Neural Network Augmented Compartmental Pandemic Models

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Abstract

Compartmental models are a tool commonly used in epidemiology for the mathematical modelling of the spread of infectious diseases, with their most popular representative being the Susceptible-Infected-Removed (SIR) model and its derivatives. However, current SIR models are bounded in their capabilities to model government policies in the form of non-pharmaceutical interventions (NPIs) and weather effects and offer limited predictive power. More capable alternatives such as agent based models (ABMs) are computationally expensive and require specialized hardware. We introduce a neural network augmented SIR model that can be run on commodity hardware, takes NPIs and weather effects into account and offers improved predictive power as well as counterfactual analysis capabilities. We demonstrate our models improvement of the state-of-the-art modeling COVID-19 in Austria during the 03.2020 to 03.2021 period and provide an outlook for the future up to 01.2024.

1 Introduction

In the period between March 15th 2020 and April 4th, Austria enacted it's first series of COVID-19 NPIs [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11], resulting in a country-wide lockdown and restrictions of public life, followed by a series of repeated loosening and tightening regulations that have not been completely taken back until today [12, 13, 14, 15, 16, 17, 18, 19]. Nonetheless, as of March 1st 2021, 8574 people were registered as deceased with or by COVID-19 [20, 21] in Austria. Although a highly socio-politically relevant question, it remains unclear how effective these NPIs were, what would have happened without any NPIs or only a subset of the historical NPIs and whether a less intrusive set of NPIs exists which provides an outcome similar to the historical one. These are all counterfactual questions which cannot be empirically answered per definition but only through simulation. Given the correlation between weather and pandemic spread [22, 23, 24, 25], we recognize that any such simulation must not only model the pandemic given a certain set of NPIs, but also account for weather effects.

1.1 Related Work

ABMs, used by Austrian government agencies as decision support tool [26], are powerful instruments for simulating disease spread under NPIs (e.g. contact tracing [27]) as they simulate individual agents and their movement, behaviour and interactions but are also capable of evaluating immunization levels [28] and vaccination strategies [29] as well as estimating undetected cases [30]. However, they are computationally complex [28] which limits their use to institutions with access to sufficient computing power or specialized hardware [31].

A computationally less expensive model is the SIR model. Since its inception [32], the SIR model has been extended numerous times [33, 34, 35] and it recently found an application in the modelling of COVID-19 [36, 37, 38, 26, 39, 40]. The predictive power of the SIR model in the context of COVID-19 and been confirmed by [41]. Currently though SIR models are limited in their capability to simulate NPIs or weather effects, with proposed solutions ranging from segmenting and picking epidemiological parameters for various phases of the pandemic by hand or automatic change point detection and inference of epidemiological parameters for different phases of the pandemic [42] to training simple exponential regression models on predicting epidemiological parameters [40]. Other publications use projections of the effects of specific NPIs on reproduction number based on empirical studies of that particular NPI and incorporate them in the SIR-Model but completely disregard weather effects [37]. In any case the mix of varying weather conditions and large combinations of different NPIs can not be modeled by SIR models currently.

1.2 Motivation and Contribution

We propose separating the problem of estimating the epidemiological parameters as function of weather conditions and NPIs, which we do in an inductively learnt pre-prepossessing step, from the computation of the SIR model and to apply an inductively learnt post-processing step to the SIR-models result to compensate for the SIR-models intrinsic lack of representative power. Using our technique, we achieve improved predictive power at slightly higher computational cost than running non-augmented SIR models and are able to provide an efficient and accurate tool for backwards analysis of NPIs.

2 Model Pipeline

As mentioned in sec. 1.2, we separated the modelling of the pandemic in three separate tasks. Our pipeline, as illustrated in fig. 1, consists modelling reproduction number as function of weather and NPIs, which we accomplish using a neural network, modeling the spread of COVID-19 based on the modelled reproduction number using a SEIR-FV-Model and subsequently using the SEIR-FV-Model output as input for a group of neural networks correcting SEIR-FVs intrinsic error and inferring hospital resource utilization.

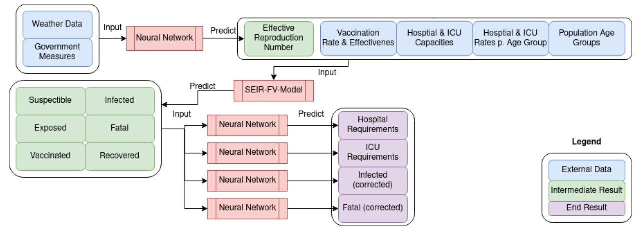

Figure 1: *Model Pipeline*

2.1 Reproduction Number

For modelling reproduction number R_{eff} as function of weather and NPIs, we used numerically encoded NPI data from Oxford COVID-19 Government Response Tracker (OxGRT) [43] which is already provided in machine-learnable format at daily resolution, monthly weather data from 1955 till today provided by Hohe Warte weather station near Austrias capital Vienna [44] and daily reproduction number estimates provided by AGES [45]. Zentralanstalt für Meteorologie und Geodynamik (ZAMG) [46], which could provide more fine granular weather data not only for Vienna but all of Austria, was contacted but unfortunately did not wish to cooperate. In order to be suitable input for a neural network, weather data is first up sampled to match OxGRT datas resolution using Fouriers method and most significant features are selected using linear regression-analysis. Based on the selected features, additional features are engineered via power and log transforms to allow more room for choice in the forthcoming step. Next OxGRT data and weather data are merged and scaled and linear regression-analysis is employed again to eliminate independent variables not affecting the dependent variable R_{eff} for a significance level of $p = 0.05$ with exception of NPIs. For NPIs, we manually selected which to keep and which to remove in order to be able to keep the model from picking measures not directly relevant for pandemic spread such as "Fiscal Measures", "Debt Contract Relief" or "Income Support" but nonetheless part of the OxGRT dataset and because we wanted measures with particularly severe potential human collateral damage (e.g. "School

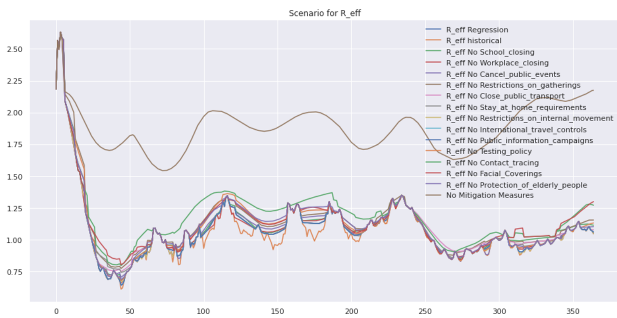

Figure 2: *Predicting R_{eff}*

	Low R_{eff}	**Mean R_{eff}**	**High R_{eff}**
R2	0.94	0.93	0.94

Table 1: R2 scores for predicting R_{eff} on 30% validation set via a neural network

Closures", "Workplace Closing") (CITE) to be kept even if not chosen for the given significance level. Finally after the preprocessing of the training data is finished, we train a neural network on each of the 3 R_eff estimates (lower, upper, mean) provided by AGES. We chose a neural network with non-linear activation functions over a linear regression model because despite achieving a good fit (R2=0.99) during regression analysis in previous steps, the linear regression model performed very poorly for OOS data (we found setting multiple NPIs in the dataset to 0.0 could lead to the linear regression model predicting negative reproduction numbers), a deficit we did not find using a non-linear neural network.

Dependent on application, for backwards-analysis we apply a post-processing step that introduces historical R_{eff} estimates as lower bound for scenarios where a specific NPI is completely removed s.t. e.g. in a scenario without mandatory face masks, R_{eff} can never be lower than in a historical case were face masks were mandatory. For forward-analysis the post-processing step is naturally not applied.

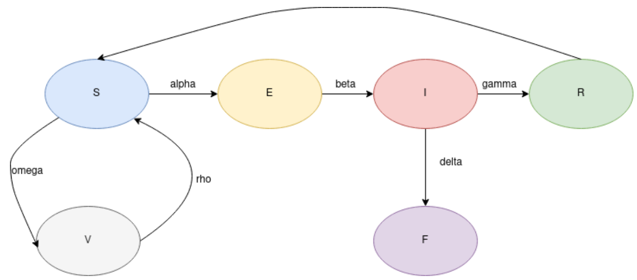

Figure 3: ***S**usceptible, **E**xposed, **I**nfectious, **R**ecovered, **F**atal, **V**accinated*

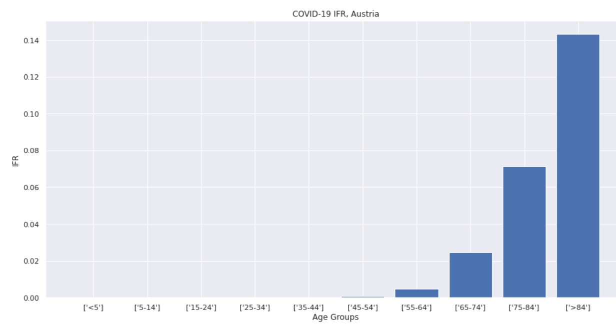

Figure 4: *Per Age Group IFR*

2.2 Pandemic Model

The predicted lower, mid and upper vectors containing daily R_{eff} values for given time interval is then handed to three SEIR-FV models (one for each estimate of lower, mid, upper R_{eff}) which, for each age group, tracks **S**usceptible, **E**xposed, **I**nfectious, **R**ecovered, **F**atal, **V**accinated population groups, see fig. 3 for a simplified illustration. The initial age group distribution is obtained from [47], Hospitalization, Intensive Care Unit (ICU), Infection Fatality (IFR) (fig. 4) ratios per age group is obtained from [48]. The age groups data is homogenized to groups from < 5 to > 84 in 5 year intervals. The rate at which people are vaccinated with any vaccine is obtained from [49] and for ease of use, an average daily vaccine doses available per day is computed by fitting a linear function through the data (fig. 5) and using its slope. The SEIR-FV models follow an old-first vaccination strategy, i.e. available vaccine doses

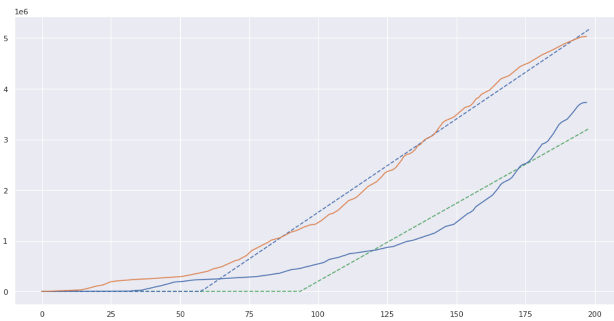

Figure 5: *Vaccination Rate in Austria*

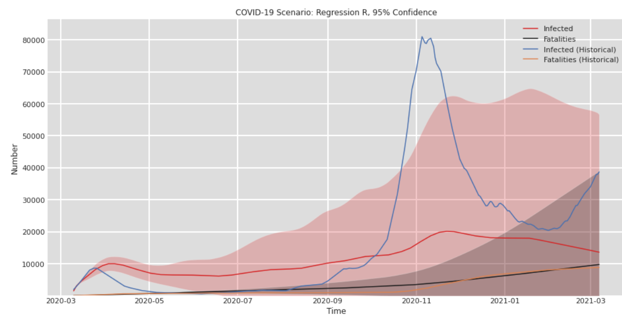

Figure 6: *SEIR-FV, R obtained from NN Regressor*

are distributed among age groups preferring older age groups over younger age groups. For duration of vaccine and recovery immunity and efficiency, we use estimates based on [50]. Incorporating ICU and Hospitalization rates into the model is done statistically: based on the a-priory known hospitalization and ICU rates for each age group as well as the current number of infected computed by the SEIR-FV model, we infer the number of persons of an age group requiring a hospital bed or an ICU bed. For cases where hospital requirements exceed hospital resources, we made the simplifying assumption that all patients requiring hospital treatment but not receiving it become a fatality.

2.3 Error Correction Networks

The pandemic models provided by SEIR-FV even for the time dependent R_{eff} computed from weather and NPI data by the NN regressor is, while qualitatively making accurate predictions where the peaks in disease spread are, quantitatively off by orders of magnitude (fig. 6). We solve this by training so called error correction neural networks (see sec. 2, fig. 1 for the step in the modelling pipeline) on correcting the SEIR-FVs outputs error (fig. 7) and furthermore predict the amount of hospital resources used (fig. 8). As illustrated by the figures, our error correction neural networks approach greatly improves the SEIR-FVs outputs quantitatively with the the historical numbers of infected and fatal cases being inside the given 95% confidence interval for the whole 03.2020 to 03.2021 time period. For hospital resources (regular and ICU beds), the augmented model produces a quantitatively and qualitatively equally accurate output for a 85% confidence interval. Regarding network architecture, we use simple 4-Layer ReLU activated MLPs. To account for the uncertainty that comes with using such networks that always incorporate randomness due to their random initial state, we train groups of 10 networks for each of the target variables (infected, fatal, hospital bes, ICU) and provide the results in the form of confidence intervals.

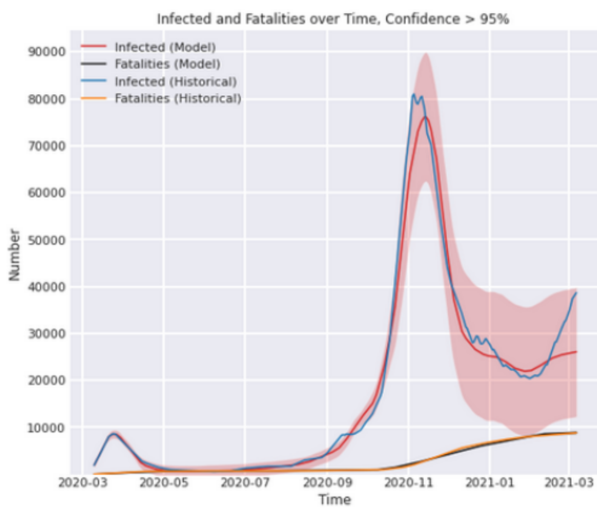

Figure 7: *NN Error Correction Augmented SEIR-FV, R obtained from NN Regressor, 03.2020 to 03.2021 time frame*

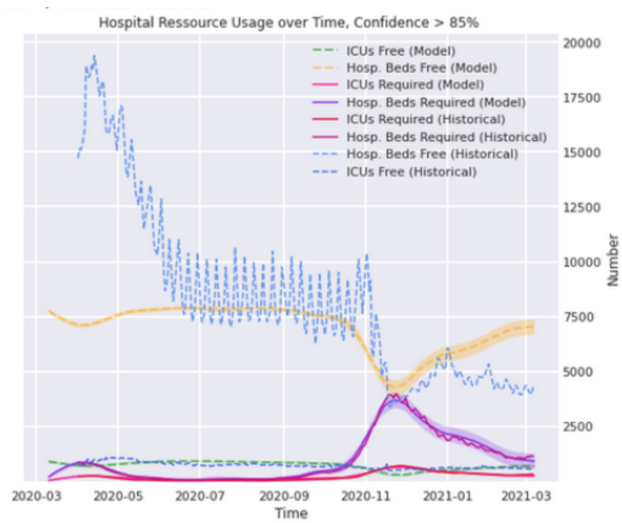

Figure 8: *Hospital Resource Requirements computed by NN, 03.2020 to 03.2021 time frame*

We do this for each of the three SEIR-FV models computed for the three estimates for R_{eff}.

2.4 NPI Collateral Damage Model

Secondary to modelling pandemic spread, we decided to model human collateral damage of NPIs as well. Our simple collateral damage model exploits the known correlation between life expectancy and health and economic development [51, 52, 53] and the observed economic depression [54, 55] during the pandemic which we conjecture to be caused by business and border closures. Other potential causes of collateral damage such as mental health [56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67], disrupted medical supply chains [68], skipping of early medical examinations [69] and problems for people with disabilities [70] were initially considered but we decided to disregard them due to a lack of useful coherent data. For our economy-based collateral damage model, we first confirmed that a statistically significant (p=0.05) relation between economic factors life expectancy existed in pre-corona times, a purpose for which we used we used OECDs GDP and life-years-lost (LYL) data sets [71], and that the same holds for NPIs and

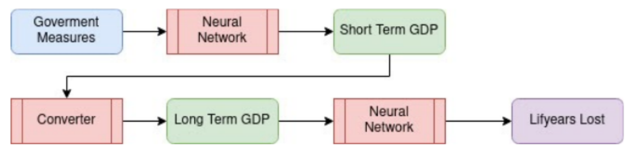

Figure 9: *NPI Collateral Damage Model*

GDP. Next, as depicted in fig. 9 we trained a NN to predict GDP dependent on NPIs and another NN to predict LYL dependent on GDP to finally obtain a pipeline modelling LYL dependent on NPIs. Admittedly this approach suffers from not taking the collateral damage produced by corona itself into account (which would certainly be strong in case of e.g. an unrestricted spread of the pandemic) but the lack of a baseline for such scenarios made it impossible to model them.

3 Results

We applied our approach in two different task. First, we applied it to the backwards analysis task, i.e. asking the counter factual question "What would have happened if NPI $< x >$ had not been in place?" to find out which NPIs were most crucial in the past. Second, we apply our approach to predicting future developments. In this case, we will make a simple statistical weather prediction for future weather based on the historical data provided by Hohe Warte weather station to use as input for our NN regressors trained to predict R_{eff}.

3.1 Backwards Analysis

For backwards analysis of NPI effectiveness, we follow a "take one out" approach. We compute each scenario under the assumption of historical weather and NPIs but with a particular NPI not implemented i.e. it's zeroed in the input data matrix. Fig. 10, 11 display infections, fatalities and hospital resource usage for the hypothetical scenario were no workplaces closures were implemented. The model predicts a slightly higher peak during the winter months and accordingly a higher hospital resource consump-

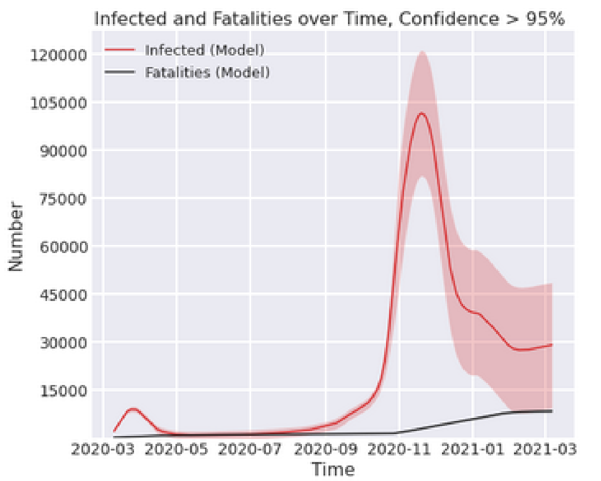

Figure 10: *No Workplace Closing, Infected and Fatalities, 03.2020 to 03.2021 time frame*

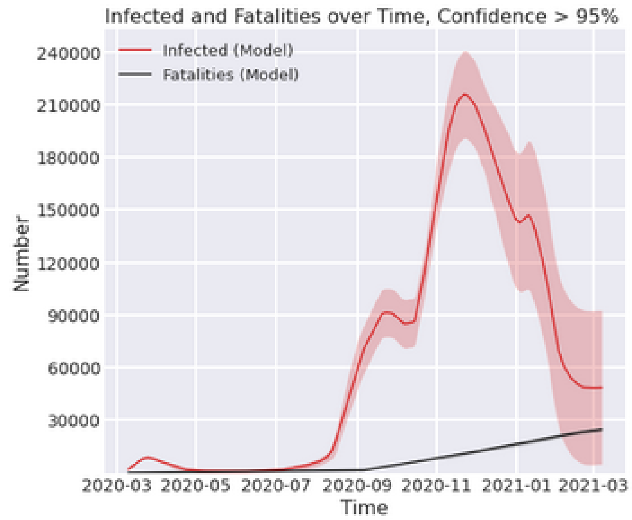

Figure 12: *No Facial Masks, Infected and Fatalities, 03.2020 to 03.2021 time frame*

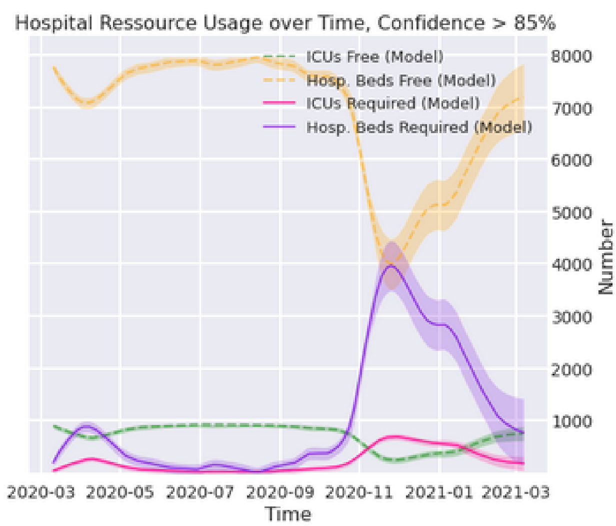

Figure 11: *No Workplace Closing, Hospital Ressource Requirements computed by NN, 03.2020 to 03.2021 time frame*

tion. Particularly critical is the elongated period ICUs are over capacity compared to the historical scenario, leading to slightly higher number of fatalities in vulnerable age groups. Another potentially interesting scenario is no obligatory facial mask usage (fig. 12, 13). Infections and fatalities nearly triple for this scenario, hospital resources are catastrophically overburdened for a period of over six month which contributes massively to fatalities in older population groups likelier to require ICU care in case of an infection. Finally, we want to explore the case where no mitigation measures were implemented at all and COVID-19s spread is only controlled by weather dynamics and population composition (fig. 14, 15). In this scenario, we see a massive peak for infections in September with multiple million people suffering a COVID-19 infections simultaneously. The massive and constant operation of hospitals over capacity over the whole evaluated time frame leads to up to a quarter million fatalities within the first 12 months of the pandemic.

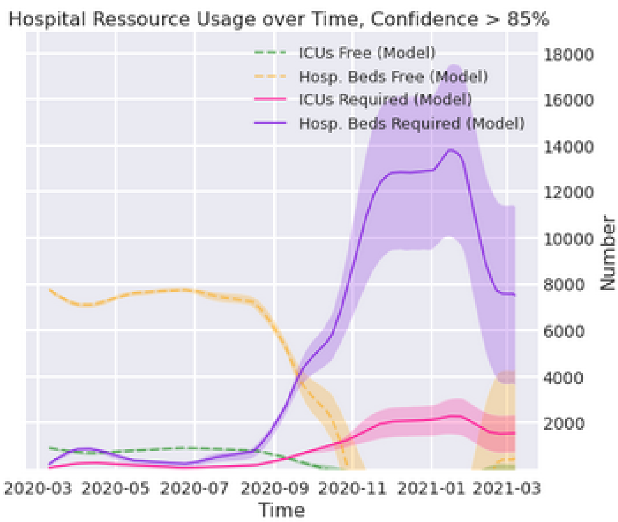

Figure 13: *No Facial Masks, Hospital Ressource Requirements computed by NN, 03.2020 to 03.2021 time frame*

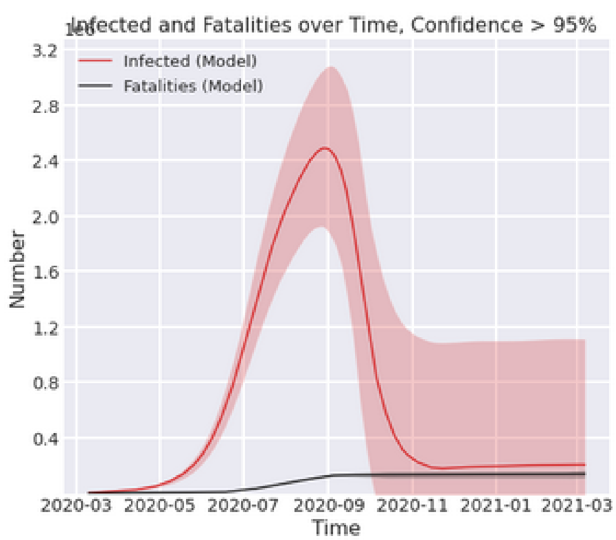

Figure 14: *No Mitigation Measures, Infected and Fatalities, 03.2020 to 03.2021 time frame*

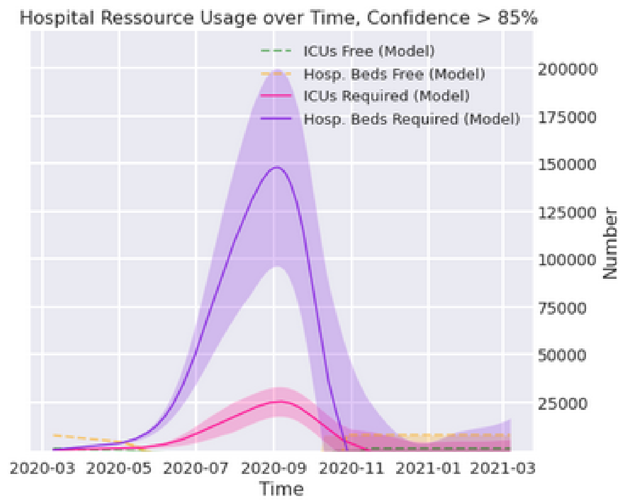

Figure 15: *No Mitigation Measures, Hospital Ressource Requirements computed by NN, 03.2020 to 03.2021 time frame*

3.1.1 NPI Collateral Damage

Using the collateral damage model described in sec. 9, computed collateral damage for two scenarios to illustrate the functionality of our model. Fig. 16 illustrates the scenario where historical NPIs were in place except "Workplace Closing". As shown by the visualization, removing the "Workplace Closing" NPI dramatically reduces collateral damage with the prediction of LYL for the next decade being not worse than what would have been the case withut any NPI induces collateral damage. A scenario with historical NPIs but no facial masks is shown by fig. 16. As you can see, our collateral damage model predicts only a slight improvement compared to historical measures.

3.2 Predictive Power

For long term predictions illustrated in fig. 18 and 19 the model pipeline is fitted on historical data of the 03.2020 to 03.2021. Future weather data for the 03.2021 to 01.2024 period is statistically generated from historical weather data and government measures are assumed to be repeated on a yearly

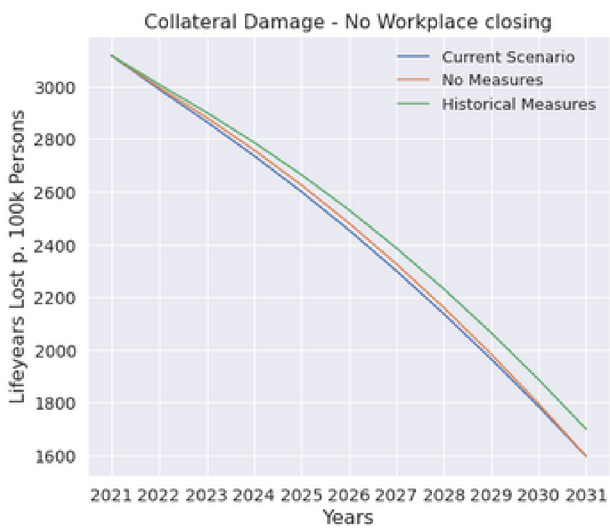

Figure 16: *No Workplace Closing, Collateral Damage, 03.2020 to 03.2021 time frame*

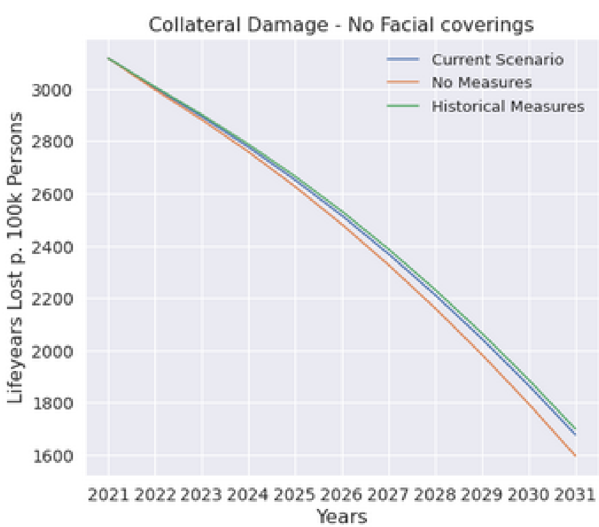

Figure 17: *No Facial Masks, Collateral Damage, 03.2020 to 03.2021 time frame*

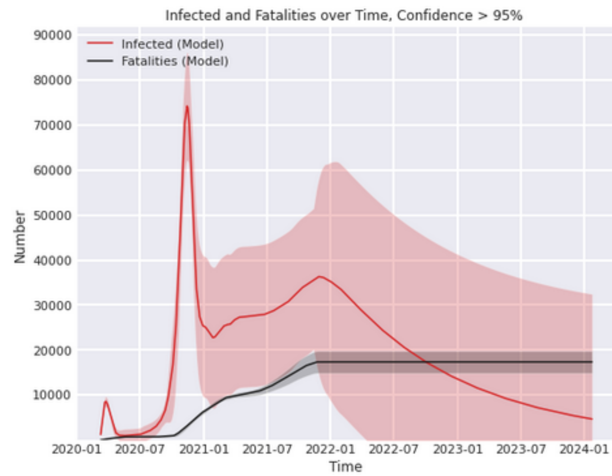

Figure 18: *Long Term Prediction computed by NN, 03.2020 to 03.2024 time frame*

basis but of course scenarios for alternative sets of future government measures could be computed as well. As you can see, the model predicts with a high probability a potential future peak in infections as well as ICU requirements exceeding capacity in December 2021 and January 2022. After the winter 2021/2022 peak, the number of infected slowly declines and fatalities have reached their maximum due to vulnerable age groups having been immunized via recovery or vaccination.

The predictive power the model pipeline is to be taken with a grain of salt though. The current prediction algorithm is only capable to predict future developments from the very beginning of the pandemic due to the way the SEIR-FV model is initialized. Correcting this deficit will be subject to future work, but it offsets the predictions quantitatively.

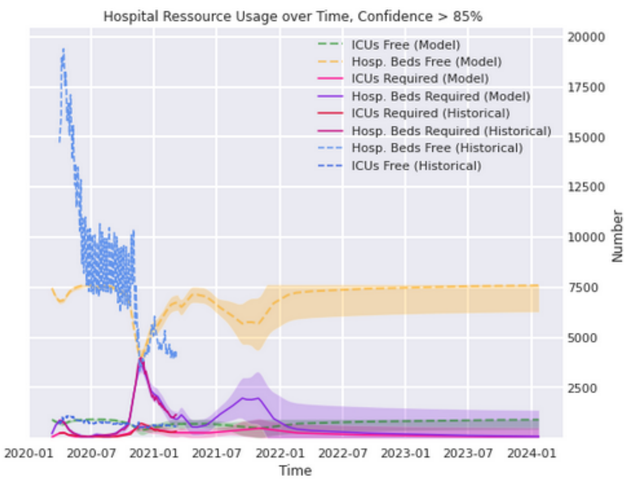

Figure 19: *Long Term Hospital Requirements computed by NN, 03.2020 to 03.2024 time frame*

4 Conclusion

We present a new approach of pandemic modelling through augmenting a regular SEIR-FV compartmental pandemic model with pre- and post-processing neural networks prediction reproduction number dependent on weather conditions and NPIs and demonstrate its usefulness for backwards analysis tasks as well its potential for predicting future developments w.r.t. COVID-19. Admittedly, the predictive power of our model leaves room for improvements, but we think that despite our approaches deficits, it still advances the state-of-the-art in cheap but accurate compartmental pandemic models due to its ability to incorporate weather data and fine granular NPI data from OxGRT. We also provide a simple NPI collateral damage model capable of predicting the development of future life-years-lost dependent on NPIs.

5 Future Work

We intend to fix the pandemic models current issues when making long term predictions and release it in the form of a web based interface to allow the public to play out hypothetical backwards analysis scenarios for various sets of NPIs as well as to make future predictions dependent on user chosen NPI sets and weather conditions. Furthermore, we intend to use this report as first draft for a publication in a journal or a conference focusing on pandemic modelling. The web interface and the potential journal or conference paper will not contain the collateral damage model because it is too weak to support the potentially strong political implications that could be derived from it.

5.1

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