The price of uncertainty during COVID-19

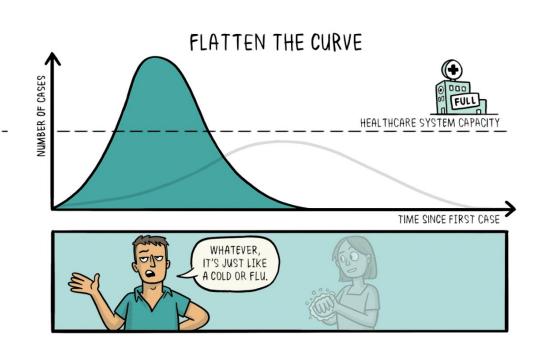
A sensitivity analysis on an extended infection model using UQpy

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Summary

SIR models and beyond

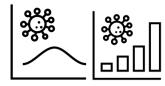
The UQpy library

Results

Takeaways, conclusions, perspectives









Project goal

Reproduce the results of a sensitivity analysis from a previously published work, using UQpy.

Focus: the dynamics of the first 180 days of a pandemic of COVID-19.

Understanding Dynamics of Pandemic Models
to Support Predictions of COVID-19
Transmission: Parameter Sensitivity
Analysis of SIR-Type Models

Chunfeng Ma®, Member, IEEE, Xin Li®, Senior Member, IEEE, Zebin Zhao®, Feng Liu®, Kun Zhang, Adan Wu®, and Xiaowei Nie

Crash course on compartmental models for epidemiology

Compartmental models in epidemiology —

- Models in which people from a population of N individuals move between compartments
- The dynamics is essentially governed by the initial conditions and the transition rates

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Simplest case: SIR (Susceptible, Infectious, Recovered)

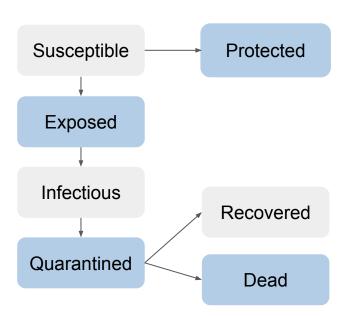
Susceptible β IS Infectious λ I Recovered β : infection rate

λ: recovery rate

$$\frac{dS(t)}{dt} = -\beta \frac{S(t) I(t)}{N}$$
$$\frac{dI(t)}{dt} = \beta \frac{S(t) I(t)}{N} - \lambda I(t)$$
$$\frac{dR(t)}{dt} = \lambda I(t)$$

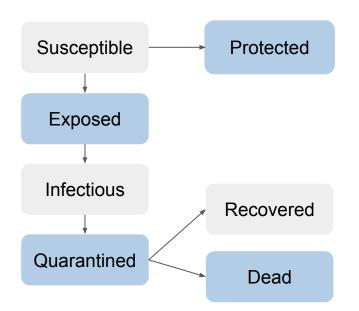
Beyond SIR: SEIQRDP models

New compartments to make the dynamics more realistic



Beyond SIR: SEIQRDP models

- New compartments to make the dynamics more realistic
- New governing equations



$$\frac{dS(t)}{dt} = -\beta \frac{S(t) I(t)}{N} - \alpha S(t)$$

$$\frac{dE(t)}{dt} = \beta \frac{S(t) I(t)}{N} - \gamma E(t)$$

$$\frac{dI(t)}{dt} = \gamma E(t) - \delta I(t)$$

$$\frac{dQ(t)}{dt} = \delta I(t) - \lambda Q(t) - \kappa Q(t)$$

$$\frac{dR(t)}{dt} = \lambda Q(t)$$

$$\frac{dD(t)}{dt} = \kappa Q(t)$$

$$\frac{dP(t)}{dt} = \alpha S(t)$$

N: total number of people

a: protection rate

 β : infectious rate

γ⁻¹: average incubation time

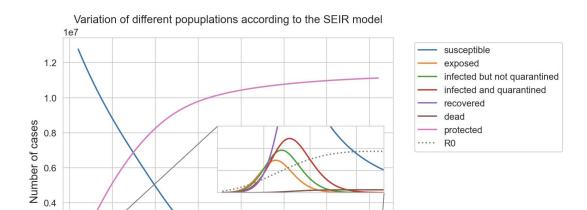
δ⁻¹: average quarantine time

κ: mortality rate

λ: cure rate

Ranges and values were set according to the paper.

Reproducing the pandemic dynamics



150

125

Days

175

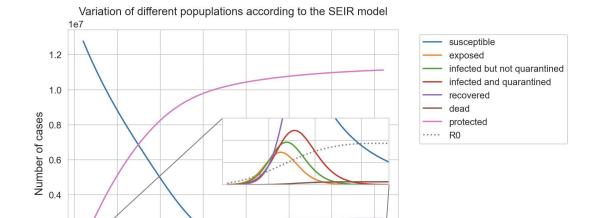
0.2

0.0

The dynamics are close to the SIR model:

- the initial compartment S is slowly emptied
- the intermediate compartments E, I, Q present a bell shaped curve
- the ending compartments
 R, D, P are monotone non decreasing functions

Reproducing the pandemic dynamics



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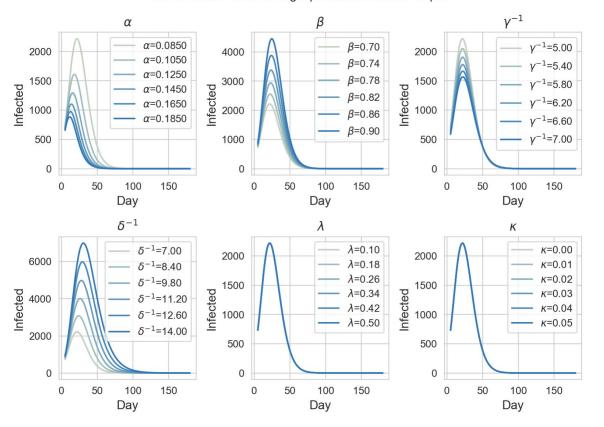
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Following the approach of the paper, from now on our output of interest will be the number of the **infectious cases I**

Varying parameters one-at-a-time





- With the light-blue parameter combination, the peak of infectious cases is around 2220, and is reached around day 16
- The mortality rate κ and cure rate λ do not seem to be influential on the infected cases
- The other parameters exert a higher influence, especially the protection rate α

On with the Global Sensitivity Analysis!

Quick recap of Sobol' indices

Exploiting the decomposition of variance, they quantify how much variability in the output each input accounts for.

First order

$$S_i = \frac{\operatorname{Var}_{X_i} \left[E_{\mathbf{X}_{\sim i}} [Y|X_i] \right]}{\operatorname{Var}[Y]}$$

Quantifies the **individual** effect of X_i on Y, **without interactions**

Total order

$$S_{T_i} = 1 - \frac{Var_{\mathbf{X}_{\sim i}}[E_{X_i}[Y|\mathbf{X}_{\sim i}]]}{Var[Y]}$$

Quantifies the **overall** effect of X_i on Y, **including interactions**

Quick recap of Sobol' indices

Exploiting the decomposition of variance, they quantify how much variability in the output each input accounts for.

First order

$$S_i = \frac{V_i}{V} = \frac{\operatorname{Var}_{\mathbf{x}_{\sim i}}(\mathrm{E}(f(\mathbf{x})|\mathbf{x}_i))}{\operatorname{Var}(f(\mathbf{x}))}$$

Total order

$$S_{T_i} = 1 - \frac{\operatorname{Var}_{\mathbf{x}_{\sim i}}(\mathrm{E}(f(\mathbf{x})|\mathbf{x}_i))}{\operatorname{Var}(f(\mathbf{x}))}$$

Main goals:

- factor prioritization
- factor fixing

The heavy artillery: UQpy

A general purpose Python **toolbox** for modeling uncertainty in physical and mathematical systems, exploiting a black-box approach.

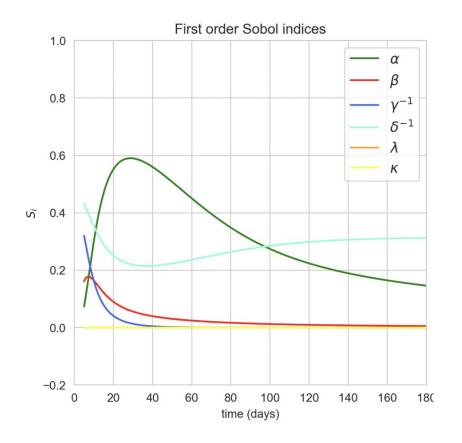
Several tools for sensitivity analysis, including computation of **Sobol' indices**.





First-order Sobol' indices on Infectious

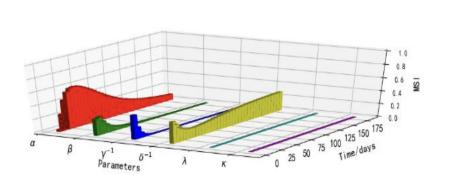


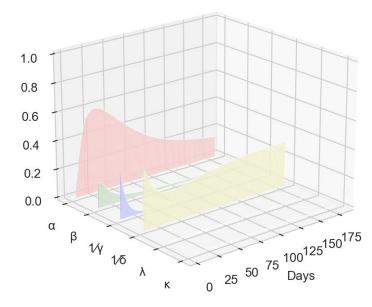


- As expected, the protection rate α and the average quarantine time
 δ⁻¹ are highly influential on the infectious cases
- The influence of the infectious rate
 β and average incubation time γ⁻¹
 quickly decrease to 0
- The mortality rate κ and the cure
 rate λ always remain close to 0

First-order Sobol' indices on Infectious







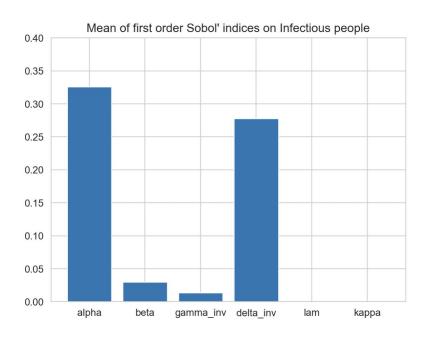
Original results

Reproduced results

Factor prioritization using Sobol' indices —



We computed the **mean over time** of the first-order Sobol' indices.



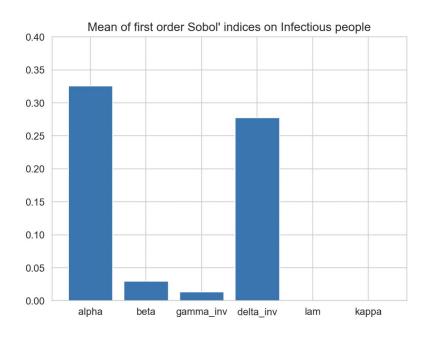
Factor ordered by influence:

- **a**: protection rate
- 2. δ^{-1} : average quarantine time
- **B**: infectious rate
- **γ**⁻¹: average incubation time
- κ , λ : mortality and cure rate

Factor prioritization using Sobol' indices



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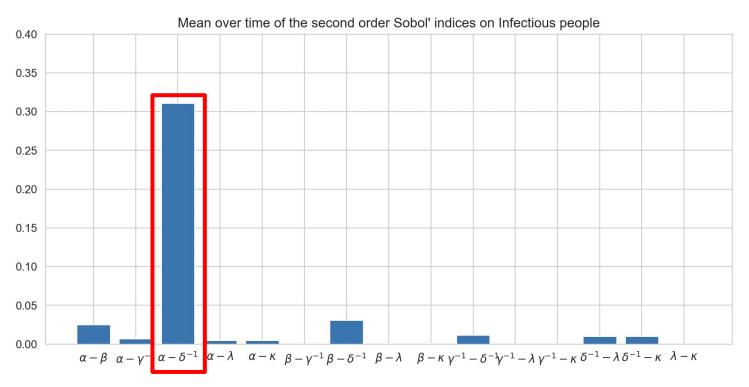
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Same conclusions obtained in the paper

Extending the results of the paper: second order interactions

Mean of second-order Sobol' indices



The most influential interaction is between the **protection rate** α and the **average quarantine time** δ^{-1} , while the other interactions are less relevant.

We're talking about pandemics, so what about R0?

The basic reproduction number R0

The average number of secondary infected cases generated by a primary case, crucial for transmissibility:

- R0 < 1 → infection-free steady state is reached asymptotically
- R0 > 1 → the pandemic will outbreak

Here computed as:

$$R0 = \left(1 + \frac{\ln(I(t)/t)}{\gamma}\right) \left(1 + \frac{\ln(I(t)/t)}{\lambda}\right)$$

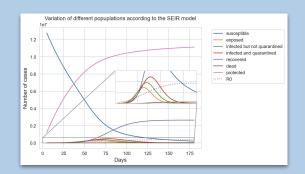
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Remember this image?

The values for R0 do not really make sense (**R0 plateauing around 10**⁶)

R0: an unsolved mystery

After many attempts and doubts on the formula we contacted the author.

He confirmed that everything was correct.

Dear Teo and Flavia,

Sorry for the delayed reply--I was doing fieldwork in a remote mountainous area with no communication signal.

- (1) According to Equation 11 and reference 11, Y(t) is the total number of infected people given by I(t), without Q(t).
- (2) inside Log.
- (3) No, gamma and lambda are variables to be analyzed for their sensitivity.

Hope this reply is clear.

Please hesitate to contact us if you have further questions.

Best regards,

Chunfeng Ma

More investigating on this topic is needed.

Conclusions

Main takeaways

- o In the extended SIR model, the **protection rate** α is the most influential on the infectious cases, together with the **quarantine** time δ^{-1} , and their **interaction**
- Other factors such as the mortality rate κ and the cure rate λ can be considered as fixed for modeling purposes

Conclusions

Main takeaways

- In the extended SIR model, the protection rate α is the most influential on the infectious cases, together with the quarantine time δ⁻¹, and their interaction
- Other factors such as the mortality rate κ and the cure rate λ can be considered as fixed for modeling purposes

Future improvements

- Solving the mystery of R0
- Extend the analysis to other quantities of interest such as the number of quarantined cases (Q)
- Apply different methods (e.g., moment-independent sensitivity measures)

Thank you for the attention!

References

Main reference paper

Ma, C., Li, X., Zhao, Z., Liu, F., Zhang, K., Wu, A., & Nie, X. (2022). Understanding Dynamics of Pandemic Models to Support Predictions of COVID-19 Transmission: Parameter Sensitivity Analysis of SIR-Type Models. *IEEE Journal of Biomedical and Health Informatics*, 26(6), 2458-2468. https://doi.org/10.1109/JBHI.2022.3168825

UQpy paper

Olivier, A., Giovanis, D. G., Aakash, B. S., Chauhan, M., Vandanapu, L., & Shields, M. D. (2020). UQpy: A general purpose Python package and development environment for uncertainty quantification. *Journal of Computational Science*, *47*, 101204. https://doi.org/10.1016/j.jocs.2020.101204

Any questions?

UQpy methods

Several methods to compute the Sobol indexes

- First-order:
 - Jensen (2014)
 - Saltelli (2002)
 - Sobol (1983)
- Second-order:
 - Saltelli (2002)
- Total order:
 - Homma (1996)
 - Saltelli (2002)