Compositional Cyber-Physical Epidemiology for effective Pandemic control in the context of New Zealand

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Abstract:

The COVID-19 pandemic has caused over twenty five million infections and one million deaths[1]. The overall economic and societal impacts are yet unknown. Governments are adopting different control measures, which are a combination of several non-pharmaceutical interventions (NPIs) in order to reduce the spread. As more information becomes available on the COVID 19 pandemic, more complex and sophisticated projection models are being developed. Deterministic differential equations based models, stochastic agent-based models and ML/AI based models are few of the various models currently under research. Although sophisticated models are believed to analyze and simulate the projections better, no one model is perfect. This is due to the lack of information, reliable data, and knowledge about the virus. Thus every model has its own set of assumptions, most researchers vary the parameters/assumptions of the model to generate the set of possible outcomes, but this compromises the robustness of the results due to the reliance on a single model. To compare and study different epidemiological models is challenging as the disease dynamics and the governing principles are often intertwined, making it difficult to evaluate the projections of different models against a single control policy.

We propose a systematic set of guidelines to separate the two components and modelling the disease dynamics as a physical process and the control policies as an adjoining controller; we are able to study the interactions between them formally. Our work is inspired by the engineering approach for the design of Cyber-Physical Systems (CPSs). Consequently, we term the new framework Compositional Cyber-Physical Epidemiology (CCPE).

Introduction:

CCPE helps to decouple the epidemiological models, and this separation improves the ability of the model to analyze complex control policy[2] and more importantly allows us to change the disease dynamics/control policy without affecting its counterpart by creating a universal interface between them. This process helps to evaluate the results of various models against a single decision(controller parameters) and can provide a set of reliable and robust predictions that can aid the decision-makers[3].

We note that there exist three core aspects of pandemic modelling and control:

1. the underlying epidemiological model covering disease dynamics,
2. the control actions and policy undertaken by governments, and
3. additional informative models, such as that of an economic model to evaluate the health vs economic tradeoffs.

This report proposes a set of guidelines which can be used for evaluating the impact of communicated diseases, along with the efficacy of various control measures. We do this in the context of New Zealand, which has the disease under control, by comparing several different COVID-19 models to the real-world data and implementing control strategies. Subsequently, we can analyze different control strategies against this range of models in terms of the health impacts that are experienced. This enables the selection of the most suitable model of disease dynamics along with the most effective control strategy for a given situation.

In addition to the health impacts of COVID-19, many countries are struggling to balance this alongside the economic impact of the disease. Using forecasted Gross Domestic Product (GDP) models generated by the New Zealand Treasury [9] for a range of control strategies, we can combine the impact in terms of both health and economy. Additional information such as this allows governments to create control strategies which can avoid sending the country into an economic hole, while also avoiding catastrophic loss of life. This tradeoff analysis helps answer important questions such as (1) How early can the government relax the restrictions without increasing the death count substantially? (2) What will be the loss in GDP if the lockdown is extended by a month?

Despite international cooperation and exchange of information, there is a lack of effective guidelines for pandemic control. Different countries have taken different approaches for handling the pandemic majorly due to their differences in cultural backgrounds, health infrastructures and financial capabilities. While few countries have succeeded in controlling the pandemic, many other countries have been struggling to manage it. Since there exists no one fit for all approach for handling the pandemic, we instead focus on providing insights and knowledge on how control policies should be developed, how to balance the economy and the health impact of the pandemic along with what should be the approach going forward for New Zealand which can be extended for any other country. Thus our work is not limited to mathematical models and economic impact analysis but instead focuses on developing a wholesome guide to effective pandemic control.

Design:

Building on previous research works on [4] we focus on extending that approach for multi-model comparisons to analyze possible outcomes by comparing various control policies and assumptions to generate a robust and a reliable set of predictions that can help develop control policies to manage the pandemic in the context of New Zealand.

We use the modified deterministic SEIR(Susceptible, Exposed, Infected and Removed) model [4], the deterministic CovidSim 1.0 model[5], and the agent-based stochastic model[6] in our analysis. These three models have widely different properties as described in table 1, which helps in generating all possible scenarios in the absence of accurate information. As expected, the disease dynamics and the governing principles are intertwined, we decouple them and model them as independent agents interacting with one another through a universal interface. We term the disease dynamics as “Plant” and the governing principles as the “Controller”.

Table 1: Comparison of various models

Models	**Type**	**Testing Rates**	**Asymptomatic Cases**	**Other Properties**
SEIR	Deterministic	Yes	No	Considers detected and undetected cases
CovidSim 1.0	Deterministic	No	Yes	Captures the flow accurately by introducing more states
Stochastic	Stochastic	No	Yes	Sensitive to cases, delay in detecting and isolation

The SEIR and the CovidSim 1.0 models use ODEs to capture the progression of a disease through the population, as people become infected, progress through their infection and infect others. The modified CovidSim 1.0 model is an advanced version of the SEIR model which includes the division between symptomatic and asymptomatic cases and also implements multiple stages for a single state to capture the flow of the infection within the population accurately.

As opposed to these macro modelling approaches the Stochastic model tracks each individual separately through various stages of the infection by assigning parameters to each individual sampled from a predefined distribution describing the parameter.

Each plant is defined as a set of states and parameters that capture the spread of the disease through a population. The definition and the dynamics of each plant are available in their respective papers as reference above. Each controller is defined as a set of alert levels inspired by the NZ government's strategic approach for pandemic control. The parameters are defined for each alert level, and the controller can switch between alert levels statically(based on predefined time factors) or dynamically(based on evolving information such as active cases or daily reported cases). The strictness of each alert level is obtained from the University of Oxford stringency index[7]. Interventions involved at each alert level in New Zealand is defined in table 2[8]. Along with the R0(reproduction rate) value other parameters such as testing rates, delay in isolation etc. could be added to the controller to generate more accurate predictions.

Intervention	Weight	Level 4	Level 3	Level 2	Level 1	Level 0
Widespread testing	0.186	✓	✓	✓	✓	✗
Temperature checkpoints	0.093	✓	✓	✓	✓	✗
Contact tracing	0.186	✓	✓	✓	✓	✗
Close contacts of confirmed cases ordered to self-isolate	0.093	✓	✓	✓	✓	✗
Large scale disinfection efforts	0.046	✓	✓	✓	✗	✗
Distribution of PPE to at-risk workers	0.093	✓	✓	✓	✓	✗
Hygiene public awareness efforts	0.186	✓	✓	✓	✓	✗
International travel ban	0.186	✓	✓	△	✗	✗
Domestic travel restrictions	0.093	✓	✓	△	✗	✗
People forced to remain home	0.186	✓	✗	✗	✗	✗
Bans on outdoor gatherings over 500 people	0.093	✓	✓	✓	✓	✗
Bans on indoor gatherings over 100 people	0.093	✓	✓	✗	✗	✗
Bans on recreational sports	0.046	✓	✓	✗	✗	✗
Bars and restaurants close	0.186	✓	△	✗	✗	✗
Schools close	0.186	✓	△	✗	✗	✗
Tertiary education facilities close	0.093	✓	△	✗	✗	✗
Small food retailers close	0.093	✓	✗	✗	✗	✗
Non-essential retail business close	0.093	✓	△	✗	✗	✗
Summation	2.184	2.184	1.673	1.116	0.930	0
Base reproduction number (R_0)		2.5	2.5	2.5	2.5	2.5
Final R value		0.316	0.827	1.384	1.570	2.5

Table 2: R0 values for various alert levels

By utilizing the capability of the compositional modelling technique, we compare three different plant models with different properties and dynamics coupled with five intelligently defined control policies to study and analyze the possible outcomes of the Covid19 pandemic in New Zealand.

Unlike previous studies which rely on a single model and vary its parameters to study different possible outcomes, the compositional approach provides a unique opportunity to compare widely different plant models coupled with the same government actions.

Implementation:

Plants and Controllers:

All the plants and the controllers defined above are modelled as HIOA(Hybrid Input-Output Automata) by using HAML(Hybrid Automata Modelling Language)[6].

Parameters:

Parameters values are shown in the table below:

Parameter	Value	
Basic reproduction number	$R_0 = 2.5$	
Total population size	$N = 5$ million	
$E \to P$ transition rate	$\alpha = 0.25$ day^{-1}	Wilson et al (2020)
$P \to I$ transition rate	$\delta = 1$ day^{-1}	Wilson et al (2020)
$I \to R$ transition rate	$\gamma = 0.1$ day^{-1}	Wilson et al (2020)
Relative infectiousness in presymptomatic period	$\epsilon = 0.15$	Wilson et al (2020)
Transmission coefficient	$\beta = \frac{R_0}{\epsilon/\delta + 1/\gamma} = 0.2463$ day^{-1}	
Testing rate for symptomatic infections	$c = 0.1$ day^{-1}	
Infection fatality rate (when ICU is under max. capacity)	$IFR_0 = 1\%$	
Infection fatality rate (for infections exceeding ICU capacity)	$IFR_1 = 2\%$	
Proportion of total infections requiring hospitalistion	$p_{\text{hosp}} = 5\%$	Wilson et al (2020)
Proportion of total infections requiring ICU	$p_{\text{ICU}} = 1.25\%$	Wilson et al (2020)
Estimated ICU maximum capacity	$n_{\text{ICU}} = 500$ beds	Ministry of Health (2005)

Table 3: Parameter values used

Initial Values:

The initial values for the models are defined by fitting the accumulative cases for the first 33 days starting from day zero(March 21st). This starting point is chosen so that the cases reported from then are due to community spread and not international travellers. The Scipy Python library[10] is used to optimize the initial values for the SEIR and CovidSim using gradient-based optimization techniques, whereas parameter search was used for the Stochastic model.

Control policy analysis:

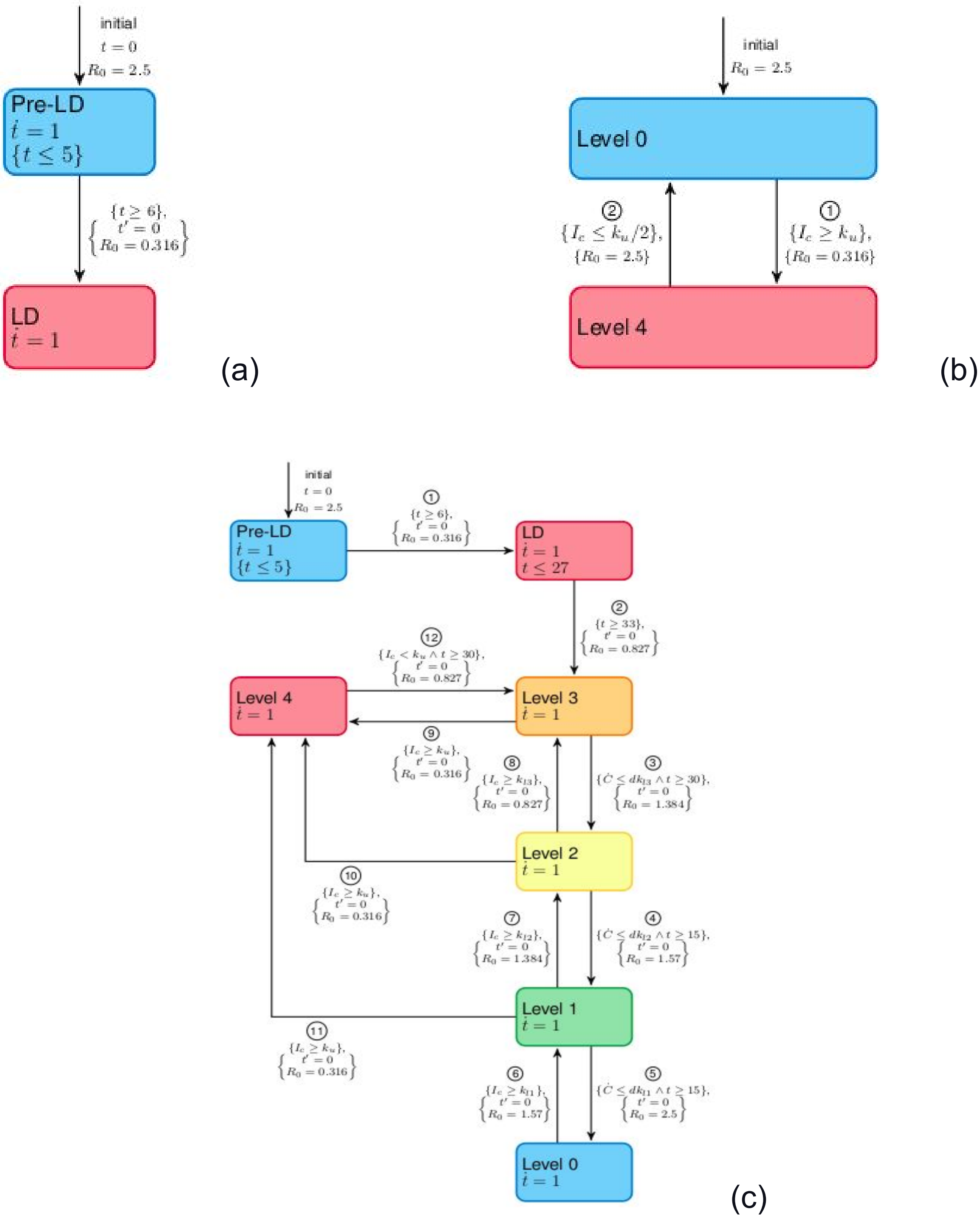

Figure 1: HIOA of all the controllers used in the analysis
(a) NZ-C1
(b) NZ-C3
(c) NZ-C2

The NZ-C1 controller is the best possible option to minimize the deaths, but unfortunately, such a control policy would require the government to enforce level-4 restrictions for almost two years or at least until a vaccine is developed which might be practically impossible as well as push the country into an economic crisis. Although such a controller might reduce the total cases and deaths, it might affect people's lives in other ways due to the economic consequences.

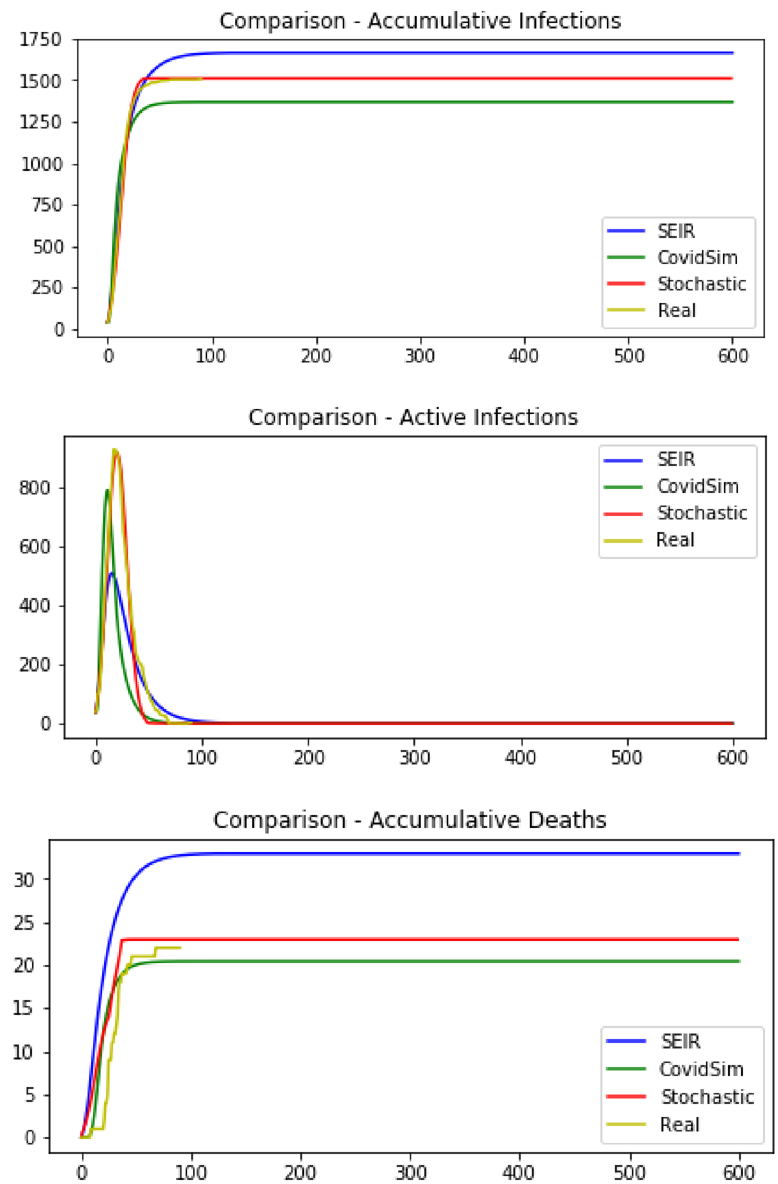

Figure 2: Comparison of various models against NZ-C1 control policy

	Accumulative Infections	Accumulative Deaths	Correlation (Accumulative Infections)	Correlation (Active Infections)	Correlation (Daily reported Cases)	Correlation (Accumulative Death)
SEIR	1668	33	0.98951809	0.969526	0.91969361	0.93760638
CovidSim	1369	20	0.9785644	0.7291041	0.7187642	0.92231525
Stochastic	1511	23	0.99767723	0.98665718	0.94119168	0.95847826

Table 4: Analysis of various models against NZ-C1 control policy

From the above figures the stochastic model is the most accurate model for capturing the flow of the disease. The figure plotted for the stochastic model is the average of 100 simulations. All the three models stabilize around 1500-1700 cases for this controller which means that the controller can manage the pandemic but as described before this required the government to maintain very long lockdowns with level 4 restrictions which might not be practically or economically possible.

The NZ-C3 controller which oscillates between level-4 and level-0 restrictions providing the citizens with the opportunity to carry out their day to day activities frequently (approximately every alternate month) might reduce the economic impact compared to the NZ-C1 controller but will lead to a substantial increase in the total number of deaths which might affect the country in other ways. This control policy will take years or might not even be able to control the spread of the virus. This oscillation will continue until the majority of the population have become immune to the virus or until a vaccine is developed.

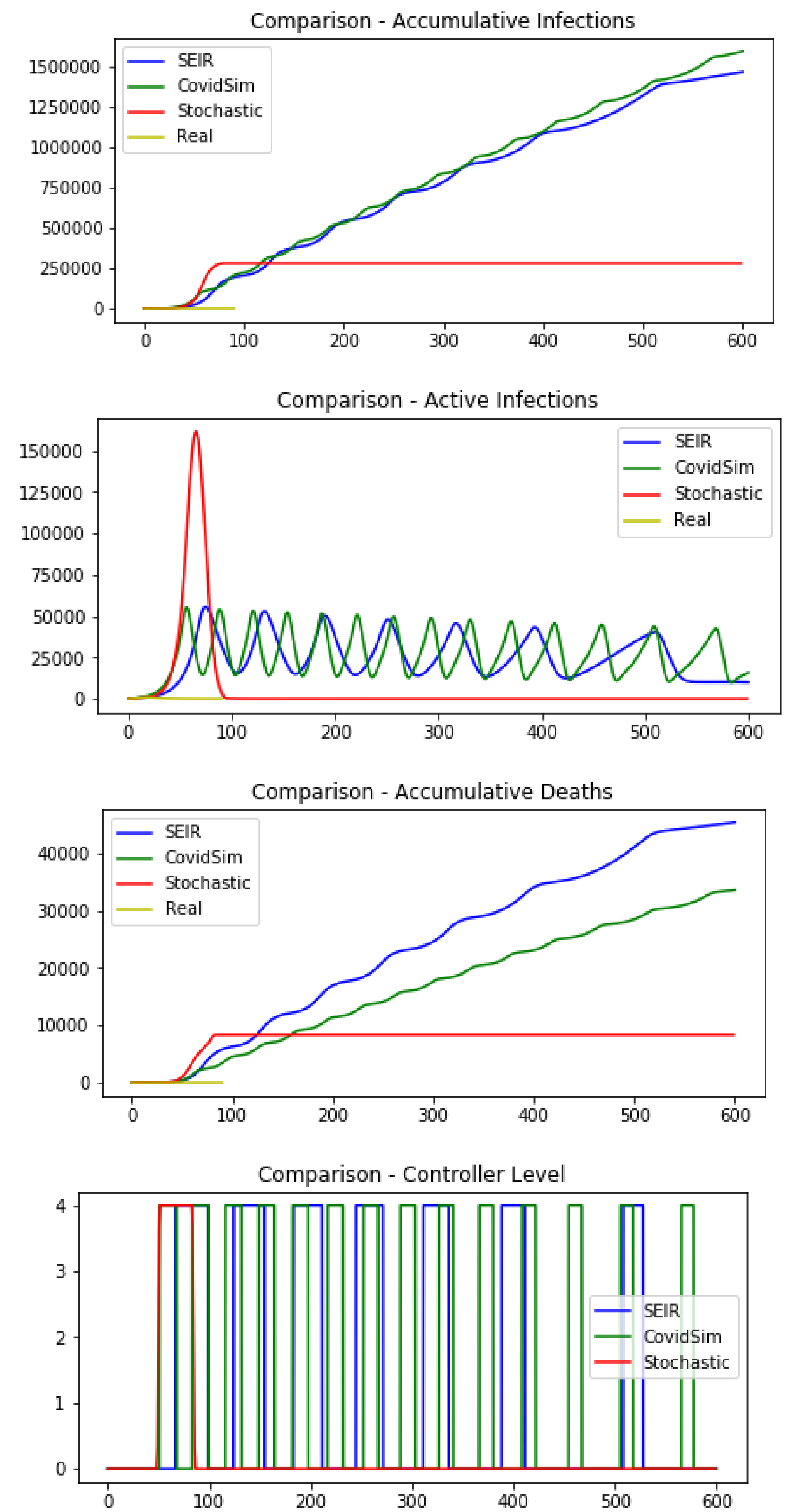

Figure 3: Comparison of various models against NZ-C3 controller

	Accumulative Infections	Accumulative Deaths	Correlation (Accumulative Infections)	Correlation (Active Infections)	Correlation (Daily reported Cases)	Correlation (Accumulative Death)
SEIR	1470361	45285	0.43922417	-0.6758392	-0.54223557	0.5842408
CovidSim	1598809	33553	0.53482249	-0.6672058	-0.58984918	0.67103505
Stochastic	283355	8370	0.4838162	-0.5699814	-0.41957796	0.65047366

Table 5: Analysis of various models against NZ-C1 control policy

Our models show contrasting results for the NZ-C3 controller where the stochastic model has one huge spike of infections and the pandemic is controlled, the SEIR and the CovidSim models show many subsequent never ending small waves of infections. These waves will only be controlled when the majority of the population are immune to the virus. As opposed to 1500-1700 infections of the NZ-C1 controller the NZ-C3 controller can lead to 0.25 - 1.5 million infections and around 8000-45000 deaths which are way higher than the NZ-C1 controller. Thus the NZ-C3 is not an ideal control policy and can lead to a worse outcome if implemented.

The NZ-C2 controller unlike the NZ-C1 and the NZ-C3 controllers balances the economic and the health impact caused due to this pandemic. It enforces level-4 control very early and reduces the restrictions based on the case numbers. Delaying the enforcement of these restrictions (NZ-C2B) or failing to impose harsh restrictions (NZ-C2C) can lead to a surge in the case numbers.

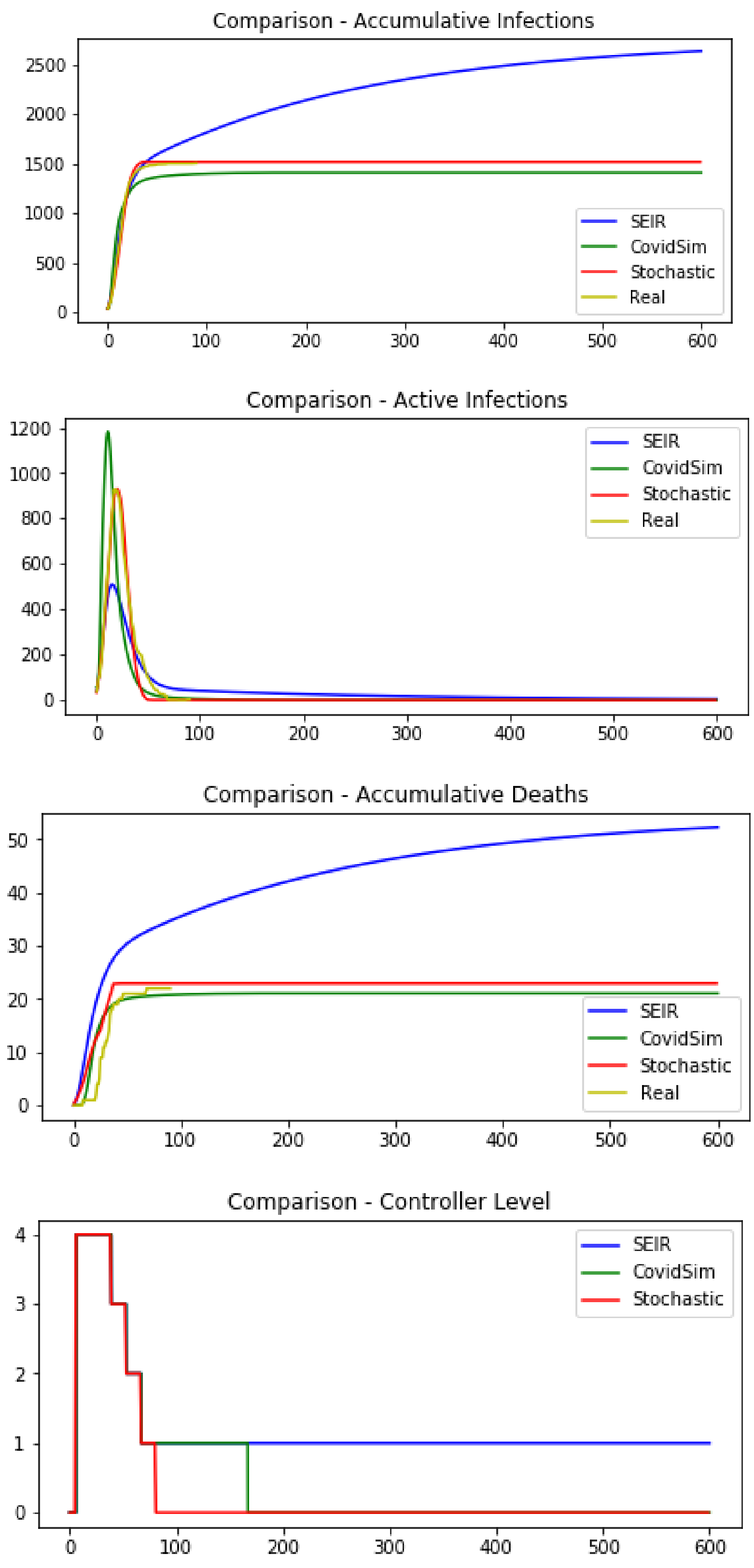

Figure 4: Comparison of various control policy against NZ-C2 controller

	Accumulative Infections	Accumulative Deaths	Correlation (Accumulative Infections)	Correlation (Active Infections)	Correlation (Daily reported Cases)	Correlation (Accumulative Death)
SEIR	2637	52	0.98102114	0.97224366	0.92099641	0.94006444
CovidSim	1411	21	0.97934491	0.72619303	0.716486	0.92439012
Stochastic	1519	23	0.99784441	0.98681476	0.94498621	0.95730714

Table 6: Analysis of various models against NZ-C1 control policy

The stochastic model achieves a correlation coefficient of **0.99784441** for accumulative infections which clearly represents that it follows the actual curve very closely. The NZ-C2 control policy might lead to 1400-2700 cases and 20-50 deaths which are much better compared to the NZ-C3 controller but poorer than the NZ-C1 controller. But unlike the NZ-C1 controller, NZ-C2 doesn’t need to implement very strict restrictions for long periods of time rather early and strict restrictions can ensure that the pandemic is controlled.

The NZ-C2B controller is an extension of the NZ-C2 controller where the policy implementation is delayed by 4 days. Delaying the implementation of the control measure just by four days might lead to a 38-66% increase in the total cases and a 36-60% increase in the total deaths as displayed by the NZ-C2B controller. This clearly demonstrates the need to take quick actions and failing to do so can lead to catastrophic results.

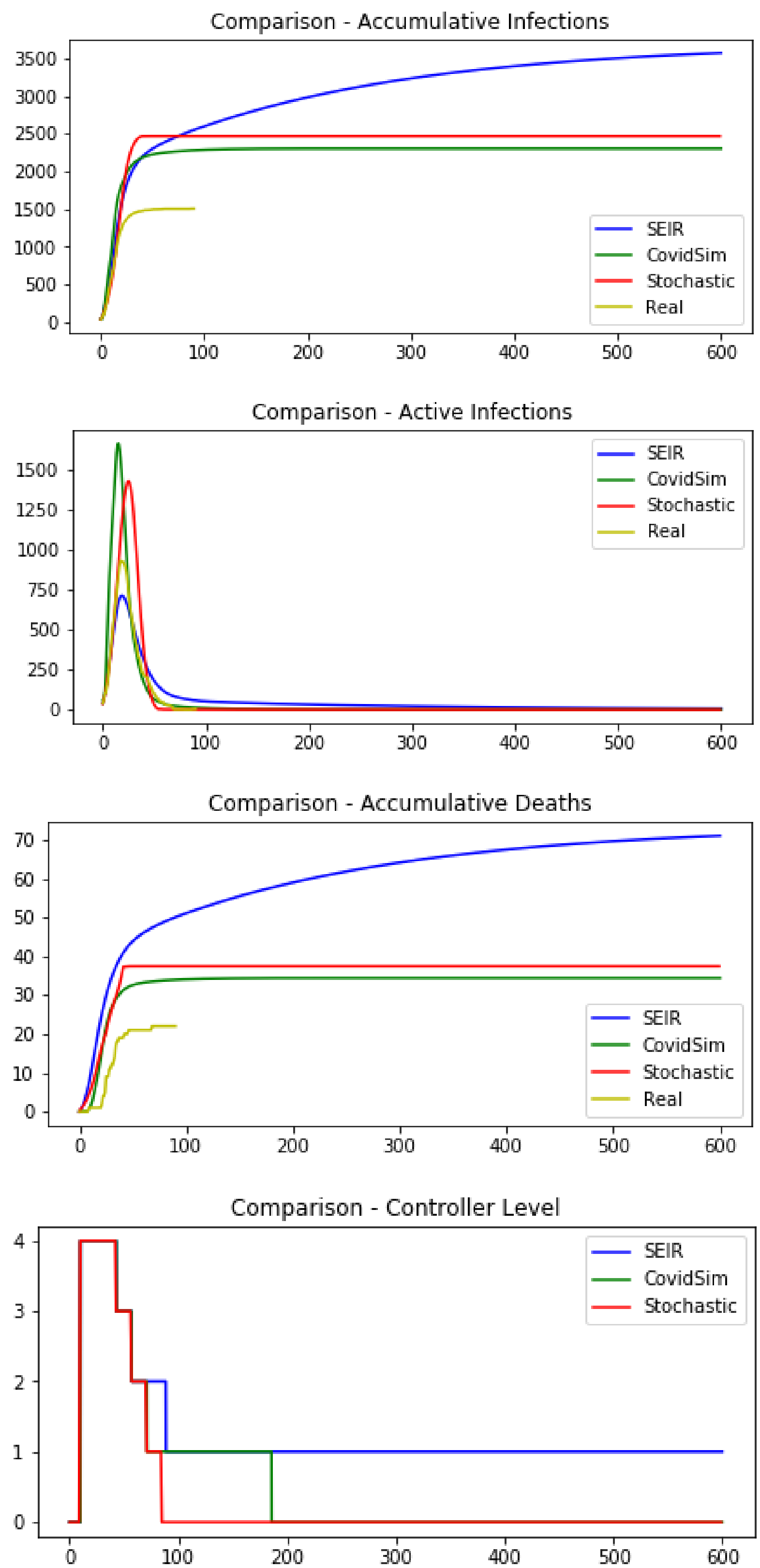

Figure 5: Comparison of various models against the NZ-C2B controller

	Accumulative Infections	Accumulative Deaths	Correlation (Accumulative Infections)	Correlation (Active Infections)	Correlation (Daily reported Cases)	Correlation (Accumulative Death)
SEIR	3575	71	0.97406078	0.9861803	0.94319528	0.95663308
CovidSim	2305	34	0.99776267	0.91092734	0.88208909	0.96212289
Stochastic	2469	37	0.97727588	0.91953237	0.79717118	0.97778473

Table 7: Analysis of various models against NZ-C1 control policy

The NZ-C2C controller is an extension of the NZ-C2 controller where the policy implementation is not delayed but instead of level 4 restrictions level 2 restrictions are enforced. Enforcing an early lenient control policy will increase the total cases by 30-90% and total deaths by 30-100%. Thus implementing quick actions that are not strict also leads to worse outcomes.

	Accumulative Infections	Accumulative Deaths	Correlation (Accumulative Infections)	Correlation (Active Infections)	Correlation (Daily reported Cases)	Correlation (Accumulative Death)
SEIR	5029	100	0.87480135	0.74940242	0.7622595	0.95978907
CovidSim	2624	39	0.95110231	0.90068172	0.79133792	0.97537483
Stochastic	2023	33	0.97448149	0.9508605	0.84367507	0.98194787

Table 8: Analysis of various models against NZ-C1 control policy

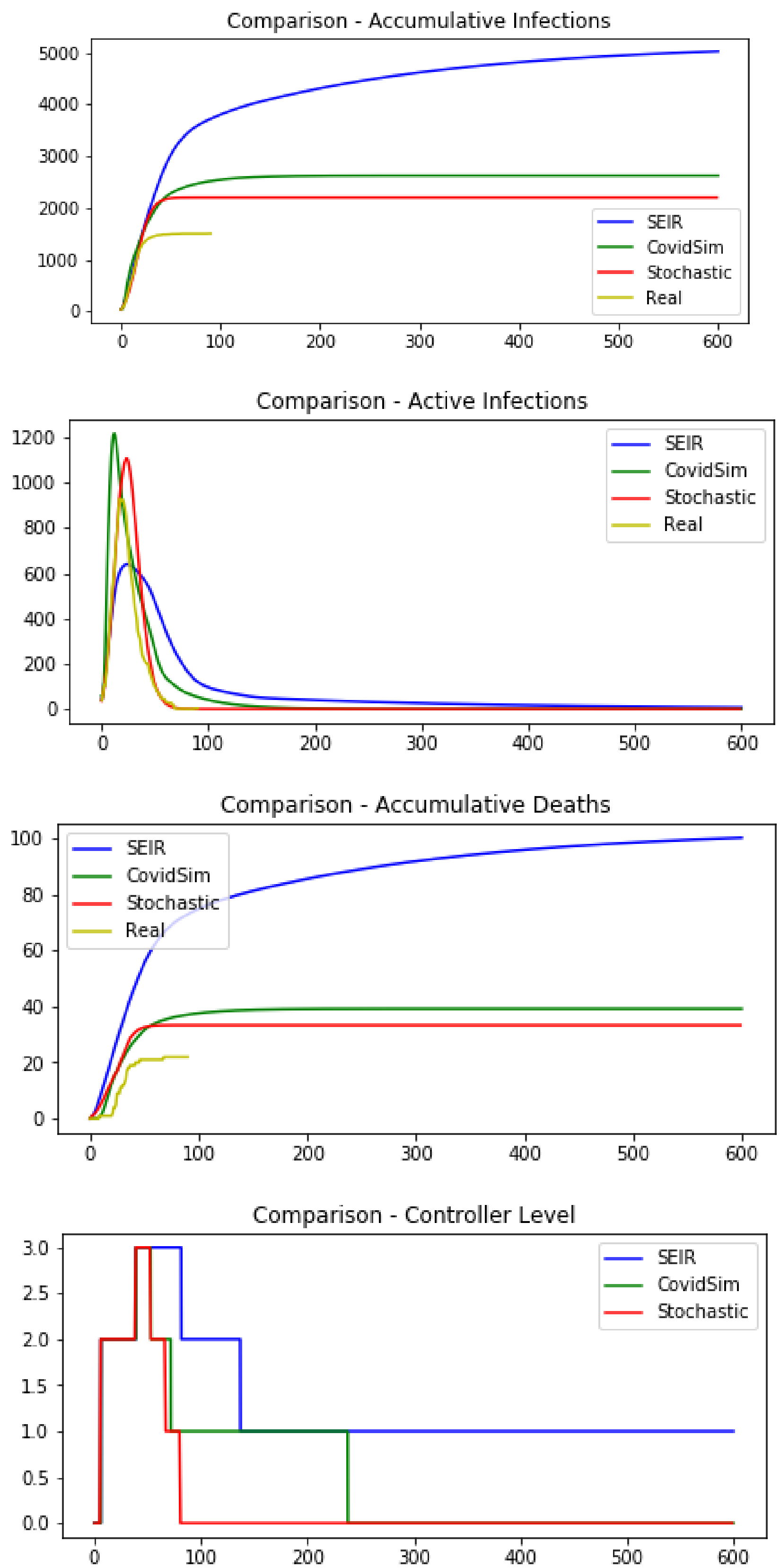

Figure 6: Comparison of various models against the NZ-C2C controller

The NZ-C2B and NZ-C2C controllers demonstrate various possible outcomes when the government fails to take early and strict actions. Although the NZ-C1 controller can reduce the cases to a minimum such a controller implementation can create an economic crisis in the country, this is explained in the following sections. Thus implementing strict and early measures are ideal for controlling the pandemic. Also monitoring the situation closely and not lifting the restrictions prematurely are also an essential requirement to ensure the safety of the public.

Economic Impact Analysis:

To analyze the economic impact of the control policies, we generate a Pareto optimal front[11] by using the epsilon constraint method where the best control policy is generated using particle swarm optimizer while GDP loss is constrained.

The SEIR model was used for this analysis and could be extended to other models as well. Using the quarterly GDP loss measured by the NZ Treasury[9] based on the alert levels enforced, we try to minimize the deaths by applying constraints on the total GDP loss.

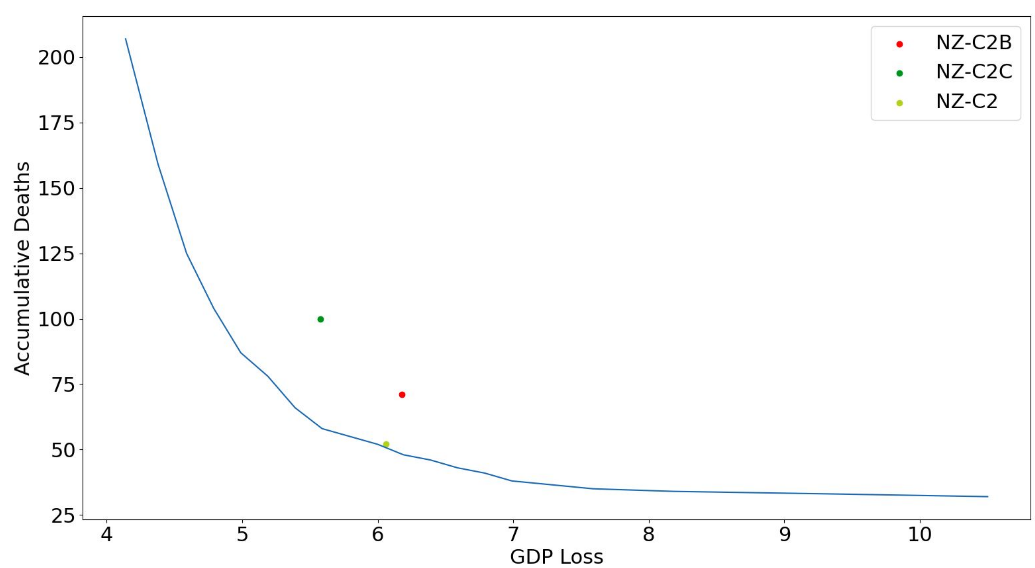

Figure 7: Deaths Vs GDP Tradeoff

From the above figure 7 it is clear that as the GDP loss increases there is a substantial reduction in the total number of deaths. The control policies that we implement should ensure that we reduce as many deaths as possible without affecting the economy of the country. The only controller that intercepts the Pareto optimal front is the NZ-C2 controller, also the controller is at the inflection point where the health and the economic impact both are minimized. Whereas the other controllers are above the curve which means that they are not the optimal strategies to manage the pandemic. The NZ-C2 controller strategy is to spend (33,14,14) days at alert levels 4, 3, and 2 respectively where as our tradeoff analysis suggests (20,43,4) both of which are very similar as they spend around 50-60 days at higher alert levels (level 4 or level 3) and the difference in the GDP loss and the deaths is only fraction. Thus the NZ-C2 controller is superior to the other control strategies analyzed and should be implemented for the best results.

The NZ-C1 and the NZ-C3 controller are not plotted in the above graph, as their GDP loss and the total deaths values are very high. The NZ-C1 controller lies on the far right of the graph where the cases are minimized but the GDP loss value is very high, the same reduction in cases could be achieved without a huge loss in GDP(36%) by lifting the lockdown sooned which would have lead to a 8-10% reduction in GDP with the same number of total deaths.

The NZ-C3 controller causes minimum 8000 deaths and 11-12% reduction in GDP due to the multiple waves of infection but as per the economic impact analysis we could restrict the GDP loss to 4-5% for the loss of around 200-250 lives. This clearly proves that the NZ-C3 controller is a bad control policy and should not be implemented.

The GDP loss function used in this analysis is a representation of the actual loss and is not an accurate measure. Other factors such as stimulus packages, Covid-19 spread in the other countries, international trades etc.

also affect the GDP loss, especially when the economy rebounds, those factors are not accounted for in our analysis. Nevertheless, the above analysis is a reflection of how policies should be developed that accounts for both the economic and the health impact of the pandemic. The analysis can provide much-needed insights for the policymakers and help understand the strength and limitations of various control measures.

Conclusion:

The report analyzes various control policies and its effects on controlling the pandemic. The multi-model analysis approach where three different models were evaluated against each control policy helps understand the possible outbreak scenarios. The CCPE framework ensures that complex control policies can be tested, and real-time decisions can be taken as the situation unfolds. On the other hand, the economic impact analysis provides a different angle for developing control policies by comparing their GDP losses. Thus building policies that proactively manage the outbreak by enforcing strict restrictions and knowing when to lift the restrictions are essential for controlling the outbreak. Lifting the lockdown prematurely might lead to the second wave of infections whereas not lifting the lockdown affects the country economically and our economic impact analysis model helps quantify these factors so that the policymakers can make well-informed decisions.

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