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# Monitoring the Health System Saturation Risk During COVID-19 Pandemics

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**Abstract.** The pressure on the sanitary system caused by the Covid-19 pandemics put in risk many lives. The unknowns of the pandemic behavior caused problems for a more accurate prediction of the demands for hospitalization and ICU. As a result, two situations were observed: unnecessary expansion of the sanitary system with campaign hospitals and, worse, the saturation of the system with or without expansion. This article proposes the use of a backwards approach to compare the data predicted by a SD model with the real data obtained from the hospitals in the Basque Country. The goal was to calibrate the model to be better prepared for the eventual new wave of infections reducing the risk of collapse or unnecessary response actions to the emergency.

**Keywords:** Covid-19, Sanitary saturation risk, SD model.

## 1 Introduction

The crisis generated by the COVID-19 has affected the entire world in a proportion never seen since the 1918 pandemics [1]. To reduce the pressure on the sanitary system, and consequently saving lives, millions of people have been in quarantine, affecting the social living and, according to some scientists, generating severe damage to the economic system [2]. For some economists, the reducing of economic activity can kill more people than the virus and they claim governments should adopt a different model to deal with fear and the deaths of almost a million people since the pandemic begun.

In an attempt to understand the evolution of the virus several predictive models have been developed and applied. [3], [4] The goal was mainly to reduce the number of “don’t knows”, the most repeated words in the news since the beginning of the covid-19 pandemics [5]. The number of deaths is still high, but it is gradually reducing in many countries. After over 6 months of fight we are gradually reducing the uncertainty, but there are still many questions without answers. [6]

The data accumulated during these last months has enabled scientists to learn and understand the evolution of the disease. “Those who cannot remember the past are condemned to repeat it.” (George Santayana). Many decisions made in the past would probably be different if we knew what we know now. With that knowledge and information, would we be able to develop more accurate predictive models? We think the answer is

Yes, and that is the approach of the work reported in this paper as a way to reduce the risk of collapse of the sanitary system.

Now that we have enough data from many communities, we can use real accurate data to apply to a predictive model and tune its parameters by comparing the predictions generated using the model and the real data published by the community. We start from an existent pandemics model, do some changes to make it resemble the covid-19 behavior and run several simulations until we get results close to the reality. The goal is to have at the same time a model tested against the reality and a review of the accuracy of published data, exposing potential incoherencies. With a more accurate model we can run simulations using data from other communities and analyze the differences of behavior through the values of parameters.

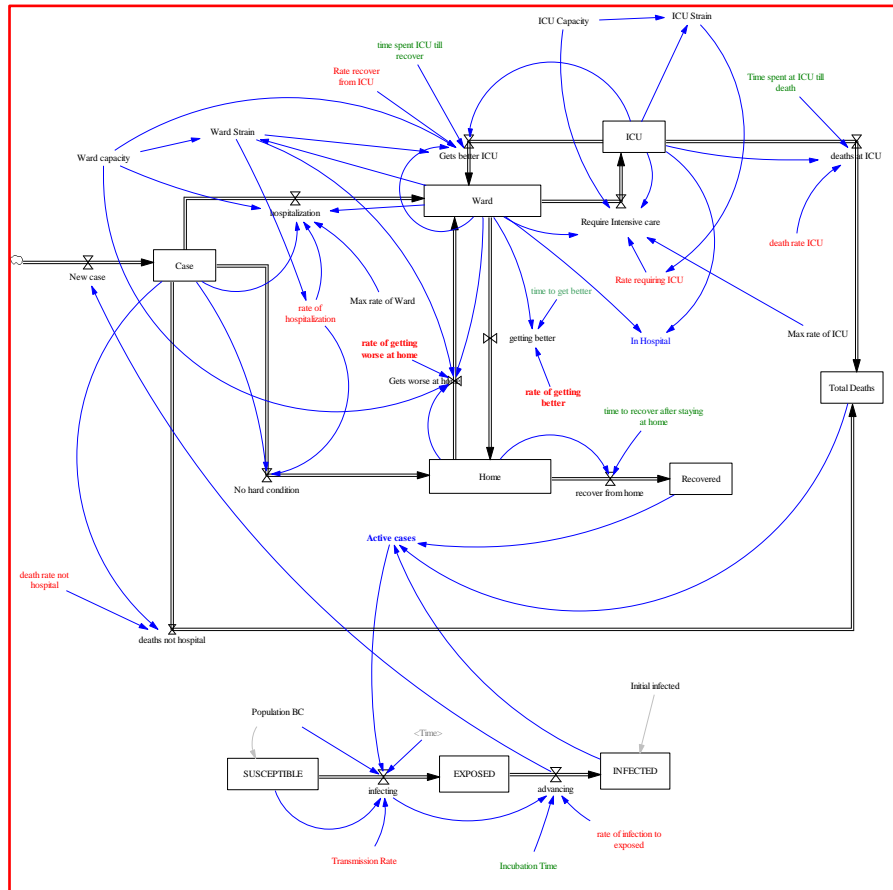
Although we tend to think of similar effects of the pandemics in different communities, the numbers do not reflect this similarity. The level of transmission and infection, the mortality and recover rates are examples of these variations. Although we don't have the necessary knowledge to point to why they are different we can at least point how different they were. Having produced a more accurate model we can use it to get prepared for the potential risks, as the covid-19 pandemic continue to produce chaos and stress in most places around the world, as the second wave of infections is demonstrating.

One of the issues that caused enormous concern during the first wave was the risk of saturation of hospitals, in particular the ICU vacancies. After adjusting the predictive model with real data from the first wave, we believe we are now better prepared to estimate the demand and anticipate recommendations to at least reduce the risk of collapse [7]. This, we believe, is the main contribution of this research. Hopefully, we won't need to use the model, but as it happens in many situations in disasters, we rather be safe than sorry (Samuel Lover).

The reminder of this paper is organized as follows. Section 2 that follows this introduction present and explain the SD model adapted to simulate the evolution of covid-19. Section 3 presents the data we obtained for our case study applied for the Basque Country Covid-19 cases. In section 4 we present the methodology and the results of the simulations contrasted against the data from reality. Section 5 we conclude by presenting a discussion on the potential benefits of these results in the form of a set of lessons learned and how this can be used to recommend actions to prevent the sanitary system saturation.

## 2 The SD model developed for the analysis

A System Dynamics model has been developed to test the real data and analyze the accuracy of the published data. System dynamics is a methodology that allows to model complex systems based on the underlying structure that creates the behavior of the system [8]. This model should be able to reproduce the behavior of the main variables of the pandemics management and in turn, verify the accuracy of the published data. Fig. 1 shows the stock and flow diagram of the SD model.



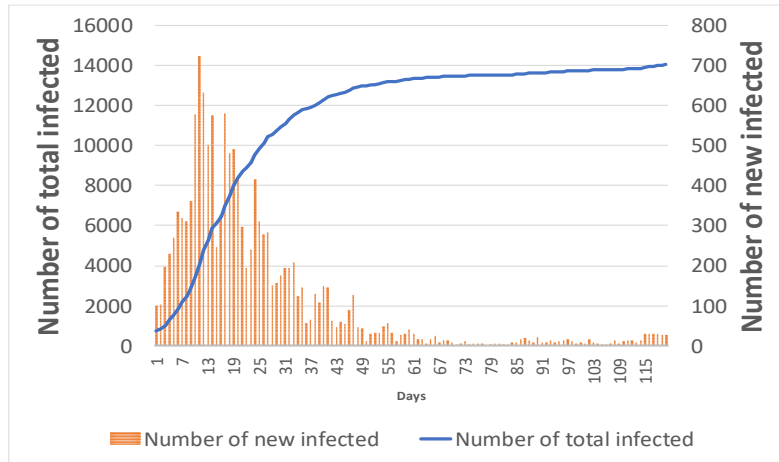
**Fig. 1.** The stock and flow diagram of the pandemics model

The stock “Susceptible” represents the population that is susceptible of getting the COVID-19 disease. Based on the transmission rate and the number of active infected cases the number of people that is exposed to the infection is calculated, and with some delay and the infection rate the number of people who finally get infected. This stock counts the number of total people who has been infected during the whole lifecycle of the pandemic. However, for the analysis of the evolution, the daily cases are represented with the new daily case stock. The current cases are divided into two groups: the ones that are recovered at home and the ones that must go to the hospital because they are more serious. Among those who are in the hospital, those who are very serious are admitted to the ICU. Once they get better they return to the plant and once they are recovered they go home and eventually to the recovered stock. Finally, based on the death rate at ICU, some of the patients who are in the ICU and at home die due to the disease. The total number of people who die is represented in the “Total Death” stock.

### 3 The data used in the Case Study

In order to tune the model to the specific case of the area of the Basque Country in Spain, we gathered data from the daily reports the Basque government published to the public [9]. In these reports, the data about the evolution of the main epidemiological variables are collected. The graphs below represent these data from March 15th to July 12th (120 days), that is, from the moment the total confinement of the population was implemented until the “new normality” was achieved.

As we can see in the graph in Fig. 2, the number of total cases increased abruptly from days 5 to 17 and then the curve continues increasing but with a minor slope. This change in the tendency occurs 3-4 weeks after the first case was detected and 2-3 weeks after the total confinement of the region was implemented. 50 days after the detection of the first case, we can say that the pandemic was under control and the increase of the curve was very low.

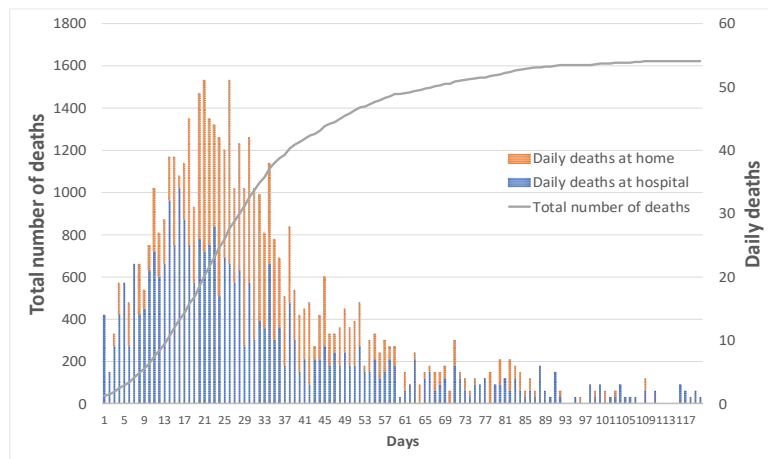


**Fig. 2.** The graph represents the evolution of the total infected cases and the new daily cases in the Basque Country

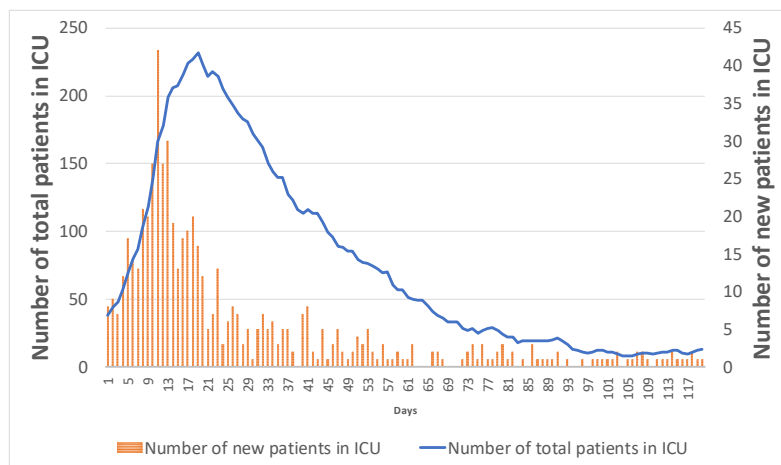
Following the same shape of the graph in Fig. 2, the graph in Fig. 3 represents the total number of deaths that occurred in the region of the Basque Country as well as the daily deaths divided into the ones that occurred in the hospitals and the ones at home. The shape of both curves are the same, with different magnitude, and with some delay since as we know the deaths come with some delay. The change in the slope is obtained in day 26 more or less, that is, 10 days after the number of new infected cases started to decrease. The curve stabilized in day 75, 2-3 weeks after the stabilization of the total infected cases.

Very related with the graphs in Fig. 3, we can analyze the total cases and daily cases in hospitals and in ICU, that represents on the one hand the total number of serious cases that can derive in deaths and on the other hand the saturation level of the health system that could also lead to more deaths due to the limited resources to attend to all

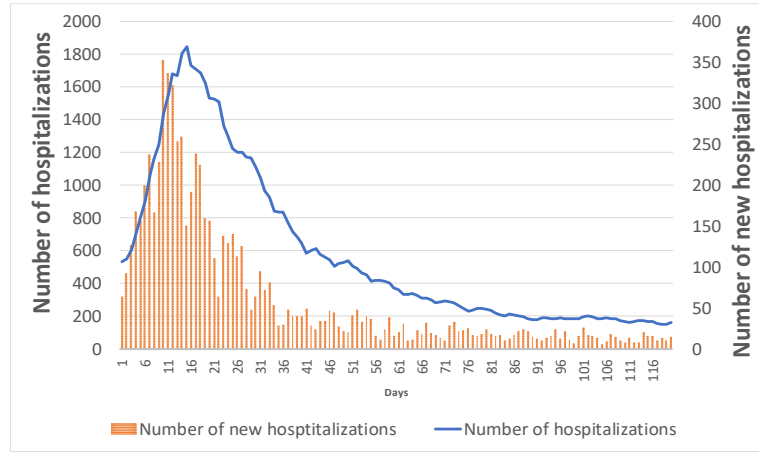
patients in an appropriate manner. Both graphs (see Fig. 4 and Fig. 5) reaches the maximum level between days 17 and 22, that is, when the curve of the total infected cases changes its tendency. The graph of the total hospitalization reaches the maximum 2-3 days before the graph of number of patients in ICU, since there is a short delay between the moment the people go to the hospital and the moment that the people get in the ICU. From this moment on, the situation was taken under control and the number of new cases start decreasing and the same happened with the number of hospitalizations and the number of cases in ICU.



**Fig. 3.** The graph represents the evolution of the total deaths in the Basque Country and the daily deaths divided into these occurred in the hospitals and those occurred at home



**Fig. 4.** The graph represents the evolution of the total cases and the daily new cases in ICU in the Basque Country



**Fig. 5.** The graph represents the evolution of the total hospitalization cases and the daily new hospitalization cases in the Basque Country

## 4 Methodology and the comparative results

### 4.1 The description of the methodology

As we mentioned in the previous section, we have four data sets of real data obtained from the evolution of covid-19 in the Basque country, showing the behavior of the following variables: total number of deaths, occupation of ICU beds, number of hospitalizations and the number of infected people. With the exception of the later, which is very dependent on the number of tests, the other three variables are reliable information that we can use for tuning the model, particularly the variables that influence the flow.

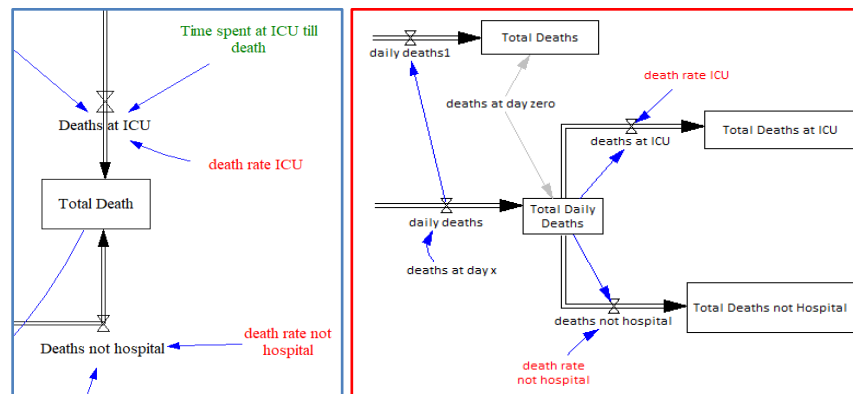
A SD predictive model is only useful if it resembles the reality [10]. Our goal then, is to obtain a model that behaves as close as possible to the reality. One way to achieve at least an approximate representation of the reality is to set the model using one or both techniques inspired by the theory of change [11]: “backwards-from-outcome” and “forwards-to outcome”. In both approaches, we need reliable information from the reality, a SD model that generates the outcomes for comparison and variables representing the rates that influence the outcome. The “backwards from outcome” approach should be applied when the most reliable data is at the end of the transformation process, in the case of covid-19 is related to the number of deaths.

Using the elements of the model, we started from this reliable data values and move backwards “one step at a time”, i.e., a step required to reach the stock for which we have another set of reliable data. For example, in the model of Fig. 1, we started with the number of deaths to find out the rate of deaths that come from Hospital (ICU stock in our model) and from cases that haven’t reached the hospital (Case Stock). The monitoring of the behavior consists of the following phases:

1. Starting from the most reliable data as input, we assign a set of values to the rates and run the simulation to obtain the output values as prescribed by the model.



2. If the outcome results of the simulation coincide with the values we obtained from the reality, then the values we assumed for the rates are correct.
3. If not, we adjust the rate values and go back to phase 1. Note that in some cases, the adjustment involves more than one rate and we may have to adjust the rates in relation to time instead of using average rates.
4. Once we have reached a behavior for this part of model that resembles the reality, we can move another backwards step and run the monitoring process again.



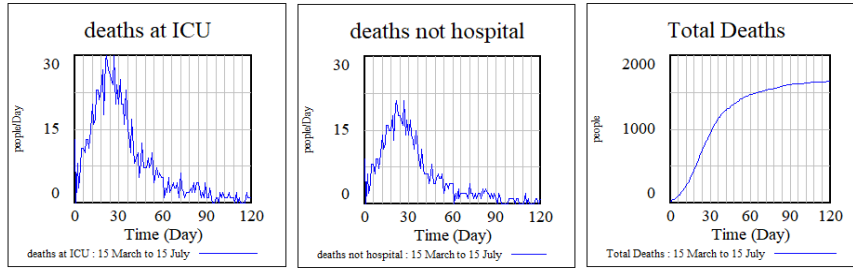
**Fig. 6.** From the original SD model to the backwards model of Total Deaths

For the monitoring process, we need the part of the full model to monitor, the corresponding backward model to simulate, and the simulation results that will be compared with the data from the reality. To create the backwards model we start from a stock variable, which values are known, create the resulting stocks, which values are also known and assign values to the rates (marked in red) that are the best fit for the resulting stocks. Fig. 6 illustrates the first backward step depicting side-by-side part of the full SD model and the corresponding backward model.

The backwards process proceeds until we reach stocks which values from the reality are not available or are not reliable. At this point on there will be uncertainty in the prediction model. In the case of Covid-19 we had to stop at the Case stock, as the real numbers of Infected are very dependent on the number of tests.

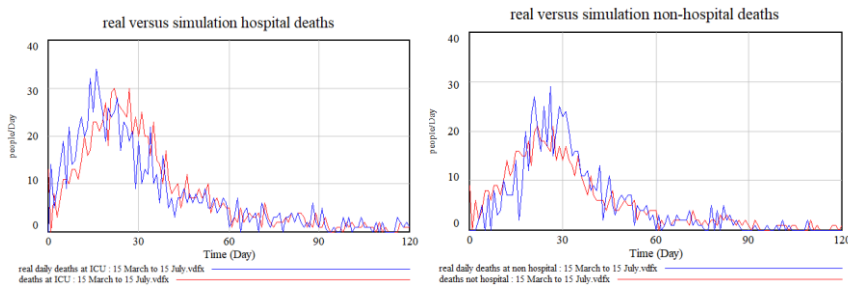
#### 4.2 Applying the backwards process – 1 – death rates from different contexts

The total number of deaths is the sum of the three components: home, hospital (not ICU) and ICU). In our model, however, we assumed that all patients who get worse are moved to ICU and therefore the number of deaths in Hospital (not UCI) and its corresponding rate is zero. The sum of rates should total 1 and the sum of deaths at ICU plus deaths elsewhere should be equal the total of deaths. To move backwards in this case is quite simple. We should know either one of the rates or one of the values of deaths besides the total number of deaths.

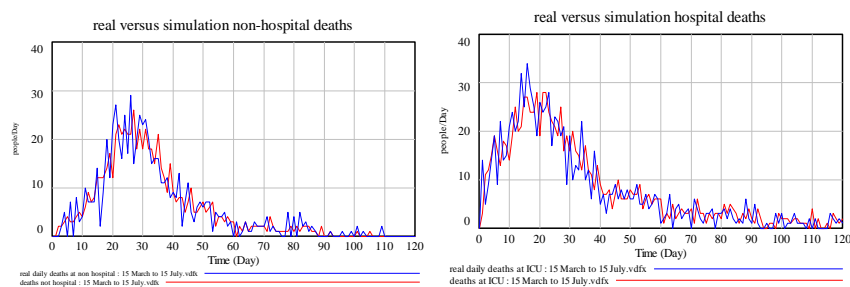


**Fig. 7.** Results from running the simulation. To be compared with the graphs in Figure 3

As we mentioned in Section 3, we collected the data for the Basque Country to serve at the basis for our backward analysis. The first step aims to find the proportion of deaths that occurred in hospitals in relation to those that occurred elsewhere (Elderly homes, home, work, etc.). The total values for the Basque country were 962 (59.2%) and 663 (40.2%) for hospital and non-hospital deaths, respectively. When we applied these average rates, we get the graphs reproduced at Fig. 7. When we compare to the graphs of the real data presented in Fig. 3, we can notice that they have similar shapes. However, when we compare the daily numbers, we notice some differences, as can be seen in Figure 8 where we compare the simulation data with the real data.



**Fig. 8.** Comparison with real data and the data obtained by simulation for daily deaths in Hospitals and not-Hospitals

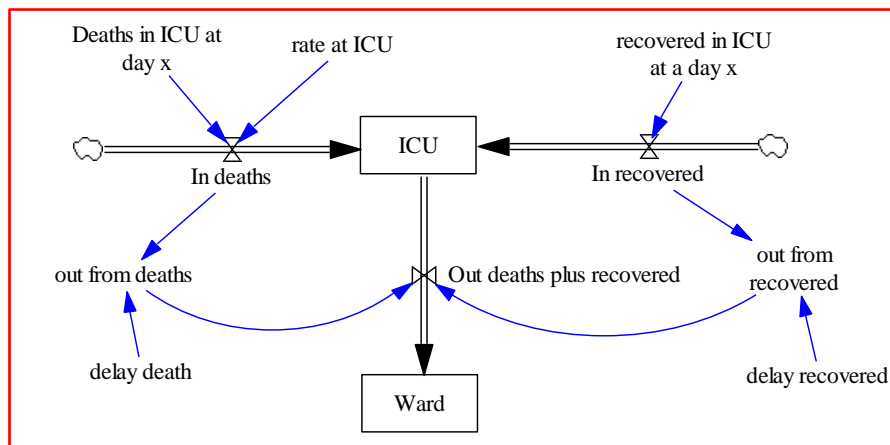


**Fig. 9.** Comparison with real data and the data obtained by simulation for daily deaths both at Hospitals and at Home, using a lookup table for 10-day rates

For generating the simulation results in Fig. 8, we assumed for all days a constant rate hospital/non-hospital obtained from the relation between the total deaths. To generate more accurate results, we assumed a different rate for a group of ten days (5 before, five after) obtained by the average proportion of these ten days. In other words, instead of assuming one constant rate for the entire period, we used 12 values corresponding to the average rate of each ten days. The results illustrated by the graphs in Fig. 9 show a better approximation to the reality. This measure is particularly important for long periods (120 days in our case).

#### 4.3 Applying the backwards process – 2 – ICU occupation rates

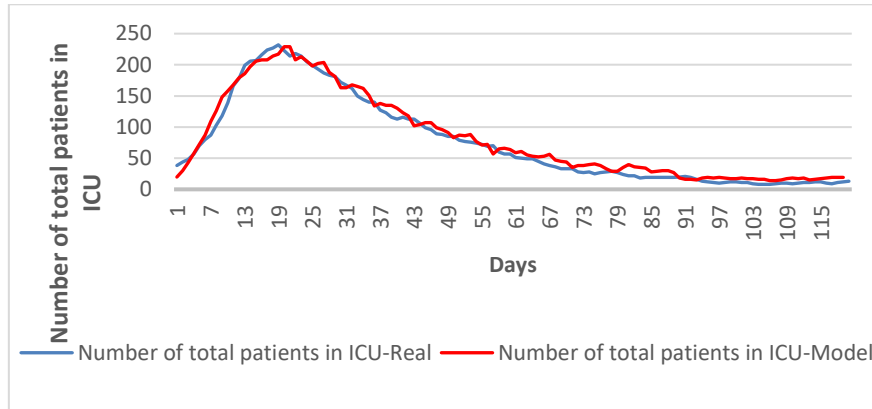
Following the ICU path backwards, the process gets more complicated. There is a delay in time between the outcome (death or recover) and the time the patient ingressed in the ICU. To calculate the ICU occupation rate at any time, we should estimate the number of days a patient stays in ICU until the outcome (death or recover). The data exists but it is not available. Thus, we must consider an average estimation to calculate the backward values. The data we have is the daily and accumulated values of all stocks. We can estimate the average time spent at ICU until the outcome by calculating the mortality and recovery rates and comparing number of deaths and recoveries with the number of patients in ICU  $x_1$  and  $x_2$  days before, being  $x_1$  and  $x_2$  the estimations of the average time before the outcome (death or recovery, respectively). To obtain more precise estimations for your model, we created another SD graph in which we can feed real data and tune the number of days spent at ICU before the outcome. Fig. 10 shows the SD Stock and Flow graph.



**Fig. 10.** SD model to explore the occupation of the ICU varying the time spent at ICI before recover or death.

To perform the simulations, we entered the real number of daily deaths occurred in the hospital and the numbers of discharges from the ICU. We could not separate the number of patients that die while in the ICU from those who died at the ward, so we assumed

50% for each origin. The main goal however was to estimate the time spent in ICU before the outcome. An average of 25 days was reported for both, which proved to be inconsistent with the occupation of ICU reported. We only got an approximation of the ICU occupation reported by setting the average rate of stay around 10 days. The results of the simulation in comparison to real data is depicted in Fig. 11.



**Fig. 11.** Real and Simulation data for ICU occupancy

Another possibility for the discrepancy was an overload of the ICU occupancy being solved by the transference of critical patients to other hospital units or an increase of ICU beds. In interviews with sanitary people, we were told the ICU capacity is limited by care takers (doctors, nurses, etc.) available. The ICU capacity can only be increased by transferring personal, suspending other surgeries, or recruiting extra personal.

#### 4.4 Applying the backwards process – 2 – Ward occupation rates

The next step is to model the ward occupation, working backwards from ICU real data. However, at this point there are many other flows influencing the hospital ward occupation. In addition to those sent to ICU, we will have those people sent home after getting better. There are also the people who died at the ward without passing through the ICU. Besides checking the rates of each of these outcomes (incomes in our backwards model), we will need to work on the variables representing the averages of the number of days a patient occupies a bed in the ward, for each of these outcomes.

There are also different types of cases demanding hospitalization. Most cases are those who get into care after testing positive and showing serious symptoms. A second type are related to those who already tested positive but were sent home because there were not showing serious condition and are returning after getting worse. Finally, those patients returning from a period at ICU that needs a recovery period before sent home.

The Stock and Flow diagram for the backwards analysis of cases is shown in Fig. 12. However, due to the complexity of the model and the lack of real data of each situation, we have not performed simulations to obtain the more precise rates.

## 5 Discussion and Conclusions

The main goal of this exercise was to reduce the uncertain of the effects of increasing number of covid-19 cases onto the sanitary system. Using the predictive model, we can simulate scenarios and based on the results, recommend actions to reduce the risk of saturation in the sanitary system, which is the main goal of this study. Although we don't need a precise model for planning the sanitary system, we think a prediction closer to the reality brings more confidence to planners.

1. After obtaining the real data for a period of time (the longest, the better) we run the model and make the adjustments in the rates to get results as close as possible of those of reality.
2. With a calibrated model, we run the simulations and generate prediction for the next days (the shortest, the better).
3. The predictions in relation to reality and make the necessary calibrations as described in step 1.

The reduction of the risk of collapsing the sanitary system comes from two alternative directions: we either reduce the income flow of patients or expand the capacity of the sanitary system. Actually, we can do both, but as these measures have consequences,

we want to produce results closest to the needs. This way, we mitigate the risks of saturation by adopting only the necessary effort, and consequently, reducing the waste of resources.

We are now in the verge of the second wave of the pandemics, most experts say [12]. We wanted to test our predictions against the real numbers after July 30th, but the number of cases was drastically reduced, and samples were not significant to produce a meaningful comparison. We are in the process of checking the estimations with the real numbers of this second wave. However, before that we need to make some adjustments in the model to resemble the change of conditions. For instance, the death rates were reduced due to advances in the treatment. This reduction also impacted the number of days spent in ICU.

Although we include the number of cases in the main model, we don't use it nor the number of infected people because these numbers are very dependent on the number of tests performed. There is, for instance, a controversial discussion about the seriousness of the second wave in relation to the first. Some scientists considered the underestimation of infections in the first wave makes the second wave not as serious as the first. On the other hand, the number of hospitalizations is higher in this second wave than in the first. This reinforces our claim to make predictions based on real data, not estimations.

## Acknowledgements.

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