Received: 2 May 2020 | Revised: 22 July 2020 | Accepted: 22 July 2020
DOI: 10.1002/sys.21557

REGULAR PAPER

WILEY

Handling the COVID-19 crisis: Toward an agile model-based systems approach

Olivier de Weck[1] | **Daniel Krob**[2] | **Li Lefei**[3] | **Pao Chuen Lui**[4] | **Antoine Rauzy**[5] | **Xinguo Zhang**[3]

[1] Institute for Data, Systems and Society, Massachusetts Institute of Technology, Cambridge, Massachusetts

[2] Center of Excellence on Systems Architecture Management Economy & Strategy (CESAMES), Paris, France

[3] Tsinghua University, Beijing, China

[4] National University of Singapore, Singapore

[5] Norwegian University of Science & Technology, Trondheim, Norway

Correspondence
Olivier de Weck, 33-410, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA.
Email: deweck@mit.edu

Abstract

The COVID-19 pandemic has caught many nations by surprise and has already caused millions of infections and hundreds of thousands of deaths worldwide. It has also exposed a deep crisis in modeling and exposed a lack of systems thinking by focusing mainly on only the short term and thinking of this event as only a health crisis. In this paper, authors from several of the key countries involved in COVID-19 propose a holistic systems model that views the problem from a perspective of human society including the natural environment, human population, health system, and economic system. We model the crisis theoretically as a feedback control problem with delay, and partial controllability and observability. Using a quantitative model of the human population allows us to test different assumptions such as detection threshold, delay to take action, fraction of the population infected, effectiveness and length of confinement strategies, and impact of earlier lifting of social distancing restrictions. Each conceptual scenario is subject to 1000+ Monte-Carlo simulations and yields both expected and surprising results. For example, we demonstrate through computational experiments that maintaining strict confinement policies for longer than 60 days may indeed be able to suppress lethality below 1% and yield the best health outcomes, but cause economic damages due to lost work that could turn out to be counterproductive in the long term. We conclude by proposing a hierarchical Computerized, Command, Control, and Communications (C4) information system and enterprise architecture for COVID-19 with real-time measurements and control actions taken at leach level.

KEYWORDS
Decision Analysis/Management, Modeling and Simulation, Systems Thinking

1 | INTRODUCTION

The COVID-19 crisis (see Refs. 1 and 2) took many by surprise. Globally, most of the nations were underprepared. Moreover, they reacted in quite different ways when the pandemic unfolded, as it can be observed by the various dynamics per country in terms of confirmed deaths due to COVID-19 per million inhabitants (see Refs. 3, 4, and 5 and Figure 1). In this paper, we argue that one of the root causes of this unpreparedness and difference in reaction is due to the lack of conceptual and methodological tools to think about the crisis as a complex system which led the global community to use inadequate modeling approaches. We advocate that *systems engineering* is a first-in-class candidate to provide such tools. The COVID-19 crisis should be seen as a *control problem with delay* and uncertainty that requires a model-based agile and multilayered systems engineering approach.

The COVID-19 crisis has a striking extent, both in time and space. It is going to have impact during an unknown, but probably prolonged period of 18 months or longer, affecting all activities on Earth, which

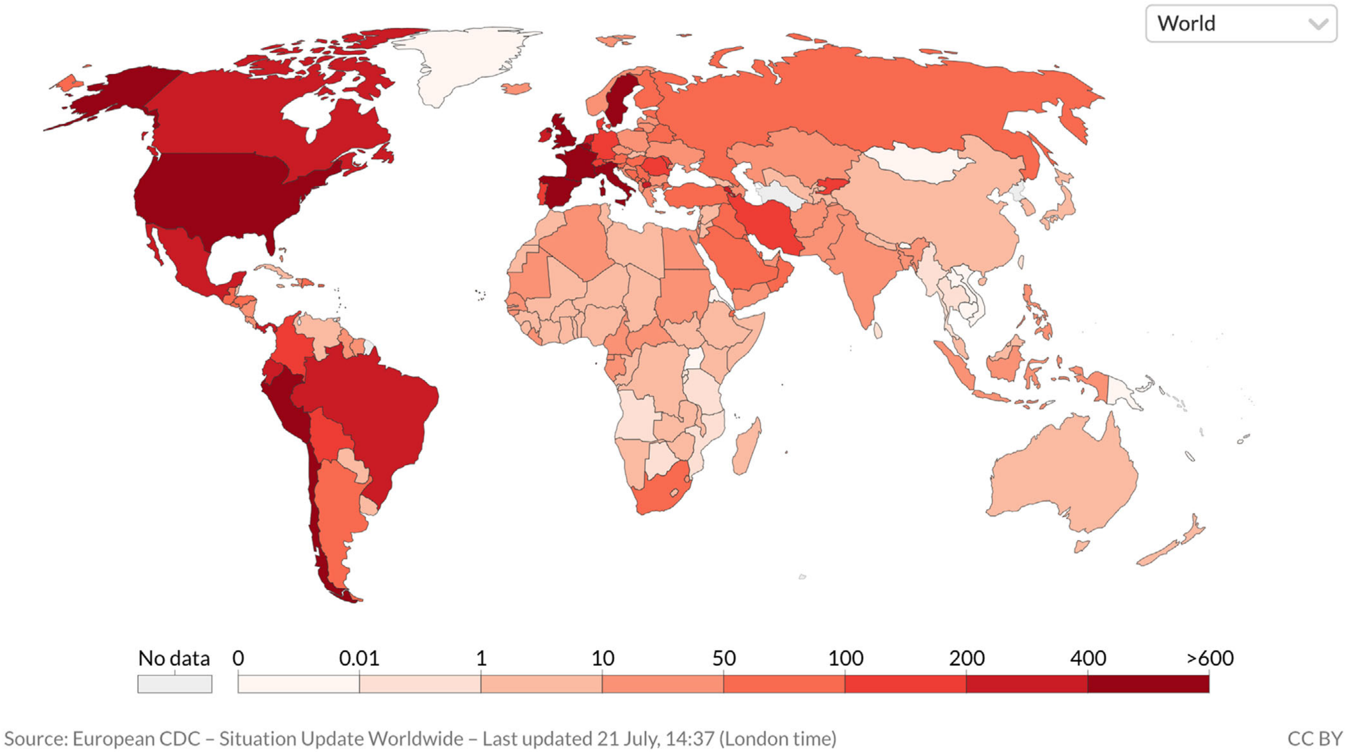

FIGURE 1 Confirmed deaths per million people as of July 21, 2020

makes it a systemic crisis and not only a pure health crisis. The closest analog we have at a global scale is the H1N1 influenza pandemic of 1917-1919 ("Spanish flu") which killed between 17 and 50 million people worldwide.[6] Thus, handling the current COVID-19 crisis requires a holistic approach taking into consideration an extremely complex system, ie., society as a whole.

Another important aspect of the COVID-19 crisis is that the pandemic propagation has been very fast, thus demanding rapid decision-making. Moreover, and we think that this is a structuring feature of this crisis, the incubation time of the disease introduces a delay—that has been estimated as being up to two weeks according to epidemiologists (Refs. 7, 8, or 9)—between the implementation of countermeasures and the observation of their effects. This is compounded by the fact that a significant fraction of the virus carriers appear to be asymptomatic, causing a large difference between the numbers of *actual* cases and of *known or confirmed* cases (see Refs. 1, 3, or 5). This explains why the problem of monitoring the COVID-19 crisis can be seen as a control-theoretic problem with delay in the feedback loop used to stabilize the situation in addition to the problem of low or *only partial observability* of the true system states. We shall elaborate further on this point.

From a system-theoretic perspective, the above characteristics raise several difficult problems. The first one, which is rather expected, regards *scalability*: can our current systems engineering and modeling methods (cf. for instance, Refs. 10–16, or 17) be extended to a system, or more precisely a system-of-systems (cf. Ref. 18 or 19), as large and as complex as human society as a whole? This question is clearly not easy to solve and appears moreover poorly addressed by the only known models of such scope, ie., the so-called World models, based on generalized Volterra equations, that followed the seminal work of Forrester in the 1970s (see Refs. 20, 21, and 22).

A second problem is caused by the *emergence of local and partial solutions* which is significant since the COVID-19 crisis impacts all sectors of society, including the medical, financial, transportation, manufacturing, and overall economic systems. Society therefore needs fast and innovative solutions in order to mitigate as much as possible the consequences of the crisis. Time pressure favors local and partial solutions, but also a strong coordination among actors in order to avoid contradictory strategies. A central question is therefore how to favor the emergence of bottom-up local actions while, at the same time, ensuring top-down monitoring and coordination of such actions, with short feedback loops. This calls for an agile approach (see Refs. 23, 24, or 25) to the global COVID-19 crisis.

Stating the above problems, we made a clear choice in this paper: we do strongly believe in the use of models, and more precisely of *systemic models* to think through and manage the crisis. Models as we consider them here are, however, not Platonic ideals, but *observational models* which rely on the observation of the reality of the COVID-19 crisis, including the effects of the decisions made based on them. Such models are intended to capture the systemic nature of the crisis in order to achieve a better understanding of the situation and to allow a better communication among stakeholders. In that respect, models have two main roles: first, the concrete calculation of key performance indicators to support the decision-making process through experiments *in silico*; and a second more metaphorical one, to help us think better about the dynamic evolution of the systems at stake.

The remainder of this paper is organized as follows. In Section 2, we discuss which systemic models may support better management of the COVID-19 crisis. Then, in Section 3, we advocate for an agile approach for crisis management. Section 4 completes the paper with several recommendations.

2 | FROM THE CRISIS OF MODELS TO THE MODELS OF CRISIS

2.1 | Beyond the COVID-19 crisis: A crisis of models

The general impression which emerges from the large and rapidly expanding literature dedicated to the COVID-19 pandemic is that this crisis was first and foremost analyzed as primarily a *health crisis* (cf. Ref. 26 or 2). Economic impacts of the crisis were of course quickly understood, but, as far as we could observe, they were rather considered as an inevitable consequence of the health crisis that has to be managed as a second priority.[27] However, the aggressive mitigation measures that were set up in many countries were and are at the same time quite efficient from a health-preservation point of view (see, for instance, Ref. 28 or 29) and *highly inefficient from an economical perspective* due to their global economic impact on all of society (see Ref. 30 or 31). In this matter, there is—to the best of our knowledge—no rational discussion in the scientific literature on what could be the best trade-off for *jointly minimizing both the health impact and the economic impact* of the COVID-19 crisis. Perhaps the biggest ethical issue around such trade-offs is that it would require placing an explicit economic value on human lives, as discussed for instance in Ref. 32. This is something that no national or regional government in the world has apparently been willing to do.

Moreover, what shall one do if the health crisis remains endemic in the near future which is one of the possible scenarios (cf. Section 2.2.2)? As one can see, thinking from a global rather than a purely local perspective can deeply change the way one addresses the crisis and its consequences.

This situation is probably the consequence of the fact that the crisis is mainly observed on daily basis, through for instance the daily COVID-19 reports provided by the World Health Organization,[5] by other institutions,[3] and by each local government, leading to a rather short-term vision of the crisis. However, changing the time scale of observation gives us immediately a totally different point-of-view on the COVID-19 crisis. If we are, for instance, observing the crisis at the time step of a quarter of a year (three months), it becomes almost instantaneous and can be considered as an event—in the classical meaning of synchronous modeling[33]—without any duration. Thus, the choice of time step and sampling frequency is critical as it is for any control system. This perspective change forces us to think what could be the next state of the system under observation, ie, human society, which may be on its way toward a deep economic crisis, at least in Western countries. Continuing the analysis at the same coarse time scale, a possible catastrophic evolution scenario would be a financial crisis resulting with some delay from an economic crisis initiated by the health crisis, thus generating the specter of a deep and prolonged recession, as pointed out as a possibility by some economists (Ref. 27 or 31). Moreover, this situation could then also lead to more "classical" health crises in the future (see Figure 2) due to the two-sided coupled interaction between the public health system and the economic system.

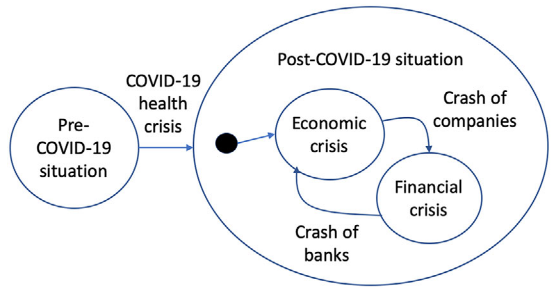

FIGURE 2 A possible catastrophic scenario that could result from the initial COVID-19 health crisis

In such a catastrophic future scenario, extending the duration of people's confinement in Western countries in order to minimize the short-term health impact during the initial crisis could, for instance, result in deeply debilitating the health of more or less the same population in the mid- to long-term future. Such a possible paradox is typical in optimal control theory where the optimal trajectory of any nonlinear system can never be obtained through local optimizations alone.[34] In order to take into account and to avoid such paradoxical consequences, one must choose a systems approach to analyze the COVID-19 crisis, integrating all existing domains of knowledge into a common understanding of the crisis, in order to obtain a global vision, both in space and time and at different possible observation scales, and thus giving a chance to find the global optimum for human society as a whole.

We can thus see that there is another crisis, hidden within the COVID-19 crisis, which is a *crisis of models*. The global community is indeed focusing on short-term health-specific models to better master the crisis, but these models are inadequate as soon as one wants to address the crisis from a longer-term society-wide perspective which requires systemic models.

In this matter, let us recall that a model is an abstraction (in the meaning of abstract interpretation theory[35]) of reality, but not reality itself, as expressed, for instance, by the famous assertion "A map is not the territory it represents, but, if correct, it has a similar structure to the territory, which accounts for its usefulness," popularized by Korzybski[36] or the well-known "All models are wrong, some are useful" by Box.[37] "Models" which are not actually reflecting reality within some error bounds are in fact not models in that observational definition and may even have negative impacts on reality since they will lead to wrong decisions or control actions. These negative impacts of wrong "models" can of course be amplified in the context of a systemic crisis such as COVID-19.

Our point of view is clearly supported by an analysis of the 2020 scientific literature to date. A search of the keyword "COVID-19" on Google Scholar[38] in April 2020, revealed that, at this moment of time, only 10 papers—ie., around 1%—of the first 900 most cited papers on

COVID-19 were not discussing primarily health issues (health covering here biology, epidemiology, medicine, and health policy and management), but rather focusing on the societal and economic consequences of the crisis. Moreover, in terms of citations, most of these 10 papers were poorly cited: two were cited around 20 times, three around 10 times, and the remaining ones less than 5 times, while the average number of citations per paper was 15 in our sample. Only very few health-oriented papers, such as Ref. 39, also discuss mixed strategies involving economic or psychological considerations to fight the coronavirus. It seems therefore that the majority of the scientific effort is focused on the short-term, without taking into account what might be the mid- and long-term societal consequences of the COVID-19 crisis.

One may also notice that there is probably another crisis of *medical models* that can be observed due to the COVID-19 crisis. This other crisis focuses around the merits of hydroxychloroquine and azithromycin as a possible treatment of COVID-19, as proposed by Raoult and his team.[40] This has since then been shown to be a proposal which was not supported by a rigorous methodological approach according to medical methodologists.[41] However, medical statistical methodology (see Ref. 42 for an introduction to this domain) appears also to be questionable from a modeling perspective: the frequency-based models used in methodological medicine usually cannot have probabilistic interpretations due to a lack of large series of experiments required to apply the law of large numbers;[43] hence such frequency-based models can only find correlations between proposed medications and observe effects on structurally limited series due to the high costs of clinical studies.[44] But since correlation is not causation, it is just not possible, without any understanding of the underlying biological mechanisms, to scientifically deduce anything from such studies, as long as we agree on the fact that science deals with causal explanations, which does however not prevent using correlation-based results from a practical perspective as soon as they are established in a sound way.[72] In this analysis, the debate around the rigor of the pragmatic and agile approach followed by Raoult may just be a new *Popperian debate*[45] opposing different medical methods for addressing an infectious health crisis, similar to the debates that existed in physics around Aristotelian theory in the 16th century[46] or aether theory in the 19th century.

To conclude this initial discussion on the crisis of models, we point out that if the scenario that we highlighted in Figure 2 comes true, we may also eventually be forced to deal with another crisis of models, namely, the crisis of mathematical models used in finance. These other "models" are not necessarily models in the observational sense that we are using in this paper since they suffer from many well-known issues such as *reflexivity*,[47] which refers to the fact that mathematical financial models are essentially observing other mathematical financial models, or more deeply the lack of evidence for the market equilibrium hypothesis,[48] which is at the heart of the probabilistic framework used in mathematical finance, but which is in fact rarely observed in practice (see, for instance, Ref. 48 or 49), especially in a financial crisis situation where the market is of course highly unbalanced and volatile and therefore out of equilibrium, as pointed out by several researchers.

The COVID-19 crisis is thus forcing us to open our eyes and to look for the "right" models to use for effectively managing human society. One should use models that are effectively capturing the reality as it is and not as we would like it to be, if we want to make nondominated decisions in the face of a crisis of such magnitude and have a chance to tackle it successfully.

2.2 | Toward a systems model of the COVID-19 crisis

As stated above, there is a crucial need for constructing a realistic observational system model of the COVID-19 crisis. We shall now present the main ingredients of such a systemic model.

2.2.1 | Ingredient 1: Constructing a systemic framework for modeling the crisis

Taking a systems approach leads us naturally to construct first a systemic framework for modeling the COVID-19 crisis. The first step toward that objective is to understand what are the main systems[10] involved in or impacted by the crisis. In that respect, the following ones are quite obvious:

- the *natural environment* from which the coronavirus which initiated the crisis is coming,
- the *social system*, which contains the population that is or can be infected by the coronavirus,
- the *health system* which attempts to cure the people infected by the coronavirus,
- the *governance system* which has to choose the optimal health policy to face the pandemic,
- the *economic system* which may be indirectly impacted by the COVID-19 crisis.

Note that the impact of the COVID-19 crisis on the economic system depends of course on the health policy choosen by the governance (political) system. If a health policy recommends or forces—as often done[5]—a large fraction of its population to stay home, it *causes a double shock*,[31] first on the supply side since economic actors which are lacking a work force must reduce their production and secondly on the demand side since people who are not working anymore are usually paid less or not at all and thus are also consuming less.

We can now sketch the first item of our generic COVID-19 systemic framework which is the high-level *environment*[10] that we modeled in Figure 3. This first system view exposes the exchanges of matter, people, information, and money—plus coronavirus here—that exist between the main systems involved in the COVID-19 crisis. Note that the overall system taken into account here, ie., human society as a whole, including its natural environment, is a closed system on our home planet Earth. As a consequence, the only levers to solve the crisis are internal to this global system.

The static view of Figure 3 only shows the space in which the COVID-19 crisis takes place. But this is not enough to model a

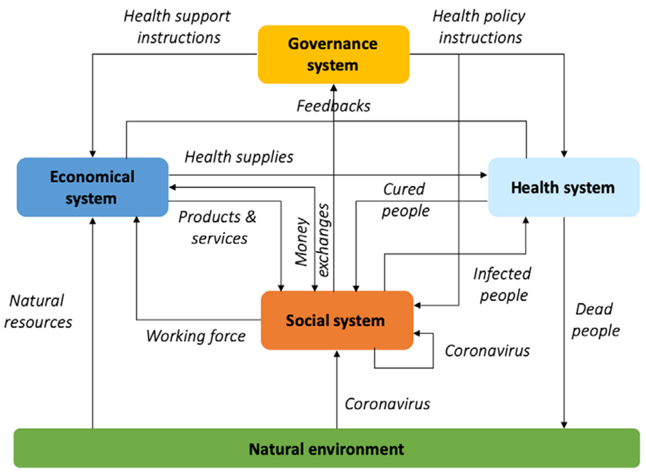

FIGURE 3 High-level COVID-19 environment

system: we also need to *consider its time evolution* to get a complete picture from both a spatial and temporal perspective.[10] This leads us to the second element of our general COVID-19 systemic framework which deals with the *lifecycle* of our system of interest, human society, where we depict its different states over time. In this matter, we now need to understand what could be the possible future(s) of human society after the COVID-19 crisis, which leads us to think in terms of lifecycle scenarios, since our future is by nature uncertain. Each such *global lifecycle scenario* can typically be obtained—using an old technique that goes back to the origins of distributed computing—through a synchronized result[50] of the domain-specific lifecycle scenarios that are modeling the evolution of each of the main systems involved in the COVID-19 environment.

Using that technique, the point is thus to be able to construct realistic domain-specific lifecycle scenarios for each system involved in the COVID-19 environment. We first focus only on the social and economic systems, since we are considering here the situation that occurs *after* the end of the COVID-19 health crisis (see Figure 2). We can then see that:

- The lifecycle of the *social system* can be analyzed to first order in terms of *wealth and health*, where these features can be, respectively, derived from the economic system lifecycle and from a posthealth crisis epidemic propagation model (see next subsection);
- The lifecycle of the *economic system* can be analyzed from an economical perspective using classical impact analysis techniques (see, for instance, Ref. 27 or 31).

In a systems approach, we will thus have to construct the different possible global lifecycle scenarios that can be achieved in this way (see Figure 4 for an illustration of this classical process), to evaluate their probabilities and to define means to mitigate the worst consequences. To obtain more detailed models, we shall moreover refine them in terms of space, to capture the geographic dimension of human society, and time, and to make optimal trade-off decisions between the short- and long-term impact of the COVID-19 crisis. Note also that these lifecycle scenarios are of course *highly country-dependent* due to the central role of the governance system in the resolution of the COVID-19 crisis, as well as the susceptibility of the population which is an initial condition.

The last element of our COVID-19 systemic framework is finally a *mission* statement,[10] ie, the core high level requirement regarding human society which expresses the objective that the governance system wants to fulfill. One can indeed understand that the behavior of our system of interest—human society—will be different depending on whether one wants to minimize the impact of the COVID-19 crisis on the social, health, or economic system or to find the best balance between the impacts on these three systems. This is a multiobjective optimization problem for which we provide a sample result below, and that we intend to explore more in details in a forthcoming paper. It is therefore of high importance—as system theory tells us (see Refs. 10, 14, or 16)—to be able to clearly define the mission to achieve.

Taking a systems approach to the COVID-19 crisis requires instantiating our systemic framework per country. Each country has its own specificities, associated with its own history and culture, that one must consider in any systems approach: for instance, Chinese traditional medicine and rigorous group behaviors are specific to China, while a centralized governance system and poorly followed health rules are specific to France, while a heterogeneous health system that favors more affluent consumers and differentiated laws and policies by state are specific to the United States of America.

2.2.2 | Ingredient 2: Modeling the epidemic propagation in a realistic way

Another ingredient of our systems approach consists in understanding the dynamics of the human population when stressed by the coronavirus. The dynamics of all other systems involved in the COVID-19 environment (see previous subsection) are indeed highly governed by that dynamic: the spatial scope, duration time, and lethality of the COVID-19 pandemic are of importance for the health system and the economic system. We shall therefore sketch out in this subsection what could be a realistic epidemiologic model of the COVID-19 crisis.

In this arena, epidemiology provides us first the so-called *compartmental models* that all originated from the seminal work of Kermack and McKendrick[51] that goes back to 1927. The main idea of these models is to decompose a population subject to an epidemic into a number of discrete compartments, such as, for instance, S (for susceptible people), I (for infected people), R (for recovered people), and D (for deceased people), and to model the propagation of an epidemic as a continuous Markov process controlled by Lotka-Volterra-like evolution equations.[52,53,22,54]

Figure 5 shows a generic SIRD-type simulation with a human population of 100 000 people. SIRD stands for "susceptible-infected-recovered-dead", the four main compartments of the population. In this model, it takes 20 days from patient 1 until the infection curve and its geometric growth become macroscopically visible. By day 38, half the population is infected, with the number of infected people peaking on day 44. The first sharp rise in deaths appears with delay around day

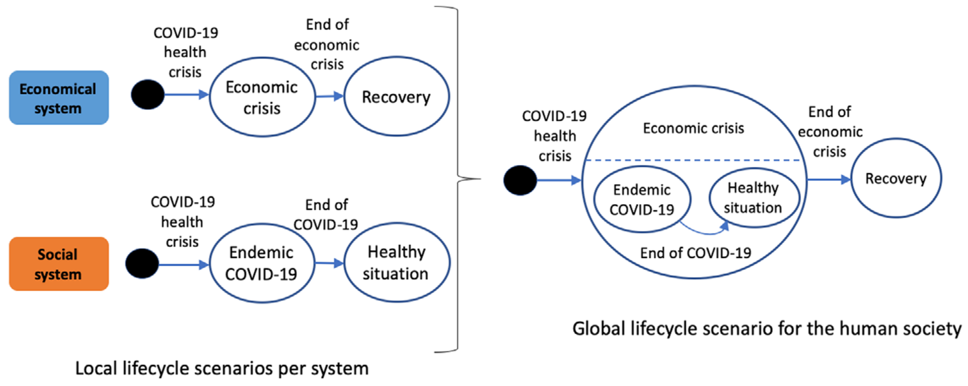

FIGURE 4 Illustration of a standard process for constructing a COVID-19 global lifecycle scenario

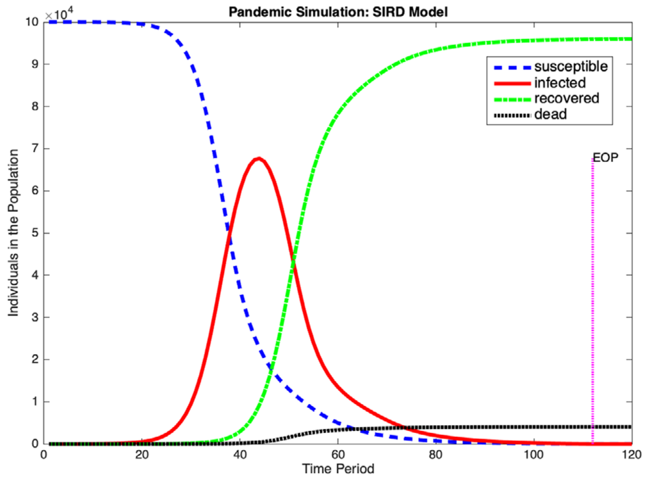

FIGURE 5 SIRD simulation with 10 average daily contacts, 2.5% propagation probability, 14 days of disease duration, 4% lethality, and no countermeasures

TABLE 1 Example of nodes distribution in a Barabási-Albert social network

Maximum degree	Cumulative proportion of nodes
2	0.05
3	0.43
4	0.62
5	0.73
10	0.91
20	0.975
100	0.999

40. Finally, there is a long tail due to late infections requiring a total of 112 days for the whole epidemic to run its course (EOP = end of pandemic), after which about 4000 individuals will have died from the disease.

These types of compartmental models have significant limitations since they only consider the human population in a macroscopic way, reacting globally in a uniform manner to an epidemic, which is not the case in reality. Furthermore, in a classic SIRD model, eventually 100% of the population is infected, which is never observed in practice. In the COVID-19 pandemic, one can also observe clusters where the epidemic seems to recursively focus,[5] which rather suggests a fractal epidemic propagation, as also mentioned in an older paper by Jansse et al in 1999[55] which did not seem to have been further explored by the epidemiology community. Such fractal behavior is however not at all captured by the classical SIRD-like compartmental models. Note also that, quite surprisingly, we did not find significant scientific papers studying the geometric multiscale structure of the geography of the COVID-19 pandemic, which also suggests that this dimension has not yet been analyzed in depth.

In order to better integrate geography, which is one of the most important features of the human population system, we choose a social-network approach to model the propagation of the epidemic as, for instance, in Ref. 56. In such an approach, the human population is modeled as a network, that is to say a nondirected graph,[57] where each node of the network represents an individual or a group of people, eg., a family, and each edge represents a connection between people. For the purpose of our study, we used networks randomly generated according to the Barabási-Albert model,[58] which is believed to capture the most important features of real social networks. We shall recall that the Barabási-Albert model generates networks by introducing nodes one by one (after an initial step). A degree d is chosen for each new node, which is then connected to d other nodes chosen at random from the nodes already in the network. To simulate a social network, the average value of the degree d is usually chosen between 2 and 3. The Barabási-Albert model produces randomized scale-free networks in which most of the nodes have a low degree (below 10), but some may have a very high degree. In order to understand how an epidemic propagates in a population modeled in this way, we used networks with 100 000 nodes and an average degree d for new nodes of 2.1. With these features, the degree of nodes in a social network is typically distributed as shown in Table 1. Potential "superspreaders" are individuals with large degree >20.

To model the propagation of an epidemic in this network, we discretized a classical SIRD-like model (see Refs. 52 and 54 and Figure 5) which leads us to represent the evolution of the state of each

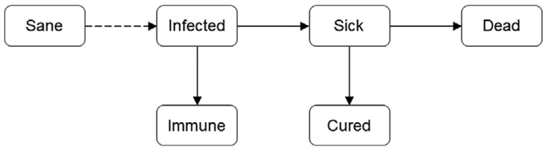

FIGURE 6 Stochastic state automaton modeling the possible evolution of a node in the social network

node of the social network that models the human population by a stochastic finite automaton whose possible transitions are described in Figure 6. Time is then discretized and all nodes evolve simultaneously at each time step, which represents a calendar day, just like in cellular automata.[59]

Transition probabilities were chosen as follows in order to be close to the most structuring COVID-19 propagation parameters[5]: (a) the incubation time is uniformly distributed between 10 and 20 days, (b) the maximum sickness time is uniformly distributed between 20 and 30 days, (c) the proportion of infected people who get sick is about 20%, (d) the proportion of sick people who die is about 20% leading to a net mortality rate of infected people of about 4%. At each step, a healthy node can be infected by one of its infected neighbors with a certain probability ρ. A node cannot be infected "spontaneously," but only through interaction with its infected direct neighbors. On this basis, we then performed Monte-Carlo simulations to study the possible evolutions of our model. Each trial of the simulation consisted of starting with a network in which all nodes are initially healthy, but one of them is picked at random and infected (patient 1), then letting the network evolve according to the above stochastic laws until it stabilizes. Note that the computational experiments that we performed on this model do not aim at fully representing "reality." Further investigation may, for instance, be done by considering other probabilistic distributions—typically Gaussian—for incubation and sickness times. We, however, think that our experiments can give us a better qualitative understanding of epidemic propagation since we believe that this social-network approach better captures the fundamentals of the social system, compared to the simpler compartment-type models. It may thus be helpful for constructing more realistic epidemic propagation models, even if it would require a very significant amount of data collection and fine tuning. The use of contact tracers in health systems is, for instance, a direct, but laborious, way to reconstruct such social networks to quickly identify infected people and to isolate them before they infect others.[60]

Our first experiment consisted of simulating increasingly virulent epidemics by assuming increasing values of the probability ρ of infecting somebody (1000 trials were done per value of ρ). Our results are described in Table 2. They show a remarkably interesting phenomenon: for all values of the probability ρ, only a tiny fraction π of the population is eventually infected in most of the number ν of simulations (less than 1 of 1000 persons in more than 90% of the cases), or when a significant proportion (greater than 1%) is infected, the fraction of infected people π depends on ρ. In simpler terms, this can be stated as follows: there are a lot of viruses circulating in the population, but only a few of them give rise to epidemic outbreaks. The reasons for which a virus gives rise to an epidemic outbreak are intrinsic to the virus itself, but

TABLE 2 Proportion π of the population that is infected, for different values of the propagation probability ρ. The value ν shows the number of simulations (out of 1000) that lead to a certain population infection threshold

ρ	π	ν	π	ν
0.005	$\pi < 0.1\%$	998	$1.7\% < \pi < 2\%$	2
0.010	$\pi < 0.1\%$	983	$21\% < \pi < 23\%$	17
0.015	$\pi < 0.1\%$	959	$43\% < \pi < 47\%$	41
0.020	$\pi < 0.1\%$	945	$58\% < \pi < 62\%$	55
0.025	$\pi < 0.1\%$	908	$70\% < \pi < 74\%$	92

TABLE 3 Lethality for different values of the reaction threshold τ and numbers of days of confinement γ

$\tau \setminus \gamma$	0	30	60	90	120	∞
0.01%	2.10%	1.32%	1.13%	1.08%	1.02%	0.98%
0.05%	2.10%	1.42%	1.35%	1.36%	1.35%	1.35%

also dependent on external factors such as who is infected first, eg, a person with few contacts and low nodal degree or a superspreader with high nodal degree as shown in Table 1, and also the behavior of the population which impacts ρ. This may explain, at least to some extent, why some countries or regions are more stricken than others, which suggests again a fractal interpretation of the geographical scope of an epidemic, as already mentioned above.

The second experiment that we shall report on in this section aimed at studying the effects of the deconfinement of a confined population that has been ordered to shelter-in-place. We studied here different proportions τ of the population that becomes sick *before* the epidemic becomes observable (ie., roughly between day 10 and 20 in Figure 5) and different values of the duration γ in terms of days of confinement. We considered that there was a delay δ of 20 days before confinement was put in place and took $\rho = 0.015$. We also simulated the efficiency of the confinement by reducing the capacity of edges in the social network to propagate the disease by a factor $1 - \varepsilon$ with $0 \le \varepsilon \le 1$. This factor represents the degree of adherence of the population to sanitary guidelines for social distancing, wearing face masks, and so forth. At each step of the simulation, representing one day, an infected node has thus probability $\rho \times (1 - \varepsilon)$ to infect an adjacent healthy node. In our experiment, we took $\varepsilon = 0.66$ (= 2/3). We then reported the computed values of the resulting lethality in Table 3. We assumed that γ is as large as necessary, which is clearly not realistic since confinement cannot be maintained too long for both economic and psychological reasons, but the results give the underlying trend. Each measure reported was obtained by means of a Monte-Carlo simulation of 2000 trials.

As expected, the longer the confinement, the fewer deaths. Note however that, to be fully efficient, the confinement must be rather long, several months (>90 days) in our virtual experiment. The most interesting part of this experiment comes however from the observation of the total duration of the epidemic outbreak. Table 4 shows these durations for the same values of τ and γ as in Table 3.

TABLE 4 Duration of the epidemic in days for different values of the reaction threshold τ and the number of days of confinement γ

$\tau \setminus \gamma$	0	30	60	90	120	∞
0.01%	243	407	539	361	220	195
0.05%	243	322	247	192	189	188

If the confinement is sufficiently long, the lethality drops significantly (in some cases below 1%), but also the total duration of the epidemic outbreak is shortened. If the confinement is not maintained sufficiently long, it is still partially effective, in that it reduces the lethality, but it has a quite paradoxical consequence: the epidemic outbreak lasts longer than if no countermeasures were taken at all. A short confinement does not prevent the disease from significantly propagating: it just slows down the propagation and avoids the sharp peak of infected shown in Figure 5 around day 40, which seems to be its main motivation in order not to overwhelm the capacity of the health care system. For this reason, when the population is deconfined too early, the disease is still present and remains endemic.

The above experiments do not pretend to fully represent reality, but are just to motivate the use of social-network models for epidemic modeling. As pointed out by Stattner and Vidot,[56] "network models turn out to be a more realistic approach than simple models like compartment or metapopulation models, since they are more suited to the complexity of real relationships." One of the limitations of existing network models is, however, that they do not distinguish between recurring social links with family members and coworkers and casual links based on one-time encounters such as in public transportation or at large events. They should therefore be further refined and integrated into a model-based agile approach for crisis management, while taking into account their limitations.

2.2.3 | Ingredient 3: Understanding the economic impact of the epidemic

In this section, we model the potential impact of the epidemic as a function of different actions of the governance system on the economic system (see Figure 3). In order to do so we must expand the prior analysis by not only considering lethality in terms of deaths (see Table 3), but also the value of lost economic activity during confinement. Reverting back to the simplified SIRD model in Figure 5 , but now accounting for the fraction of population ε actually adhering to confinement during a lockdown of duration γ, which is ordered with some delay δ after a critical cumulative threshold τ of the population has become infected, we run a set of simulations. The baseline run of the model shown in Figure 5 is considered as scenario 0 with no countermeasures and it is gradually modified using the one-factor-at-a-time (OFAT) technique to test a number of actions by the governance system, including reducing the delay δ to order a lockdown, increasing the level of rigor ε of the confinement, as well as its duration γ . Table 5 shows the results of a number of numerical experiments to probe these trade-off in terms of the value of human lives lost, versus productive work lost in the economic system. In order to estimate the economic impact of the epidemic a number of assumptions were made:

- The average value of a human life lost is \$1 million. This is a nominal assumption somewhere between the three years of GDP/capita/year recommendation made by the WHO for evaluating medical interventions at the low end (this would be about \$200 000 based on the \$63 000 GDP per capita in the United States in 2018) and the ~\$8 million value of a statistical human life used by U.S. government agencies such as the Federal Aviation Administration (FAA) at the high end.
- The economic damage is the sum of work hours lost by infected people who cannot work during their illness, plus the value of work lost by all susceptible plus recovered individuals during a potential lockdown. For simplicity, we assume an hourly wage of \$28 (U.S. average in 2018) and that the population is completely unproductive during a lockdown
- We do not account for the secondary impacts of prolonged shutdowns, such as the failure of firms and permanent disappearance of jobs (see long-term scenario in Figure 2)

By perturbing the model in a number of ways that reflects the large range of policy responses we observe in different countries during the COVID-19 pandemic, see Figure 1, we can generate vastly different outcomes, not only in terms of mortality, but also in terms of total economic damages.

In the baseline scenario 0, we do not take any countermeasures and the bulk of the \$4.38B total loss is due to the deaths of 4% of the population. The \$312M in lost work are due to the inability of the infected and sick population to perform work during their illness, which is assumed to last for 14 days. This is the kind of situation we would expect to see in a country with a government that is either unable or unwilling to intervene in the crisis.

Scenarios 1-3 institute a partial lockdown ($\varepsilon = 66\%$) after either 10 or 20 days delay after recognizing the onset of the epidemic and the confinement lasts either 30 or 60 days. The results are not satisfactory, since the total damages exceed the baseline case where no action is taken. This outcome is due to the fact that one-third of the population does not adhere to the confinement and continues to be infected, making the disease endemic. A prolonged partial lockdown for 60 days with only 66% effectiveness as shown in scenario 3 is the worst case and leads to both a high number of deaths (about 4000) as well as high economic damages totaling \$6.1B due to the prolonged shutdown, which ultimately is ineffective. This scenario is representative of the overall situation in the United States in mid2020. In scenarios 4-7, we shorten the reaction time to trigger the confinement after only five days (quick government action) and we gradually increase the rigor of the confinement to 90% (strong government enforcement). It turns out that these actions are highly effective, yielding a best-case scenario 7 with only 66 deaths, a short epidemic duration of 61 days and only \$740M in damages, mainly due to the strict but short 30-day confinement in which 90% of the population participates. This essentially prevents the epidemic from blossoming and quickly snuffs out the disease. The

TABLE 5 Scenario analysis with SIRD model for assessing total human and economic damages: n, number of daily contacts, ρ, probability of infection, τ, fraction of population infected to trigger confinement, ε, fraction of population adhering to confinement, δ, delay to confinement start, γ, confinement duration, t, duration of epidemic, total number of deaths, lost work in millions \$M, and total damages including lost human lives and lost work in billions \$B, N = 100,000 population size

Scenario N = 10^5	n	ρ %	τ %	ε	δ days	γ days	T days	Total deaths	Lost work \$M	Total damages \$B
0	10	2.5	100	0	0	0	112	4060	312	4.38
1	10	2.5	0.01	0.66	20	30	179	4080	852	4.93
2	10	2.5	0.1	0.66	10	30	309	3989	950	4.95
3	10	1.5	0.05	0.66	20	60	286	3994	2106	6.1
4	10	2.5	0.05	0.8	5	30	334	3975	954	4.94
5	10	2.5	0.05	0.835	5	30	223	524	696	1.22
6	10	2.5	0.05	0.85	5	30	114	160	675	0.86
7	10	2.5	0.05	0.9	5	30	61	66	672	0.74
8	10	2.5	0.05	0.835	10	30	366	2904	858	3.76
9	10	2.5	0.05	0.835	15	30	312	3284	858	4.14
10	10	2.5	0.05	0.835	20	30	261	3505	806	4.31
11	5	2.5	0.05	0.835	20	30	88	190	674	0.86
12	5	1.25	10	0.835	20	30	201	1959	766	2.73

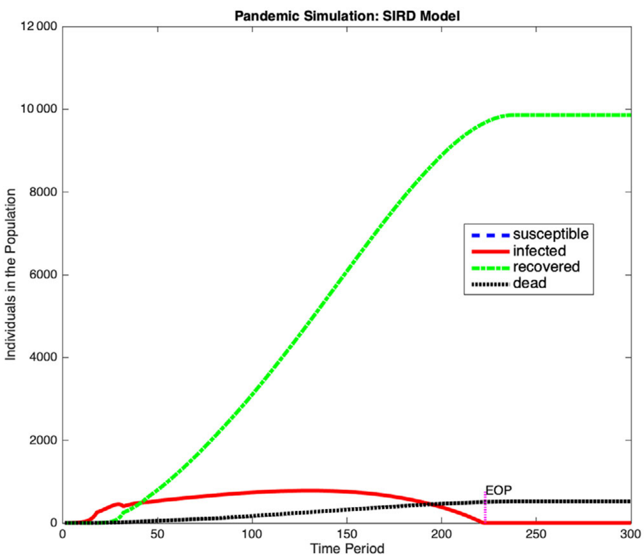

FIGURE 7 Simulation of epidemic for scenario 5 with a 30 day confinement (83.5% adherence) triggered after 5 days

trajectory for scenario 5 resulting in a lethality of only about 0.5% is shown in Figure 7. This may reflect the situation in countries that recognized the danger posed by COVID-19 early and took rapid and strong action (eg., China).

In order to understand whether it is the rapid reaction time or the rigor of the confinement that is more important in minimizing economic damages, we maintain the duration ($\gamma = 30$ days) and a critical confinement effectiveness ($\varepsilon = 83.5\%$) while allowing for increasing delays δ from 5 to 20 days, reflecting increasing governmental hesitance in triggering a lockdown. Unfortunately, scenarios 8-10 show that this is not a recommended strategy leading to between 2900 and 3500 deaths and total damages between \$3.7 and \$4.3B. The reason for this is that while the confinement is rigorous, it starts too late and the epidemic is already out of hand. Only between 500 and 1000 lives (0.5%-1%) can be saved compared to the "do nothing" scenario. This situation is reminiscent of the evolution of COVID-19 in some European countries such as France, where a strict lockdown was instituted, but relatively late after the virus had already propagated to a substantial fraction of the population. Finally, scenarios 11 and 12 show how economic damages can be limited, even when confinement is both late and short ($\delta = 20$ days, $\gamma = 30$ days). In these two scenarios, the initial conditions are different because either the population is sparsely populated (scenario 11) with only 5 instead of 10 average daily contacts (eg., Canada), or the population is already used to wearing face masks (scenario 12), hence dropping the infection probability from 2.5% to 1.25% as may be the case in some Asian countries such as Japan.

The economic analysis shows that the initial conditions, speed of response, and rigor of response by the governance system are crucial in determining the outcome. Figures 8 and 9, respectively, show the sharp contrast between the ratio of human loss (deaths) and economic work loss for scenarios 0 (do nothing) and scenario 5 (rapid and strong government response).

There is indeed a trade-off between deaths and lost work, as in scenario 5 the economic loss due to lost work is \$696M and it exceeds the economic loss of scenario 0 of \$312M. However, when looking at the *total losses* including the value of human lives lost (valued at \$1M each), scenario 5 only incurs 27.8% of the losses of the "do nothing" baseline. In order for a government to justify scenario 0 over scenario 5 it would have to implicitly value a human life lost at less than \$108,600—only about 10% of the nominal value—which is the marginal difference in the

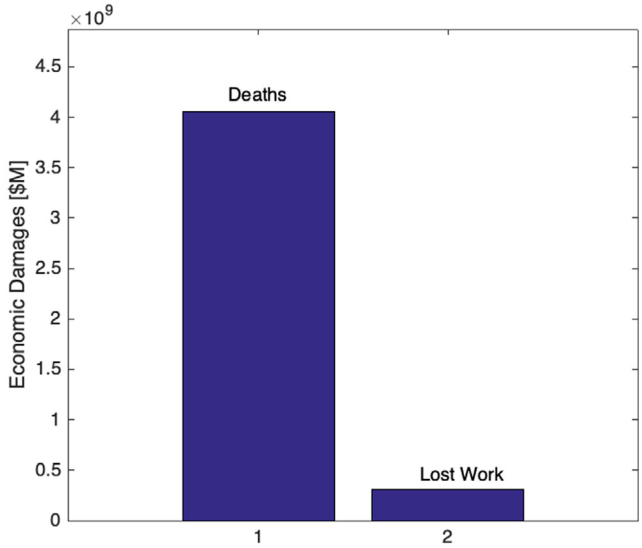

FIGURE 8 (Left)- Economic losses in scenario 0 total $4.38B due to 4% lethality

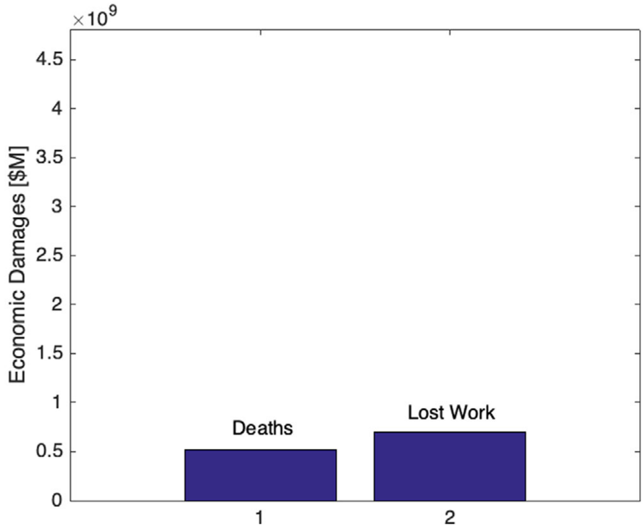

FIGURE 9 (Right) - Economic losses in scenario 5 total $1.22B with a lethality of 0.5%

economic loss of work divided by the difference in lives lost due to the epidemic. This may be the case in countries like Brazil (GDP per capita of $8,921 in 2018) that have responded poorly to the pandemic. We note that policy models that rely on explicitly stating an economic value of human life to justify government action will always be contested and controversial. However, without including such economic models in the overall systemic model of society it is not possible to justify any policy, whether interventionist or not.

3 | TOWARD AN AGILE APPROACH OF THE CRISIS

In the previous section, we identified a deep crisis of models that has been exposed by the COVID-19 pandemic and proposed to mitigate this issue by constructing a systemic model of the crisis. In this section, we shall deal with some possible solutions to master the crisis using a systems approach.

3.1 | Stating the problem to solve

As is well known in any scientific discipline, the solution of a problem highly depends on the clarity and rigor of the way the problem is framed. We will therefore dedicate this short section to the statement of the problem that we need to solve in the context of the COVID-19 crisis.

A first characteristic of the COVID-19 crisis is its *global impact* on human society. This crisis can thus be considered as a common cause failure—in the meaning of system safety theory[61]—for all main systems forming human society. If we are taking a safety approach, the first problem to solve is thus to mitigate the impacts of the crisis on the vulnerable systems forming human society, that is to say the social, health, and economic systems, as results from the system analysis of Section 2.2.1.

A second characteristic of the COVID-19 crisis comes from the need to take into account *strong feedback delays*. In this matter, a first type of delay comes from the fact that it is most of the time too late for deploying mitigation actions to limit the epidemic propagation when significant numbers of infections are observed somewhere, since the effects of these actions will only be observable two weeks later. This was clearly shown in Table 5 in scenarios 8-10. Moreover, a second–totally different type of delay comes from the fact that focusing on short-term health impacts of the crisis may lead to long-term issues of an economic nature, which forces to arbitrate between short- and long-term consequences of a given action.

Finally, a last characteristic of the COVID-19 crisis is *uncertainty*. Due to the global nature of the crisis and the rather short period of time on which it is concentrated, uncertainty is everywhere. Clinical data about the infection are permanently partial, so difficult to interpret. Understanding of the real social system network structure is never easy to capture. The exact nature and size of the impact on the economic system are difficult to evaluate. Precise data on the capabilities on which to rely may be tricky to obtain. Last, but not least, the crisis also results in a massive, heterogeneous and often contradictory amount of data in which the really interesting signals may be either weak or hidden.

Synthesizing these three features of the crisis, the problem to solve in our context can now be clearly stated: *how to optimally mitigate the short- and long-term consequences of the COVID-19 pandemic on human society, taking into account delays and uncertainties that are specific to this crisis?*

One can notice that this statement is a typical control problem—in the sense of control theory[62]—integrating here delay and uncertainty, which can be addressed by many existing techniques (see Refs. 63 and 64). Consequently, the objective should be to design a new system that can support this controllability objective. Based on the closed-loop control principle, which is the only one that allows to achieve a given target behavior along the time axis,[62] such a

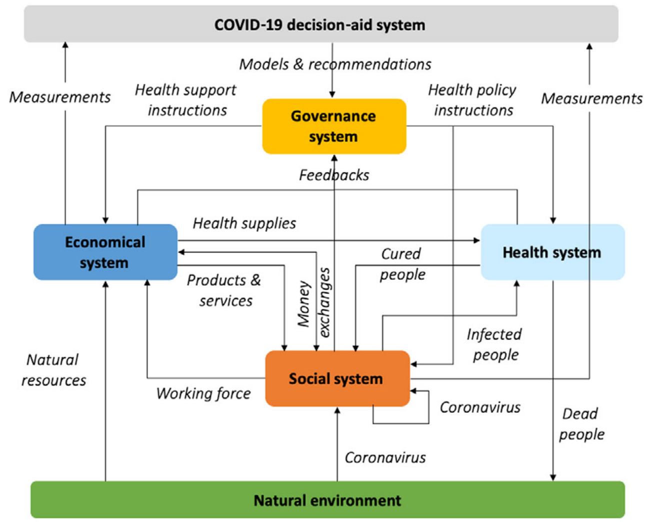

FIGURE 10 High-level COVID-19 environment integrating a specific decision-aid system that has yet to be designed

COVID-19 decision-aid system (shown as the gray box at the top of Figure 10) will have to measure the current state of the main systems forming human society in order to provide effective feedback actions on the social system through the governance system, the only legitimate one to make decisions and take control actions. Figure 10 depicts how such a decision-aid system could be integrated into the high-level COVID-19 environment.

3.2 | A possible answer: An agile COVID-19 decision-aid system

There is at least one domain where making decisions under structural uncertainties on an underlying geographic scope is quite well known since a long time in human history, which is the *military domain*. Architecting a COVID-19 decision-aid system using the typical architectural pattern of a Computerized, Command, Control, and Communications (C4) system (see Ref. 65 or 66), used in the defense area, seems thus quite a natural idea, as it is also quite often used in a system-of-systems engineering context (see Ref. 18 or 19). This leads us to propose an organization for a COVID-19 decision-aid system based on the following three hierarchical layers, that correspond to three natural levels of abstraction associated with a given geographic scope (that may be either the international, country, and local levels or country, region, and city levels in practice), exactly like C4 systems are organized:

1. The *strategic layer* is the place where global situational awareness is required to master the crisis on a given large-scale geographic scope: its mission is to monitor at a high level the crisis and to elaborate strategic decisions based on an overall vision, fed by tactical information;
2. The *operation layer* is intended to master the crisis on a given medium-scale geographic scope: it is thus a distributed system which has to capture and synthesize tactical information and make operational decisions on their basis in accordance with the upper strategic decisions;
3. The *tactical layer* is intended to master the crisis on a local geographic scope: it is thus again a distributed system which has to capture and synthetize field information and make tactical decisions on their basis in accordance with the upper operational decisions.

Note that this architecture shown in Figure 11 shall be understood as a hierarchical enterprise architecture, which defines how an organizational system, supported by suitable information systems and systemic models as discussed previously, shall be organized and behave.

The main idea underpinning it is the *principle of subsidiarity*: decisions should be taken as close as possible to the level that is the most appropriate for their resolution. This principle means in particular that an upper level shall avoid to make decisions that are too intrusive at a lower level in order to let each local level take always the more appropriate actions depending on the real local conditions that it can observe, while following at the same time global orientations when locally relevant. This is crucial in the military sphere, but even more so in the context of the COVID-19 crisis where speed of decision making is fundamental due to the latency of the epidemic propagation as seen in Section 2.

Note that one shall also capture weak signals of systemic importance at each level of the proposed architecture: to illustrate that point, the fact that a police officer is infected in a certain area is, for instance, a typical weak signal since we may infer from it that there is a certain probability that the whole police force in the concerned area is or will be infected, at least in the near future (since the number of daily contacts or nodal degree of police officers may exceed $n > 10$, see Tables 1 and 5).

Proposing the previous hierarchical architectural pattern is, however, of course not enough to specify how a COVID-19 decision-aid system shall work. In this matter, the first point is to organize the systemic model that we sketched out in Section 2.2 according to the hierarchy that we just presented and which is used to organize the proposed decision-aid system. Hence, such a model shall not be monolithic, but consist of a series of interrelated models describing human society and epidemic propagation—using the society decomposition, social network modeling, and economic parameters presented in the last section—at each level of the geographic decomposition underlying the systems architecture layers of our COVID-19 decision-aid system. These system models shall be complemented by key systemic indicators, also structured according to the same hierarchy, which will allow decision makers at each level to see at each moment what is the current and possible short- , mid-, and long-term future state of the different systems forming human society in their scope of responsibility. Typical examples may be:

- Number of tested, infected, hospitalized, and dead people for the human population;
- Number of hospitals, beds, and ventilators used by COVID-19 patients for the health system;

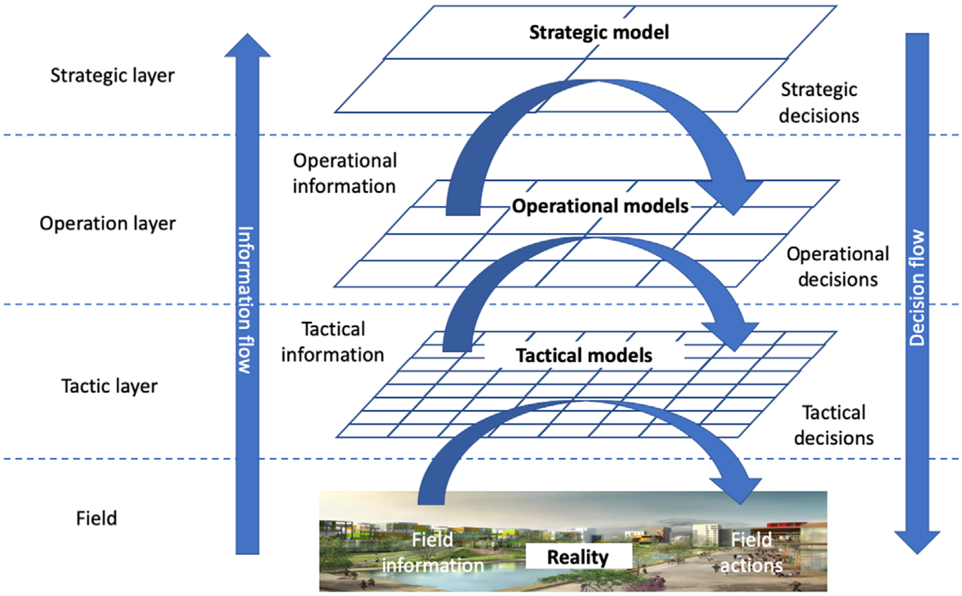

FIGURE 11 Proposal of generic systems architecture layers for a COVID-19 decision-aid system

- Number of closed companies, furloughed workers, work hours lost and decreased wage bills, filed un- or underemployment claims, for the economic system.

Note that these system models do play a fundamental role due to the latency of the COVID-19 crisis. They shall be used at each level of the decision-aid architecture that we are proposing in order to guide decision makers, by anticipating the consequences of the decisions that have to be made on the key systemic indicators chosen to track the crisis. Optimal control actions with delay techniques may of course also be used here in order to find what could be the best mitigation strategies, such as ordering the wearing of masks, social distancing, testing or partial or total confinement, at each level (see Ref. 67 or 64). COVID-19 is indeed a totally new phenomenon for which one does not usually have a lot of similar past data: a realistic systems model, permanently fed by field data and permanently recalibrated and modified to capture as accurately as possible the reality of the crisis, can therefore play an important role to support the best possible decisions in the context of a complex and fast changing crisis. Note also that a similar proposal—at least in its core principle—was proposed by Zhang et al, but in the context of a classic epidemic.[60]

Last, but not least, the COVID-19 decision-aid system that we sketched here shall behave in an agile way, in the meaning of agility in software or industrial development (see Refs. 68–70, 71 or 24). A pending problem is to have a plan, do, check, and act process that can quickly adapt to a quite fast-changing reality. Agility allows to solve that issue by structuring in a very rigorous way the analysis, decision, and action processes, while providing a lot of flexibility to all involved actors, which are two mandatory features for addressing a complex crisis like COVID-19. In practice, an agile COVID-19 decision-aid process has typically to be organized around regular agile rituals—managed at different time scales (for instance, daily and weekly) and levels of synthesis—where the main scenarios, views, and indicators have to be shared and challenged regularly at each level of the chosen decision-aid architecture. The point here is to provide regularly a synthesis of the current situation of the crisis to the relevant domain actors in order to allow them to manage their missions with the best possible understanding of the situation and of the consequences of their actions.

4 | CONCLUSIONS

In this paper, we draw attention to the core importance of having realistic system models to manage and to mitigate a systemic crisis of the order of magnitude such as the COVID-19 crisis. We also sketched out what could be an agile approach to use in this kind of crisis. Our purpose was of course not to propose some definitive solution which is probably impossible. We do, however, think that the ideas contained in this paper are valuable contributions that may be of interest in the context of the COVID-19 crisis, especially due to the fact the underlying health crisis will probably be endemic for a certain period of time (at least for 200-300 days according to most of our simulation runs) and be coupled with future short- and mid-term economic outcomes. While there are economic impacts due to strong mitigation actions such as mandated confinements (causing lost economic activity), the value loss due to human deaths at an estimated lethality rate of 4% would far exceed the economic losses. We have shown that this depends strongly on the average valuation of a human life, which is in itself a highly controversial issue.

There are of course many detailed aspects of the proposed COVID-19 decision support system that require further detail and elaboration. We focused on the issue of delay and rigor of action in the overall epidemic control system in this paper. However, as we discover more about the particular nature of this particular coronavirus, the issue of *observability* of human society (testing) may for instance be an even larger one.

We would finally like to stress the fact that *systems engineering* has an important role to play in the COVID-19 context since it can enable the necessary collaboration of the various disciplines—such as biology, economics, engineering, epidemiology, finance, geography, health policy management, immunology, logistics, manufacturing, medicine, safety, sociology, urban systems, and so forth—that are all providing a piece of the complex puzzle posed by the global COVID-19 crisis.

ACKNOWLEDGMENTS

The authors would like to thank the three anonymous referees for their valuable comments which contributed to a substantial improvement of the paper.

ORCID

Olivier de Weck https://orcid.org/0000-0001-6677-383X
Daniel Krob https://orcid.org/0000-0003-4418-8300
Li Lefei https://orcid.org/0000-0001-6816-6267
Antoine Rauzy https://orcid.org/0000-0003-0926-5286

REFERENCES

1. Chinese Center for Disease Control & Prevention (CCDC). *The Epidemiological Characteristics of an Outbreak of 2019 Novel Coronavirus Diseases (COVID-19) – China*. 17 Feb., 2020. https://weekly.chinacdc.cn/en/article/id/e53946e2-c6c4-41e9-9a9b-fea8db1a8f51. Accessed July 21, 2020.
2. World Health Organization. *Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19)*. WHO; 2020. www.who.int/docs/default-source/coronaviruse/who-china-joint-mission-on-covid-19-final-report.pdf
3. CSSE. *COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins*. Center for Systems Science and Engineering (CSSE), Johns Hopkins University. 2020. Accessed July 21, 2020. https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6. Accessed July 21, 2020.
4. Roser M, Ritchie H, Ortiz-Ospina E, Hasell J. *Statistics and Research – Coronavirus Pandemic (COVID-19)*. Our World in Data, 2020. https://ourworldindata.org/coronavirus. Accessed July 21, 2020.
5. World Health Organization. *Coronavirus Disease 2019 (COVID-19) situation reports*. www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports/. Accessed July 21, 2020.
6. Barry JM. The site of origin of the 1918 influenza pandemic and its public health implications. *J Transl Med*. 2004;2(1):3. https://doi.org/10.1186/1479-5876-2-3
7. Huang C, Wang Y, Li X, et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet* 2020;395(10223): 497-506.
8. Zhang J, Litvinova M, Wang W, et al. Evolving epidemiology and transmission dynamics of coronavirus disease 2019 outside Hubei province, China: a descriptive and modelling study. *Lancet* 2020; 20(7):793-802. https//doi.org/10.1016/S1473-3099(20)30230-9
9. Zhu N, Zhang D, Wang W, et al. A novel coronavirus from patients with pneumonia in China, 2019. *N Engl J Med*. 2020;382(8):727-733.
10. CESAMES. *CESAM: CESAMES Systems Architecting Method – A Pocket Guide*. CESAMES; 2017:134 pp.
11. de Weck O. *Strategic Engineering – Designing Systems for an Uncertain Future*. MIT; 2006.
12. Maier MW, Rechtin E. *The Art of Systems Architecting*. CRC Press; 2002.
13. Ramo S, St Clair RK. The Systems Approach: Fresh Solutions to Complex Problems through Combining Science and Practical Common Sense. *Commons Lab| Case Study Series 2*. Anaheim, CA: TRW Inc.; 1998.
14. Sage AP, Armstrong JE Jr. *Introduction to Systems Engineering*. Wiley; 2000.
15. Severance FL. *System Modeling and Simulation—An Introduction*. Wiley; 2001.
16. Sillitto H. *Architecting Systems—Concepts, Principles and Practice*. College Publications; 2014.
17. Zeigler BP, Praehofer H, Kim TG. *Theory of Modeling and Simulation—Integrating Discrete Events and Continuous Dynamic Systems*. Academic Press; 2000.
18. Luzeaux D, Ruault JR, Wippler JL. *Complex System and Systems of Systems Engineering*. ISTE Ltd. and Wiley; 2011.
19. Ring J, Madni A M. *Key challenges and opportunities in'system of systems' engineering*. In 2005 IEEE International Conference on Systems, Man and Cybernetics, vol. 1, pp.973-978. IEEE, 2005.
20. Forrester JW. *World Dynamics*. Productivity Press; 1971.
21. Meadows D, Randers J, Meadows D. *The Limit to Growth*. Earthscan; 2004.
22. Volterra V. Fluctuations in the abundance of a species considered mathematically. *Nature*. 1926;118:558-560.
23. INCOSE. Agile systems engineering. www.incose.org/ChaptersGroups/WorkingGroups/transformational/agile-systems-se. Accessed July 21, 2020.
24. Krob D. *CESAF: cESAM Engineering Systems Agile Framework*. 10th International Conference on Complex Systems Design & Management 2019, Invited talk, Paris; 2019.
25. Woodcock H. *The Agile Manifesto Reworked for Systems Engineering*. INCOSE UK, ASEC Conf., 2012.
26. Walker PGT, Whittaker C, Watson O, et al. *Report 12: The Global Impact of COVID-19 and Strategies for Mitigation and Suppression*, Imperial College COVID-19 Response Team, Imperial College. March 26, 2020. www.imperial.ac.uk/media/imperial-college/medicine/mrc-gida/2020-03-26-COVID19-Report-12.pdf
27. McKibbin WJ, Roshen F. *The Global Macroeconomic Impacts of COVID-19: Seven Scenarios*. CAMA Working Paper No. 19/2020. 2020: 45pp.
28. Anderson RM, Heesterbeek H, Klinkenberg D, Déirdre Hollingsworth T. How will country-based mitigation measures influence the course of the COVID-19 epidemic? *Lancet*. 2020;395(10228):931-934. https://doi.org/10.1016/S0140-6736(20)30567-5
29. Armstrong M. COVID-19 cases per million inhabitants: A comparison. *Statista*. April 8, 2020. www.statista.com/chart/21176/covid-19-infection-density-in-countries-most-total-cases/. Accessed July 21, 2020.
30. International Monetary Fund. Confronting the crisis: priorities for the global economy. April 2020. www.imf.org/en/News/Articles/2020/04/07/sp040920-SMs2020-Curtain-Raiser. Accessed July 21, 2020.
31. Strauss-Kahn D. *L'être, l'avoir et le pouvoir dans la crise*, Politique Internationale (to appear) www.leclubdesjuristes.com/letre-lavoir-et-le-pouvoir-dans-la-crise/. Accessed July 21, 2020.
32. Herby J. We pay minimum five times as much for a life year with the corona measures than we normal do. CEPOS, March 3, 2020. cepos.dk/media/4701/we-pay-minimum-five-times-as-much-for-a-life-year-with-the-corona-measures-than-we-normally-do.pdf
33. Marwedel P. *Embedded System Design*. Kluwer; 2003.
34. Bellman R. *Adaptive Control Processes: A Guided Tour*. Princeton, NJ: Princeton University Press; 1961.
35. Cousot P, Cousot R. *Abstract Interpretation: A Unified Lattice Model for Static Analysis of Programs by Construction or Approximation of Fixpoints*. Conference Record of the Fourth ACM Symposium on Principles of Programming Languages. Los Angeles, CA: ACM Press: 1977:238-252, https://doi.org/10.1145/512950.512973
36. Korzybski A. *Science and sanity—an introduction to non-Aristotelian systems and general semantics*. The International Non-Aristotelian Library Pub. Co.; 1933: 747-761.

37. Box GEP. All models are wrong, but some are useful. *Robustness in Statistics*. 1979;202(1979):549.
38. Harzing A-W. *The Publish or Perish Book*. Melbourne: Tarma Software Research Pty Ltd; 2010.
39. Haushofer J, Metcal JE. *Combining Behavioral Economics and Infectious Disease Epidemiology to Mitigate the COVID-19 outbreak*. Princetone, NJ: Princeton University; 2020.
40. Gautret P, Lagier JC, Parola P, et al. Hydroxychloroquine and azithromycin as a treatment of COVID-19: results of an open-label non-randomized clinical trial. *Intl J Antimicrob Agents* March 2020. https://doi.org/10.1016/j.ijantimicag.2020.105949
41. Dahly D, Gates S, Morris T. *Statistical Review of Hydroxychloroquine and Azithromycin as a Treatment of COVID-19: Results of an Open-Label Non-Randomized Clinical Trial*. March 23, 2020. https://doi.org/10.5281/zenodo.3724167
42. Babu AN. *Clinical Research Methodology and Evidence-Based Medicine: The Basics*. Anshan Ltd; 2007.
43. Feller W. *An Introduction to Probability Theory and Its Applications*. Vols. I and II. Wiley; 1966.
44. Fassbender M. Clinical trial cost is a fraction of the drug development bill, with an average price tag of 19 M$. *Outsourcing Pharma*, Sep. 26, 2018. www.outsourcing-pharma.com/Article/2018/09/26/Clinical-trial-cost-is-a-fraction-of-the-drug-development-bill. Accessed July 21, 2020.
45. Popper K. *Conjectures and Refutations: The Growth of Scientific Knowledge*. London and New York: Basic Books; 1962.
46. Koyre A. *Galileo Studies*. Branch Line; 1977.
47. Greenwood R, Hanson SG, Lin LJ. *Reflexivity in Credit Markets*. California Institute of Technology, Preprint, April 2019. ww.its.caltech.edu/~jin/GHJ_Paper_FINAL_20190403.pdf
48. Ackerman F, Nadalwith A, Benetti C, Gallagher KP, Salas C. *The Flawed Foundations of General Equilibrium: Critical Essays on Economic Theory*. London: Routledge; 2004.
49. Choi Y, Douady R. Financial Crisis Dynamics: Attempt to Define a Market Instability Indicator. *Quant Finance*. 2012;12(9):1351-1365.
50. Alur R, Dill DL. A theory of timed automata. *Theor Comput Sci*. 1994;126(2):183-235.
51. Kermack WO, McKendrick AG. A contribution to the mathematical theory of epidemics. *Proc R Soc A* 1927;115(772):700-721. https://doi.org/10.1098/rspa.1927.0118
52. Capasso V. *Mathematical structure of epidemic systems*. Springer Verlag; 1993.
53. Lotka AJ. *Elements of Physical Biology*. Williams & Wilkins Company; 1925.
54. Vynnycky E, White RG, Eds. *An introduction to infectious disease modelling*. Oxford University Press; 2010.
55. Jansse HK, Oerding K, van Wijland F, Hilhorst HJ. Lévy-flight spreading of epidemic processes leading to percolating clusters. *Eur Phys J B*. 1999;7:137-145.
56. Stattner E, Vidot N. *Social network analysis in epidemiology: Current trends and perspectives*. Research Challenges in Information Science, Gosier; 2011:1-11. hal-00624364
57. Berge C. *The Theory of Graphs and Its Applications*. Wiley; 1964.
58. Albert R, Barabási AL. Statistical mechanics of complex networks. *Rev Mod Phys*. 2002;74(1):47-97. https://doi.org/10.1103/RevModPhys.74.47
59. Wolfram S. Statistical mechanics of cellular automata. *Rev Mod Phys*. 1983;55(3):601-644.
60. Zhang Z, Wang H, Wang C, Fang H. Cluster-based epidemic control through smartphone-based body area networks. *IEEE Trans Parallel Distrib Syst*. 2015;26(3):681-690.
61. Rausand M, Hoyland A. *System Reliability Theory—Models, Statistical Methods & Applications*. Wiley; 2004.
62. Sontag E. *Mathematical Control Theory: Deterministic Finite Dimensional Systems*. 2nd ed. Springer Verlag; 1998.
63. Ackermann J. *Uncertainty and Control*. Proc. of an International Seminar organized by Deutsche Forschungs- und Versuchsanstalt für Luft- und Raumfahrt (DFVLR), Germany; 1985.
64. Marshall E. *Control of Time-Delay Systems*. Peter Peregrinus Ltd.; 1979.
65. Alberts DS, Hayes RE. *Understanding Command and Control*. Washington, DC: US Department of Defense CCRP Publication Series; 2006.
66. United States, Joint Chiefs of Staff. *Doctrine for Command, Control, Communications, and Computer (C4) Systems support to Joint Operations*. Vol. 6. Joint Chiefs of Staff, 1995.
67. Gul Z, Kang YH, Jung IH. Optimal treatment of an SIR epidemic model with time delay. *Biosystems*. 2009;98(1): 43-50.
68. Agile Manifesto. *Agile Manifesto*. http://agilemanifesto.org/. Accessed July 21, 2020.
69. Dingsoyr T, Nerur S, Balijepally V, Moe NB. A decade of agile methodologies: towards explaining agile software development. *J Syst Softw*. 2012;85(6):1213-1221.
70. Douglas BP. *Agile Systems Engineering*. Morgan Kaufman; 2015.
71. Dawber TR, Gilein MD, Meadors MD, Moore FE Jr. National Heart Institute, National Institutes of Health, Public Health Service, Federal Security Agency. *Epidemiological Approaches to Heart Disease: The Framingham Study*. Joint Session of the Epidemiology, Health Officers, Medical Care, and Statistics Sections of the American Public Health Association, 78th Annual Meeting in St. Louis, MO, Nov. 3, 1950.
72. Gordon T, Kannel WB. Multiple risk functions for predicting coronary heart disease: the concept, accuracy, and application. *Am Heart J*. 1982;103:1031-1039.

AUTHOR BIOGRAPHIES

OLIVIER de WECK is a professor of Aeronautics and Astronautics and Engineering Systems at MIT where he teaches Technology Roadmapping, Satellite Engineering, and Systems Engineering as well as Multidisciplinary Design Optimization. He has authored over 400 publications (12 best paper awards since 2004) and is a Fellow of INCOSE, an Associate Fellow of AIAA, and a Senior Member of IEEE. He and his group worked with NASA's Office of Emerging Space to develop new Commercial Space Technology Roadmaps in 2018 and he is a former Senior Vice President of Technology Planning and Roadmapping at Airbus where he was responsible for roadmapping a $1 billion R&D portfolio for the world's largest aircraft manufacturer. His passion is to improve life on our home planet Earth through research and education in systems engineering while paving the way for humanity's future off-world settlements. He served as Editor-in-Chief for the journal *Systems Engineering* from 2013 to 2018.

DANIEL KROB is currently president of CESAMES (Centre of Excellence on Systems Architecture, Management, Economy, & Strategy), the leading French company in systems architecting & engineering. He was also senior researcher in Computer Science in the French National Center for Scientific Research and, up to 2019, an institute professor in Computer Science at Ecole Polytechnique, the most prestigious French engineering school, where he directed the Thales industrial chair "Engineering of complex systems" during 12 years. Graduated from Ecole Normale Supérieure (1981-1986), he received both his Ph.D. thesis (1988) and his second thesis in Computer Science (1991) from University Paris 7. He wrote more than 100 scientific papers and he is the author of several books and of four patents in various domains (computer security, mobile communications, and traffic optimization). He is one of the leading professional experts in systems engineering in the world, recognized as an INCOSE Fellow. He developed the CESAM (CESAMES Systems Architecting Method) and CESAF (CESAM Engineering Systems Agile Framework) methodologies.

Dr. Li Lefei is an associate professor in the Department of Industrial Engineering at Tsinghua University. He is the Deputy Chair of the department and the deputy director of the Tsinghua Smart Logistics and Supply Chain Systems Research Center. He received his B.S. degree in Electronic Engineering from Zhejiang University in 2002, M.S. (2004) degree in Industrial Engineering, and Ph.D. (2006) degree in Systems and Industrial Engineering from the University of Arizona. He joined Tsinghua University in 2006, conducting research in Systems Engineering, Service Operations and Management, Logistics and Complex Systems Modeling and Simulation. He has been serving as an associate editor for the *IEEE Transactions on Intelligent Transportation Systems, IEEE Intelligent Systems and Asian Pacific Journal on Operational Research*. He is the chair of IEEE ITSS Technical Committee on Logistics and Services. He is also the assistant director of INCOSE Academic Council and the past president of the INCOSE Beijing Chapter.

Professor Pao Chuen Lui retired in 2008 after serving 41 years in the Ministry of Defence of Singapore and 22 years as Chief Defence Scientist. He is currently serving as an adviser to the National Research Foundation, Prime Minister's Office and an adviser to six other Ministries and Government Agencies. He serves on the board of 12 research institutes and corporations. He is a member of the Changi Airport Group Executive Committee for Airport Development, a member of the MPA Next Generation Port 2030 Steering Committee, a member of CARTS (Committee on Autonomous Road Transport in Singapore), and a member of the ERP2 Technology Advisory Panel. In 2002, he received the National Science & Technology Medal *"For his outstanding leadership in the build up of science and technology capability for the nation and its exploitation for major systems of national impact."* In 2009, he received the rare Pioneer Award of International Council on Systems Engineering (INCOSE) *"for dedicating his life to systems thinking and application, resulting in both an unparalleled impact in Singapore, and advances in the development of systems engineering around the world."* In 2011, he was conferred an Honorary Fellow of the ASEAN Federation of Engineering Organizations and received the Institute of Physics of Singapore President Medal. In 2014, he received the IES the Lifetime Engineering Achievement Award and the Scout distinguished service silver award from President Dr. Tony Tan. In 2015, he received the Defence Technology Medal (Outstanding Service) from Ministry of Defence and Aviation Pioneer Award from the Singapore Institute of Aviation Engineers.

Antoine B. Rauzy is currently a professor at the Norwegian University of Science and Technology (Trondheim, Norway) and head of the chair Blériot-Fabre, sponsored by the group SAFRAN, at CentraleSupélec (Paris, France). During his career, he moved back and forth from academia to industry, being notably senior researcher at CNRS, associate professor at the Universities of Bordeaux and Marseilles, a professor at Ecole Polytechnique and CentraleSupélec, CEO of the start-up ARBoost Technologies, and a director of the R&D department of Systems Engineering at Dassault Systemes (largest French software company). He got his Ph.D. in 1989 and his habilitation à diriger des recherches (tenure) in 1996, both in computer science. He worked on reliability engineering for more than 20 years and on systems engineering for about 10 years. He has published over 200 articles in international journals and conferences. He is on the advisory boards of several international conferences and journals and is regularly invited to deliver seminars and keynote talks.

Xinguo Zhang (Ph.D. & DBA), is the Distinguished Professor and Director of Complex Systems Engineering Research Center at Tsinghua University, President of Beijing Chapter of INCOSE, a Fellow of RAeS, a Fellow of AIAA, INCOSE ESEP, TOG DA, and INCOSE Founder Award 2018.

How to cite this article: de Weck O, Krob D, Lefei L, Lui PC, Rauzy A, Zhang X. Handling the COVID-19 crisis: Towards an agile model-based systems approach. *Systems Engineering*. 2020;1-15. https://doi.org/10.1002/sys.21557