Pandemic Dynamics with Social Effects: Rapid Model Prototyping with Fuzzy Logic

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Abstract

The human behavior aspect of pandemic prevention and mitigation involve uncertainties manifested as a range of responses, from the extreme to the indifferent. Relationships between variables influencing human behavior are usually described qualitatively, and as such do not suffice for stock and flow models. These uncertainties can slow down the modelling process considerably, thus limiting the effectiveness of a model-based approach in time-critical studies such as an impending pandemic outbreak. Our proposed approach utilizes fuzzy modelling concepts integrated within the system dynamics modelling framework to create a rapid model prototyping process of developing a pandemic dynamics model. This can facilitate quantitative analysis for policy making in pandemic mitigation interventions. We use the recent H1N1 pandemic in Singapore as a case example to demonstrate the practical usefulness of our approach.

Keywords: pandemic dynamics, social effects, system dynamics, fuzzy logic

Introduction

In the past decade, we have witnessed the impact of pandemic on our modern society (Keogh-Brown and Smith, 2008). As an illustration, the 2003 Severe Acute Respiratory Syndrome (SARS) outbreak affected a number of countries and the total economic loss can amount to at least a few US$ billion. Apart from economic impact, the pandemic can trigger other risks pertaining to the operation of critical infrastructures. If the effect of pandemic is not checked, it will propagate to a national crisis of a much larger scale, where human resources are removed from all sectors including critical infrastructure and essential services. When this happens, the daily functioning of a society may be severely affected.

To counter the spread of pandemic in a community, there are various strategies employed by the government (Ferguson et al 2005). Usually a combination of prophylaxis and social distancing measures is proved effective to contain the spread of disease (Ooi et al 2005). During the 2003 SARS outbreak in Singapore, the government adopted two main strategies (i.e. early detection and isolation of all cases and quarantine of all close contacts of symptomatic cases) and it helped to break the chain of transmission. In addition, Singapore's national plan for pandemic response makes reference to mitigating the effect of the first pandemic wave through securing the co-operation of the general public (Singapore Ministry of Home Affairs, 2009). This is to be achieved by impressing the need for each individual to have a sense of collective responsibility in detecting and preventing the spread of flu. The public will be educated and expected to practice improved personal hygiene and adopt socially responsible behavior.

In general, the pandemic response strategy in Singapore is founded on the key observation that pandemic dynamics is significantly dependent on the rich interplay between the dynamics of pathogen transmission and the structure and behaviors of social responses. Given the high population density in Singapore (7,022/km^2) (Singapore Department of Statistics, 2009), which is perhaps one of the most densely populated country in the world (United Nations Department of Economic and Social Affairs, 2009), there has to be a more significant consideration of social effects in understanding pandemic dynamics.

In the literature, various attempts have been made to use large-scale population dynamics models to evaluate the socio-economic impacts of a pandemic and the effectiveness of various mitigation strategies. Ewers and Dauelsberg (2007) integrated an industrial system model to evaluate the impact of an outbreak on labor, sales and economic performance. Lant et al. (2008) used a hierarchical system dynamics modelling approach to simulate the execution of the pandemic preparedness plan in a public university. Other than influenza, Ritchie and Galvan (1999) studied the effects of strategies such fumigation, implementation of larvacide programs and education in a dengue fever outbreak in Mexico. These studies however, remain as open-loop analysis. In a small country such as Singapore, it is postulated that closed-loop effects can become significant and thus should be appropriately accounted for in a system model.

In this study, we will propose an approach to investigate how societal responses may be incorporated as a feedback in a pandemic model. Considering the nature of pandemic transmission, such an approach has to inevitably account for the difficulty in obtaining quality data for the modeling of pandemic dynamics in traditional statistical pandemic models. The rapidity of pandemic transmission is of more significant concern to Singapore considering its high population density. In fact, we lack the luxury of time to collect quality data for intricate statistical modeling of pandemic dynamics especially for a model that considers social effects. Hence, a rapid prototyping approach based on fuzzy-modeling integrated within system dynamics modeling framework would be proposed to deal with the time-compression impact on data availability for modeling pandemic dynamics with social effects.

The structure of this paper is as follows. The basic Susceptible-Exposed–Infectious-Recovered (SEIR) model most commonly used for influenza modelling is first discussed. In order to incorporate social effects and considering the need to rapidly develop useful pandemic dynamics model under the dual constraints of data insufficiency and time pressures, the fSEIR model, incorporating fuzzy modelling concepts with a system dynamics model, is proposed. A simple case study is described to demonstrate the improvement of the fSEIR model for the predicting of the evolution of pandemic over time using real data from the Singapore government. The study is still ongoing. This paper will focus on the Influenza A (H1N1) virus and the model described in this paper is a preliminary one.

Pandemic Dynamics Models

SEIR model

A compartmental model (Ma and Li, 2007) is typically used for studying pandemics. Of such models, the Susceptible-Exposed–Infectious- Recovered (SEIR) model is most commonly used for influenza pandemic modelling. The SEIR model is essentially a set of ordinary differential equations which are solved to derive the dynamic behaviour of the system over time. One of the advantages of the SEIR model is that it has few variables which can be determined relatively quickly by experts. State variables include the stock of susceptible and infectious population, and rate-related parameters include the probability of viral transmission and the “infectivity” of the cases over time. In order to consider biological, social and environmental effects on infectiousness, infectivity can be decomposed into these 3 effects respectively. For example, it can be decomposed into a product of biological infectiousness and contact rates, thus allowing the assessment of interventions aimed to mitigate the social effects on infectiousness.

We first conducted a preliminary investigation on using the basic SEIR model for predicting the evolution of H1N1 pandemic in Singapore. In the SEIR model, the driver of the pandemic is the rate of infection within the susceptible population. This rate of infection is determined by the probability of transmission, the size of the susceptible population (“susceptible” in the model) and the number of infectious people in the system. The probability of transmission (“Beta” in the model) can incorporate more complex real-world considerations, such as the impact of human behaviours, to produce a more representative model. After infection, the susceptible population moves into the exposed stock where the disease will undergo an incubation period before manifesting symptoms. When this happens, the person joins the infectious stock, where he has a chance to infect other members of the susceptible population in the system, before he recovers and joins the recovered stock. The SEIR model can be summarized in the Stock and Flow model shown in Figure 1.

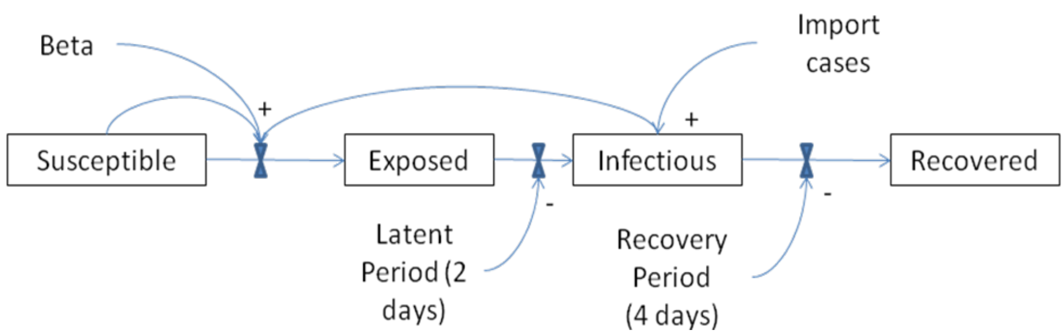

Figure 1: A SEIR model using stock and flow diagram

We developed a basic SEIR system dynamics model for the H1N1 pandemic cases in Singapore. Parameters of the virus gathered from official WHO sources as shown in Figure 2. It is clear that the "Number of infectious" produced from the model and the "Reported number of infected people" from the MOH press releases differ greatly. The SEIR model alone is unable to replicate past data satisfactorily[1]. Since the pandemic occurred while the pandemic preparedness plan was in effect, we hypothesise that the pandemic preparations have had an effect on the probability of transmission. This provides some evidence that the SEIR model may not be adequate when social effects are significant but not considered.

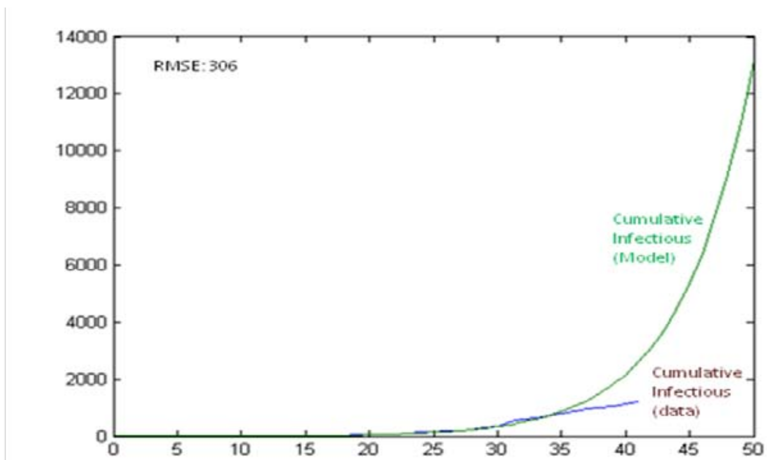

Figure 2: An example of poor replication of the SEIR model

fSEIR – Fuzzy-Based Rapid Model Prototyping

The premise of our work is to develop a more representative model of the system by integrating the influence of human behaviour to the probability of transmission over the progression of the pandemic. The dynamic hypothesis is shown in Figure 3. In the actual system, the population behaviour responds to the spread of the pandemic. In particular,

[1] It is possible that with more data training, the SEIR model can replicate the actual number of infected people with better accuracy. However, our study focus aims to look at incorporating other societal factor that is not taken into consideration in SEIR model.

the rise in the stock of infectious people sets up three balancing loops which act to reduce the beta value and thus reduce the number of susceptible getting infected. DORSCON which impacts the temperature regime compliance among the population is a specific policy measure in Singapore. It is the acronym for “Disease Outbreak Response System” and it lists out the pandemic responses that Singapore will take as a nation when threatened by a pandemic flu or infectious agent. The different levels of DORSCON are green, yellow, orange, red and black. The different policy levers within each threat level can have varying structural impact on the probability of transmission. Furthermore, the frequency of temperature regime, social distancing and better hygiene practices rises as the rise in the number of infectious people within the population is telegraphed by the media attention paid to it. The process is not instantaneous, as delays exist in the system due to perception and reporting delays. Some mitigation measures are easier to adopt while others take longer to come into effect.

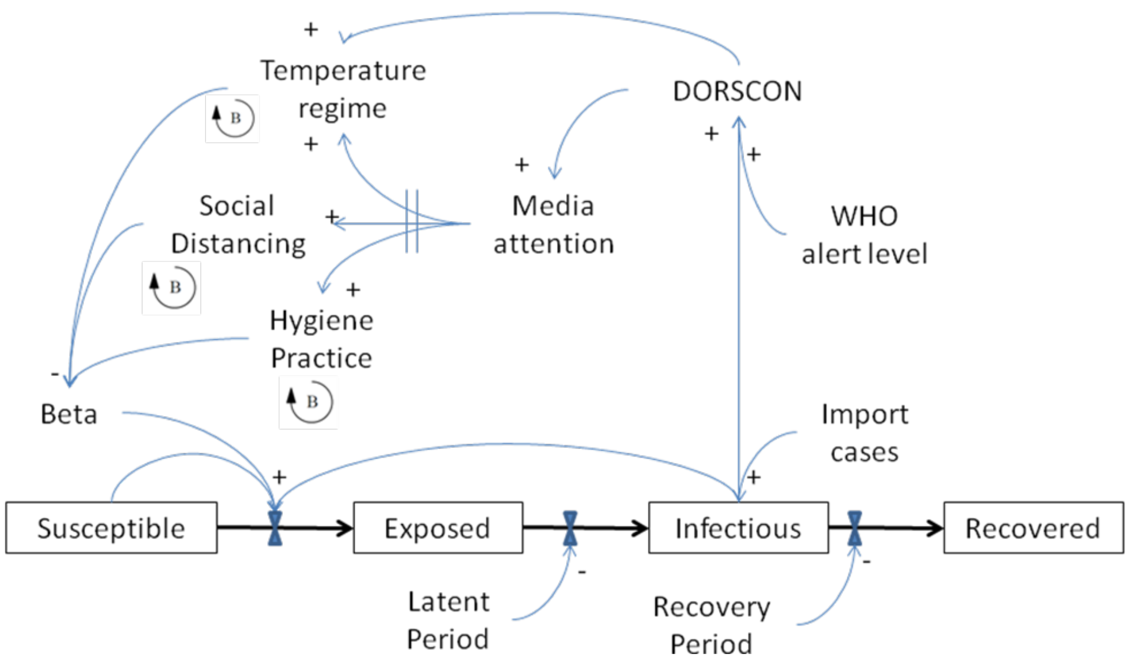

Figure 3: Integrating societal response in SEIR model

In the modelling process, implementing changing aspects of human behaviour in response to stimuli poses a quantitative dilemma. There is no universally accepted way of quantifying these relationships. However, we do have an idea of what the policy makers' mental model of the system is from the pandemic preparedness plan. In view of this, a fuzzy-logic based SD modelling approach (Ng et al, 2009) is proposed to mitigate the difficulties of handling the issues of incomplete structural information of the system Fuzzy numbers (Tanaka and Niimura 1996, Bojadziev and Bojadziev, 2007) provide the most natural interface for modellers to incorporate linguistic expert knowledge into a quantitative model. Fuzzy logic has been used extensively in modelling qualitative variables such as those that may arise from the modelling of social response during pandemics. During the early stages of model conception, knowledge sharing sessions with those who are familiar with the system may take the form of more qualitative descriptions on how the system works and the variables that are involved. Thus, implementing a framework to formulate SEIR models with support for linguistic variables using fuzzy logic will allow for a quicker modelling process, particularly when social effects are considered. We term the fuzzy pandemic dynamics model as the fSEIR.

We translate the limited information that has been gathered from public domain resources into a form amenable to simulation using the fuzzy logic tool (Bojadziev and Bojadziev, 2007). This is represented in the block diagram shown in Figure 4, with the inputs and outputs of each of the various fuzzy logic blocks displayed.

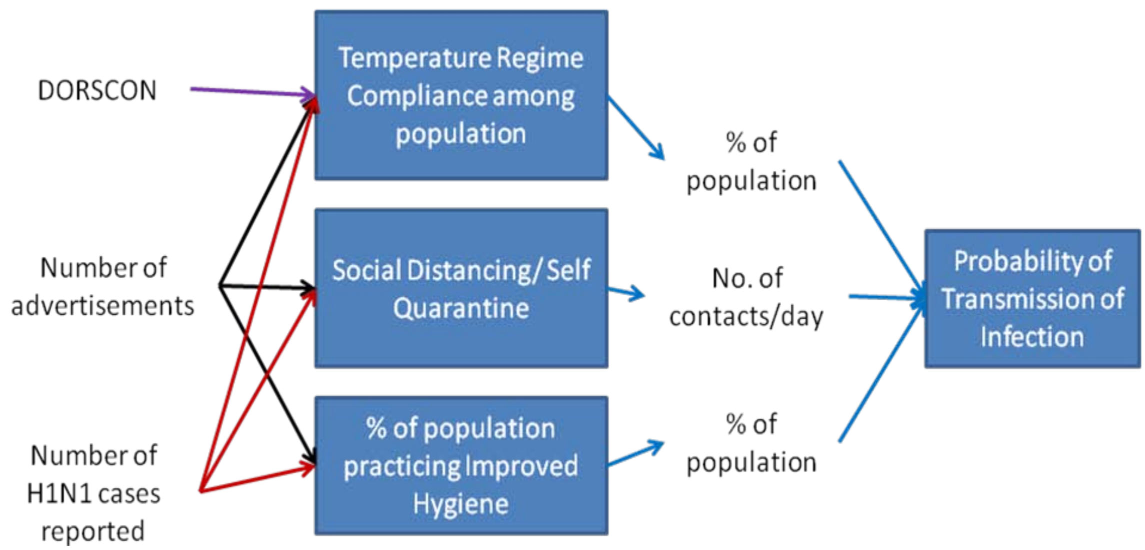

Figure 4: Factor effects on probability of transmission

Each of the blocks in Figure 4 represents a single fuzzy logic controller that consists of a rules base and membership functions for each of the inputs and outputs. Most of the blocks are self explanatory. The rules base in the logic structure shown in Figure 4 is a collection of IF-THEN rules which capture how the variables are related to each other qualitatively. It attempts to capture the mental model of the system as is held by the domain experts. Relationships between the variables are not the only aspect which can be qualitative. The variables themselves can be described in qualitative terms. The membership functions which represent these variables map the range of values the variables can take into levels such as HIGH, LOW, MANY or FEW etc. Each variable has its own unique membership functions, with as many levels as appropriate.

The rules and membership functions can be gleaned from sources such as reports, expert knowledge, intuition, or data mining. The last piece of the puzzle is the fuzzy inference method which translates the qualitative descriptions used in the construction of the fuzzy logic controller into quantitative output which can is used in simulation. The Mamdani-Sugeno method (Tanaka and Niimura 1996) has been used in this model.

The fuzzy logic blocks are incorporated into the structure of the SEIR model is shown below in Figure 5.

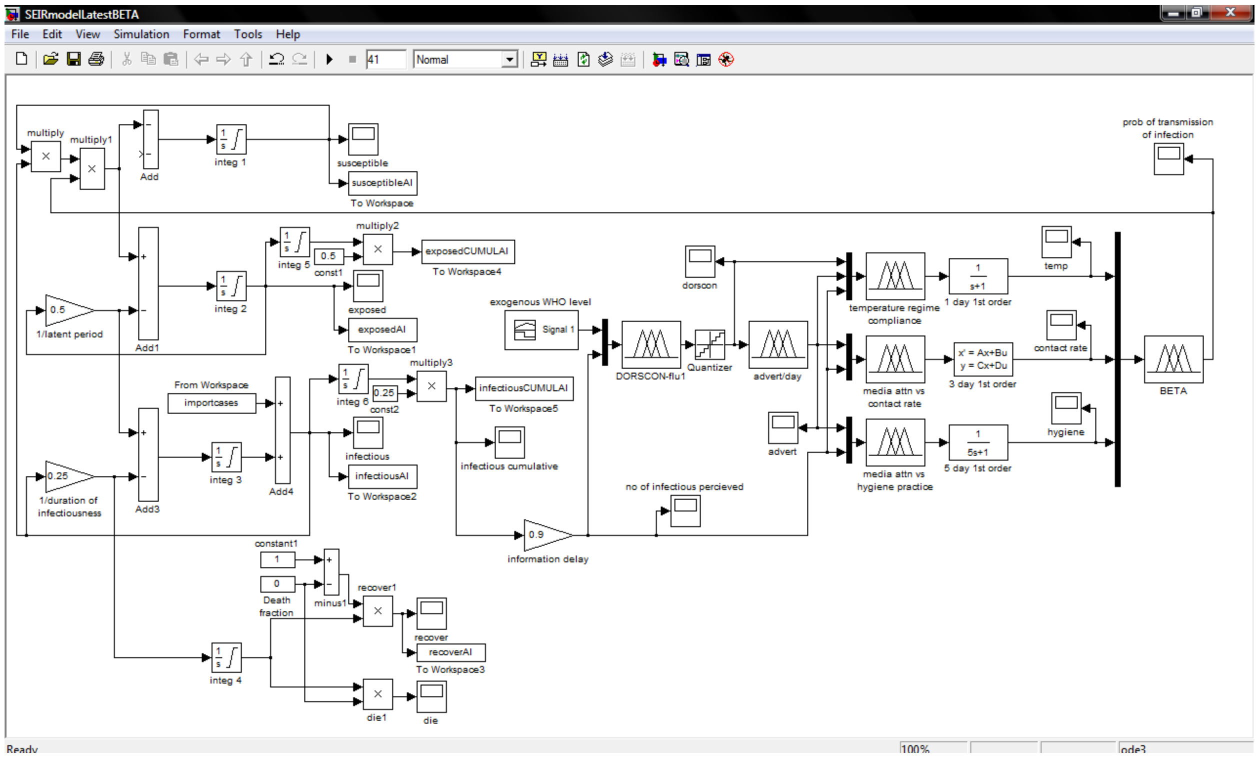

Figure 5. Structure Diagram of the fSEIR Pandemic Model

Preliminary Results

The incorporation of AI tools into the model produces a better match for the initial stages of the pandemic spread (see Figure 6). Compared to the original SEIR model, the model output is not seen to diverge wildly as time passes, lending credibility to the results of the model. Using AI tools has allowed us to make use of what limited quantitative and qualitative information is available and still be able to construct a model that mimics the behavior of the actual system.

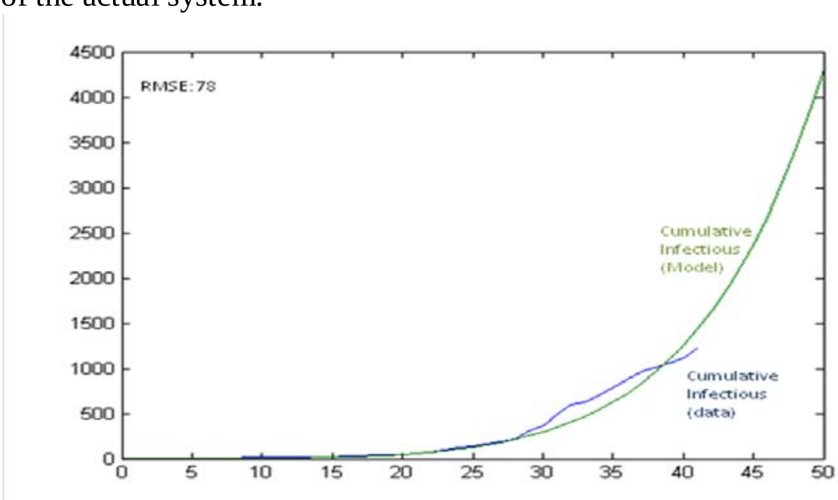

Figure 6: Integrating societal response in SEIR model

Without access to domain experts, the only sources available to us are journal articles and government releases. Despite this limitation, sufficient knowledge can still be learnt about a system from these sources to allow the formulation of an fSEIR model. In situations where rapid prototyping is required, or data is unavailable or in a qualitative form, the fSEIR model can be used to quickly bridge the gap between a causal loop diagram and a stock and flow model useful for simulations. With better information about the system available, the model can be further refined and improved. For example, data on the number of infected residents over a longer time period will provide for better calibration of the model parameters. The Fuzzy Logic controllers can also be improved by incorporating empirical data. Specifically, the fuzzy logic rules and linguistic variables and memberships can be better calibrated through surveys on public reaction to DORSCON and media attention, as well as SME's domain knowledge on DORSCON determination policies. The structure of the human behaviour system can be further improved with the input of domain experts as well.

Comparing the infection rates over time for the SEIR and fSEIR models (Figure 7), the peak of the pandemic has been observed to be delayed by about 1 month and lowered by approximately half. Using this result instead of the pure SEIR model can mean, for example, that policy makers can allocate lesser beds for pandemic purposes, which allows for lesser disruptions to normal hospital operations and the related economic costs. Stocks of anti-virals and prophylaxis that have to be maintained can be suitable adjusted as well. The time gained can be used to gauge how much time is available before the pandemic peaks, and how long the measures have to be continued before they are rescinded.

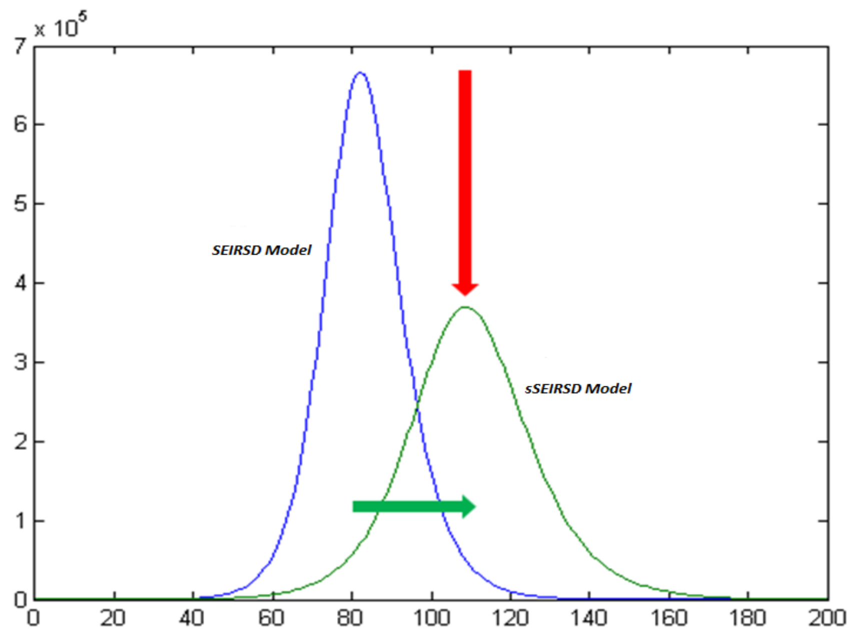

Figure 7: Comparison of infection rates over time for SEIRSD and sSEIRSD models

The predictions can be improved by estimating statistical prediction or confidence intervals for pertinent measures through simulation. The pandemic peak value and time involved, the number of infectious people expected can all fall within a certain range that reflects the uncertainty inherent in the system. Using this information, policy makers can make better and more optimal decisions for the well being of society.

Conclusion and Future Direction

In this paper we developed the dynamic systems model of a pandemic attack with inclusion of the feedback effects of social response on the disease infectivity. This closes the pandemic-socio-behavioral loop and in particular is of relevance to a closely knit society such as Singapore. Such a model serves as a valuable decision-support to healthcare policy-makers looking to evaluate the dynamic impacts of various pandemic mitigation instruments. Furthermore, our proposed fSEIR model and approach enables the rapid prototyping of system models for effective deployment under time-critical situations. Ongoing work includes model calibration with medical domain experts, disaggregation of the susceptible into different behavior groups, and optimizing budget allocations in pandemic preparedness accounting for social effects.

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