A COVID-19 Recovery Strategy Based on the Health System Capacity Modeling. Implications on Citizen Self-management.

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ABSTRACT

Confinement ends, and recovery phase should be accurate planned. Health System (HS) capacity, specially ICUs and plants capacity and availability, will remain the key stone in this new Covid-19 pandemic life cycle phase. Until massive vaccination programs will be a real option (vaccine developed, world wield production capacity and effective and efficient administration process), date that will mark recovery phase end, important decisions should be taken. Not only by authorities. Citizen self-management and organizations self-management will be crucial. This means: citizen and organizations day a day decision in order to control their own risks (infecting others and being infected).

This paper proposes a management tool that is based on a ICUs and plants capacity model. Principal outputs of this tool are, by sequential order and always according to last best data available: (i) ICUs and plants saturation estimation data (according to incoming rate of patients), (ii) with this results new local and temporal confinement measure can be planned and also a dynamic analysis can be done to estimate maximum Ro saturation scenarios, and finally (iii) provide citizen with clear and accurate data allow them adapting their behavior to authorities' previous recommendations. One common objective: to accelerate as much as possible socioeconomic normalization with a strict control over HS relapses risk.

Keywords: Health system management, capacity planning, Covid-19 recovery strategies, Citizen Self-management, Queue theory, System Dynamics

1. Introduction

Recovery phase is starting, or is going to start in few weeks, in some of most pandemic affected countries as Spain. The duration of this new phase is uncertain and linked to the development and availability of the vaccine. Minimize fatalities while minimizing the number of new infections demands effective management strategies. That allows health system (HS) optimal response (Mcclellan et al., 2020). Meanwhile, to achieve these objectives, it is essential that population is aware its fundamental role fighting against COVID-19. Citizen behavior after opening the confinement is key in order new infections do not grow exponentially again, leading back the country to a new quarantine with numerous deaths and a massive economic loss.

Saturation of hospitals plants and ICUs have been a fact during phase 1 (spread or expansion). This will also be one of the most important risk in the recovery phase. To deal with new massive demands of HS capacity, governments should find quick solutions (asap) and supported by contingencies plans and studies in order to guide as best as possible these quick investments.

In our previous work (Crespo et al., 2020), suitability of local adapted strategies was discussed, considering local quarantine times and local GDP reduction impact. Now, the paper focuses on feasibility of local planning for CoVid-19 recovery phase. We model Health System Capacity in order to control the optimal HS response.

This way is possible to use and take advantage of great research community effort in infection prediction models to:

i) optimal decision making of sanitary resources allocation and
ii) early detection of the force of infection the system can face under several circumstances and
iii) support citizen and organizations self-management.

According to our previous results based on the prediction model of Gañán-Calvo and Hernández Ramos (2020) we focus the study at local level (Indenture level definition). Relapses will emerge at local level. But also new HS saturation events will happen at local level. Inhabitants of a population will go to local hospitals, which will cause saturation in those hospitals in the provinces where the number of new infections is high. Through this work, it will also be possible to determine those provinces that, being the health system less saturated, will be able to receive people infected from other provinces that are in worse conditions, thus achieving an overall improvement in the health system.

For the management point of view, recovery is the most complex phase. Not only owing to great number of decisions to take but also to real relapses risk. To be aware relapses may happen is the first step to control recovery. In this moment of the pandemic (real evolution and generated knowledge), relapses risk is critical because it's high probability and "not admissible" consequences. Especially if correct measures are not designed or not applied properly, and citizen and organizations do not contribute with the best possible self-management decisions.

Once the confinement is underway, the arrival of infected people to the HS will decay and there is a time window, an opportunity, to design a strategy, a plan, to adjust the activity recovery to the existing HS's capacity.

2. Approaches and variables for the Health System (HS) Modelling

The capacity planning problem, or sometimes the capacity expansion problem, is a classical problem in operations management literature. The problem the health systems face has important short-term dynamics, in fact, one can find some similarities to the problem that some organizations face with products rollouts to limit their short-term exposure while positioning themselves to capture the maximum long-term upside.

In this study, for instance, the magnitude of possible relapses will be uncertain and for our strategy development it is extremely important to know how quickly assumptions about can be converted to knowledge, and what to do when any assumption is invalidated, so managers must develop a kind of "discovery-driven planning" (as explained by McGrath et al. (2000). In these cases, the use of a disciplined process to uncover, test, and revise the assumptions behind the health system's response to pandemic, systematically, is required. By doing so, there is exposure to uncertainties common to pandemics, but uncertainties can be addressed at the lowest possible cost in public and economic health.

The problem the paper faces in this paper is the one of striking a balance between the levels of the restrictive measures to take at the province level vs. the province HS's required capacity to deal with potential relapses. There are two common approaches to deal with this problem:

1. *Analytical models*. At this point, queue theory models are the most commonly used models. The utilization of these models requires the knowledge of the rates of patient's arrival, and the distribution of the time for patients' treatments, in hospitals plants and intensive care units (ICUs). Other analytical models to deal with this problem such as Linear Programming models can also be used (Duffuaa, 2000), although many authors of these models recognize that it is very complex to treat the general capacity planning problem in a single optimization model including all aspects of the problem.
2. *Monte-Carlo Simulation models*. A more general approach is based in stochastic simulation (Dekker et al., 1995). The simulation will be carried out in the computer, and estimates will be made for the desired measures of performance (Hoyland et al, 1995). The simulation will be then treated as a series of real experiments, and statistical inference will then be used to estimate confidence intervals for the desired performance metrics.

High number of variables allow us to define the system accurately, but on the other hand, this will increase the complexity of the model and therefore it will be more difficult to solve. Modelling optimization entail reaching an intermediate point where the system is well defined without making its resolution very difficult. The variables chosen to define the queuing model and the simulation model are shown in Table 1. The variables are divided into three groups.

Note that although many variables depend on the study region or time, there are certain variables that have been assumed constant in this study. The ratios of people who recover from the hospital and go home (Rph), of people who die on the hospital Plant (Rpd) and of people who die in the ICU (Rid) have remained fairly constant over time and for the different provinces (Sources). Therefore, we have decided to keep its values constant throughout the study. On the other hand, for the average times that a person has spent at the Plant (Ttp) or ICU (Tticu), we have calculated (Sources) a reference value that we have used in all the provinces and that, therefore, we have also assumed constant throughout the study. The rest of the variables are assumed to be variables with the region and with time. All the used variables of the health system from now on in both the queuing model and the simulation model are defined in Table 1.

3. Modelling the HS response using QT analytical models.

Queuing processes can be modelled as continuous time stochastic processes with a discrete number of states. When the distribution function is exponential, the process is said to be a homogeneous Poisson process (HPP). In this case Poisson processes, because of their definition, have properties that are interesting to us, for instance:

- Reproductive property: If we mix n independent Poisson processes, the result is another Poisson process which has an arrival rate equal to the sum of the rates of the processes considered;
- Divisible character. That is to say, if the arrivals are ruled by a Poisson process of rate λ and every arrival is directed to a certain subsystem i with probability pi,

with i=1, …, n. Then each of the subsystems is a Poisson process with arrival rates λp1, λp2,…,λpn;

– If a phenomenon of arrivals is obtained from a great number of renovation independent processes, the above-mentioned process it is approximately a Poisson process. At least in intervals of time of short duration in comparison with the times between arrivals of the individual processes.

Variables group	Variables definition	Notation	Units
System states related variables	Number of infected that goes to the hospital	C	People/day
	Treated at the Plant (Queue or bed)	Ntp	People
	Treated in Bed at the Plant	Np	People
	Waiting for Plant	Nwp	People
	Treated at the ICU (Queue or bed)	$Nticu$	People
	Treated in Bed at the ICU	$Nicu$	People
	Waiting for ICU	$Nwicu$	People
	Death Toll	$Dtoll$	People
	Confined at home	Nch	People
	Immunized	Ni	People
Flows related variables	Entering at the plant	λep	People/day
	With bed assigned at the Plant	μba	People/day
	Directed to the ICU from triage	λicu	People/day
	Entering the ICU	$\lambda eicu$	People/day
	Entering home confinement	λehc	People/day
	Entering Plant from ICU	$\mu epfi$	People/day
	Entering the ICU from Plant	$\mu eifp$	People/day
	Dying at the ICU	μid	People/day
	Dying at the Plant	μpd	People/day
	Released for home confinement	μrhc	People/day
	Cured at home	μch	People/day
	Leaving plant	μp	People/day
	Leaving ICU	μicu	People/day
Ratios, times and capacities variables	Ratio of patients derived to Plant	Rp	Ratio
	Ratio of patients derived to ICU	$Ricu$	Ratio
	Plant to Home ratio	Rph	Ratio
	Plant Death ratio	Rpd	Ratio
	ICU Death ratio	Rid	Ratio
	Average total time spent in Plant per patient	Ttp	Days
	Average total time spent in ICU per patient	$Tticu$	Days
	Time spent in Bed at the Plant	Tp	Days
	Time spent in Bed at the ICU	$Ticu$	Days
	Average time at home	Th	Days
	Time waiting in Plant	Twp	Days
	Time waiting in ICU	$Twicu$	Days
	Plant capacity	Cpb	Beds
	ICU capacity	$Cicu$	Beds

Table 1. Variables of the Health System (HS) Modelling

Although one of the queuing problem hypotheses is to use a FIFO policy (First Inside, First Outside), circumstance that will not happen in real life, since the severity of the patient in the queue will finally prevail over the arrival order, due to the small percentage of the cases that occur daily, it is assumed that calculated averages will not be altered and therefore the use of this model continues to be successful.

Considering previous properties, following formulation of stationary queuing problem (presented in Table 2 and Figure 1) is applied to the HS.

Variables	Notation	Units	Value
Daily number of infected arriving to hospitals	C	People/day	Province based
Ratio of patients derived to Plant	Rp	Ratio	Province based
Ratio of patients derived to ICU	$Ricu$	Ratio	Province based
Average total time spent in Plant per patient	Ttp	Days	11
Average total time spent in ICU per patient	$Tticu$	Days	14
Plant capacity	Cpb	Beds	Province based
ICU capacity	$Cicu$	Beds	Province based
Plant to Home ratio	Rph	Ratio	80%
Plant Death ratio	Rpd	Ratio	15%
ICU Death ratio	Rid	Ratio	13%

Table 2. Input data to solve the queuing problem applied to HS.

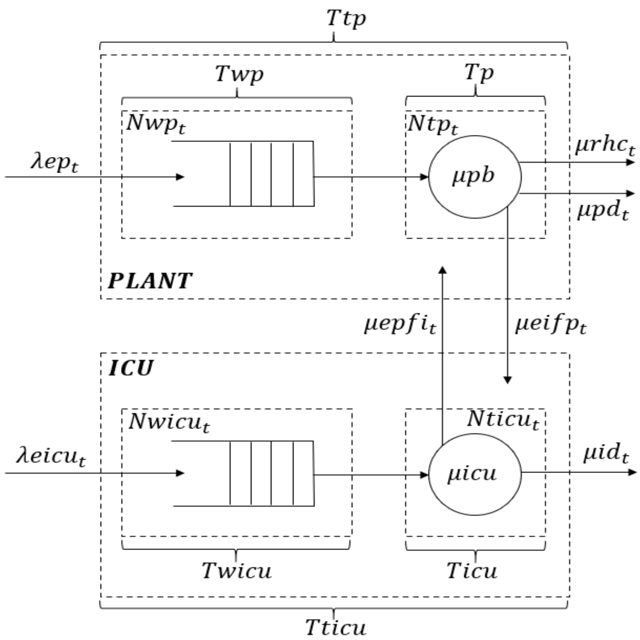

Figure 1. Queuing problem applied to Plant and ICU

The first step to solve the stationary problem will be to calculate the number of people entering the Plant and the number of people entering the ICU, which can be done directly with the following equations:

$$\lambda ep = C \cdot Rp \quad (1)$$

$$\lambda eicu = C \cdot Ricu \quad (2)$$

Secondly, once these two flows of people are known, we will calculate the four remaining flows will be calculated using, on the one hand, the ratios of people who recover in Plant and the people who die in the ICU and, on the other hand, the two equations that are obtained when applying continuity in the Plant and ICU systems, that is, equalizing the input and output flows of each system.

$$\mu rhc = Rph \cdot (\lambda ep + \mu epfi) \quad (3)$$

$$\mu pd = Rpd \cdot (\lambda ep + \mu epfi) \quad (4)$$

$$\mu id = Rid \cdot (\lambda eicu + \mu eifp) \quad (5)$$

$$\lambda ep + \mu epfi = \mu eifp + \mu rhc + \mu pd \quad (6)$$

$$\lambda eicu + \mu eifp = \mu epfi + \mu d \quad (7)$$

This is a system of 4 equations with 4 unknown variables that is easy to solve and from which it is obtained all the flows of the queuing problem. Once flows are known, everything else can now be calculated using the equations presented above from the queuing theory. According to little's law, total number of people within each system can be calculated:

$$Ntp = (\lambda ep + \mu epfi) \cdot Ttp \quad (8)$$

$$Nticu = (\lambda eicu + \mu eifp) \cdot Tticu \quad (9)$$

To calculate the number of people waiting in each queue, and the waiting time, it is useful to calculate the patient exit rate (μ) and the saturation rate (ro) of each system.

$$\mu pb = Cpb/Ttp \quad (10)$$

$$\mu icu = Cicu/Tticu \quad (11)$$

$$\rho p = (\lambda ep + \mu epfi)/\mu pb \quad (12)$$

$$\rho icu = (\lambda eicu + \mu eifp)/\mu icu \quad (13)$$

Once these variables are calculated, it is time to apply the following equations and obtain the people in the queues and the average time they have to wait.

$$Nwp = {\rho p^2}\Big/{(1 - \rho p)} \quad (14)$$

$$Nwicu = {\rho icu^2}\Big/{(1 - \rho icu)} \quad (15)$$

$$Twp = {\rho p}\Big/{\mu pb \cdot (1 - \rho p)} \quad (16)$$

$$Twicu = {\rho icu}\Big/{\mu icu \cdot (1 - \rho icu)} \quad (17)$$

Finally, applying continuity again, we can calculate the average number of people in bed on the floor and in the ICU are obtained, as well as the time they are there.

$$Np = Ntp - Nwp \quad (18)$$

$$Nticu = Nicu - Nwicu \quad (19)$$

$$Tp = Ttp - Twp \quad (20)$$

$$Ticu = Tticu - Twicu \quad (21)$$

It is essential for the problem to converge that the saturation rate (ro) in both Plant and ICU is always less than one, which means that the patient entry rate remains below the patient exit rate that can give the system due to its capacity. Therefore, for the problem to have a solution, it is an essential condition:

$$\rho p = \frac{(\lambda ep + \mu epfi)}{\mu pb} < 1 \rightarrow \lambda ep + \mu epfi < \mu pb \quad (22)$$

$$\rho icu = \frac{(\lambda eicu + \mu eifp)}{\mu icu} < 1 \rightarrow \lambda eicu + \mu eifp < \mu icu \quad (23)$$

This can be considered as a sort of calculator, that assuming a given HS capacity, give us the maximum input rate of patients the system can handle, considering of course stationary conditions. Obviously, the HS under the pandemic thread will never be under a stationary state but this result offers an interesting tool to understand the expected system conditions at certain scenarios, for instance capacity versus patients arrival rate.

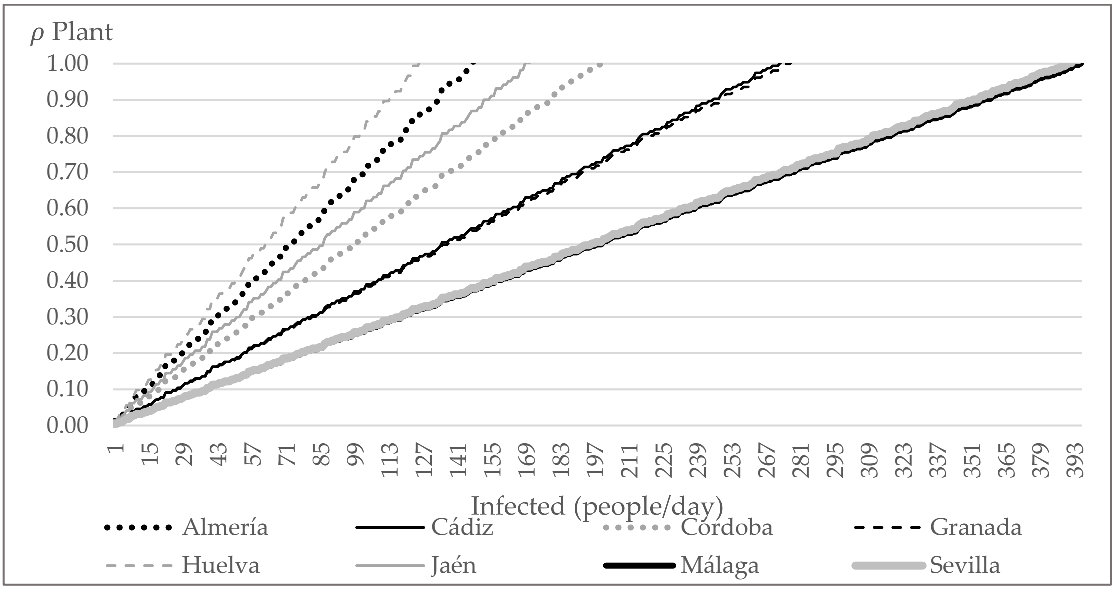

Figure 2. Plant saturation per province vs Infected people going to hospital

Notice that Figure 2 & 3 results are calculated assuming stationary conditions with the intention to stablish reference patient flow limits for HS units saturation.

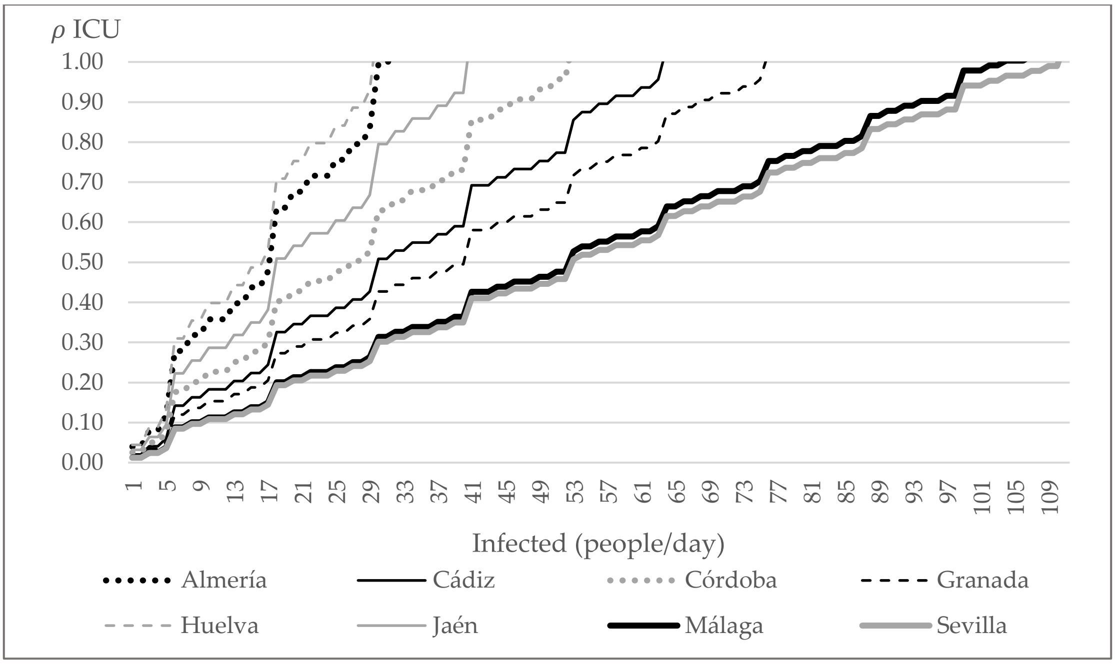

Figure 3. ICU saturation per province vs Infected people going to hospital

Figure 2 shows the evolution of the saturation of the plant in each province (*ρp*) versus the number of infected patients who pass through the hospital in that province. In this number of infected people grows daily, and saturation of the plant increases, reaching a number from which the plant cannot handle it. Similarly, Figure 3 shows the saturation of the ICU (*ρicu*) versus the number of infected registered in the province. Note that since the capacity of the ICUs is much less than that of the Plants, they are saturated for a smaller number of infected in each province.

However, managers cannot allow hospitals to reach such a saturation level (*ρ=1*), since the number of people in the queue at the Plant and ICU will greatly increase and also the time they are waiting, causing deaths that can be preventable. To avoid these long queues and waiting times we have limited the waiting time in the queues to 1 hour, which leads to maximum saturations for the Plant and the ICU in each province. These results are shown in Table 3 (see also Figure 4). This table shows first the capacity of the plant and the ICU of each province, in number of beds.

PLANT	**Almería**	**Cádiz**	**Córdoba**	**Granada**	**Huelva**	**Jaén**	**Málaga**	**Sevilla**
Plant capacity (beds)	1003	1847	1347	1873	857	1160	2686	2650
Average $\boldsymbol{\lambda ep + \mu epfi}$	9	20	22	44	12	27	57	45
Average $\boldsymbol{\rho p}$	0.11	0.13	0.20	0.28	0.17	0.28	0.25	0.20
$\boldsymbol{\rho p}$ **Sat. (Tw>1h)**	0.79	0.87	0.83	0.88	0.76	0.81	0.91	0.91
Average $\boldsymbol{\lambda ep + \mu epfi}$ **in saturation**	66	134	93	136	54	78	204	201
ICU	**Almería**	**Cádiz**	**Córdoba**	**Granada**	**Huelva**	**Jaén**	**Málaga**	**Sevilla**
ICU capacity (beds)	88	172	139	205	79	110	279	290
Average $\boldsymbol{\lambda eicu + \mu eifp}$	3	5	5	11	4	6	13	12
Average $\boldsymbol{\rho icu}$	0.44	0.49	0.63	0.87	0.75	0.95	0.78	0.66
$\boldsymbol{\rho icu}$ **Sat. (Tw>1h)**	0.79	0.90	0.81	0.89	0.71	0.76	0.90	0.96
Average $\boldsymbol{\lambda eicu + \mu eifp}$ **in saturation**	5	11	8	13	4	6	18	20

Table 3. Maximum saturations allowed for the Plants and ICUs of each province. Public and private hospitals (source: Junta de Andalucía)

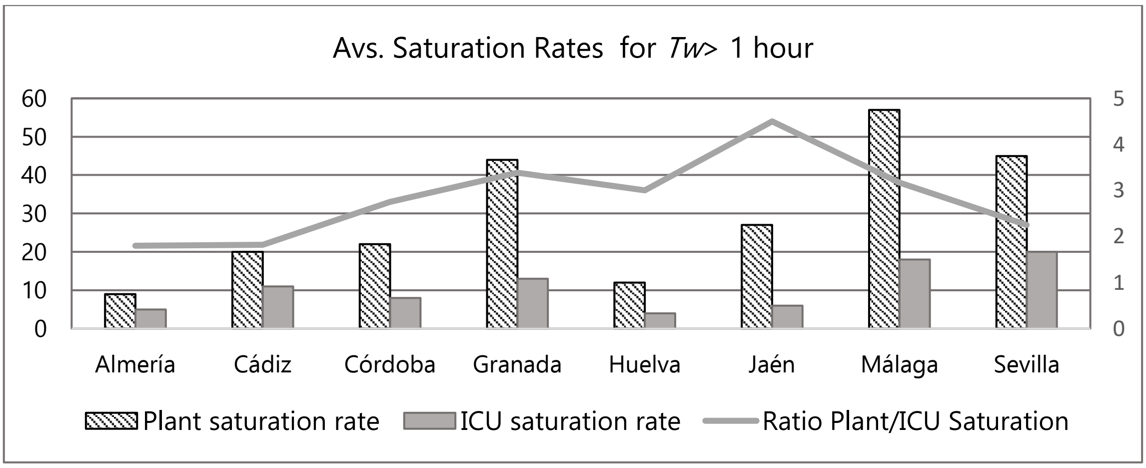

Figure 4. Summary of saturation rates results for Tw> 1hr. in plant and ICU and their quotient.

Logically, the higher this capacity, the more saturation is able to achieve without greatly increasing queuing times. Second, the average number of people entering the Plant and ICU currently in each province and the average saturation of both services are shown. Note that currently having carried out an effective confinement in the provinces of Andalusia, the Plants show a saturation level in almost all cases below 25%. Likewise, the ICUs, although they are more saturated because they have less capacity, do not reach a very critical value in any province except in Jaén, which if this had been the entry rate since the beginning of the pandemic would have been saturated.

Having evolved with a variable entry rate, this did not actually happen. Finally, it is we shown the saturation of the plant and the ICU and the number of patients in each service for which the queues of the services would take more than an hour (considered unacceptable). In the provinces that have more capacity, such as Malaga or Seville, the plant can be more saturated, even reaching 90% and the waiting time will not exceed 1 hour, however, in others with less capacity, such as Huelva or Almería, this time of one hour is expected to be reached for saturations of less than 80%.

4. Modelling the HS response using Monte-Carlo simulation.

In this section, Monte-Carlo simulation method is applied to the problem of designing a COVID-19 response management strategy, in a way that the expected relapses of the pandemic when the confinement is finished, can be properly managed. This method allows considering relevant aspects of the health systems operation in order to create a realistic dynamic scenario of the system through the generation of certain random and discrete events, which cannot be easily captured by analytical models, such as: variable and seasonal demand, stand-by facilities, dynamic capacity adjustments, treatment priorities, etc. By doing so, we can avoid restrictive modelling assumptions that had to be introduced to fit the models to the numerical methods available for their solution, at the cost of drifting away from the actual system operation and at the risk of obtaining sometimes dangerous misleading results (Pidd et al., 2003). The weak point of the Monte-Carlo method is the computing time (Marseguerra et al.,2000) especially when the search space for the control variables of the problem to test increases, though the computation levels of recent servers minimizes this dependence.

For a better understanding, the simulation problem by Monte-Carlo is structured in two blocks: The Health System Capacity Planning Problem and Hospital Demand Dynamic Model Determination Problem.

4.1. HS System Capacity Model for COVID-19 Planning Problem

The health system capacity planning problem will now be modeled (see Figure 5) using continuous time stochastic simulation (other examples can be found in the literature in discrete event simulation too, like un Günal et al, 2010) . This simulation will evaluate the system state every constant time interval ($\Delta t = 1$ day), the new system state will be recorded and statistics collected. We will consider chronological issues by simulating the number of patients to be treated at any time in the different units. The model is built using VENSIM (Ventana, 2004) as simulation tool, which has special features to facilitate Monte-Carlo type of simulation experiments, and to provide confidence interval estimations.

The following are the formal difference equations for the continuous time stochastic simulation model considered:

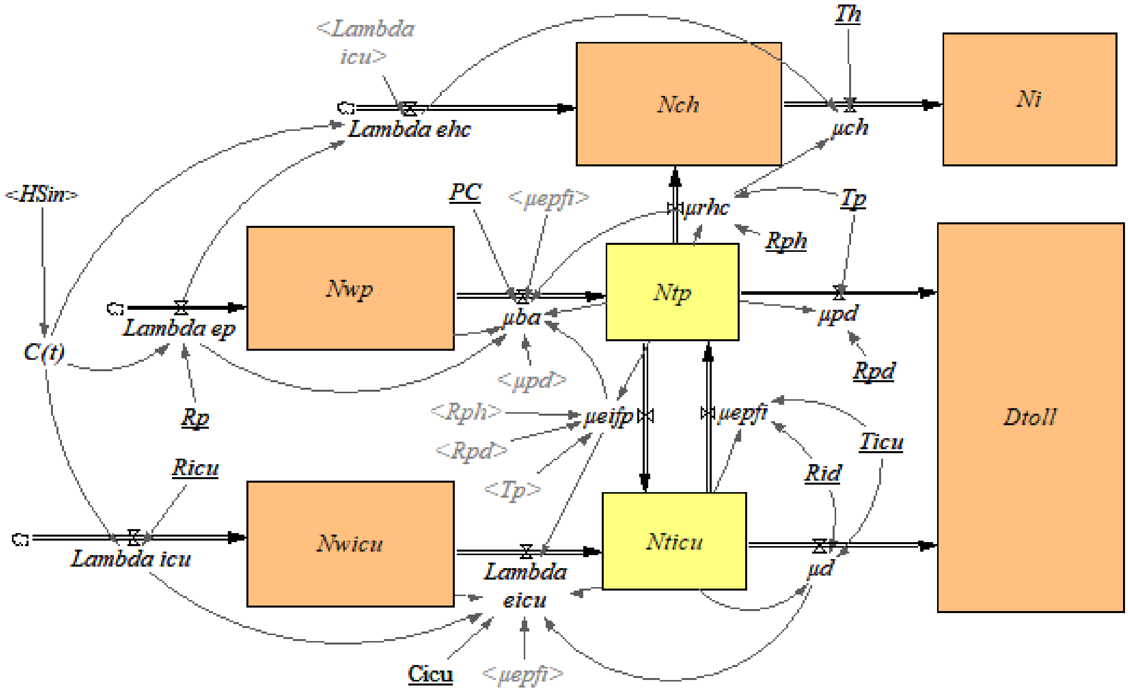

Figure 5. Stock and flow diagram of the health system.

State variable equations

The patients waiting for treatment, at the ICU:

$Nwicu_t = Nwicu_{t-1} + \lambda icu_t - \lambda eicu_t$, with the following initial conditions: (24)
$Nwicu_{to} = Nwicu_0$ (25)

The patients waiting for a bed in the plant:

$Nwp_t = Nwp_{t-1} + \lambda ep_t - \mu ba_t$, with the following initial conditions: (26)
$Nwp_{to} = Nwp_o$ (27)

The number of patiens confined at home would be:

$Nch_t = Nch_{t-1} + \lambda ehc_t + \mu rhc_t - \mu ba_t$, with the following initial conditions: (28)
$Nch_{to} = Nch_o$ (29)

These leaving the home confinement would me immunized:

$Ni_t = Ni_{t-1} + \mu ch_t$, with the following initial conditions: (30)
$Ni_{to} = Ni_o$ (31)

The number of patiens treated at the ICU would be:

$Nticu_t = Nticu_{t-1} + \lambda eicu_t + \mu eifp_t - \mu epfi_t - \mu id_t$, with initial conditions: (32)
$Nticu_{to} = Nticu_o$ (33)

The number of patiens treated at the plant would be:

$Ntp_t = Ntp_{t-1} + \mu ba_t + \mu epfi_t - \mu rhc_t - \mu epfi_t - \mu pd_t$, with initial conditions: (34)
$Ntp_{to} = Ntp_o$ (35)

Finally, part of tse treated at the ICU will die:

$Dtoll_t = Dtoll_{t-1} + \mu id_t + \mu pd_t$, with the following initial conditions: (36)

$Dtoll_{to} = Dtoll_o$ (37)

Flow variables equations:

$$\lambda icu_t = I(C_t \times Ricu) \quad (38)$$

$$\lambda ep_t = I(C_t \times Rp) \quad (39)$$

$$\lambda ehc_t = C_t - (\lambda icu_t + \lambda ep_t) \quad (40)$$

$$\mu ch_t = I(Delay3(\lambda ehc_t + \mu rhc_t,\ Th)) \quad (41)$$

$$\mu rhc_t = I(Rph \times Ntp_t/Tp) \quad (42)$$

$$\mu epfi_t = I((1 - Rid) \times\ (Nticu_{t-1}/Ticu)) \quad (43)$$

$$\mu pd_t = I(Rpd \times Ntp_{t-1}/Ticu)) \quad (44)$$

$$\mu id_t = I(Rid \times Nticu_{t-1}/Ticu)) \quad (45)$$

$$\mu eifp_t = I((1 - Rph - Rpd) \times Ntp_t/Tp) \quad (46)$$

$$\lambda eicu_t = MIN(Cicu - Nicu_{t-1} - \mu eifp_t + \mu epfi_t, Nwicu_{t-1} + \lambda icu_t) \quad (47)$$

$$\mu ba_t = MIN(Cp - Ntp_{t-1} - \mu epfi_t + \mu eifp + \mu pd, Nwicu_{t-1} + \lambda ep_t) \quad (48)$$

Where:

$I(x)$: Funtion providing the integer value for x

$Delay3(x, y)$: Funtion providing a third order delay of input x for the timedelay y

Then, for a greater resemblance to reality, it is crucial to determine hospital demand caused by COVID-19 in order to feed the previous model.

4.2. Selected model for HS demand for COVID-19 determination

For the dynamic modelling of the problem dealing with hospital demand determination, it is selected a type of SEIR model similar to others in literature (Iwata et al., 2020), that has been then re-formulated in a particular way. The general formulation of the SEIR model is a set of four first order differential equations as follows:

$$dS/_{dt} = -\beta \times {}^{(S \times I)}/_{P} \quad (49)$$

$$dE/_{dt} = \beta \times {}^{(S \times I)}/_{P} - a \times E \quad (50)$$

$$dI/_{dt} = a \times E - \gamma \times I \quad (51)$$

$$dR/_{dt} = \gamma \times I \quad (52)$$

Where *S*, *E*, *I* and *R* are for *Susceptible*, *Exposed*, *Infectious* and *Recovered* populations, respectively. P is the complete population, β is the force of infection or the disease transmission rate, *a* is the inverse of the latent infection period and γ is the inverse of the infection duration time. For this model Ro, the disease basic reproduction number, is defined as $R0 = \beta/\gamma$. In Figure 6, the model design that has been selected for the empirical resolution of the above differential equations is presented. The list of complete used variables that we use are in Table 4.

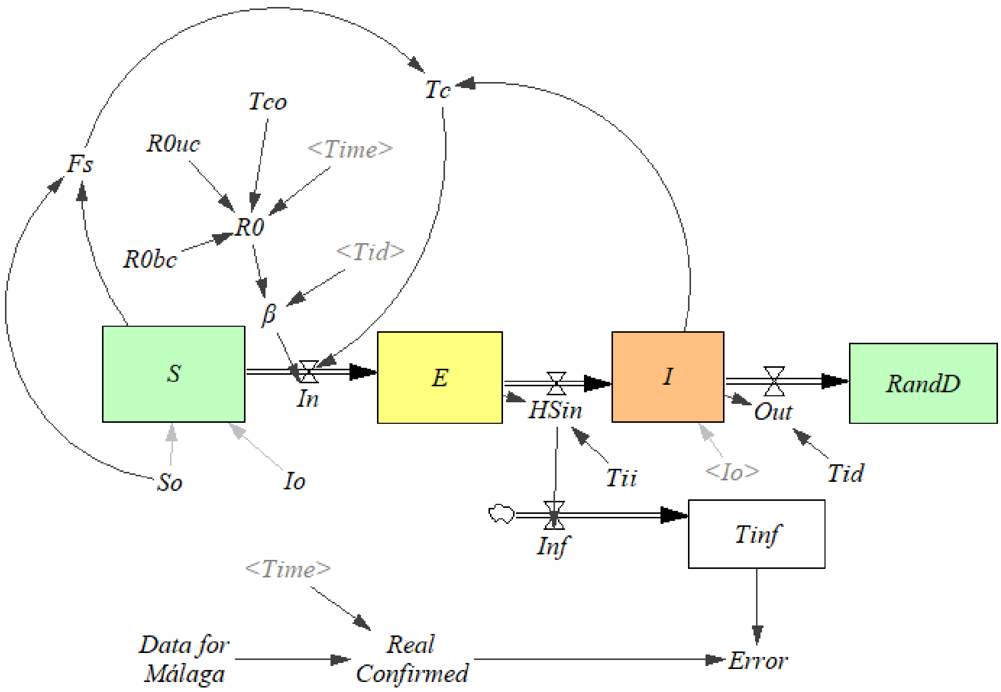

Figure 6. Stock and flow diagram of the pandemic SEIR&D model.

State variables	**Notation**	**Units**
Infectious population	I	People/day
Exposed	E	Ratio
Population susceptible to be infected	S	Ratio
Recovered and Deaths	$R\&D$	Days
Total infected (Prediction)	$Tinf$	Days
Flow variables	**Notation**	**Units**
Infecting	In	People/day
Health system input flow	$HSin$	People/day
Output flow	Out	People/day
Auxiliary variables	**Notation**	**Units**
Fraction of population susceptible	Fs	Ratio
Contacts between infected and susceptible	Tc	Ratio
Basic reproduction number before(bc) and (uc) confinement.	$R0$	People
Force of infection or transmission rate	β	People/day
Model parameters	**Notation**	**Units**
Time of confinement	Tco	Days
Time of infection incubation	Tii	Days
Time of infection duration	Tid	Days

Table 4. Notation of the variables used in SEIR&D model.

These are the formal difference equations for the continuous time stochastic simulation model considered are:

State variable equations

The population supceptible to be infected:

$S_t = S_{t-1} - In_t$, with the following initial conditions: (53)

$S_{to} = S_o$ (54)

The exposed population is:

$E_t = E_{t-1} + In_t - HSin_t$, with the following initial conditions: (55)

$E_{to} = E_o$ (56)

The infectious population:

$I_t = I_{t-1} + HSin_t - Out_t$, with the following initial conditions: (57)

$I_{to} = I_0$ (58)

The population Recovered ad death is:

$R\&D_t = R\&D_{t-1} + Out_t$, with the following initial conditions: (59)

$R\&D_{to} = R\&D_o$ (60)

Flow variables equations:

$In_t = I(\beta \times Tc_t)$ (61)

$Fs_t = S_t/So_t$, with So, the initical susceptible population (62)

$HSin_t = I({}^{E_t}/_{Tii})$ (63)

$Out_t = I({}^{I_t}/_{Tid})$ (64)

Aauxiliary variables equations:

$Fs_t = S_t/So_t$, with So, the initical susceptible population (65)

$Tc_t = Fs_t \times I_t$ (66)

$\beta_t = {}^{R0_t}/_{Tid}$ (66)

4.3. Calibrating and Deduced behavior patterns of the Models

With the aim of validating the models with data, calibrating parameters according to fit observed real-life behavior patterns, a real case is selected for the Malaga province. In Figure 7, it is presented results for *Tinf* in Málaga, the predictor for the total infected people. Picture shows the parts of the curve that are critical for its calibration.

In Málaga the confinement took place *Tco*=19 days after the first person was found infected, Io=1 and So=1.6M People, the curve best fit obtained, assuming a basic reproduction number *R0bc*=7 persons (within limits presented in Biao Tang et al, 2020) are for: *Tid*=7 days and *Tii*=4.1 days. $R0_{uc}$ could be calibrated as in Figure 8, where the reader can notice that R=<1 was reached in less than 30 days after the confinement (this result that we will remind later). Notice the R0 is substantially reduced under confinement to reach values close to 0.37 persons.

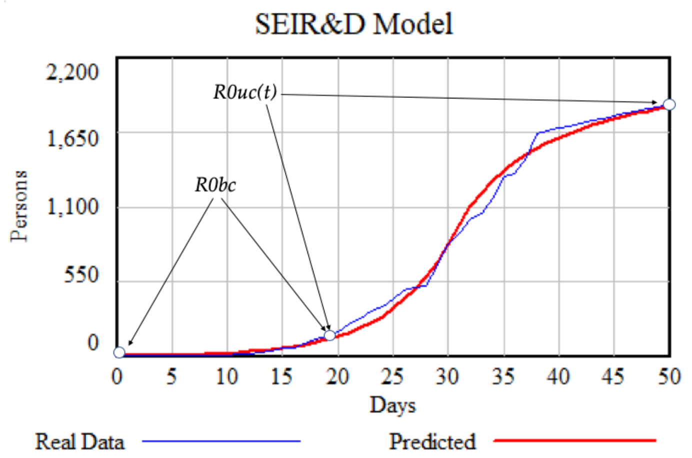

Figure 7. Model results for prediction of Total Infected (*Tinf*) in Málaga.

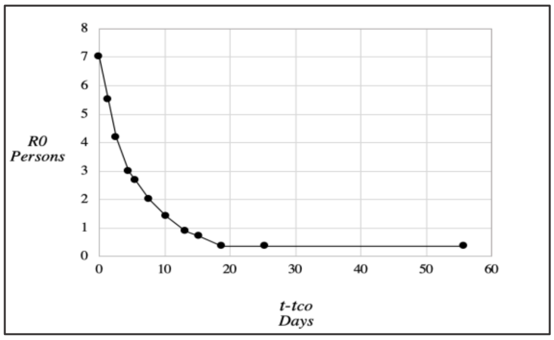

Figure 8. Result for RO calibration under confinement $RO_{uc}(t - T_{co})$.

Once the model is calibrated, Monte-Carlo simulation can evaluate the saturation of ICU or Plant before and under the confinement. This is relevant to gain understanding about the pandemic and HS dynamics when releasing confinement measures. The calibrated model replicated how, despite possible punctual hospital problems in ICUS, the HS in Málaga was far from saturation thanks to the early confinement of the population.

4.4. Citizen self-management. Relevant information obtained from the model application.

Last part of this paper is dedicated to understand, with the model, the effort that must be expected from the citizens when the confinement ends. In this new phase of the Covid-19 pandemic, recovery phase. What is the force of infection that our HS can bear? What is the basic information that citizens should perfectly know in order take good decisions to collaborate in relapses risk reduction? How long will this next phase last?

In order to consider this important aspect projecting the model results until day 200, that is to say, 125 days after the release of the confinement, assuming this will take place the day 75, 56 days after the confinement (May 10th for Málaga). Multivariate sensitivity analysis has been done. It is considered the following hypothesis:

- [$Tinf_t$ ±30%] variability added in prediction for infected (random uniform),
- [R & T ±20%] variability added in flow rates and times in HS (random uniform),
- $R0ac$, after confinement, within the interval $[0.85 - 1{,}5]$, also (random uniform).

Results for the sensitivity analysis 400 simulations are presented in Figures 9 and 10, where plant and ICU occupations for 125 days since the release of the confinement are analyzed. These results show:

- The risk of ICU saturation is very low only 5% of the simulations.
- No saturation would take place in Plant, since we would never reach the 2000 patients regardless the possible queue of patients in plant waiting for ICU.
- Although this would be the maximum level of risk to bear within the period analyzed (R0=1.5), ensuring control to limit R0 to 1.1 persons maximum would be advisable, monitoring the status of the variable, preparing for eventual confinement that could take place if needed due to an important relapse, and in a number of days that could be stablished following the curve in Figure 8.
- According to Figure 8, and the data and calibration of the model in Málaga, in case of sudden relapses (monitored over a certain period, for instance 5 days) a 2 weeks quarantine would be enough to lower R0 to reach levels below 1 person (see strategy in Qun Li et al, 2020).

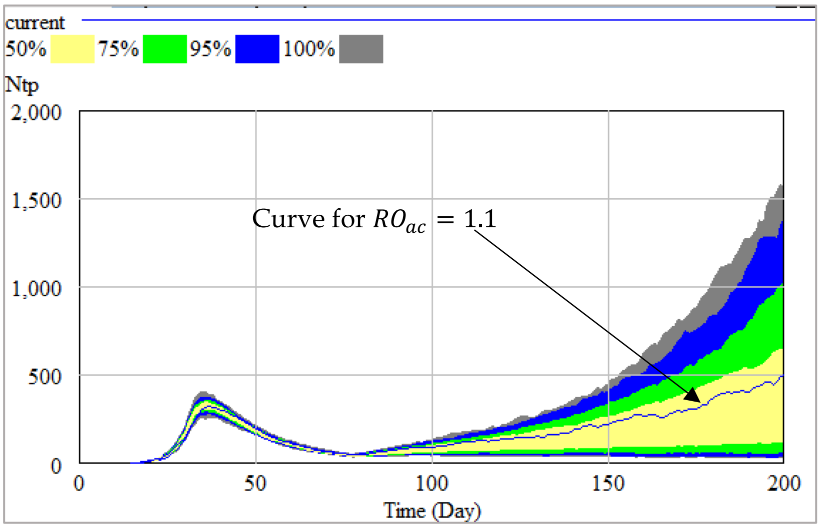

Figure 9. Sensitivity results for plant occupation.

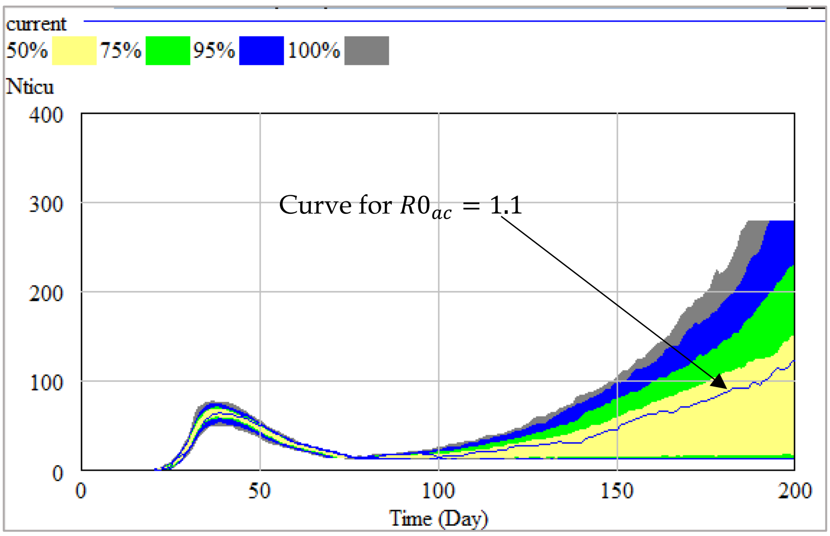

Figure 10. Sensitivity results for ICU occupation.

Finally, in figure 10 we present the graph with Monte-Carlo analysis results for the expected death toll for the province. The reader can have look at the impact in number of deaths when relaxing the R0. Again, here simulation results are for a uniform distribution in R0 within the interval $[0.85 - 1{,}5]$. We call readers attention in the simulation horizon, that would end very close to the point when a vaccine could be available. This mark the end of recovery phase and the beginning of the following phase of Covid-19 pandemic life cycle. May be an "stationary phase" with seasonal peaks, as other viruses.

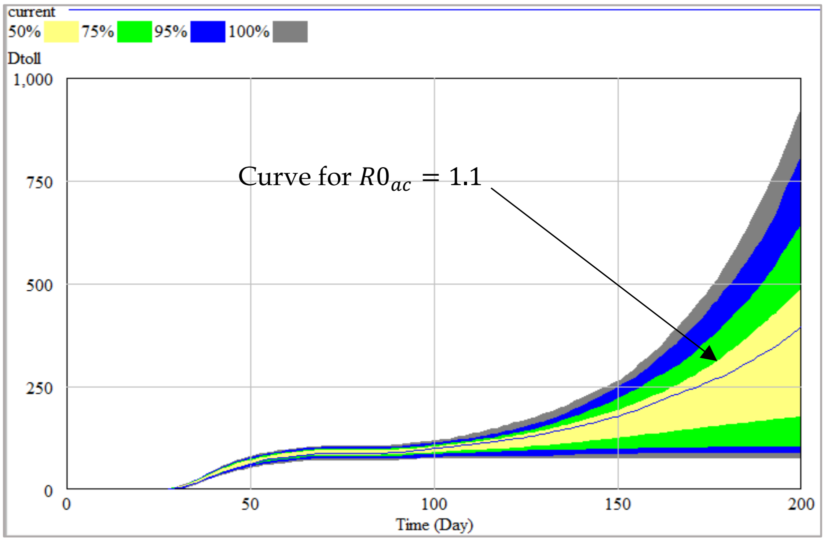

Figure 11. Sensitivity results for Death Toll.

Another important discussion that could be possible with the model, not done in this paper, is the impact in measures of any antiviral medicine that could be available at a certain moment in time, and whose doses could be supplied with a certain delay time.

To maintain the R0 mentioned enormous effort must be done by citizens and society in general. R0 results of multiplying the average number of contacts (Nc) that infectious people have with people susceptible to be infected (I× F_s), times the ratio of infection of a contact (Ri), times the time of infection duration (T_{id}).

$$RO = \beta \times T_{id} = (Nc \times Rin) \times T_{id}$$

Therefore, citizens must be aware about the personal effort in contacts reduction (mobility, events, meetings, etc.) and in lowering the ratio of infection (PPEs, social distancing, hygiene, etc.) that will be expected from them.

5. Conclusions

Reaching the end of the second phase of the pandemic life cycle determined by the end of the confinement suffered in almost all countries of the world, there is a common objective for the next phase, to be prepared not to cause an exponential growth of the virus again leading to a second quarantine. With the tools proposed in this manuscript, the aim is to face this new phase of possible relapses, facilitating decision-making. The end of this phase will be determined by the appearance of a vaccine or that a significant percentage of the population has suffered from the virus, leading to the last phase of the virus life cycle or post-pandemic phase.

The presented simulation model is a powerful tool to cope with the virus phase of possible relapses. First, when the confinement is released it will be essential to control the new infections. The recovery phase requires everyone to act in an environment of tremendous uncertainty. Our model gives accurate and easily interpreted data so that the citizen knows how to adapt their behavior until a cure appears. Those same data can be used in the self-management of companies and work centers.

Conversely, if citizens are unable to adapt their behavior, it would cause a relapse of the virus that the model can detect in time. Our model identifies these data and allows us to follow the evolution of possible relapses, predicting whether it is possible that hospitals will become saturated in the future. This is the key information to make decisions, both for companies and citizens.

Finally, if new confinement is required, this tool makes it easier to locate resources where they are really needed, supplying more resources in those areas that are close to saturation than in other regions that do not have the need. These three characteristics that the model presents are therefore essential to face this new phase of the virus life cycle that is coming and to minimize the impacts that this may cause.

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