Abstract. In this Chapter, several efforts that the SIM Research Group, from the University of Seville, accomplished during the Covid-19 pandemic lockdown in March-June 2020, are introduced. These efforts had an important impact on media and were mainly concern with the pandemic recovery phase.

When confinement ends, recovery phase must be accurate planned at a local level. Health System (HS) capacity, specially ICUs and plants capacity and availability, would remain the key stone in this pandemic life cycle phase.

This Chapter describes: First the important of the action plans design by local level, while a unique decision-making center is considered by country; Second, a management tool based on a ICUs and plants capacity model to estimate ICUs and plants saturation, and with these results, set new local and temporal confinement measures. The tool allows a dynamic analysis to estimate maximum Ro saturation scenarios; Third, a practical management tools to tackle the deconfinement strategy design problem. A proper control system to follow the course of action, especially in a scenario with unprecedent uncertainty, is developed.

In all cases, it is remarked the importance of R (the pandemic basic and effective reproductive number), first as a variable to monitor and control the pandemic, to ensure its decline; second as a target to score risks associated to start certain activities over, after confinement. Reducing the potential increase in the value of R, when any type of activity is re-opening, guides the strategy.

One common objective in these initiatives: Applying asset management principles to accelerate as much as possible socioeconomic normalization with a strict control over HS relapses risk.

Keywords: Asset management principles · Indenture level · Health system capacity planning · Covid-19 recovery strategies · Basic reproductive number
system’s performance at a certain expense requires the identification of the most suitable indenture level for management [3]. In complex systems: reaching desired system performance is more expensive when the data, and management of their failures, are handled at higher indenture levels; Cost of strategies to ensure dependability of complex systems increases linearly when the cost of restoring the low-level item increases and the higher the indenture level the higher the increase rate; Cost of the strategy grows inversely proportional when dealing with high frequency of these systems’ failure, triggering the cost when managing at the higher levels. In this Section of this Chapter, it is proposed:

- A local pandemic management indenture level: In Spain, current decision-making (until May 5th) applies to the entire country, simultaneously. We analyzed how applying adapted measures by lower geographical management units (management Indenture Levels) allow optimizing local and global behavior and socio-economic impact faster. Considering the political distribution of Spanish territory, this level could be assimilated to provinces (provincias). It is very important to note that sanitary resources allocation in Spain has, historically, a fundamental distribution by provinces. Nevertheless, decision making should be keeping centralized in a unique decision center.

- Quarantine time local determination: In accordance with the lower indenture level identification, it is possible to assume and predict different quarantine time levels by provinces. For instance, the prediction model used established a recommended quarantine of only 40 days for Huelva, while considering the global a unique decision for Spain (same measure simultaneously) would impose 70 days of quarantine using the same law, which means 40% more confinement than what Huelva really needs. This conclusion can be extended to other provinces where the “hard control measures” were taken before local pandemic free expansion point.

- Early relapses detection: During the recovery phase, once quarantine ends, it is critical to detect potential relapses as soon as possible. The development of a unique method to monitor most important descriptors (not only test but also new infections rates, mobile geolocation data, etc.) detecting local relapses is a main concern to benchmark evolution of different provinces, which is crucial for getting a faster learning curve for decision making.

1.2 Modelling Health System Capacity

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 [4]. In this research The Health System (HS) capacity is modeled in order to control the optimal HS response. In this way, it is possible to
use and take advantage of the great research community effort in infection prediction models for:

- Optimal decision making of sanitary resources allocation;
- Early detection of the force of infection the system can face under several circumstances; and
- Support citizen and organizations self-management.

The study is focused at local level (Indenture level definition). Relapses will emerge at local level 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.

1.3 A Control System to Follow the Pandemic Behavior

Reaching the end of the confinement phase, it is essential to have a strategy to face the recovery phase with the best possible guarantees. Previous studies demonstrated that saturation in hospitals could be modelled based on parameter \( R \) [5]. This is considered as the key parameter for designing recovery or de-escalation phase strategies. To propose an effective strategy, the parameter \( R \) will have to be known, monitored and controlled [6]. But uncertainty and lack of accurate knowledge are the principal handicaps of any attend of Covid 19 pandemic control. This crisis is not an IT problem or a mathematical modeling challenge. It is a catastrophe which impacts should be minimize with management reinforcement. Simplest management principles could be summarized and related to recovery management problem as follow:

- **Risk-benefit assessment** is the principal element of any decision. For pandemic recovery management the risk is composed by the high likelihood of relapses and their consequences severity. Consequences including not only infected and casualties but also the HS saturation. \( R \) parameter is emerging day by day as best risk indicator (short, mid and long term);
- Management can always be improved, even more, should always be improved. This is the **continuous improvement principle** that is universally accepted. In this moment, Covid19 crisis management has a tremendous improvement margin, because there is not any previous experience in the world;
- **A tool for planning** (measure and activities) and **a tool for checking** (control parameters and method) are needed. Both things are intimately related because you cannot manage what you cannot measure (Lord Kelvin *dixit*).
- **Hierarchization.** Not all possible options have the same relevance in terms of recovery optimization.

To start the recovery phase and to return the country to its “new” normal activity, a tool to monitor and control how the pandemic is evolving is needed. Otherwise, relapses
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could occur without realizing it and an essential time to stop the relapse could be lost. To that end, a control system allowing the detection, diagnosis and prognosis of pandemic abnormal behavior was proposed. Once there is a tool proposed to control the evolution of the pandemic, the work proceeds to design the post-confinement strategy. The methodology selected to design a strategy for the sequential opening of activities will minimize the risk of the potential impact of these activities on $R$. In order to do so, the number of contacts, the intensity of the contacts and the modification potential of each one of the activities will be assessed. Based on this evaluation, strategies are established for each level of risk, minimizing the possibility of contagion [7]. Logically, those activities with a higher risk of contagion will take longer to start up than those with a minimal risk. Companies whose activity is in a high-risk area will have to take measures to reduce the probability of contagion to an acceptable level and thus re-enter into economic activity.

2 Research Development

2.1 Selecting a Model to Calculate New Indenture Level Confinement Periods

In this Chapter we propose to follow Gañán-Calvo et al. [8] approach, which allows to model the pandemic “Confirmed” $C(t)$ and “Deaths” $D(t)$ using only time as independent variable, and supports the existence of a power-law in this variable. In their proposal, they concentrate in two non-dimensional parameters both: (i) the fundamental properties that the medium exposes to the action of the virus, and (ii) a simple model for the early behavior of the system prior to the asymptotic regime.

More precisely, a self-similar simple universal time-power law of the type $\varphi = \tau^\alpha$ is used to predict the behavior of COVID-19 pandemic before containment measures are enacted, where $\tau$ is the appropriate non-dimensional time since the onset of the free expansion, $\alpha$ is a fitting parameter with a value $\alpha = 3.75$ and $\varphi$ the non-dimensional time descriptor of the infected population and mortality.

The predictors are defined as $\varphi_C = C/C_C$ or $\varphi_D = D/(m \cdot C_C)$ for confirmed and deaths respectively, where $C_C = 1.2 \times 10^4$ is a characteristic size of the pandemic infectious population, and $m$ is an average early mortality descriptor observed with respect to confirmed cases, which may depend on the population structure and health system (showing homogeneity around the value $m = 0.15$, regardless the country).

Their more relevant result to this paper is the total confinement quarantine that they recommend after the first 100 cases of any unknown infection produced by a coronavirus are reported. They suggest to take a quarantine of the order of two times the period given by

$$T_Q = (t_{90\%} - t_c) = T_L \times (1 + (t_m - t_c))$$

(1)

Where $t_m$ is the day when measures are enacted, $t_c$ the time where the expansion takes place and $t_{90\%}$ is the time when the 90% of the total maximum expected people infected is reached, specific for each geographic region. COVID-19 exhibits a characteristic infection time $T_L = 20.1$ days according to measurements from the evolution of the pandemic in China. In the case that confinement is not yet in place, and the pandemic is...
in free expansion, quarantine measures must be taken immediately, and the death toll and quarantine period can be estimated using $\varphi_D(t)$ results once $t_m$ is fixed. The model was applied to do the economic impact analysis of COVID-19 pandemic in Spain, Andalusia and its provinces and results obtained for these three government indenture levels as presented in Table 1.

| Date    | $t_c$ (days) | $t_m - t_c$ (days) | $T_Q$ (days) |
|---------|--------------|-------------------|--------------|
| Spain   | 25-feb       | 0                 | 18           | 76            |
| Andalusia | 4-mar       | 8                 | 6            | 52            |
| Almería | 8-mar        | 12                | 2            | 44            |
| Cádiz   | 10-mar       | 14                | 1            | 42            |
| Córdoba | 12-mar       | 16                | 2            | 44            |
| Granada | 12-mar       | 16                | 2            | 44            |
| Huelva  | 16-mar       | 20                | 0            | 40            |
| Jaén    | 11-mar       | 15                | 3            | 46            |
| Málaga  | 5-mar        | 9                 | 5            | 50            |
| Seville | 12-mar       | 16                | 2            | 44            |

Table 1. Table with model results for the three main government levels within Spain

2.2 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. [9]). 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 reaching 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 (QT) models (also known as compartmental models) are the most commonly used ones. 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 [10], 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 [11]. The simulation will be carried out in the computer, and estimates will be made for the desired measures of performance [12]. 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.

In this Chapter both simulation modelling approaches are used. First a QT model is built to understand HS constraints under stationary conditions. Second a simulation model helps in the process of forecasting HS conditions under certain dynamic scenarios. Both approaches are found to be complementary, and QT model results offer a good information to validate patterns in simulation models results.

High number of variables allowed 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 2. The variables are divided into three groups.

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. The formulation of the stationary queuing problem (in Table 3 and Fig. 1) is applied to the HS.

Once the steady state problem was analyzed with the model in Fig. 1. The health system capacity planning problem was modeled (see Fig. 2) using continuous time stochastic simulation (other examples can be found in the literature in discrete event simulation too, like un Günal et al. [13]). Chronological issues are considered by simulating the number of patients to be treated at any time in the different units. The model is built using VENSIM [14] as simulation tool, which has special features to facilitate Monte-Carlo type of simulation experiments, and to provide confidence interval estimations. Thus, for the dynamic modelling of the problem dealing with hospital demand determination, we selected a robust, understandable SEIR model similar to others in literature [15], 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:

\[
\frac{dS}{dt} = -\beta \times \frac{(S \times I)}{P}
\]  

(2)


| 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)      | \( N_{tp} \)         | People   |                 |
| Treated in Bed at the Plant              | \( N_p \)            | People   |                 |
| Waiting for plant                        | \( N_{wp} \)         | People   |                 |
| Treated at the ICU (Queue or bed)        | \( N_{ticu} \)       | People   |                 |
| Treated in bed at the ICU                | \( N_{icu} \)        | People   |                 |
| Waiting for ICU                          | \( N_{wicu} \)       | People   |                 |
| Death toll                               | \( D_{toll} \)       | People   |                 |
| Confined at home                         | \( N_{ch} \)         | People   |                 |
| Immunized                                | \( N_i \)            | People   |                 |
| **Flows related variables**              |                      |          |                 |
| Entering at the plant                    | \( \lambda_{ep} \)   | People/day |                 |
| With bed assigned at the plant           | \( \mu_{ba} \)       | People/day |                 |
| Directed to the ICU from triage          | \( \lambda_{icu} \)  | People/day |                 |
| Entering the ICU                         | \( \lambda_{eicu} \) | People/day |                 |
| Entering home confinement                 | \( \lambda_{ehc} \)  | People/day |                 |
| Entering plant from ICU                  | \( \mu_{epfi} \)     | People/day |                 |
| Entering the ICU from Plant              | \( \mu_{eifp} \)     | People/day |                 |
| Dying at the ICU                         | \( \mu_{id} \)       | People/day |                 |
| Dying at the plant                       | \( \mu_{pd} \)       | People/day |                 |
| Released for home confinement            | \( \mu_{rhc} \)      | People/day |                 |
| Cured at home                            | \( \mu_{ch} \)       | People/day |                 |
| Leaving plant                            | \( \mu_{p} \)        | People/day |                 |
| Leaving ICU                              | \( \mu_{icu} \)      | People/day |                 |
| **Ratios, times and capacities variables** |                      |          |                 |
| Ratio of patients derived to plant       | \( R_{p} \)          | Ratio    |                 |
| Ratio of patients derived to ICU         | \( R_{icu} \)        | Ratio    |                 |
| Plant to home ratio                      | \( R_{ph} \)         | Ratio    |                 |
| Plant Death ratio                        | \( R_{pd} \)         | Ratio    |                 |
| ICU Death ratio                          | \( R_{id} \)         | Ratio    |                 |
| Average total time spent in plant per patient | \( T_{ip} \)     | Days     |                 |

(continued)
Table 2. (continued)

| Variables group                          | Variables definition                  | Notation | Units |
|------------------------------------------|---------------------------------------|----------|-------|
| 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 3. Input data to solve the queuing problem applied to 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%     |

\[
\frac{dE}{dt} = \beta \times \frac{(S \times I)}{P} - a \times E \quad (3)
\]

\[
\frac{dI}{dt} = a \times E - \gamma \times I \quad (4)
\]

\[
\frac{dR}{dt} = \gamma \times I \quad (5)
\]

Where \(S, E, I\) and \(R\) are for Susceptible, Exposed, Infectious and Recovered populations, respectively. \(P\) is the complete population of the region under study (e.g., the population of a province), \(\beta\) is the force of infection or the disease transmission rate, \(a\) is the inverse of the latent infection period and \(\gamma\) is the inverse of the infection duration time. For this model \(R_0\), the disease basic reproduction number, is defined as \(R_0 = \beta / \gamma\).
In Fig. 3, the model design selected for the empirical resolution of the above differential equations is presented.
2.3 Checking Tool: A Monitoring and Control System Proposal, Based on R

R parameter is the key element to pay attention to. It can be demonstrated that to control the pandemic rate of infection, \( R < 1 \), that means

\[
R = \frac{N_C}{(\gamma \times I)} < 1
\]  

(6)

Where \( N_C \) is the number of new cases that are diagnosed every day. Therefore, to monitor the number \( R \), the three variables: \( N_C, \gamma \) and \( I \), must be monitored. \( N_C \) and \( I \) would be taken from the information provided by the corresponding NHS and the estimation of \( \gamma \) must be improved as much as possible over time, incorporating not only accurate data for more infected cases, but also the evolution of knowledge from medical research about time duration and propagation potential of infected people, which is being improving significantly by week. Short-time \( R \) rising (days) will become mid-term (months) health system high strain scenarios. In order to implement a plan for a post-confinement de-escalation phase, tools for monitoring the status of the pandemic must be in place, and models for predicting its future potential evolution and consequences for the health system must be ready too. Beside the fact that the number \( R \) represents the pandemic status and its potential evolution at a given indenture level [16, 17], a very important point is that all re-opening measures can be evaluated in terms of their “\( R \) contribution” [7]. Also, any measure non-compliance and/or measure malfunction will increase the expected value of \( R \). In summary, it is possible to employ \( R \) to monitor pandemic and to design, and control, measures that will be included in different recovery phase scenarios.

When \( R \) increases over one (principal warning threshold), this can be a clear symptom of a possible pandemic relapse. Most accurate alarm thresholds are supposed to be established in relation to HS capacity, as suggested in previous papers [18]. For instance, assuming a 1.5 \( R \) would generate a serious strain on the HS in less that 3 months, establishing an alarm threshold of 1.2 \( R \) could result in a reasonable conservative level.
for the threshold. Therefore, $R$ is not only a good monitor but also what is defined a
good descriptor of the post-confinement plan situation (See Fig. 4). Consequently, there
must be a Control System focused on $R$, and on the implementation of mechanisms for
monitoring and integrating variables about the activities and resources that contributes
to it. This Control System has the responsibility as a unique repository of information
and governance coordination.

A pre-existing methodology, that is being applied successfully to monitor and control complex engineering assets [19, 20], was used to deal with this problem. The fundamentals of this proposal are:

- Providing a clear data/information structure for monitoring related to detection,
diagnosis and prognosis issues;
- Offering a clear methodology for the accurate definition of the descriptors and inter-
pretation rules, which are linked with different decisions and temporal horizons,
formalizing expert knowledge within the monitoring process;

In order to describe, practical implementation of this Control System for $R$ mon-
toring, Fig. 5 is a UML proposal about how structure data and integrate information
flows. For this purpose, five different blocks are proposed (see Table 1) according to
International standards.

Each one of the five blocks is considered a level of information, first two are sources
of resources and activities variables, which are processed into monitors in block 3, block
4 behavior is centered on $R$ and other predictors definitions, and the last one is oriented
to standardize analysis and guide the decision making, see an example in next Table.
The term “measure” is used here to name concrete activities of the pandemic recovery
plan. Obviously, data quality is crucial for an adequate control, and control mechanisms
have to evaluate continuously this issue, as it is explained in the next section.
3 Results

3.1 Economic Impact of Confinement When Changing the Management Level

The model has been applied to do the economic impact analysis of COVID-19 pandemic in Andalusia, defining the following three scenarios:

- **Scenario 1.** The management Indenture Level is Spain. Confinement period is calculated with data aggregated at a national level and confinement applies to the entire country, regions and provinces, simultaneously.
- **Scenario 2.** The management Indenture Level is Andalusia. Quarantine time is obtained with data aggregated at regional level and confinement applies to all region’s provinces, simultaneously.
- **Scenario 3.** The management Indenture Level is each province. Quarantine time is obtained with data of the province and confinement applies to each province, separately.

In Table 4, results of the tree different scenarios are presented by province. In the last two columns we show potential reductions of the GDP loss toll relative to the first scenario. Considering an estimated value for the Andalusia’s GDP around 160,222 M€ (For precise data see [21, 22]), the absolute savings in GDP loss toll for would be around $160,222 \times (4.579\% - 2.712\%) = 2,991.34$ M€ result of using the estimated quarantine times by province (which supposes an earlier return to economic activity) instead of the estimated quarantine time for the whole country.

3.2 HS Capacity Modelling and Implications on R

In the recovery phase of the Covid-19 pandemic, 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, the model is projecting results until
Table 4. Expected impact on current GDP per region, provinces and scenario

| Region     | GDP Loss (Scenario 1) | GDP Loss (Scenario 2) | GDP Loss (Scenario 3) | Reduction of GDP loss toll SC3 vs. SC1 | Reduction of GDP loss toll SC3 vs. SC2 |
|------------|----------------------|----------------------|----------------------|----------------------------------------|----------------------------------------|
| Andalusia  | 4,579%               | 3,133%               | 2,712%               | 40,776%                                | 13,441%                                |
| Almería    | 4,745%               | 3,247%               | 2,747%               | 42,105%                                | 15,385%                                |
| Cádiz      | 4,682%               | 3,203%               | 2,587%               | 44,737%                                | 19,231%                                |
| Córdoba    | 4,239%               | 2,900%               | 2,454%               | 42,105%                                | 15,385%                                |
| Granada    | 4,521%               | 3,093%               | 2,617%               | 42,105%                                | 15,385%                                |
| Huelva     | 4,490%               | 3,072%               | 2,363%               | 47,368%                                | 23,077%                                |
| Jaen       | 4,214%               | 2,883%               | 2,550%               | 39,474%                                | 11,538%                                |
| Málaga     | 5,207%               | 3,563%               | 3,426%               | 34,211%                                | 3,846%                                 |
| Seville    | 4,176%               | 2,857%               | 2,418%               | 42,105%                                | 15,385%                                |

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:

- $[T_{inf} \pm 30\%]$ variability added in prediction for infected (random uniform),
- $[R&T \pm 20\%]$ variability added in flow rates and times in HS (random uniform),
- $R_{0ac}$, after confinement, within the interval $[0.85 - 1, 5]$, also (random uniform).

An example of results for the sensitivity analysis 400 simulations is presented in Fig. 6, where ICU occupations for 125 days since the release of the confinement is analyzed. These results show:

- The risk of ICU saturation is very low, in only 5% of the simulations.
- No saturation would take place in Plant, never reaching 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 ($R_0 = 1.5$), ensuring control to limit $R_0$ to 1.1 persons maximum would be advisable. It would be attainable by monitoring the status of the variable, preparing for eventual confinement that could take place if needed due to an important relapse.
- According to 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 $R_0$ to reach levels below 1 person (see strategy in Qun Li et al., 2020).

3.3 Planning Tool: A Plan for De-escalation of Confinement Based on $R$

Once understood the important of the effective reproductive number $R$, and established in advance a surveillance, monitor and control system for $R$, a plan for the de-escalation
of confinement will now be elaborated with the intention to reduce the risk of sudden \( R \) increase. At this point, and before proceeding with any possible escalation of activities, the following advice should be a golden rule [23]: (i) to keep physical distancing measures, and to ask people to remain at home; (ii) To increase access to diagnostic testing (focusing testing and resources on individuals with disease who may be infectious and their close contacts); (iii) Sectors to start reopening when the following 4 criteria are met: (1) two weeks decline in the number of new cases; (2) rapid diagnostic testing capacity sufficient to test people with symptoms, close contacts and those in essential roles; (3) the HS has appropriate PPE for healthcare workers; and (4) there is sufficient public health capacity to conduct contact tracing for all new cases and their close contacts.

Considering that all previous paragraphs requirements are fulfilled, this Section provides a strategy, a manner to proceed with a staggered reopening of activities, that is based on modelling their risk, and the expected time to the establishment of effective risk mitigation measures preventing the spread of the virus.

Two features of an activity, with a direct impact on \( R \), will drive this course of action [7]: The activity contact rate (\( R_C \)) and the likelihood of infection per contact (\( R_I \)) — between a susceptible person and an infectious person or vector—during the time the activity takes place. In addition, the contact rate will be characterized by: the contact intensity (\( C_I \)) and the expected number of contacts (\( N_C \)) that the infected is supposed to have during that activity. The activity contact intensity (\( C_I \)) is now rated as either low, medium, or high. It depends on the contact type (close-to-distant) and its duration (brief-to-prolonged). Low contact intensity activities are brief and fairly distant interactions while high contact intensity activities involve prolonged close contact (like sharing a dormitory). Sharing a meal in seats separated by several feet can be considered a medium contact intensity activity. The number of contacts (\( N_C \)) will also be rated as either low, medium, or high. Defined as the approximate number of people in the setting at the same time, on average. A higher \( N_C \) is presumed to be riskier. Finally, each activity will have a
modification potential (the degree to which mitigation measures can reduce those risks, $R_i$). For instance, businesses that can effectively incorporate physical distancing and engineering controls are considered to have a higher modification potential than those relying on administrative controls or personal protective equipment, to reduce risk. A hierarchy of COVID-19 mitigation measures can look like:

- Physical Distancing: wherever possible having people work from home; including restructuring efforts to minimize physical presence.
- Engineering controls: creating physical barriers between people.
- Administrative controls: restructuring responsibilities to reduce contacts and using technology to easy communication.
- PPE: having people wear gloves and masks.

Depending on the location in the matrix, the risk of the activity changes and so changes the likelihood of that risk to be mitigated in the near term (Fig. 7). Thus, the rules for the reopening strategy can be formulated.

![Risk Matrix](image)

**Fig. 7.** Risk matrix definition and action plan for the activities.

Of course, the de-escalation of activities must be applied to their non-operative portion only, thus allowing to recover the “normal” sectors’ conditions. Figure 8 shows the recovery of six relevant national economic sectors over a one-year horizon. Note that sectors such as agriculture and industry will be the first to achieve full recovery, while the entertainment sector will not return to full normality until May 2021 (where we may expect a vaccine could be released). It is very important the fact that, although the sector reaches 100% of activity, that does not mean the production will be at the same level since demand may drop. For example, in the case of hostelry, it could be working 100%
after the end of 2020, but transportation activities would not reach 100% until February 2021, which would cause a drop in hostelry sector’s revenues.

4 Conclusions

In this Chapter, the efforts done by the SIM research group in Spain concerning COVID19 pandemic management analysis are presented. SIM group aim was always to put the best skills and experience serving the society facing this unprecedent situation. The first impression when reading, in mid-march, very serious papers on COVID 19 emergency was that the generation of practical management tools to tackle the crisis was being forgotten. A great volume of data, mathematical models, etc. could be found, but the question was: how could government, companies and citizen take advantage of these results to reduce the pandemic impact?

Since the very beginning the SIM group highlighted great similarities and analogy points between pandemic recovery management and maintenance management of a complex engineering asset. Our research discipline provides specific verified tools and powerful analysis methodologies that we really think can be used as reference for this brand-new scenario management. At this point, and as a conclusion of this work, we would like to highlight the main SIM group contributions:

- Analysis of the importance of correct determination of the indenture level to manage the COVID recovery. This level was linked with geographical areas where management should focus on. We proposed and justify for Spain to use at least the province level as a reference, from local different quarantine time estimation according with real local pandemic behavior and GDP province expect impact. Three weeks after
paper 1 publication date, Spain Government has followed a similar strategy, either also countries as Germany. Thus confirms, at least by the current knowledge, the goodness of this approach.

- A tool based on a ICUs and plants capacity model. Principal outputs: (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. Just releasing this research to be published we could see Chancellor Angela Merkel presenting a similar approach in Germany.

- A complete process (end-to-end) describing with great detail a tool to control the performance of proposed recovery measures and their impact. Three fundamental pillars are considered: Definition of activities and their hierarchy in terms of risk in R contribution, consideration of uncertainty of data and R model calculation and monitoring and control system proposal.

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