Patients Infected with SARS-CoV-2 in Singapore". *Journal of the American Medical Association* 323(15):1488–1494.
Zhou, F., T. Yu, R. Du, G. Fan, Y. Liu, Z. Liu, J. Xiang, Y. Wang, B. Song, X. Gu, L. Guan, Y. Wei, H. Li, X. Wu, J. Xu, S. Tu, Y. Zhang, H. Chen, and B. Cao. 2020. "Clinical Course and Risk Factors for Mortality of Adult Inpatients with COVID-19 in Wuhan, China: A Retrospective Cohort Study". *The Lancet* 395(10229):1054–1062.
Zhu, Z., B. H. Hen, and K. L. Teow. 2012. "Estimating ICU Bed Capacity Using Discrete Event Simulation". *International Journal of Health Care Quality Assurance* 25(2):134–144.
Zwietering, M. H., I. Jongenburger, F. M. Rombouts, and K. van 't Riet. 1990. "Modeling of the Bacterial Growth Curve". *Applied and Environmental Microbiology* 56(6):1875–1881.

AUTHOR BIOGRAPHIES

DANIEL GARCIA-VICUÑA studied industrial engineering at the Public University of Navarre, Spain. Currently, he is a Ph.D. student at the Institute of Smart Cities of the Public University of Navarre. His research interests lie in the field of complex real problems simulation modelling. His email address is daniel.garciadevicuna@unavarra.es.

FERMIN MALLOR is Full Professor of Statistics and Operations Research at the Public University of Navarre, Spain. He holds a Ph.D. and MSc in Mathematics. He has been visiting researcher at the Missouri Science and Technology University, among others. His research interests include applications of simulation-optimization (classical and metaheuristics methods) in health, energy, logistics, and production. He is the director of the research group q-UPHS (quantitative methods for Uplifting the Performance of Health Services, www.unavarra.es/quphs). His email address is mallor@unavarra.es.

LAIDA ESPARZA is a physician at the Department of Intensive Care Medicine, Navarre Hospital Compound, Spain. Currently, she is a Ph.D. student at the Department of Statistic, IT and Mathematics at the Public University of Navarre. Her research interests lie in the field of simulation modelling and in the study of clinical decision-making processes and bed management in intensive care unit settings. Her email address is lesparza@navarra.es.