

Regarding the COVID-19 crisis from a systems engineering perspective

Santiago Pantano-Calderón

LAAS-CNRS, INSA Toulouse, Université de
Toulouse
spantanoca@laas.fr

Claude Baron

LAAS-CNRS, INSA Toulouse, Université de
Toulouse
baron@insa-toulouse.fr

Jean-Charles Chaudemar

ISAE-SUPAERO
jean-charles.chaudemar@isae-supero.fr

Élise Vareilles

ISAE-SUPAERO
elise.vareilles@isae-supero.fr

Rob Vingerhoeds

ISAE-SUPAERO, LAAS-CNRS
rob.vingerhoeds@isae-supero.fr

ABSTRACT

In the beginning of 2022, the world is still fighting the crisis caused by the COVID-19 outbreak. The scientific community is still dedicating significant efforts to identify which are the better strategies to mitigate the pandemic and establish how and when to apply them. Modeling and simulation are a common method to replicate and foresee the behavior of the epidemic curve, but traditional analytical models are not capable to explain and reproduce the real evolution of the number of infections and deaths as they only concentrate in the epidemiological aspects of the virus. The COVID-19 crisis has an impact in all fundamental levels of society, and this is the reason why its modeling requires a global perspective and a holistic approach. Though the engineering scope is not common in the study of public health crises, this paper concludes that some engineering tools such as systems analysis and control theory may be the answer to build a high-fidelity model to support the decision-making facing the emergency.

Keywords

COVID-19, Crisis, Modeling, Simulation, Holistic approach

INTRODUCTION

In the very beginning of 2022, humanity is still fighting the most important public health crisis of the last years, the pandemic caused by the COVID-19 (OECD 2020a; OECD 2020b). At this point, it is possible to assert that governments have settled on an universal way to reduce the impacts of the coronavirus pandemic, placing trust in vaccination plans, lockdowns and simple health recommendations (Mallah et al. 2021; Alfano and Ercolano 2020; Xing et al. 2021). An example of this is the insistent call to take booster shots of COVID-19 vaccines in order to contain the wave of infections of January 2022, presumably caused by the Omicron variant (Abbany 2022). Either by countermeasures taken or the characteristics of this variant, a far fewer number of deaths than previous waves has been observed in most of countries (Abbany 2022; Joly 2022). However, around 5.5 millions of deaths were reported in the first two years of the pandemic (WHO 2022) and the virus is still threatening the stability of healthcare sector (Joly 2022).

The COVID-19 outbreak forced humanity to act rapidly, even if there was not enough knowledge to make well-informed decisions (Brinks and Ibert 2020) and, indeed, in this state of emergency, there was a necessity to act as no acting would have led to a worse situation (Nazir et al. 2021). This characteristics of urgency, uncertainty and threat lead the entire globe into a deep crisis that affected not only the healthcare system but also economic,

social and political sectors (Shinde et al. 2020; de Weck et al. 2020). This means that societies, and especially power agents such as governments, are not trying to control a pure health crisis, but a systemic crisis that requires an holistic approach to respond to (de Weck et al. 2020).

Therefore, as the pandemic is still threatening society and the crisis withstand all countermeasures applied until present, it is completely necessary to find tools that allow scientists to propose the best alternatives facing public health crises. Modeling and simulation has been proven to satisfactorily replicate and predict the behavior of complex systems (Abhishek et al. 2012; Batstone et al. 2002), and during these last years, as a result of the COVID-19 outbreak, different models have been proposed to reproduce the behavior of specific aspects of the pandemic in order to understand the occurring phenomenon (Chen, Rui, et al. 2020; Arino and Portet 2020; de Weck et al. 2020). However, most of proposed models focus on its epidemiological characteristics and omit the real range of the crisis, where social and economic factors are closely involved.

For this reason, this paper has the purpose to contend the necessity of using systemic and holistic model-based approaches, not only to confront the current crisis but also to aid informed decision-making for future public health events. After this introduction the current modeling for the COVID-19 crisis is presented. In the next section, some advantages of using systems engineering methods are identified to generate a more realistic model of the pandemic, and the possibility to call systems analysis and control theory concepts is contended to better visualize the crisis. The last section proposes a discussion and recommendations for future works.

THE MODELS FOR THE CRISIS

Modeling and simulation are tools currently in use when studying the COVID-19, as they may be able to replicate the behavior of different variables involved in its corresponding epidemiology, such as the dynamics of the transmission of the virus or its mortality. This reproduction helps scientists and governments to predict the progress of the virus in the population over time, and so, it supports the decision-making facing the emergency. In this order of ideas, models are potentially useful to anticipate infection waves and new focal points, and they can help authorities to create strategies to limit the propagation of the disease, for example, imposing lockdowns or individual quarantines, limiting the transit in borders and airports or redistributing the available vaccine doses.

Current models of the pandemic are based on both medical and non-medical parameters (Shinde et al. 2020). For example, the medical parameters are several statistical and epidemiological indicators such as the transmissibility of the virus, the incubation period, proportion of asymptomatic infections and virus lifespan (Shinde et al. 2020; Chen, Rui, et al. 2020; Arino and Portet 2020). On the other hand, among the non-medical parameters, it is possible to find geographical statistics and demographic data, such as population, birth and death rates, age and gender (Shinde et al. 2020; Chen, Rui, et al. 2020). Even if there are several parameters that can be easily identified when building a pandemic model, there are many other hidden factors that may strongly affect the transmission or mortality of the virus, and this is the main reason why the behavior of the COVID-19 should be observed from a holistic approach.

The complexity of the pandemic

There are numerous reasons why the evolution of a pandemic is difficult to model and foresee. First, the measures taken by the governments and the appearance of novel variants of the virus cause variations in the infections rate, therefore, the transmissibility of the disease is not constant over time (Alfano and Ercolano 2020; Xing et al. 2021; Chowdhury et al. 2020). On the other hand, economic, social, cultural and political factors may be involved in the strategies proposed by authorities confronting the crisis. For instance, even if the imposition of general quarantines proved to be an effective way to reduce the transmission of the virus among people (Alfano and Ercolano 2020), the implementation of long lockdowns is an inviable alternative due to large costs not related to epidemiological factors, as it causes huge economic losses and several social and psychological problems in medium and long term (Michalski 2021; Brooks et al. 2020).

Furthermore, some cultural, demographic and social aspects may play an important role in the transmission of the virus (Bayeh et al. 2021). Cultural practices and habits, such as the population beliefs, the gender roles and the discipline and obedience of people, may influence the infectious rate. In the present pandemic, more men than women have been hospitalized or have died by COVID-19 related causes (Cañelles López et al. 2021; Jin et al. 2020), and some authors propose that the difference of severity and mortality rates between men and women may correspond to gendered behavioral aspects and gender-segregated occupations and not to pure biological factors (Galasso et al. 2020; Shattuck-Heidorn et al. 2020). In the same way, populations with psychological predispositions to reject scientific researches suffer bigger risks of aggravation of the emergency (Bayeh et al. 2021).

Mathematical and data science techniques are largely employed to predict the progress of the pandemic and, certainly, the sources and amounts of data collected have an important role in forecasting (Shinde et al. 2020). On

the basis of analytical approaches, different mathematical models have been proposed to replicate the evolution of the number of infections over time, for example, the Bats-Hosts-Reservoir-People (BHRP) model, simplified to Reservoir-People (RP) model, which is expressed in six differential equations (Chen, Rui, et al. 2020), and the computational model on COVID-19 based on cellular automata (Ghosh and Bhattacharya 2021). However, the main issue that we found is that most of traditional approaches used today do not fit the reality as expected since they usually concentrate only on the epidemiological aspects of the disease.

The suitability of a traditional model

In order to analyze the reliability and suitability of traditional analytical models, we tested the BHRP transmission network model, proposed by Chen, Rui, et al. 2020, since it is one of the nine most commonly used models based on mathematical implementations (AlArjani et al. 2022) and it is an extension of another traditional compartmental model in epidemiology, the Susceptible–Infectious–Recovered (SIR) model (Chen, Leung, et al. 2014). The major contribution of this approach stands in the consideration of the complete transmission route from the bats to the people through the seafood market in Wuhan, China (Chen, Rui, et al. 2020), though the model was simplified into a RP model and normalized in order to explore it more clearly. Afterwards, the normalized RP model can be used to calculate the basic reproduction number R_0 to evaluate the transmissibility of the SARS-COV2 (Chen, Rui, et al. 2020). This model is also capable to estimate and reproduce the dynamic of transmission of the virus by introducing several epidemiological parameters: Incubation period, duration of symptoms, fraction of asymptomatic infections and lifespan of the virus in the reservoir. A population and its birth and death rates are also required to perform a simulation.

In order to test the model, we collected the data of the epidemic curve of Bogota, Colombia, from February 26th, 2020, date of the first reported case in the city, to June 5th, 2020 (SALUDATA 2021). The sample frequency of the data is 1 day. The epidemic curve and the date of the implementation of the first lockdown, on March 25th, 2020, are shown in figure 1. Following the method and the parameter values suggested in Chen, Rui, et al. 2020, two curve fitting processes using the method of least squares were performed to estimate the value of the normalized diffusion rate of the virus. A simulation for each curve fitting result was carried out with a step time of 1 day. To do so, and in order to soften the abrupt changes in the epidemic curve, real data was processed by calculating, for each sample, the average of the number of new symptomatic cases of three days, as shown in equation 1, where \dot{I} is the number of new symptomatic cases in the day i after the detection of the first symptomatic case. At first, processed real data from February 26th, 2020 to April 16th, 2020 were used to do the curve fitting. In a second case, processed real data from April 17th, 2020 to June 5th, 2020 were used to perform the same procedure. The corresponding simulation results are shown in figures 2 and 3.

$$\dot{I}_{i \text{ processed}} = \begin{cases} \dot{I}_{i \text{ real}}, & i = 0 \\ (\dot{I}_{i-1 \text{ real}} + \dot{I}_{i \text{ real}})/2, & i = 1 \\ (\sum_{k=i-2}^i \dot{I}_{k \text{ real}})/3, & i > 1 \end{cases} \quad i \in \{\mathbb{N} \cup 0\} \quad (1)$$

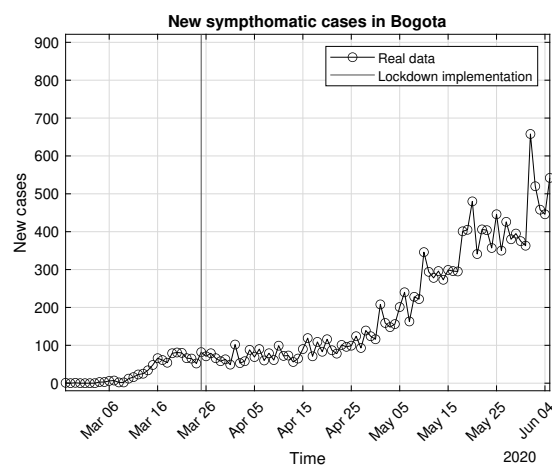


Figure 1. Curve of new symptomatic cases per day in Bogota from February 26th, 2020 to June 5th, 2020

The first round of simulation, where the normalized diffusion rate of the virus was estimated using the processed real data of the first 50 days of epidemic, resulted in a simulated behavior completely distant from reality. According to

the simulation, we found that, on June 5th, health authorities should have detected 5,156 new symptomatic cases, but in fact, there were 542 new symptomatic cases reported in Bogota on that day. This discrepancy may be explained by the omission of the lockdown imposed in the city 28 days after the detection of the first infected person, as this probably caused an overestimation of the transmissibility of the disease in the model. This was the reason why a second estimation of the normalized diffusion rate was needed, using the epidemic curve a few weeks after the lockdown was declared, in order to perform a second simulation.

In the second round, the normalized diffusion rate of the virus was estimated using the processed real data from the day 51 to the day 100 after the first reported case on February 26th, 2020. This time simulation fit better the real new symptomatic cases over all the 100 days of data collected. Therefore, it was possible to notice that the model would be able to predict the evolution of the epidemic curve, at least, in short term. This was confirmed when the simulation was extended 15 days more, where the simulated data estimate 1,493 new symptomatic cases on June 20th, 2020, and real data shows 1,397 new symptomatic cases in the city on the same date (SALUDATA 2021), i.e. on that day we found a discrepancy of 96 cases, or 6.9%. Nevertheless, when extending the simulation 15 days more, or 30 days in total until July 5th, 2020, we clashed with a divergence of 1219 cases, or 65,6%, as simulation estimates 3,076 new symptomatic cases, whereas there were in fact 1,857 new symptomatic cases on that day in Bogota (SALUDATA 2021).

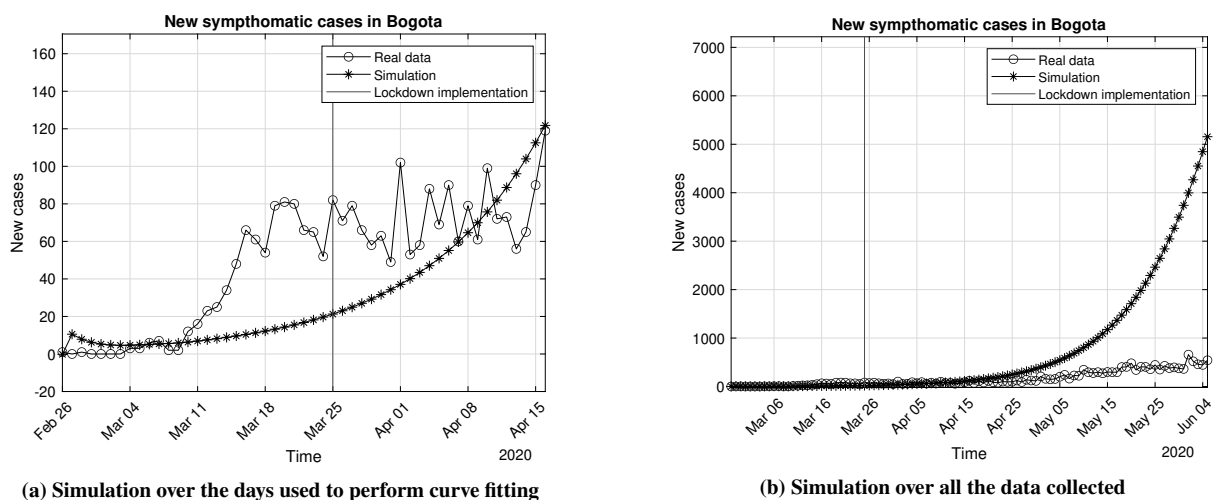


Figure 2. Simulation of the BHRP model using data of the first 50 days of pandemic to perform the estimation of the normalized diffusion rate

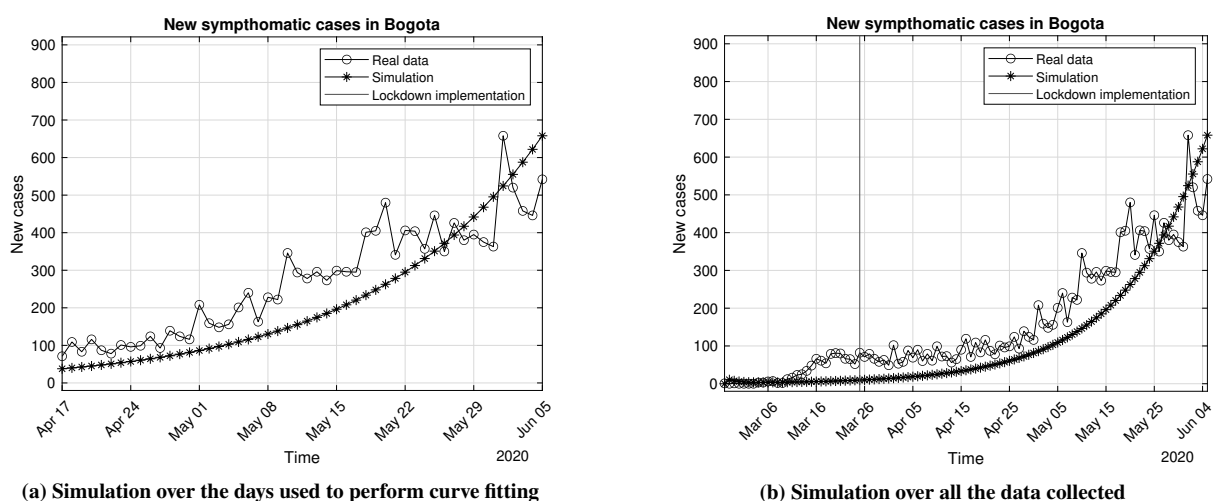


Figure 3. Simulation of the BHRP model using data from the day 51 to day 100 of pandemic to perform the estimation of the normalized diffusion rate

It is possible to identify the reasons why the model cannot foresee the evolution of the infection rate in the medium and long term. First, the diffusion rate of the virus is treated as a constant while, as it was established in the

previous subsection, the transmissibility of the disease is variable over time due to the health strategies introduced by governments. On the other hand, the virus itself does not remain invariant in time. So far, 12 variants of the SARS-COV2 have been detected and classified (CDC 2021b), each one having its own infection ability and mortality (CDC 2021b). Likewise, the complexity of real relationships was completely omitted in the BHRP model. Overall, this kind of traditional mathematical models, rather usual in the study of the COVID-19 pandemic (Shinde et al. 2020; Chen, Rui, et al. 2020; Arino and Portet 2020), are very limited and do not fulfill the fidelity expectations to support the decision-making facing the current crisis.

SYSTEMIC APPROACH OF THE PANDEMIC

After the explanation of the current crisis and the formulation of the problem, it is possible to identify three main characteristics of COVID-19 emergency. To begin with, it exhibit a *global impact* (de Weck et al. 2020), where society find itself out of normal functioning in all essential levels, i.e. in social, economic and health systems (de Weck et al. 2020; Brinks and Ibert 2020). In addition, there is a strong intrinsic *feedback delay* when fighting the spreading of the disease, as the virus cannot be detected during its incubation period (Winkelhake 2021), and the strategies deployed by authorities are often centered in mitigating health issues in short term due to the necessity to respond urgently, omitting medium-term and long-term consequences (Simon et al. 2021; Brooks et al. 2020; Michalski 2021). Moreover, there is also a *strong uncertainty* bound to the nature of the crisis, as the portion of infections that were not detected by the healthcare authorities is considerably large, around 75% (95% CI¹, 70.6% - 78.7%) in the U.S. until November 2021 (CDC 2021a). Likewise, uncertainty is bound to the complexity of the human behavior and social relationships (Bayeh et al. 2021).

Consequently, in order to move towards an approach capable of replicating the first of the three characteristics of the crisis mentioned previously, i.e., its global impact, it is necessary to construct a holistic framework that takes into account all the involved forming components of society. In this sense, de Weck et al. 2020 managed to identify that there are five primary systems are involved in the COVID-19 pandemic: Biological system, social system, healthcare system, political system and economic system. Indeed, interactions between them must be equally considered. As it was stated in the previous section, models are hardly realistic whether they only consider the biological characteristics of the disease, that is to say, its epidemiology. Additionally, government decisions and economy play an important role in the evolution of the epidemic (Alfano and Ercolano 2020; Chowdhury et al. 2020). Taking into account the previous conceptions, a global framework is proposed in figure 4. This holistic approach derives into a system-of-systems that allows the model to be more loyal and closer to reality.

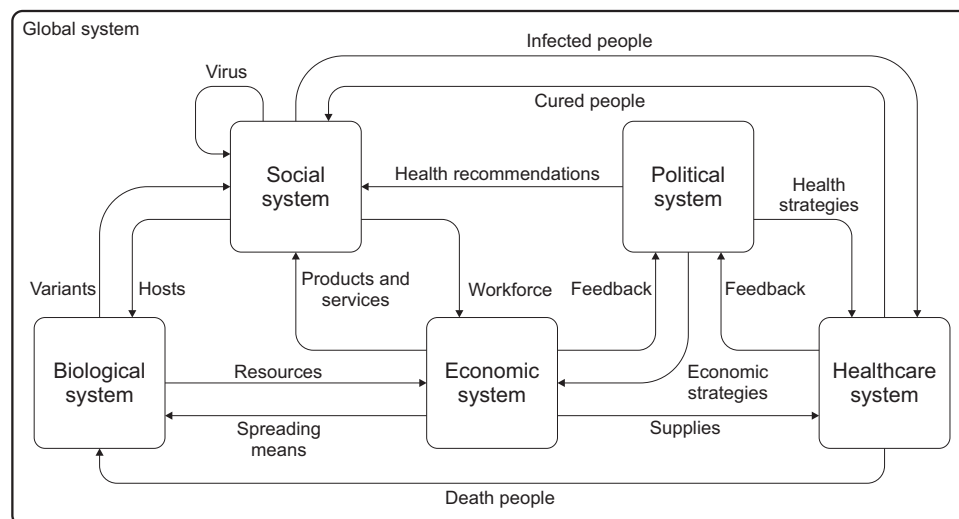


Figure 4. Holistic approach of the crisis, based on the work of de Weck et al. 2020.

The presented framework implies that the crisis encompasses five different sub-systems, complex interactions, internal feedback loops and a distributed behavior. This ensemble of properties, in turn, indicates that the COVID-19 pandemic should be treated as a complex system. On the other hand, analytical approaches require a prior complete understanding of the system since, to apply them, a detailed description of the behavior of each involved element is needed (Aziza et al. 2016). Then, it is possible to realize that pure analytical modeling would not be an advantageous

¹Confidence interval

method to model the pandemic. However, systems engineering, and more specifically, systemic approaches may provide the most appropriate modeling methods to reproduce the behavior of the emergency (de Weck et al. 2020), as they are capable to represent a large number of nonlinear interactions, guided by objectives and not by details (Aziza et al. 2016).

Otherwise, it is also necessary to contend with the existing feedback loop delays and the uncertainties inherent to the crisis. Alone, in its fundamental behavior, the pandemic acts like an unstable open-loop system that grows exponentially (Stewart et al. 2020). However, when infections are detected and health strategies are implemented, the pandemic can be seen as a traditional control system of which feedback signal and control signal are the number of new infections and the countermeasures, respectively. Moreover, control engineering methods are already in use in the containment of the pandemic, for example, when authorities declare a lockdown after the basic reproduction number R_0 reaches a threshold (BBC Mundo 2020), resembling an on-off control system. Fortunately, as many other systems, pandemics can be stabilized and controlled (Stewart et al. 2020).

On the other hand, regarding the mitigation plans for the COVID-19 pandemic, control theory may provide interesting approaches to respond to the crisis. According to the proposed holistic approach, there are two main feedback signals that authorities use to conceive and introduce health and economic strategies: public health and economic indicators. These feedback signals may have a delay caused by the nature of the crisis, as established in the beginning of this section. Compensating delayed feedback requires prediction, and in order to contend with it, predictive control methods, such as the Smith predictor and the Kalman filter, may be profitable (Frank 2018). Likewise, uncertainty can be reduced with predictive control methods, since they can estimate the non-observed variables of the system, and also with adaptive control methods, as they can adapt to different variations on the pandemic parameters over time.

CONCLUSIONS

After contemplating the way the COVID-19 pandemic has been modeled, this paper highlights the need to develop more realistic models to find effective strategies to mitigate the spread of the disease. The imposition of strong health policies led to serious economic impacts in a short time, which caused the deterioration of other forming aspects of society. Consequently, the pandemic requires a systemic approach that considers the different sectors as a whole system in order to understand its multi-level structure, feedback loops and distributed decision-making. This paper is part of a work in progress, and indeed, there are several elements in this analysis that require further elaboration. However, different tools such as systemic approaches, high-complex systems analysis and control theory may be truly useful to understand and model the occurring phenomena, and likewise, systems and control engineering may have an important role to face and mitigate the crisis.

REFERENCES

- Abbany, Z. (Jan. 2022). “COVID: Have we reached the peak of omicron infections?” In: *DW*.
- Abhishek, K., Singh, M. P., Ghosh, S., and Anand, A. (Jan. 2012). “Weather Forecasting Model using Artificial Neural Network”. In: *Procedia Technology* 4, pp. 311–318.
- AlArjani, A., Nasseef, M. T., Kamal, S. M., Rao, B. V. S., Mahmud, M., and Uddin, M. S. (Jan. 2022). “Application of Mathematical Modeling in Prediction of COVID-19 Transmission Dynamics”. In: *Arabian Journal for Science and Engineering*.
- Alfano, V. and Ercolano, S. (Aug. 2020). “The Efficacy of Lockdown Against COVID-19: A Cross-Country Panel Analysis”. eng. In: *Applied health economics and health policy* 18.4, pp. 509–517.
- Arino, J. and Portet, S. (2020). “A simple model for COVID-19”. In: *Infectious Disease Modelling* 5, pp. 309–315.
- Aziza, R., Borgi, A., Zgaya, H., and Guinhouya, B. (Feb. 2016). “Simulating Complex Systems - Complex System Theories, Their Behavioural Characteristics and Their Simulation”. In: *8th International Conference on Agents and Artificial Intelligence*. Rome, Italy: SCITEPRESS - Science and Technology Publications.
- Batstone, D., Keller, J., Angelidaki, I., Kalyuzhnyi, S., Pavlostathis, S., Rozzi, A., Sanders, W., Siegrist, H., and Vavilin, V. (May 2002). “The IWA Anaerobic Digestion Model No 1 (ADM1)”. In: *Water Science and Technology* 45.10, pp. 65–73.
- Bayeh, R., Yampolsky, M. A., and Ryder, A. G. (2021). “The Social Lives of Infectious Diseases: Why Culture Matters to COVID-19”. In: *Frontiers in Psychology* 12, p. 3731.
- BBC Mundo (May 2020). “Contagio del coronavirus: qué es el número de reproducción básico R_0 y por qué es crucial para decidir el fin de los confinamientos”. In.

- Brinks, V. and Ibert, O. (2020). “From Corona Virus to Corona Crisis: The Value of An Analytical and Geographical Understanding of Crisis”. eng. In: *Tijdschrift voor economische en sociale geografie* 111.3, pp. 275–287.
- Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., and Rubin, G. J. (Mar. 2020). “The psychological impact of quarantine and how to reduce it: rapid review of the evidence”. In: *The Lancet* 395.10227, pp. 912–920.
- Cañelles López, M., Campillo, N., and Jiménez Sarmiento, M. (Mar. 2021). “Coronavirus: 3 datos que explican por qué la covid-19 afecta de manera diferente a hombres y mujeres”. In: *BBC News*.
- CDC (Nov. 2021a). “Estimated COVID-19 Burden”. In: *COVID-19*.
- CDC (Dec. 2021b). “SARS-CoV-2 Variant Classifications and Definitions”. In: *COVID-19*.
- Chen, T., Leung, R. K.-k., Zhou, Z., Liu, R., Zhang, X., and Zhang, L. (Mar. 2014). “Investigation of Key Interventions for Shigellosis Outbreak Control in China”. In: *PLOS ONE* 9.4, e95006.
- Chen, T., Rui, J., Wang, Q.-P., Zhao, Z.-Y., Cui, J.-A., and Yin, L. (Feb. 2020). “A mathematical model for simulating the phase-based transmissibility of a novel coronavirus”. In: *Infectious Diseases of Poverty* 9.1, p. 24.
- Chowdhury, R., Luhar, S., Khan, N., Choudhury, S. R., Matin, I., and Franco, O. H. (Aug. 2020). “Long-term strategies to control COVID-19 in low and middle-income countries: an options overview of community-based, non-pharmacological interventions”. eng. In: *European journal of epidemiology* 35.8, pp. 743–748.
- de Weck, O., Krob, D., Lefei, L., Lui, P., Rauzy, A., and Zhang, X. (2020). “Handling the COVID-19 crisis: Toward an agile model-based systems approach”. In: *Systems Engineering* 23.5, pp. 656–670.
- Frank, S. A. (2018). “Time Delays”. In: *Control Theory Tutorial: Basic Concepts Illustrated by Software Examples*. Cham: Springer International Publishing, pp. 95–102.
- Galasso, V., Pons, V., Profeta, P., Becher, M., Brouard, S., and Foucault, M. (Nov. 2020). “Gender differences in COVID-19 attitudes and behavior: Panel evidence from eight countries”. In: *Proceedings of the National Academy of Sciences of the United States of America* 117.44, pp. 27285–27291.
- Ghosh, S. and Bhattacharya, S. (2021). “Computational Model on COVID-19 Pandemic Using Probabilistic Cellular Automata”. eng. In: *SN computer science* 2.3, pp. 230–230.
- Jin, J.-M., Bai, P., He, W., Wu, F., Liu, X.-F., Han, D.-M., Liu, S., and Yang, J.-K. (2020). “Gender Differences in Patients With COVID-19: Focus on Severity and Mortality”. In: *Frontiers in Public Health* 8, p. 152.
- Joly, J. (Jan. 2022). “COVID in Europe: France reports ‘tidal wave’ of new infections as records broken in Italy”. In: *Euronews*.
- Mallah, S. I., Ghorab, O. K., Al-Salmi, S., Abdellatif, O. S., Tharmaratnam, T., Iskandar, M. A., Sefen, J. A. N., Sidhu, P., Atallah, B., El-Lababidi, R., et al. (May 2021). “COVID-19: breaking down a global health crisis”. eng. In: *Annals of clinical microbiology and antimicrobials* 20.1, pp. 35–35.
- Michalski, T. (July 2021). “The Economic Impact of Different COVID-19 Lockdown Strategies in France”. In: *HEC Paris*.
- Nazir, G., Zeb, A., Shah, K., Saeed, T., Khan, R. A., and Ullah Khan, S. I. (2021). “Study of COVID-19 mathematical model of fractional order via modified Euler method”. In: *Alexandria Engineering Journal* 60.6, pp. 5287–5296.
- OECD (Mar. 2020a). “Beyond containment: Health systems responses to COVID-19 in the OECD”. In: *OECD Policy Responses to Coronavirus (COVID-19)*.
- OECD (Nov. 2020b). “The territorial impact of COVID-19: Managing the crisis across levels of government”. In: *OECD Policy Responses to Coronavirus (COVID-19)*.
- SALUDATA (Nov. 2021). “Casos confirmados de COVID-19 en Bogotá D.C.” In: *Secretaría Distrital de Salud*.
- Shattuck-Heidorn, H., Reiches, M., and Richardson, S. (June 2020). “What’s Really Behind the Gender Gap in Covid-19 Deaths?” In: *The New York Times*.
- Shinde, G., Kalamkar, A., Mahalle, P., Dey, N., Chaki, J., and Hassanien, A. (2020). “Forecasting Models for Coronavirus Disease (COVID-19): A Survey of the State-of-the-Art”. eng. In: *SN computer science* 1.4, pp. 197–197.
- Simon, J., Helter, T. M., White, R. G., Boor, C. van der, and Łaszewska, A. (Feb. 2021). “Impacts of the Covid-19 lockdown and relevant vulnerabilities on capability well-being, mental health and social support: an Austrian survey study”. In: *BMC Public Health* 21.1, p. 314.

- Stewart, G., Van Heusden, K., and Dumont, G. (July 2020). “How control theory can help us control COVID-19”. In: *IEEE Spectrum*.
- WHO (Jan. 2022). *WHO Coronavirus (COVID-19) Dashboard*.
- Winkelhake, H. (Sept. 2021). “If you’re fully vaccinated, wait a few days after a COVID-19 exposure before getting tested”. In: *Norton Healthcare*.
- Xing, K., Tu, X.-Y., Liu, M., Liang, Z.-W., Chen, J.-N., Li, J.-J., Jiang, L.-G., Xing, F.-Q., and Jiang, Y. (Mar. 2021). “Efficacy and safety of COVID-19 vaccines: a systematic review”. eng. In: *Chinese journal of contemporary pediatrics* 23.3, pp. 221–228.