COVID-19 Modelling and the Challenges of Modelling Complex Systems

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Outline

1. Introduction

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- Large amounts of data have been gathered about various aspects of the pandemic
- An invaluable asset for researchers to model the pandemic and understand its behaviour
- Very useful for predictions about the future course of the pandemic

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- This project is an archetypal example of modelling a complex system composed of several interacting aspects
- Detailed modelling requires the consideration of biological, socio-political, and economic systems.
- Involves collecting data from various sources, reconciling inconsistencies between them, and using the combined insights from these fields to understand the pandemic and its evolution through time.

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- The contact rate parameter β needs to be estimated at various time periods of the pandemic

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- Additional units were considered for various subdivisions of Bengaluru
- Being one of the largest cities in the country, it may be appropriate to subdivide it into smaller units.

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$$W(t; \kappa, \tau) = \frac{\kappa}{\tau} \left(\frac{t}{\tau}\right)^{\kappa-1} \exp\left[-\left(\frac{t}{\tau}\right)^{\kappa}\right]$$

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- These optimize for the expected number of cases on a single day, and the expected number of cases over an interval of time respectively
- Infected proportions were also compared with data obtained from the second seroprevalence survey in Karnataka

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Future	2021-04-22	2022-12-31	

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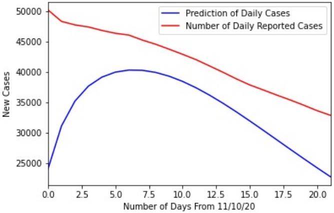
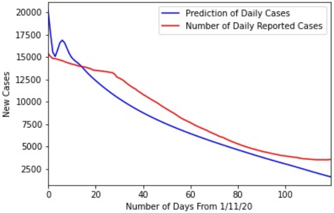
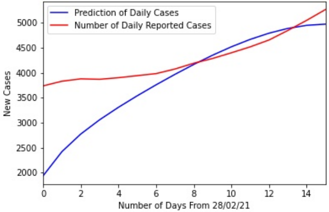
- The SEIR model fails when case counts are low, such as during the stochastic phases
- The SEIR model requires modelling discrete events (infections) in a continuum manner, which necessitates high case counts.



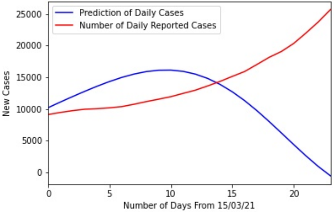
(a) Phase 1 predictions



(b) Phase 2 predictions



(c) Phase 3 predictions



(d) Phase 4 predictions

Figure: Optimized model predictions compared to actual case counts (CIR corrected)

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- Optimization did not yield any significant deviation from these initial guesses

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- But this leads to very large CIR values that lead to absurd conclusions
- Such as CIR-corrected case counts in many BBMP zones being over twice the population of the zone itself.

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- CIR is influenced by several external factors such as the strain on the health sector, the extent of testing, the efficacy of tests, political influence, and even the definitions of infection
- Therefore, a more robust model is needed which considers, at the very least, the fact that tests are not performed uniformly randomly on the entire population

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- It cannot accurately predict the interval between waves
- In these phases, a probabilistic approach to may be a better alternative

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- However we may resort to biological experiments to gain more accurate insights
- This also indicates that using the SEIR model beyond the end of the second wave is ill-advised
- New waves of the pandemic likely arise through random processes as opposed to the deterministic nature of the SEIR model

Contact rates and Mobility

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- Our naive mobility matrices treat all districts of Karnataka equally, which is not a good assumption to make
- This is illustrated by the fact that the error in our predictions were largest in the various zones of Bengaluru
- This is likely because the zones are highly connected and so show a large mobility among themselves

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- But we gained insights into the strengths and weaknesses of the SEIR model
- Our previous assignment on this topic illustrates the utility of the SEIR model during the peak of the pandemic's waves
- This project illustrates the shortcomings when attempting to use the same model for the stochastic phases

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- We must accept that our models are fallible and limited in their applicability