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Complex Systems and Network Science
Project Work

# SARS-CoV-2 spread in a company

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**Abstract**

In this project we simulate SARS-CoV-2 spread in a fictional and simplified company. We define an epidemic model with 6 classes and 5 control parameters to simulate epidemic evolution and test the efficiency of some population-wide countermeasures.
The company has a team-based organizational structure and we use a power-law distribution to build the network of contacts. Among the tested countermeasures, we focus on contact tracing technique by comparing the subgraph of traced contacts with the original network of contacts.
Finally, we define 20 different scenarios using the model control parameters and we compare repeated runs of each scenario. The results show that face masks and vaccination are the most effective countermeasures, while other scenarios end up in a configuration where there is no possibility of eradicating the virus.
In the end, we summarize our model potentialities and weaknesses, and we suggest some possible extensions.

# Contents

# 1 Introduction

On 30th December 2019 *World Health Organization's Country Office* in the People's Republic of China picked up a media statement by the W*uhan Municipal Health Commission* from their website on cases of 'viral pneumonia' in Wuhan [1]. In the very first months of 2020 COVID-19 disease spread all around the globe, and on 11th March 2020 WHO characterized it as a pandemic [2].

Europe has been strongly affected by the pandemic, with severe impact on economy, education, health system and many other sectors. Also Small and Medium-sized Enterprises (SMEs), which represent 99% of all businesses in the EU, have been deeply affected [3].
In this project we will focus on a fictional and simplified SME called *CSNS Group* to understand the epidemic evolution and test the efficiency of some population-wide strategies, such as personal protective equipment, contact tracing and vaccination.
Since the very first stages of COVID-19 pandemic, research groups focused their efforts on studying the phenomenon from different points of view. One of the possible strategies is represented by compartmental models based on Kermack–McKendrick theory [4][5][6]. We will rely on them to model SARS-CoV-2 spread in *CSNS Group* by defining an epidemic model with different control parameters to mimic several scenarios. In particular, we will test different countermeasures in 20 scenarios using `NetLogo` environment [7] and we will use `Gephi` platform [8] to analyze more in depth the contact tracing strategy.

# 2 Model Description

## 2.1 Epidemic Model

To simulate SARS-CoV-2 epidemic, we define a compartmental model with the following classes:

- **Susceptible** (**S**): people who can be infected.
- **Infected** (**I**): highly infective people.
  We refer to the infectivity of this class of people with letter $\alpha$.
- **Hospitalized** (**H**): infected people who have been diagnosed and hospitalized, so they cannot infect anyone.
  Hospitalized people do not have contacts with other people.
- **Exposed** (**E**): people who have been infected, but are not completely infective yet. Exposed people are less infective than infected people (the infectivity is reduced by a factor $\epsilon_E = 0.6$).
- **Quarantined** (**Q**): people who have been infected and quarantined, thanks to contact tracing.
  The quarantine is not perfect: quarantined people may have contacts and infect other people, but their infectivity is reduced according to *Quarantine Efficiency*. As a result, the infectivity of quarantined class is equal to

$$\epsilon_Q \times (\alpha \times \epsilon_E), \quad \text{with} \quad 0 \leq \epsilon_Q \leq 1 \tag{1}$$

- **Immune** (**V**): people who have been vaccinated and are not susceptible anymore.

**H**, **Q** and **V** classes may or may not be present according to *Quarantined*, *Diagnosed* and *Vaccination Efficiency* parameters ($\theta, \xi$ and $\nu$ respectively) described in section 2.2. Therefore, we can gradually increase the model complexity by introducing new classes thanks to these control parameters.

As shown in the model diagram (Fig. 1), infected people (**I** class) may die due to COVID-19 with a **death rate** of 3.4% since "*globally, about 3.4% of reported COVID-19 cases have died*", as stated by the WHO Director-General T. A. Ghebreyesus in March 2020 [9]. However, the population size is maintained steady by replacing missing people with new susceptible ones.
Exposed and quarantined people may recover from the virus with a chance of 20%, while hospitalized people have a higher chance to recover (30 %). The recovery chance of infected employees is computed accordingly to the *Diagnose Efficiency* value (see section 2.2)[1].

[1]SARS-CoV-2 recovery rates are still unknown, therefore the transition rates **E** → **S**, **Q** → **S**, **I** → **S**, **H** → **S** have been chosen without relying on any scientific evidence.

Finally, the vaccination, that can be either present or not, is performed only on healthy people (**S** class) and makes people completely immune (**V** class).

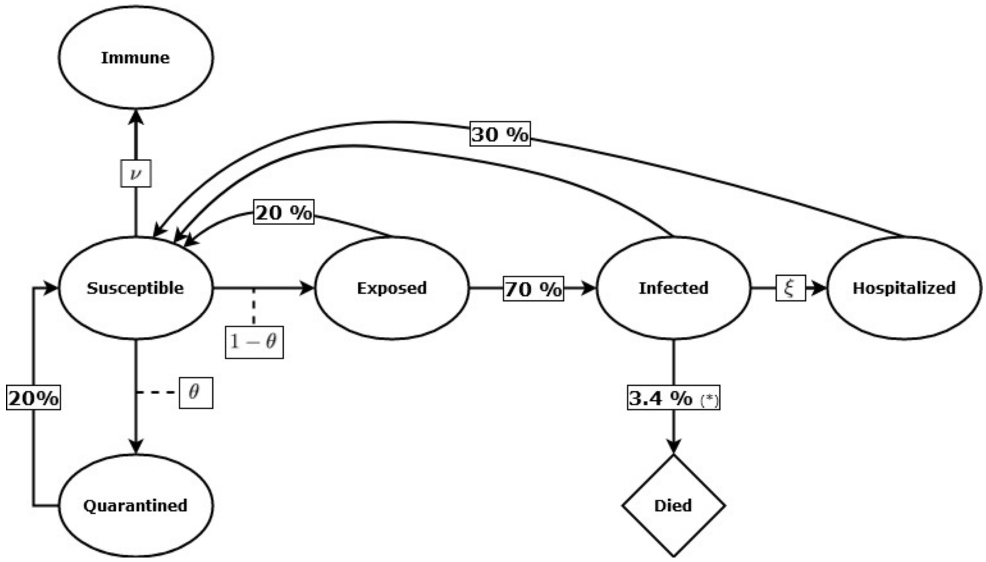



Figure 1: Epidemic model diagram.
(*) Death rate is zero when the *Diagnose Efficiency* ($\xi$) is perfect (100%).

## 2.2 Control Parameters

The model has 5 control parameters which may be used to simulate different scenarios:

1. *Contact Tracing Efficiency* ($\theta$)
2. *Diagnose Efficiency* ($\xi$)
3. *Vaccination Efficiency* ($\nu$)
4. *Quarantine Efficiency* ($\epsilon_Q$)
5. *Face Masks*

Parameters $\theta$, $\xi$ and $\nu$ can be set to:

- 0% (`"zero"`)
- 10% (`"low"`)
- 50% (`"medium"`)
- 90% (`"high"`)
- 100% (`"perfect"`)

The transition rate **I** →**S** - i.e. the recovery chance of the infected people - is computed according to $\xi$ so that, if an infected employee is neither diagnosed nor died, he has a chance of 20% to recover ( see Tab. 1 ).

| **Diagnose Efficiency** | **I → H** ($\xi$) | **I → S** | **Self-Loop** | **Death rate** |
|---|---|---|---|---|
| *perfect* | 100 | 0 | 0 | 0 |
| *high* | 90 | 1.32 | 5.28 | 3.4 |
| *medium* | 50 | 9.32 | 37.28 | 3.4 |
| *low* | 10 | 17.32 | 69.28 | 3.4 |
| *zero* | 0 | 19.32 | 77.28 | 3.4 |

Table 1: Transition rates of class **I** according to different diagnose efficiencies.
**Self-Loop** refers to the chance of remaining infected.

*Quarantine Efficiency* $\epsilon_Q$ goes from 0 (perfect isolation) to 1 (no isolation) to mimic the efficiency of self-quarantine (see equation 1).

*Face Masks* is a Boolean variable:

- `"False"`: without wearing face masks the infection chance $\alpha$ is equal to 95%;
- `"True"`: with face masks the infection chance is reduced by a 65% [10].

## 3 Simulation Description

### 3.1 CSNS Group

As briefly described in Section 1, we use *NetLogo* environment to simulate a fictional **medium-sized enterprise with** 100 **employees** called *CSNS Group*.
*CSNS Group* has a team-based organizational structure: employees are divided in small teams, which communicate with each other thanks to supervisors. Therefore, there are few people with many contacts (*connectors*), while the vast majority of the employees has very few contacts.
Moreover, *CSNS Group* employees do not have any contacts with external people: the company is perfectly isolated.

To build *CSNS Group* network of contacts we use the **power-law distribution**, which is a heavy-tailed distribution that generates a scale-free network with few hubs and many low-degree nodes. In the simulation, we set the power-law exponent to 2, and it is important to keep in mind that the way in which the network is built - that is the way in which people make contacts with each other - strongly affects the simulation.

In Fig. 2 we display one possible initial network of contacts of the company and the corresponding degree distribution. As we can see, the large majority of the employees has at most 5 contacts, while only few of them have more than 6 contacts, which is consistent with *CSNS Group* team-based organization.

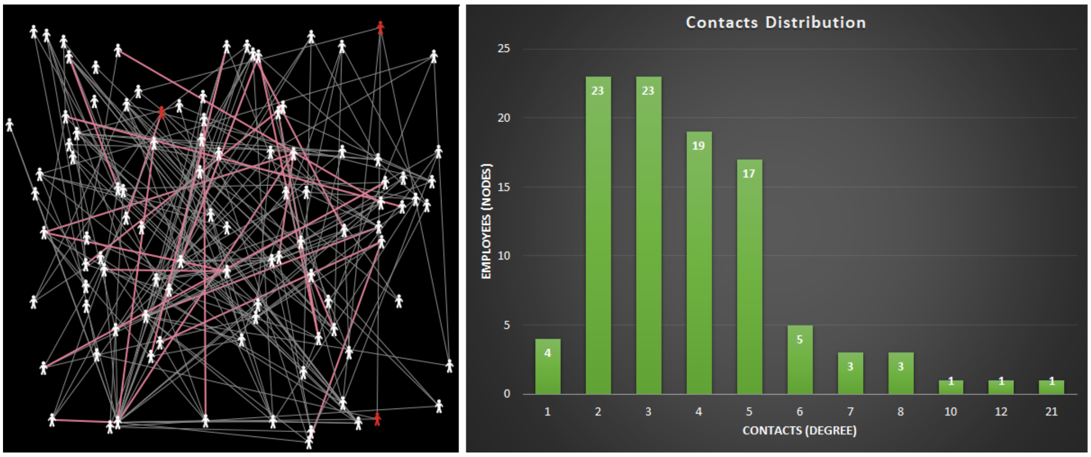



Figure 2: *On the left*: an example of initial network of contacts. Red people are infected, while white people are susceptible. Gray links are contacts between people which are not traced, while the pink ones are traced. *On the right*: an example of initial degree distribution of the network of contacts.

In a disease-free scenario, the network of contacts of *CSNS Group* does not change over time, since the working teams and the supervisors are supposed to be the same during all the simulation.
However, there are two epidemic-related factors that can modify the network:

1. some employees may die because of COVID-19 and be replaced with new susceptibles who make new contacts;
2. some employees may be completely isolated (enter in **H** class) and, once they recover, they make new working contacts.

Even though *CSNS Group* is a strong simplification of a real-world company, the internal assumptions of the scenario are consistent and allow us to predict and reason upon the model behaviour.

### 3.2 Temporal Evolution

The simulation is daily-based and continues until there are only susceptible or immune people.

**At day** 0 (`setup`):

- 100 employees come to their offices and make working contacts following the power-law distribution described in the previous section. All the employees are susceptible except for an initial number $N$ of infected, which can be set by the observer.
- A fraction of working contacts may be traced thanks to the *Contact Tracing Program* (see section 3.3) and the tracing last forever[2].

**Each day** (`go`):

- **I**, **E** or **Q** employees infect their susceptible contacts according to the epidemic model parameters.
- Then, according to the corresponding transition rates:
  - **infected people** may be diagnosed and isolated; they may also recover, die or remain infected;
  - **exposed people** can recover or move to **I** class or even remain exposed;
  - **quarantined people** may either recover or remain quarantined, as well as **hospitalized people**, who can either recover or remain isolated;
  - **susceptible people** may be vaccinated and enter in **V** class.
- At the end of the day, missing people are replaced by new susceptible employees, so the headcount remains steady.

[2]This means that a traced contact cannot become not traced; it can only disappear due to the death or the isolation of one of its nodes.

### 3.3 Contact Tracing Program

One of the control measures used to slow down the spread of disease or even to eradicate infection is the contact tracing, which aim is to gather information about the network of contacts and identify asymptomatic infected individuals who can then be treated or quarantined. Conversely to other techniques, contact tracing has not been applied as a network evaluation device, but as a control tool. Moreover, it strongly relies on people accuracy and correctness, since each person should provide all the information about his relationships to have a perfect contact tracing [11] [12].

We introduce contact tracing into *CSNS Group* simulation by giving the employees the chance of taking part at the ***Contact Tracing Program***. The degree at which an employee joins the *Program* is determined by the *Contact Tracing Efficiency* $\theta$ (see Section 2.2), which simulates employees accuracy on providing complete and precise data about their working relationships.
The *Contact Tracing Program* works as follows:

- when an employee joins the company, he reports each of his working contacts with a probability equal to $\theta$;
- whenever an employee $A$ is infected by a colleague $B$ and their contact $A-B$ is traced, $A$ self-quarantines.

Self-quarantine is different from isolation: quarantined people do not loose their working-contacts. Moreover, self-quarantine efficiency is determined by $\epsilon_Q$ (see Section 2.2), thus $A$ may still infect his colleagues with an infection chance determined by (1).

#### 3.3.1 A closer look at the network of contacts

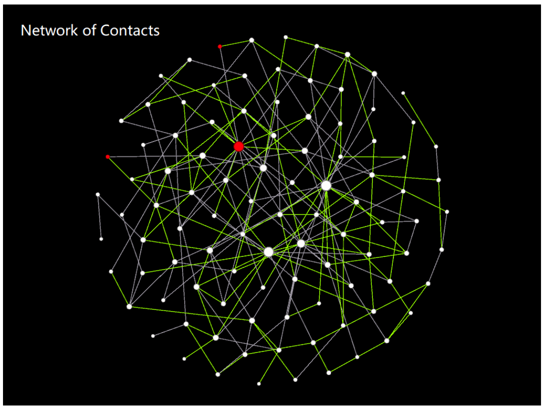
Let's explore the limits of contact tracing technique by analyzing an example of the real network of contacts **C** (Fig. 3 - *on the left*) and the corresponding subgraph of traced contacts **T** (Fig. 3 - *on the right*) obtained with $\theta = 50\%$. In Table 2 we also report some meaningful statistics related to the two graphs[3].

In the analyzed example, only 46.8% of the edges of **C** are traced, which is consistent with the *Contact Tracing Efficiency*: as a result, **T** has a lower *graph density* w.r.t. **C**, since **T** is obtained by removing 53.2% of the edges of **C**.
In Fig. 4 we display the *eccentricity* distribution of the two graphs, from which we can determine both the *radius* (*minimum eccentricity*) and the *diameter* (*maximum eccentricity*): as expected, **T** has a lower *diameter*, since it is less dense. Moreover, the *radius* of **T** is 0, since the graph is disconnected (**C** is a connected graph, while **T** has 17 *connected components*)[4].

[3] Both the images and the statistics were generated using `Gephi 0.9.2`.

[4] Isolated nodes are considered to have an *eccentricity* of 0, instead of infinity, in order to be able to compute the *diameter* of the disconnected network **T**.

By looking at the difference between the *average clustering coefficient* ($CC$) and the graph *density* ($\rho$), we can easily conclude that **C** is more clustered than **T** ($CC_{\mathbf{C}} - \rho_{\mathbf{C}} = 0.599$ vs $CC_{\mathbf{T}} - \rho_{\mathbf{T}} = 0.061$).
The traced subgraph is also unable to correctly estimate the *average degree* and *average path length* of the network of contacts: as a result, many potentially exposed people may not be quarantined. Moreover, **T** also has a higher *modularity* w.r.t. **C**, which may lead to wrong conclusions on the graph community structure.



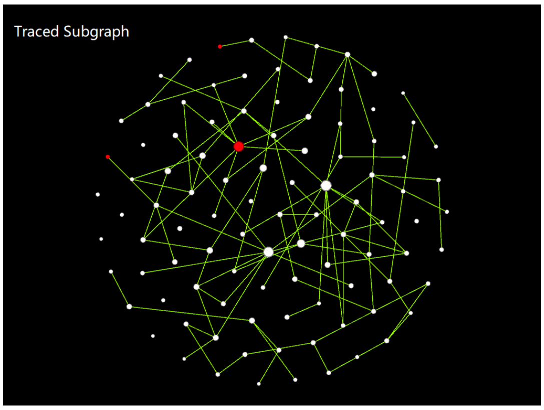




Figure 3: *On the left*: the whole network of contacts.
*On the right*: the corresponding subgraph of traced contacts.
Gray edges are not traced, while green ones are traced. White nodes refer to susceptible employees, red ones to infected; the size of a node is proportional to its degree.

| | **Network of Contacts** | **Traced Subgraph** |
|---|---|---|
| *Avg. Degree* | 4.06 | 1.90 |
| *Avg. Path Length* | 3.33 | 5.92 |
| *Avg. Clust. Coeff.* | 0.64 | 0.08 |
| *Connected Comp.* | 1 | 17 |
| *Diameter* | 8 | 15 |
| *Graph Density* | 0.041 | 0.019 |
| *Modularity* | 0.440 | 0.754 |
| *Radius* | 4 | 0 |

Table 2: Statistics of the two graphs displayed in Fig. 3 computed with `Gephi`.

This simple comparison clearly points out the network definition issues related to contact tracing technique: in order to have an effective estimate of the real network of contacts we need a huge amount of data, that is a high degree of people cooperation and responsibility. This is not always possible, especially when the required data are sensitive, and, as a result, we may end up with a non effective or even misleading subgraph.

# 4 Testing different Countermeasures

As described in section 2.2, our compartmental model has 5 control parameters which allow us to introduce different epidemic countermeasures in the simulation.
The following section will be focused on describing the tested scenarios and the simulation results. Each scenario is run 10 times for a maximum of 10 years with an initial number of infected employees of 3.

## 4.1 Epidemic Scenarios

### 4.1.1 Scenario 0: Baseline

In this scenario, the virus is free to spread in the company without any preventive or containment measures: the employees simply continue their work like nothing happened and the epidemic model has only 3 classes (**S, E, I**).
In Table 3 we report the control parameters of this scenario[5].

| Control Paratemeter | Value |
|---|---|
| *Contact Tracing Efficiency* | `"zero"` |
| *Diagnose Efficiency* | `"zero"` |
| *Vaccination Efficiency* | 0 |
| *Quarantine Efficiency* | - |
| *Face Masks* | `False` |

Table 3: Control parameters of Scenario 0.

### 4.1.2 Scenarios 1-2-3-4: Degree of hospitalization

In these scenarios there are no preventive measures, but infected employees have a certain chance $\xi$ of being diagnosed and hospitalized (i.e. we introduce the **H** class in the model):

- Scenario 1: low hospitalization ($\xi = 10\%$)
- Scenario 2: medium hospitalization ($\xi = 50\%$)
- Scenario 3: high hospitalization ($\xi = 90\%$)
- Scenario 4: perfect hospitalization ($\xi = 100\%$)

In Table 4 we report the control parameters of these scenarios.

[5] *Quarantine Efficiency* is not specified, since it does not effect the simulation in this scenario: *Contract Tracing Efficiency* is set to zero, thus there are no possibilities of being quarantined.

| **Control Paratemeter** | **Value** |
|---|---|
| *Contact Tracing Efficiency* | `"zero"` |
| *Diagnose Efficiency* | $\xi$ |
| *Vaccination Efficiency* | 0 |
| *Quarantine Efficiency* | - |
| *Face Masks* | `False` |

Table 4: Control parameters of Scenarios 1-2-3-4.

#### 4.1.3 Scenarios 5-6-7-8: Contact Tracing

In these scenarios there is no chance of being hospitalizated, but employees join the *Contact Tracing Program* with a degree $\theta$ (see Section 3.3):

- Scenario 5: low contact tracing ($\theta = 10\%$)
- Scenario 6: medium contact tracing ($\theta = 50\%$)
- Scenario 7: high contact tracing ($\theta = 90\%$)
- Scenario 8: perfect contact tracing ($\theta = 100\%$)

The *Quarantine Efficiency* is equal to 0.5 for all the 4 scenarios, which means that self-quarantined employees may infect their colleagues with a probability equal to 28.5%.

In Table 5 we report the control parameters values:

| **Control Paratemeter** | **Value** |
|---|---|
| *Contact Tracing Efficiency* | $\theta$ |
| *Diagnose Efficiency* | `"zero"` |
| *Vaccination Efficiency* | 0 |
| *Quarantine Efficiency* | 0.5 |
| *Face Masks* | `False` |

Table 5: Control parameters of Scenario 5-6-7-8.

### 4.1.4 Scenarios 9-10-11-12: Contact Tracing and Hospitalization

In these scenarios we test different combinations of *Contact Tracing Efficiency* and *Diagnose Efficiency* to see their impact on the epidemic evolution.

- *Scenario 9*: low contact tracing and hospitalization ($\theta = \xi = 10\%$)
- *Scenario 10*: medium contact tracing and hospitalization ($\theta = \xi = 50\%$)
- *Scenario 11*: high contact tracing and hospitalization ($\theta = \xi = 90\%$)
- *Scenario 12*: perfect contact tracing and hospitalization ($\theta = \xi = 100\%$)

The *Quarantine Efficiency* is equal to 0.5 for all these 4 scenario, which means that self-quarantined employee may infects his colleagues with a probability equal to 28.5%.

In Table 6 are reported the control parameters of this scenario.

| Control Paratemeter | Value |
|---|---|
| *Contact Tracing Efficiency* | $\theta$ |
| *Diagnose Efficiency* | $\xi$ |
| *Vaccination Efficiency* | 0 |
| *Quarantine Efficiency* | 0.5 |
| *Face Masks* | `False` |

Table 6: Control parameters of Scenario 9-10-11-12.

### 4.1.5 Scenarios 13-14-15-16: Face Masks

With *Face Masks* enabled, each employee wears a face mask and the infection chance is reduced by a 65% (see Section 2.2).
We test this preventive measure into 4 already defined scenarios: *Scenario 0* (*Baseline*), *Scenario 2* (*Medium Hospitalization*), *Scenario 6* (*Medium Contact Tracing*) and *Scenario 10 (Medium Contact Tracing and Hospitalization*).

### 4.1.6 Scenario 17-18-19-20: Vaccination

In these scenarios susceptible employees have 30% chance of being vaccinated, so that the number of immune people progressively increases over time.
We test this countermeasure into 4 already defined scenarios: *Scenario 0* (*Baseline*), *Scenario 2* (*Medium Hospitalization*), *Scenario 6* (*Medium Contact Tracing*) and *Scenario 10 (Medium Contact Tracing and Hospitalization*).

### 4.2 Results

In this section we report and compare the results of the 20 scenarios described in the previous section. All the figures mentioned below are reported in Appendix A.

**Degree of Hospitalization**
In Fig. 5 we compare the epidemic duration and the total number of deaths of *Scenario 1,2,3* and *4* with the *Baseline*.
As expected the number of deaths decreases with the increasing of the *Diagnose Efficiency*, since less infected people are left without medical treatments (i.e. less people lie in the infected class, which is the only class that may lead to death).
In all the *Degree of Hospitalization* scenarios we are not able to eradicate the virus, whereas `RUNS 2, 4` and `7` of the *Baseline* terminate before 10 years.
If we have a look at the temporal evolution of the population status in the 4th run of *Scenario 0* (Fig. 10 - top), and we compare it with the population status in *Scenario 3* (Fig. 10 - bottom), we can clearly see that the *Baseline* scenario is much more unstable: the system jumps from a configuration to another, without reaching a stable one. This behaviour gives *Scenario 0* a chance to end up in a configuration which leads to the epidemic eradication. On the other hand, by introducing the **Hospitalized** class, the system enters a quite stable configuration in which the vast majority of the employees are isolated; as a consequence, SARS-CoV-2 will be never eradicated.

**Contact Tracing**
With respect to *Diagnose Efficiency*, *Contact Tracing* parameter strongly contributes in eradicating the epidemic.
For example, by looking at Fig. 6, we can easily conclude that a `"medium"` contact tracing efficiency (*Scenario 6*) is able to eradicate the virus in less than 3 years with a relatively small amount of victims compared to the *Baseline*.
As expected, by setting the *Contact Tracing Efficiency* to 100% (*Scenario 8*) we have no victims, but the system enters a stable configuration where there is no possibility of eradicating the virus: after few days the vast majority of the employees are quarantined and the remaining are susceptible (Fig. 11 - bottom).

**Contact Tracing and Hospitalization**
In Fig. 7, we display the epidemic duration (top) and the number of victims (bottom) of *Scenarios 9-10-11-12* compared with the *Baseline*.
As expected, by using `"high"` and `"perfect"` *Contact Tracing* and *Hospitalization* efficiency (*Scenarios 11 and 12*) we have nearly 0 victims, but the virus cannot be eradicated: after few days, the vast majority of the employees are quarantined and the remaining are susceptible (Fig. 12), as in *Scenario 8*.
By setting the efficiencies at `"medium"` (*Scenario 10*) we have less than 50 victims per run, and the stochastic nature of the system may lead it into the equilibrium state in which the epidemic has been eradicated.
In Fig. 13 we display the temporal evolution of the system in `RUNS 1, 3` and `7` of

*Scenario 10*: in each run, the system reaches a configuration in which the majority of the employees are susceptible and the remaining are quarantined (opposite situation w.r.t. *Scenarios 8, 11* and *12*). If the gap between these two classes is large enough - i.e. there are much more susceptible than quarantined people - then the stochastic nature of the system may cause the virus eradication (`RUN 3` and `RUN 7`).

**Face Masks and Vaccination**
As described in sections 4.1.5, 4.1.6, we test two preventive measures on the same 4 scenarios.
We expect that both *Face Masks* and *Vaccination* strongly affect the simulation results, since the former reduces the infection chance by a 65% and the latter introduces the **Immune** class.

The results of *Face Masks* scenarios are displayed in Fig. 8, and are consistent with our expectation: the virus has been eradicated in all the scenarios in a reasonable small amount of time (within 1 year).
Looking at the epidemic duration and the number of victims, we can conclude that *Scenario 14* (`"Medium"` *Hospitalization*) is the best among the 4 compared, while the 15*th* (`"Medium"` *Contact Tracing*) is the most unstable. To understand this result, let's consider the two models characteristics:

- in *Scenario 14*, susceptible people can only flow into **Exposed** class which transition rate to **Infected** class is quite high (70%); infected employees have 50% chance of being hospitalized, which is higher than the self-loop chance (see Table 1). Along with the infection chance decrease caused by face masks, the above mentioned considerations determine an epidemic evolution in which the two most frequent classes are **S** and **H**, so the eradication is quite fast (Fig. 14 - *top*).

- On the other hand, in *Scenario 15* we have also the **Quarantined** class whose members may infect susceptible employees until they themselves become susceptible again. As a result, the eradication is slow because there is a direct interchange between **S** and **Q** classes (Fig. 14 - *bottom*).

As expected, vaccination turns out to be an effective measure to slow down and eradicate the epidemic: with a vaccination chance of 30%, SARS-CoV-2 was eradicated within 100 days even in the *Baseline* scenario (Fig. 9), and by combining the vaccination with other countermeasures, the number of deaths strongly decreases. In particular, *Scenario 18* and *20* have the best results among all the 20 scenarios in terms of epidemic duration and number of victims.

## 5 Conclusions

Although *CSNS Group* simulation is a strong simplification of a real-case scenario, it is a powerful tool to understand the dynamics of an epidemic and the impact of different countermeasures. The potentiality of epidemic models resides in their simplicity and modularity: we can build a quite realistic model by sequentially extending a very simple one adding complexity to it and taking track of the variations. For example, the simplest form of our compartmental model had only 3 classes (**S,E,I**), and we sequentially added the classes **Q**, **H** and **V**. Then, by testing the resulting models, we were able to effectively compare different epidemic scenarios.

When we work with network epidemic models a commonly stated challenge is to understand how network structure affects the dynamics and control of infection [13]. Our model relies on a scale-free network whose degree distribution is determined by a power-low. It could be interesting to test how different exponents and different degree distributions affect the epidemic dynamics.
Network characteristics also affect the efficiency of network-based countermeasures. In Section 3.3 we analyzed the contact tracing technique and we underlined the main limit of it: the needed of a huge amount of data to build an effective estimate of the real network of contacts.

By looking at the results reported in Section 4.2 we can see how different combinations of countermeasures affect the epidemic evolution. As expected, personal protective equipment and vaccination are the best countermeasures against the infection, but it could be interesting to test other combinations of parameters. For example, we may combine face masks with vaccination and test whether it has the expected good impact. We may also introduce new countermeasures, such as split the company in clusters to locally quarantine different areas of the company (*Local Lockdown*). Moreover, we could exploit the contact tracing network to identify and monitor hubs. We may then use this additional information to build a more refined quarantine strategy that assigns each node a probability of being quarantined proportional to its degree (i.e. the number of working contacts).

## References


[1] ProMED. Undiagnosed pneumonia - china. https://promedmail.org/promed-post/?id=6864153%20#COVID19.

[2] T. A. Ghebreyesus. Who director-general's opening remarks at the media briefing on covid-19 - 3 march 2020. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-

[3] European Commission. Internal market, industry, entrepreneurship and smes - sme definition. https://ec.europa.eu/growth/smes/sme-definition/.

[4] W. O. Kermack and A. G. McKendrick. Contributions to the mathematical theory of epidemics — 1. *Bulletin of Mathematical Biology*, 53(1-2):33–55, 3 1991.

[5] W. O. Kermack and A. G. McKendrick. Contributions to the mathematical theory of epidemics – 2. the problem of endemicity. *Bulletin of Mathematical Biology*, 53(1-2):57–87, 3 1991.

[6] W. O. Kermack and A. G. McKendrick. Contributions to the mathematical theory of epidemics – 3. further studies of the problem of endemicity. *Bulletin of Mathematical Biology*, 53(1-2):89–118, 3 1991.

[7] U. Wilensky. Netlogo, 1999. http://ccl.northwestern.edu/netlogo/.

[8] Mathieu Bastian, Sebastien Heymann, and Mathieu Jacomy. Gephi: An open source software for exploring and manipulating networks, 2009.

[9] T. A. Ghebreyesus. Who director-general's opening remarks at the media briefing on covid-19 - 3 march 2020. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---3-march-2

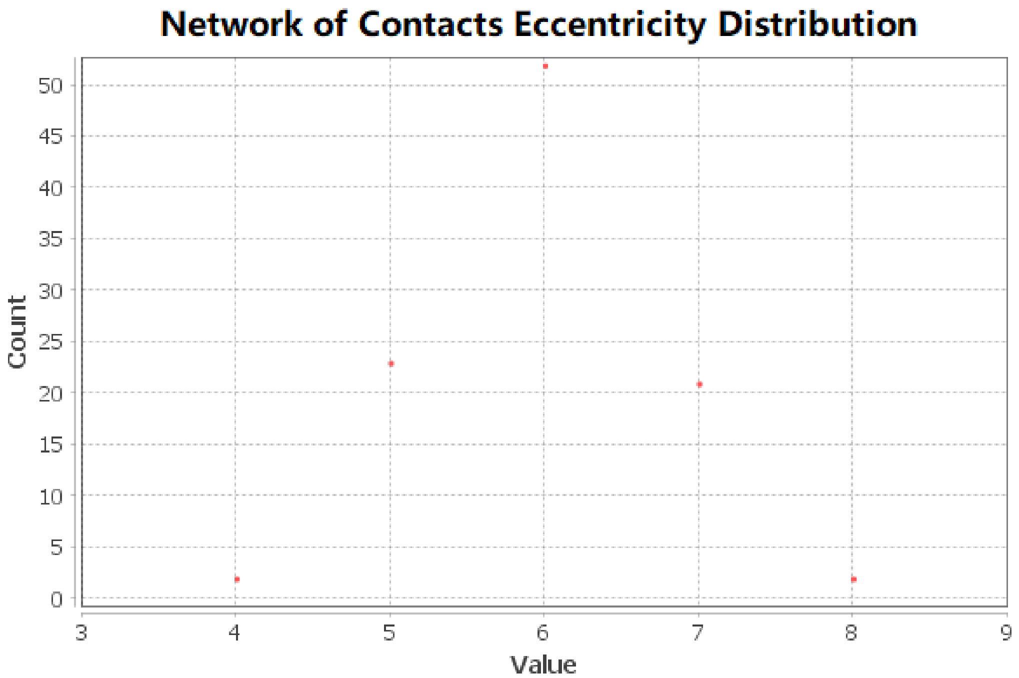
[10] S. Yaacoub H. J. Schünemann Derek K. Chu et al. S. Duda, K. Solo. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of sars-cov-2 and covid-19: a systematic review and meta-analysis. *The Lancet*, 08 2020.

[11] Matt Keeling and Ken Eames. Networks and epidemic models. *Journal of the Royal Society, Interface / the Royal Society*, 2:295–307, 10 2005.

[12] KTD Eames and Matt Keeling. Contact tracing and disease control. *Proceedings Biological sciences / The Royal Society*, 270, 01 2003.

[13] Lorenzo Pellis, Frank Ball, Shweta Bansal, Ken Eames, Thomas House, Valerie Isham, and Pieter Trapman. Eight challenges for network epidemic models. *Epidemics*, 10:58 – 62, 2015. Challenges in Modelling Infectious DIsease Dynamics.

# A Figures



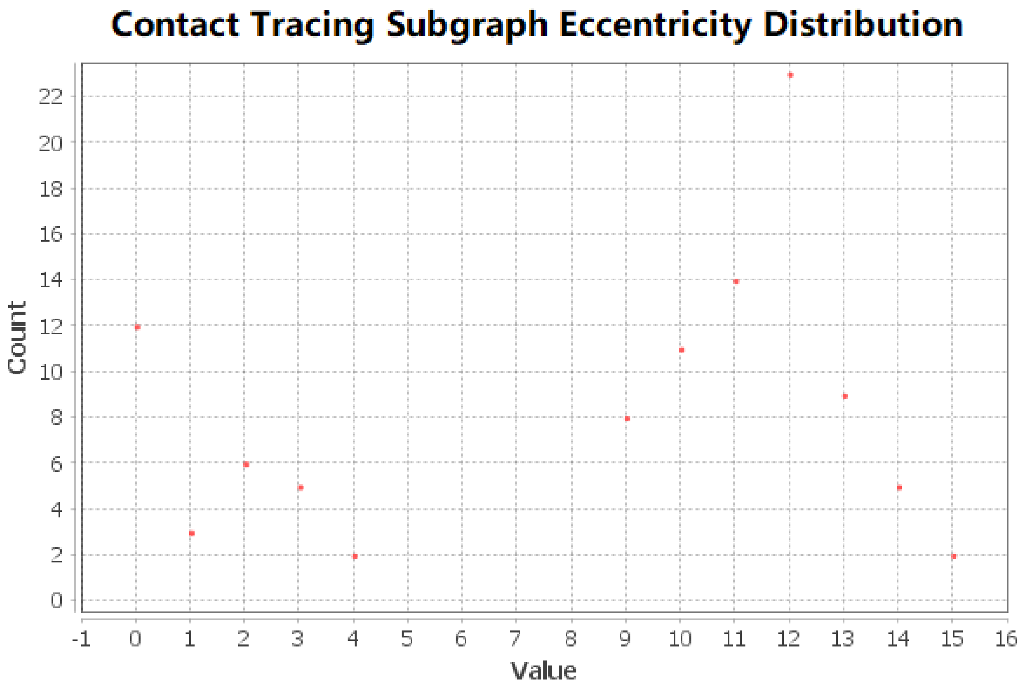
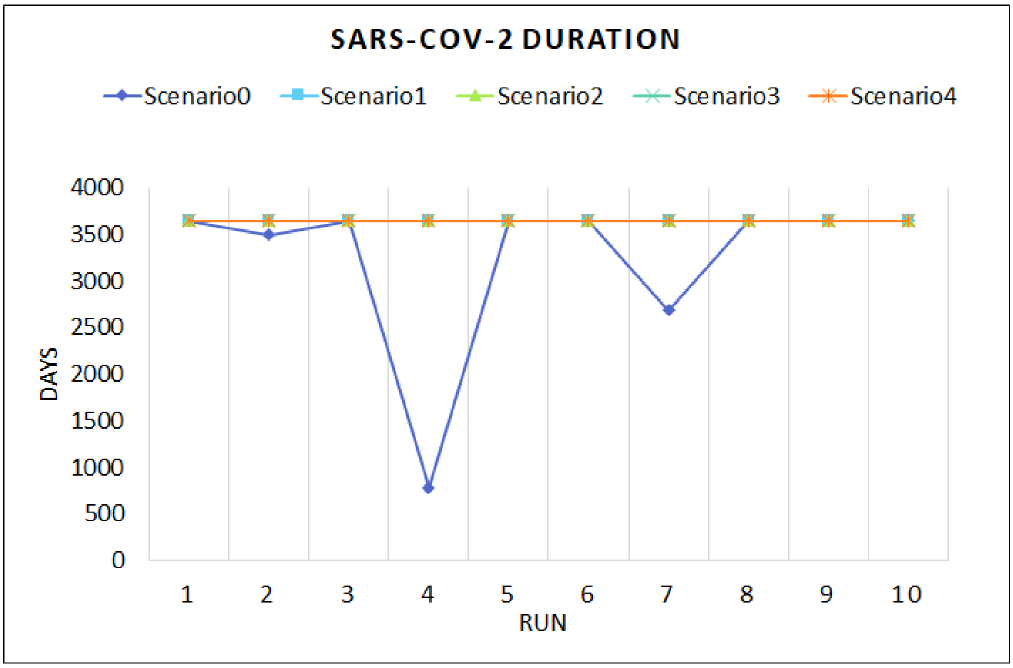




Figure 4: Eccentricity distribution of the network of contacts and the corresponding tracing subgraph described in section 3.3.1.



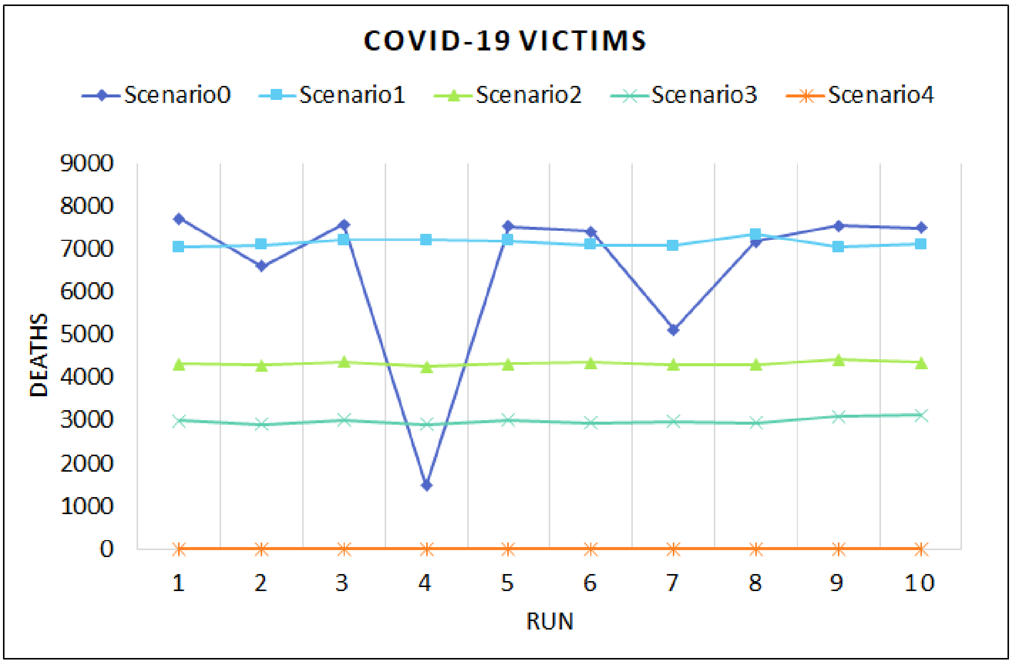
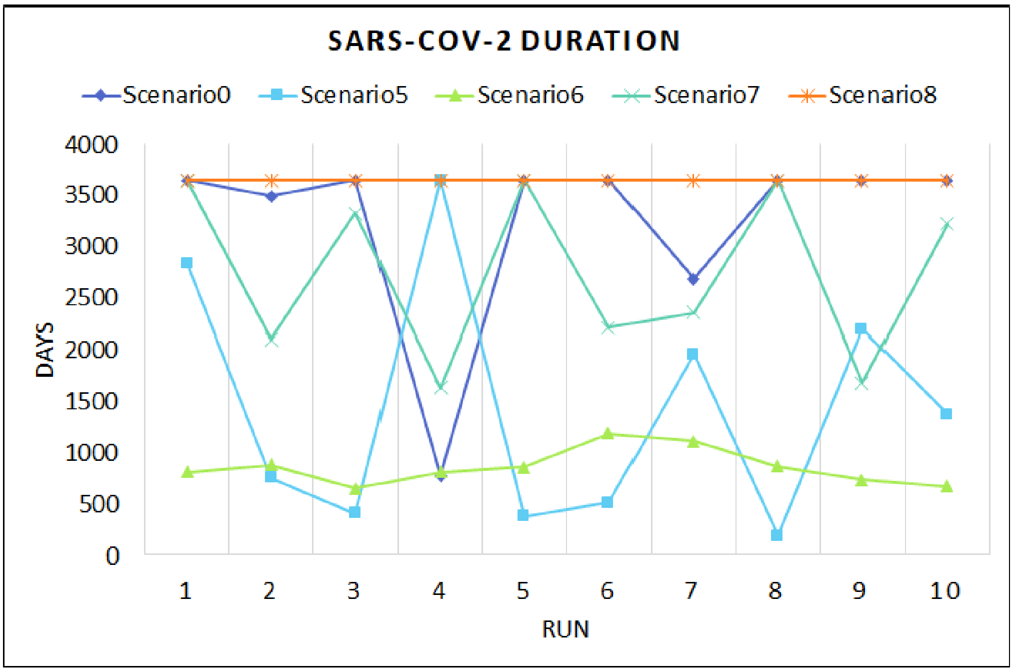




Figure 5: Epidemic duration in days and total number of deaths of *Scenarios 1,2,3* and *4* compared with the *Baseline*.



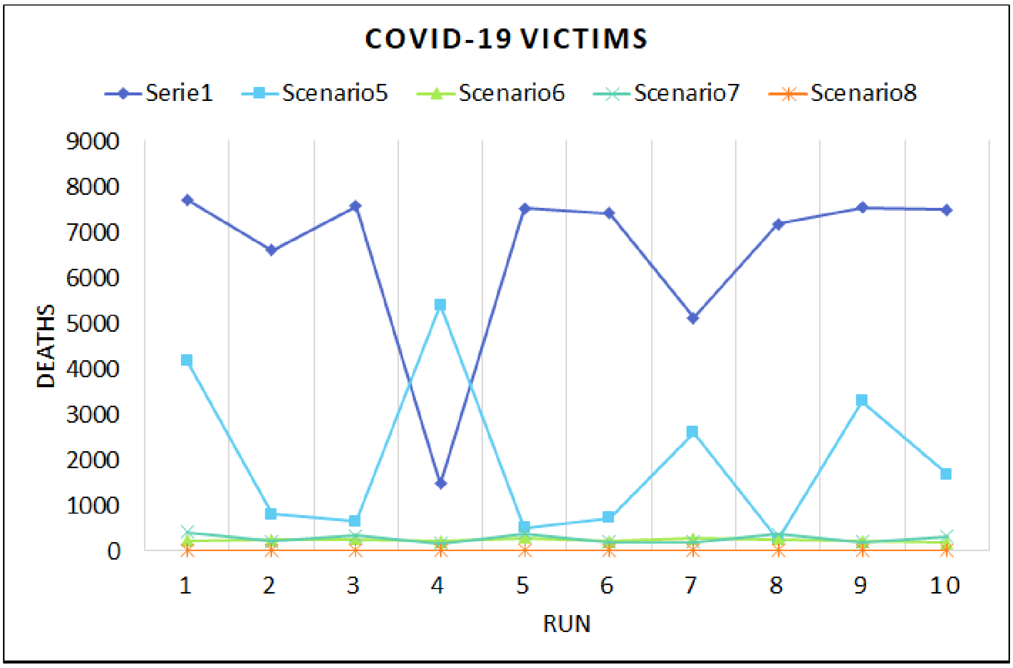
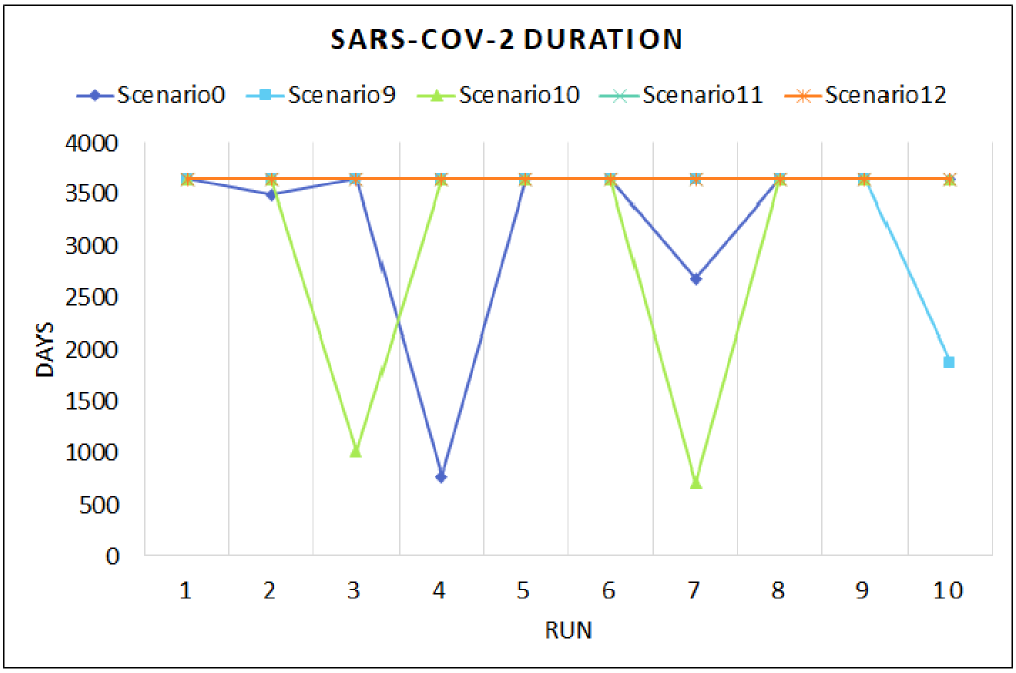




Figure 6: Epidemic duration in days and total number of deaths of *Scenarios 5,6,7* and *8* compared with the *Baseline*.



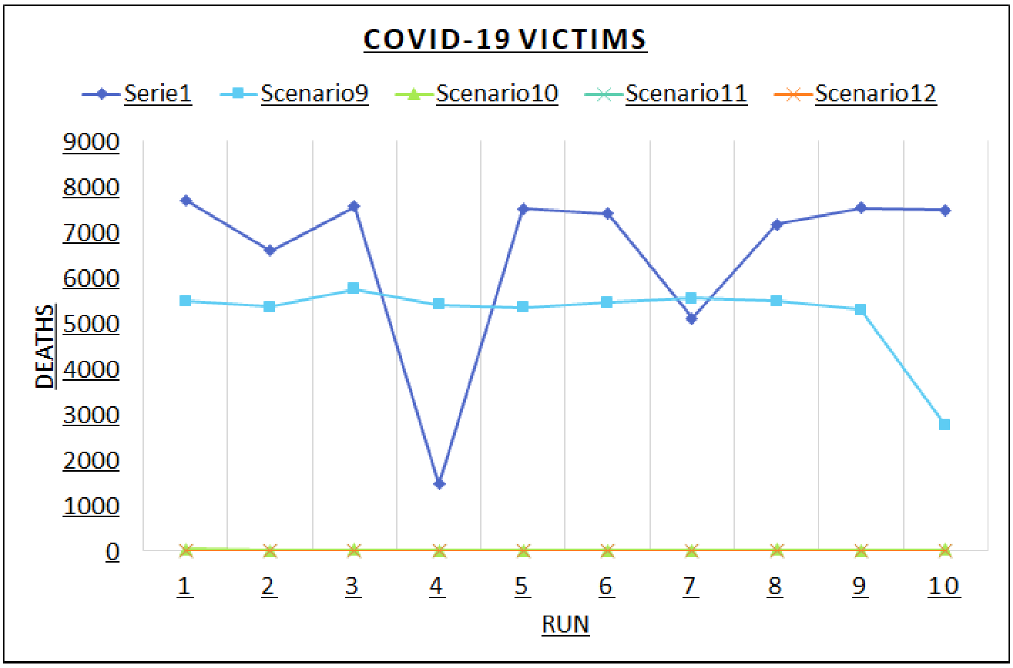
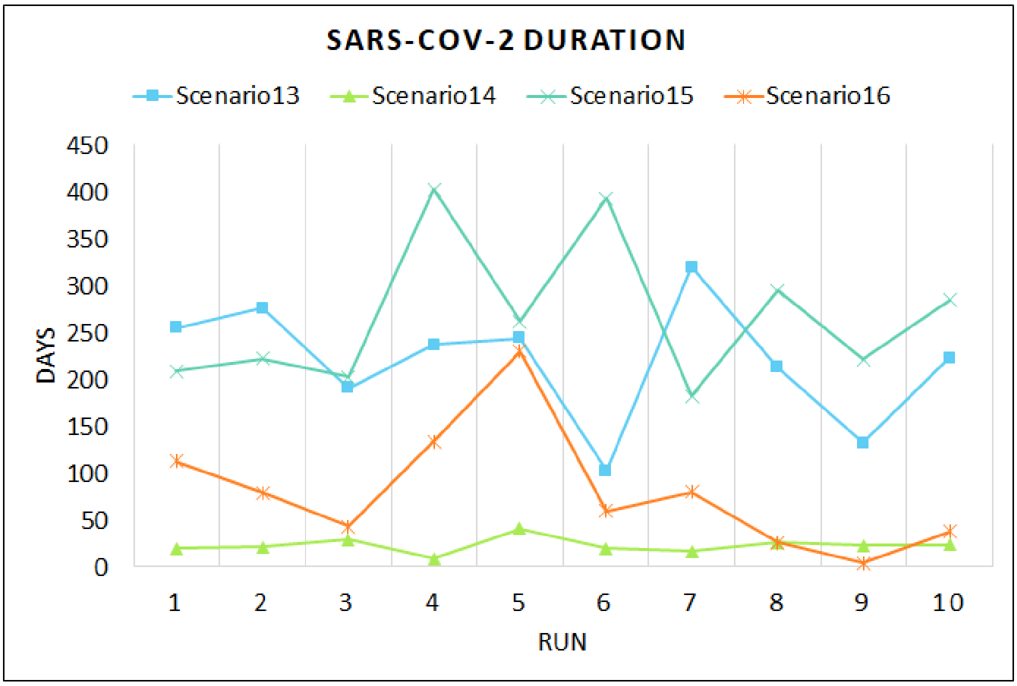




Figure 7: Epidemic duration in days and total number of deaths of *Scenarios 9,10,11* and *12* compared with the *Baseline*.



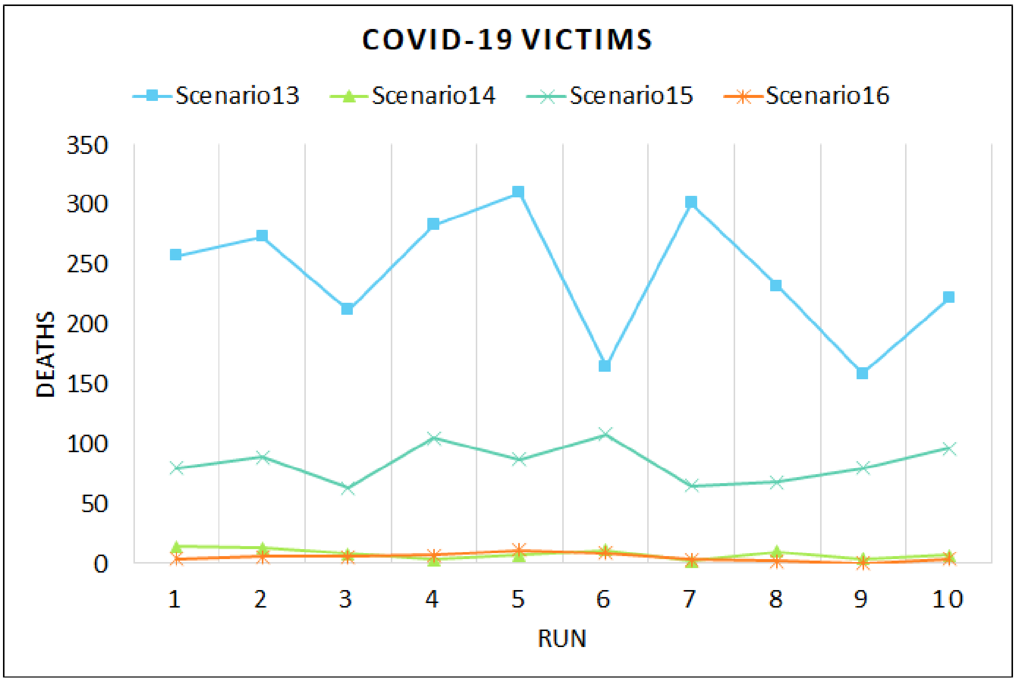
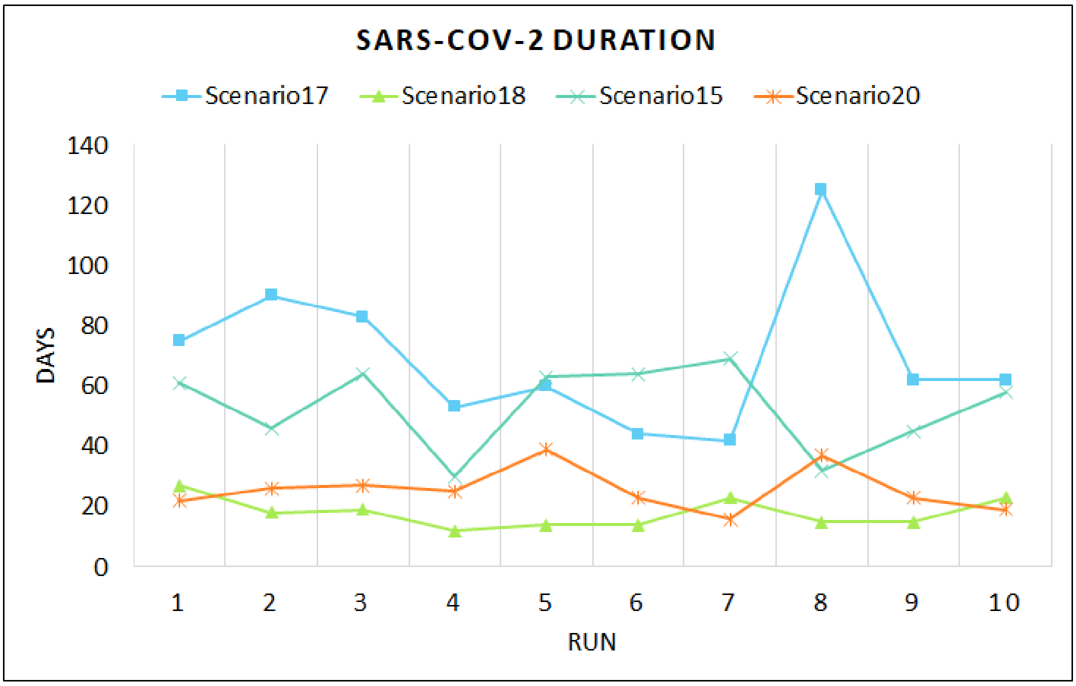




Figure 8: Epidemic duration in days and total number of deaths of *Scenarios 13,14,15* and *16*.



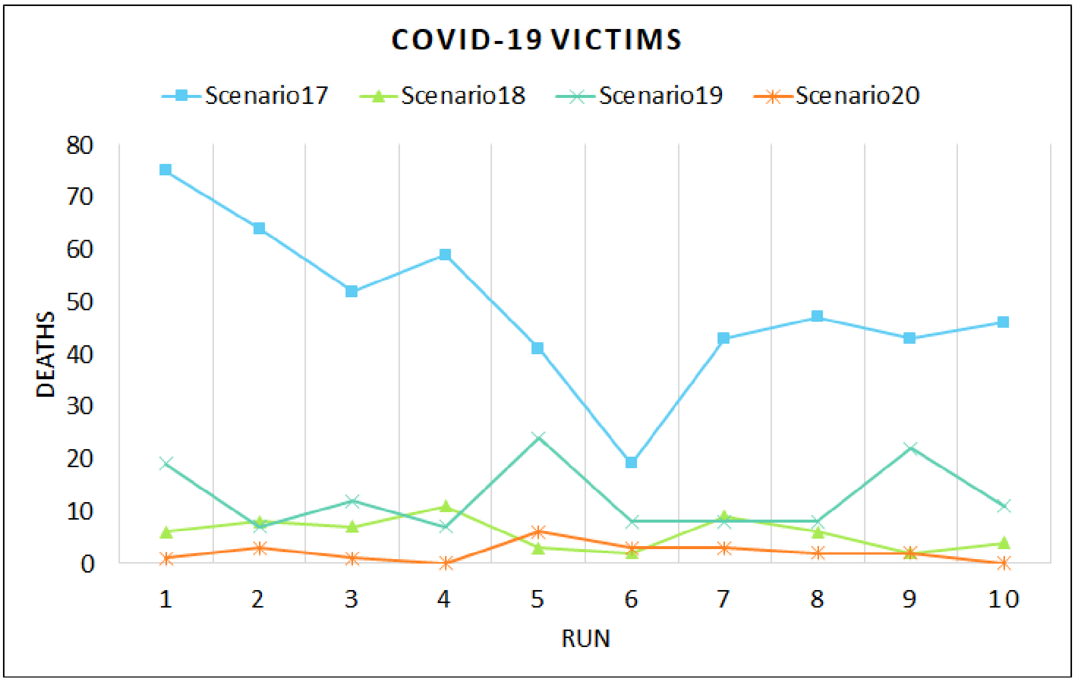




Figure 9: Epidemic duration in days and total number of deaths of *Scenarios 17,18,19* and *20*.

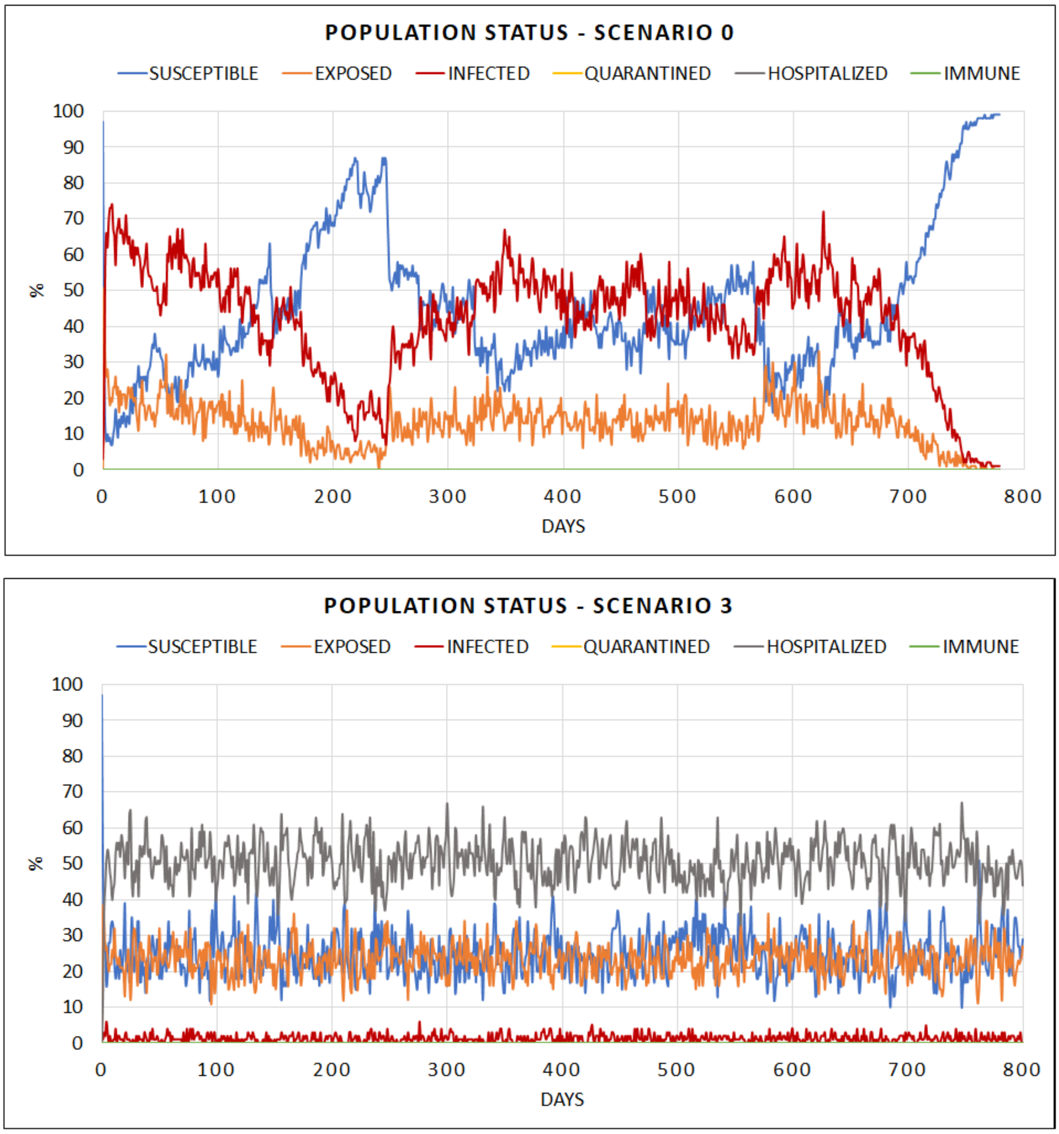
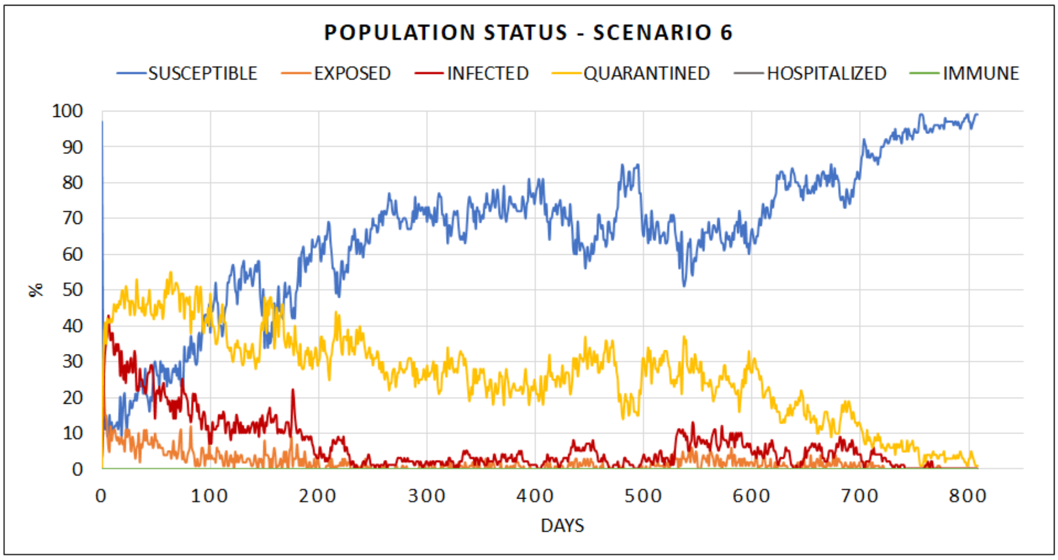



Figure 10: Temporal evolution of the population status in *Scenario 0* (top) and *3* (bottom).We focus on the first 800 days of *Scenario 3* to better compare it with *Scenario 0*, which simulation terminates after 779 days.



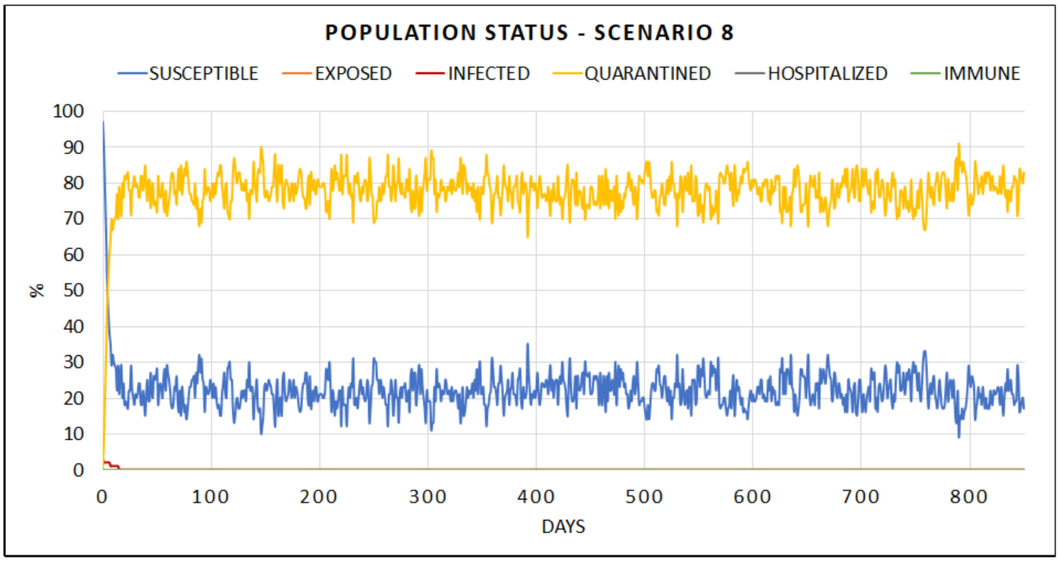
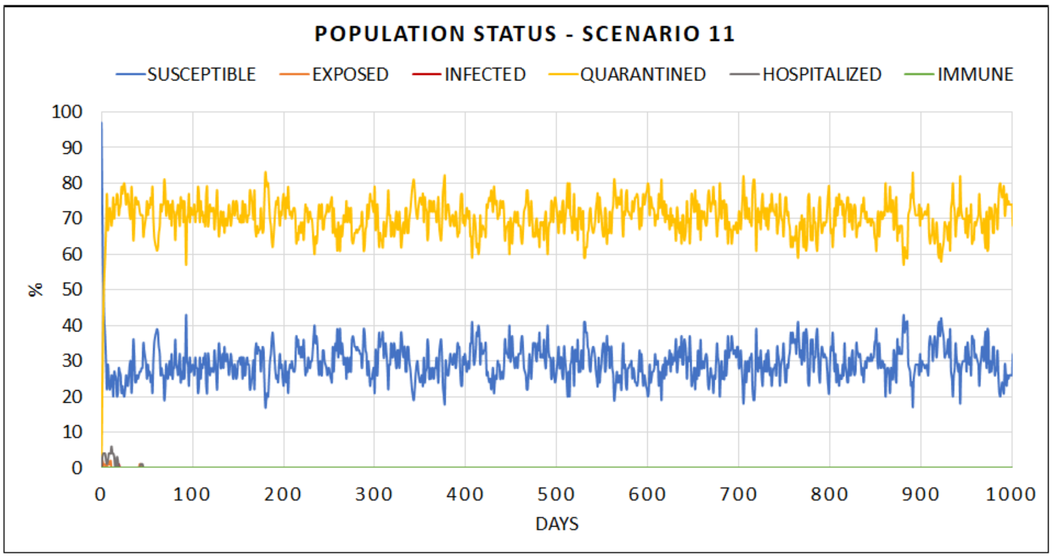




Figure 11: Temporal evolution of the population status in *Scenario 6* (top) and *8* (bottom).We focus on the first 850 days of *Scenario 8* to better compare it with *Scenario 6*, which simulation terminates after 808 days.



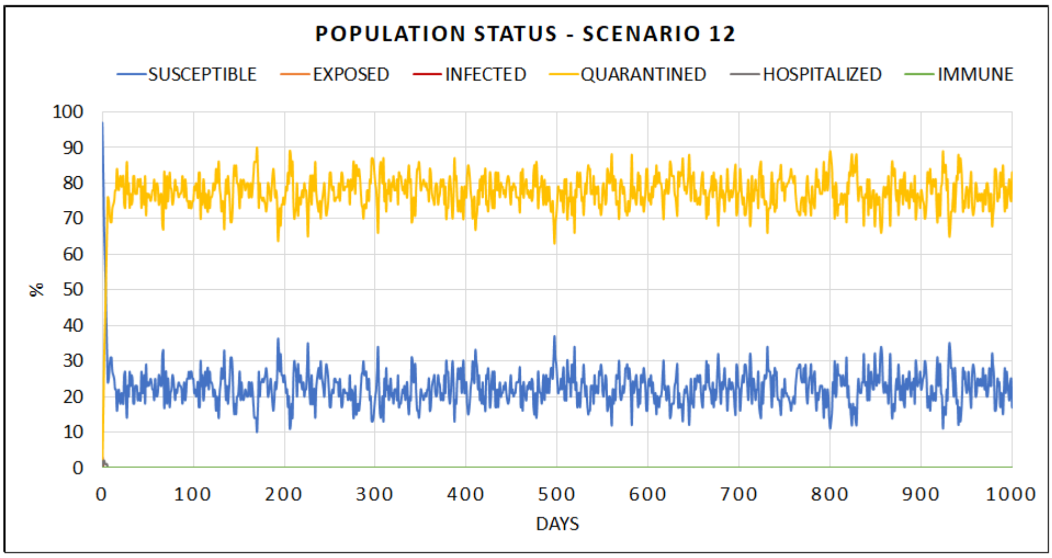




Figure 12: Temporal evolution of the population status in *Scenario 11* (top) and *12* (bottom).

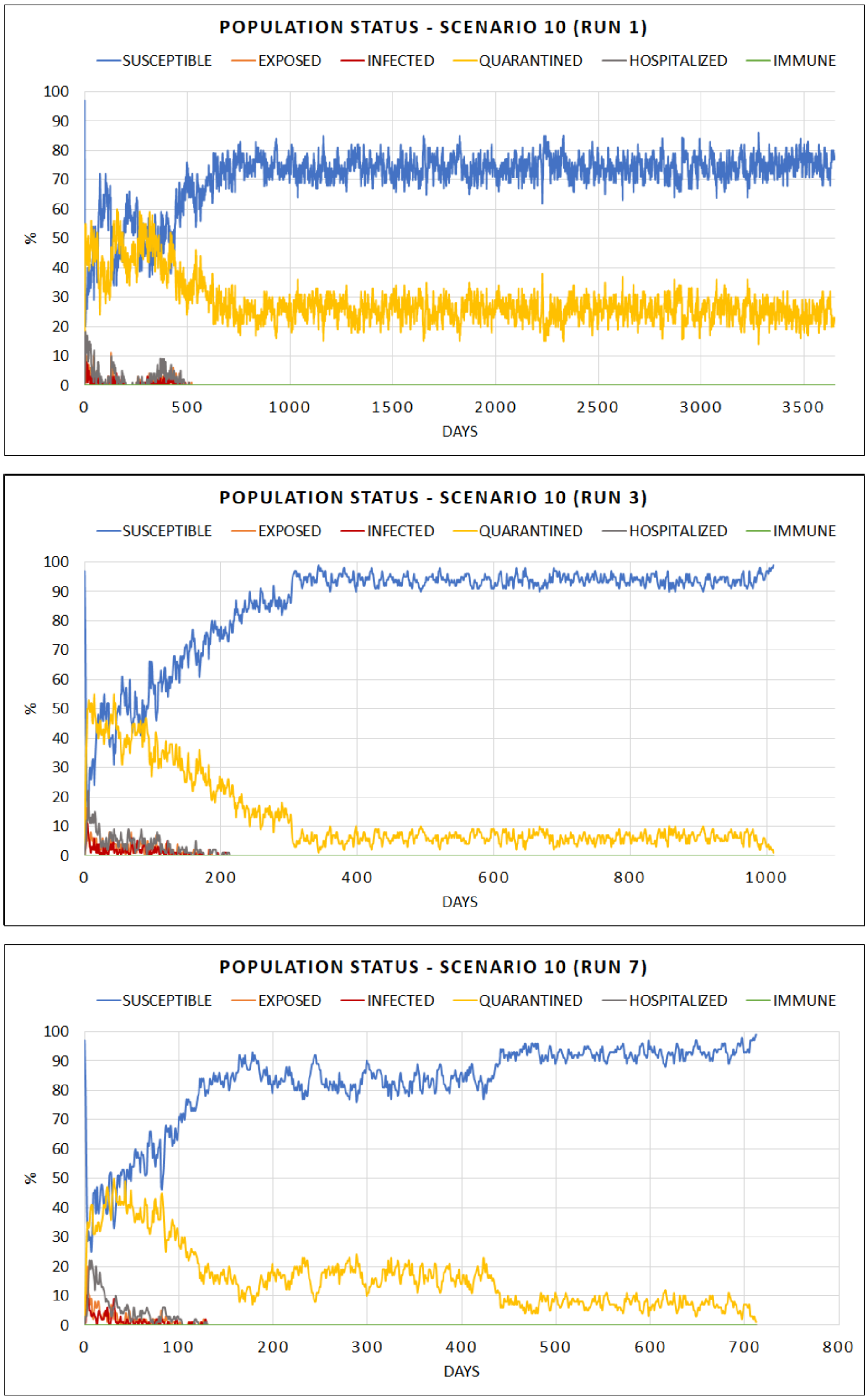
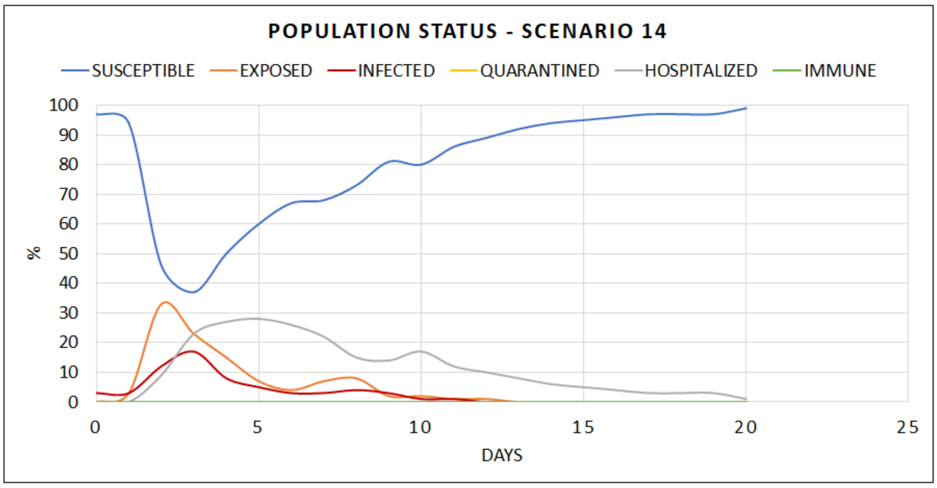



Figure 13: Temporal evolution of the population status in three runs of *Scenario 10*.



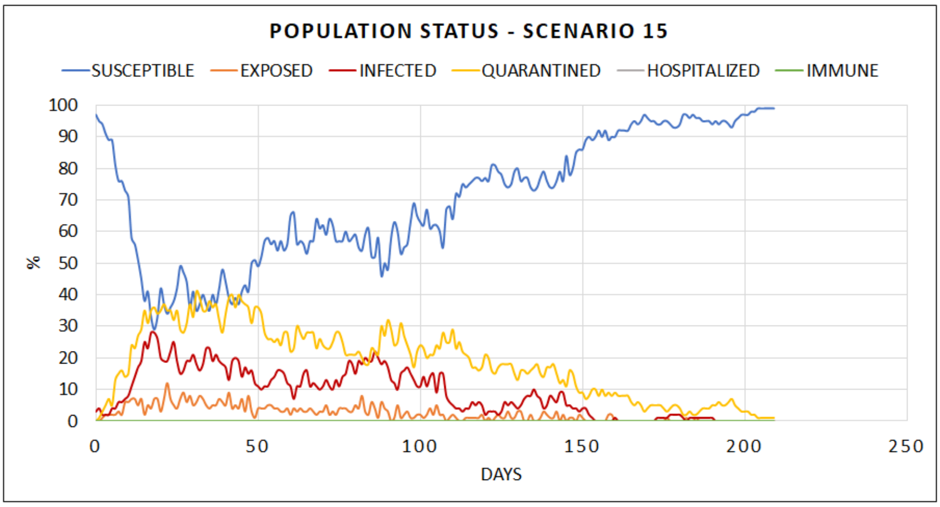




Figure 14: Temporal evolution of the population status in *Scenario 14* (top) and *15* (bottom).