What-If Analysis of Countermeasures Against COVID-19 in November 2020 in Slovenia

Vito Janko
Jožef Stefan Institute
Department of Intelligent Systems
Ljubljana, Slovenia
vito.janko@ijs.si

Nina Reščič
Jožef Stefan Institute
Department of Intelligent Systems
Ljubljana, Slovenia
nina.rescic@ijs.si

Tea Tušar
Jožef Stefan Institute
Department of Intelligent Systems
Ljubljana, Slovenia
tea.tusar@ijs.si

Mitja Luštrek
Jožef Stefan Institute
Department of Intelligent Systems
Ljubljana, Slovenia
mitja.lustrek@ijs.com

Matjaž Gams
Jožef Stefan Institute
Department of Intelligent Systems
Ljubljana, Slovenia
matjaz.gams@ijs.com

ABSTRACT

Choosing best sets of countermeasures against COVID-19 is a difficult task, and it is often not clear whether the the countermeasures that were actually chosen were justified. In this paper we studied if the introduction of masks and school opening in the times of exponential growth in November 2020 in Slovenia were justified or not.

KEYWORDS

COVID-19, epidemiological models, multi-objective optimization, non-pharmaceutical interventions

1 INTRODUCTION

Coronavirus disease 2019 (COVID-19) is an infectious disease that has rapidly spread across the world. Due to its high mortality rate [4], most countries deemed it too disruptive to let it run unchecked and have thus implemented countermeasures against it. The main type of countermeasures, in particular in the times when the vaccines were not yet available, were the *non-pharmaceutical interventions* (NPI) that include lockdowns, closure of schools and workplaces, and required mask usage. Due to the lack of precedent in the recent history, and several variables that influence the effect in a particular country, e.g. weather and cultural circumstances, it was and still is hard for decision-makers and domain experts to determine which NPIs to implement in a given epidemiological situation and what effect would a particular combination of NPIs have.

As we are now in the second year of the pandemic, large databases of data regarding the spread of the virus and implemented NPIs aimed at stopping it, became available. This in turn allows for the use of artificial intelligence (AI) methods to analyze the data, create predictive models, and consequently help the decision-makers in their task. It also enables reevaluation of the influence of particular NPIs at a particular time.

In our previous work [5] we built such an AI system, as part of the XPRIZE: Pandemic Response Challenge. At that competition, our system achieved second best results, and was significantly upgraded since that time.

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Information Society 2021, 4–8 October 2021, Ljubljana, Slovenia
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In the study reported here we used the improved version, specialized for Slovenia, to objectively answer a few what-if questions, such as whether school closure and mask usage were justified at a particular point in time, or were they an unnecessary burden.

These questions were posed to us by the Slovenian Ministry of Health. Namely, in August 2021 we sent the our XPRIZE system to all EU Ministries of Health with the motivation to help decision-makers better select NPIs. No ministry was able or eager to use the system itself so far, but we got some replies and requests for particular studies, such as the one tackled in this paper.

2 DATASET

Our system was trained on the data from 235 world regions between the dates of March 1, 2020 and April 14, 2021. While taking data from Slovenia only might result in a more localized model, this data does not provide the necessary range of implemented NPIs and their combinations.

The main source of data was the "COVID-19 Government response tracker" database, collected by the Blavatnik School of Government at Oxford University [2], that defines which (and in what time interval) NPIs were implemented in each country. The NPIs in this database are listed in Table 1. The database also provides the strictness of the implementations in the form of numbers, e.g., "Workplace closing – 1" represents that government only suggests closure, while "Workplace closing – 3" strictly demands it. The detailed description for each level of strictness is provided by the database authors [2].

Other key data needed for training the system are the numbers of infections and deaths, obtained from the same database. In addition we used data on weather, mobility, hospitalizations, vaccination and 93 features based on country characteristics (e.g., culture, development) from our previous work [3].

3 METHODS

The results in this work were made using an upgraded version of our XPRIZE system that can predict the number of infections given the active NPIs, and propose best NPIs to counter them.

The whole system is thoroughly described in our previous work [5]. Here, a quick overview is provided. The system first uses historical data of all regions to create a model that predicts COVID-19 infections given a set of NPIs. A SEIR epidemiological model is used for this purpose, combined with a machine-learning model that predicts the SEIR models's parameters as a function of NPIs. This model is used to predict the infections resulting

Table 1: The NPIs used in our study, and the range of values representing their strictness.

NPI	Value range
C1: School closing	[0-3]
C2: Workplace closing	[0-3]
C3: Cancel public events	[0-2]
C4: Restrictions on gatherings	[0-4]
C5: Close public transport	[0-2]
C6: Stay at home requirements	[0-3]
C7: Restrictions on internal movement	[0-2]
C8: International travel controls	[0-4]
H1: Public information campaigns	[0-2]
H2: Testing policy	[0-3]
H3: Contact tracing	[0-2]
H6: Facial Coverings outside the home	[0-4]

from a sequence of NPIs (referred to as "intervention plan") – its benefit.

The system also estimates the cost of each intervention plan. Calculating costs of NPIs is a complex issue that will be discussed in a forthcoming paper. In brief, they consist of economic costs (due to disruption of business and similar), for which some sources are available in the literature [6, 1], and social costs (due to isolation, restriction of freedom and similar). The cost of each plan is traded off against its benefit, as stricter plans results in fewer infections, but are costlier. Finally, the system uses multi-objective optimization to find intervention plans with good trade-off between benefits and costs.

The two major improvements of the system for the purpose of this paper are: 1) the added possibility to set a constraint on the maximal number of infections allowed – no plan exceeding this constraint is generated and 2) the added possibility to limit the strictness of any individual NPI. This two changes allowed us to analyze the what-if scenarios of what would happen if a certain NPI were not implemented, and what plans can we implement to have a similar number of infections, but not the undesired NPI.

The plans presented in this paper were evaluated using only their economic component (estimated GDP loss [in %] for that month), but not with the social one. While we repeated all the experiments using social costs, the results were similar, and the social costs we used are less objective than the economic ones.

4 RESULTS

All the predictions were made for the time interval 30. 10. 2020 – 30. 11. 2020, for Slovenia. That time interval was chosen because of the high number of infections observed and strict countermeasures imposed.

In the first experiment, we tested what would have happened if masks were not worn in closed spaces, and all other NPIs would remain the same as the actually implemented. The results are shown in Figure 1. They indicate an increase of infections, which was expected considering that we are simulating lowering the countermeasures during the epidemic peak, and no other NPI was simulated instead of masks.

A similar experiment was made for the hypothetical case where schools fully re-opened for a month. The results (Figure 2) show that the number of infections would grow even faster. This happens due to the exponential nature of the epidemiological model, encapsulating the actual nature of the virus infection in favorable conditions. Obviously, this reduction in strictness

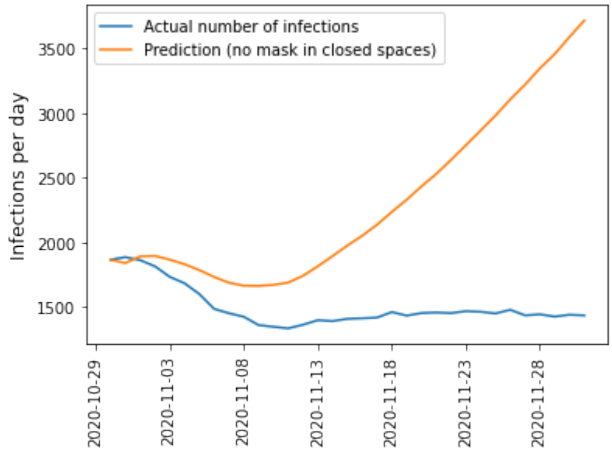

Figure 1: A comparison of actual number of daily infections, with predicted number of infections for the hypothetical case where masks were not used.

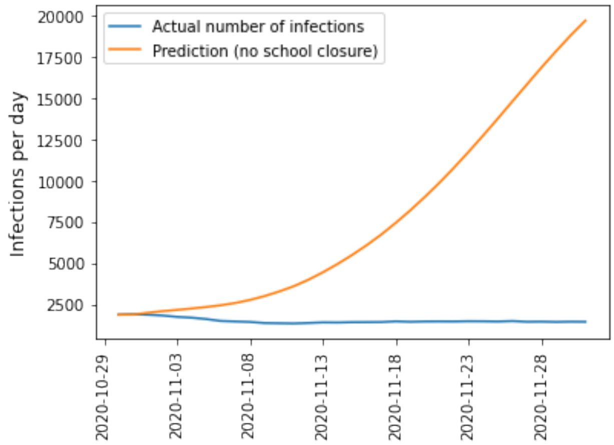

Figure 2: A comparison of actual number of daily infections, with predicted number of infections for the hypothetical case where schools were re-opened.

greatly changes the reproduction rate and consequently leads to the exponential growth.

Such fast growth as was predicted in these to experiments is probably too pessimistic, as in reality in the case that the number of infections were starting to grow so alarmingly, the population's behavior would likely become more cautious – counterbalancing the growth. Nonetheless, the model indicates that the school closure is a major contributor to regulating COVID-19, even more important than the masks. Please note that scale of the y axis differs between Figures 1 and 2.

The two described experiments show that removing an NPI from the implemented intervention plan will likely result in substantial growth, which decision-makers would not allow. Therefore, we attempted to compensate for the missing NPIs with other NPIs to prevent the exponential growth.

We used multi-objective optimization to show the best plans one can make given the restriction that a certain NPI cannot be used, at least not with a strictness exceeding a given threshold. These plans were compared based on the predicted infections

Table 2: The weekly strictness of selected intervention plans. The letters identify the plan on the Pareto front approximations in Figures 3 and 4. Strictness 0044 would indicate that the lowest strictness is used for the first two weeks, and highest for the last two ones.

NPI	a	b	c	d	e	f	g	h	i
C1: School closing	3333	3333	3333	2222	2222	1111	1111	3333	3333
C2: Workplace closing	2222	0000	2000	1000	3000	3002	3301	0000	3000
C3: Cancel public events	2222	2222	2222	2222	2222	2222	2222	2222	2222
C4: Restrictions on gatherings	4444	4444	4442	4444	4444	4444	4444	4444	4444
C5: Close public transport	0022	2222	2222	2222	2222	2222	2222	2222	2222
C6: Stay at home requirements	2222	0010	1100	1111	1110	1111	1111	1100	3110
C7: Restrictions on internal movement	2222	0000	1000	1000	2000	2011	2210	0000	2200
C8: International travel controls	2222	4343	4443	4444	4444	4444	4444	4444	4444
H1: Public information campaigns	2222	2222	2222	2222	2222	2222	2222	2222	2222
H2: Testing policy	2222	3333	3333	3333	3333	3333	3333	3333	3333
H3: Contact tracing	1111	2222	2222	2222	2222	2222	2222	2222	2222
H6: Facial coverings outside the home	4444	4444	4444	4444	4444	4444	4444	0000	0000

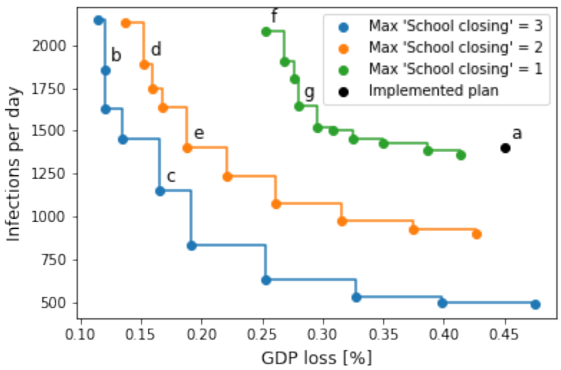

Figure 3: Proposed intervention plans using different restrictions on the value of "School closing". They were evaluated based on the predicted number of infections and estimated GDP loss. The marked plans are explained in Table 2.

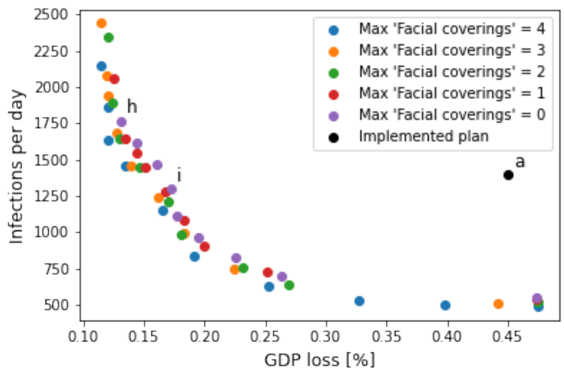

Figure 4: Proposed intervention plans generated using different restrictions on the value of "Facial covering". They were evaluated based on the predicted number of infections and estimated GDP loss. The marked plans are explained in Table 2.

and predicted GDP loss for that month. The resulting Pareto-front approximations for school closure with different levels of strictness are shown in Figure 3.

The blue line in Figure 3 represents the case with no limitations when constructing an intervention plan, and obviously these solutions are substantially better than the intervention plan actually implemented, and the plans with limitations. The orange and green lines represent plans that have schools partially or fully open. These plans are visibly worse in terms of the two desired objectives: this happens because the system is compensating for the lack of "School closing" NPI with "Workplace closing" NPI, which is more expensive. A sample of the generated plans is given in Table 2.

This experiment was repeated, this time restricting the strictness of the "Facial Coverings" NPI. The results are shown in Figure 4 and sample plans are given in Table 2.

For the mask analysis, the system found comparable solutions that compensate for the reduced "Facial Coverings" NPI. While this NPI has a good ratio between benefit and economic cost, its benefit in absolute terms is nevertheless smaller than of the "School closing" NPI, so it is easier to replace by increasing other NPIs.

5 DISCUSSION AND CONCLUSIONS

In this study we analyzed what-if scenarios in regards to reduced wearing of masks and school re-openings for Slovenia at peak infection time in November 2020. The study showed that both of these changes would worsen the epidemiological situation in the country if no other NPI was introduced instead. Furthermore, for school closure the AI model could not find proper replacement in that situation, suggesting that school closure was justified. The closest viable solution was "Solution *e*" that proposes only partial school closing, but compensates it with increased testing and international travel control. On the other hand, the model indicated that mask usage could be almost completely compensated with an increase of other NPIs. It cannot judge whether this is desirable – that may depend on social costs.

The study has a number of limitations:

(1) The study was done using historic data for Slovenia, while the AI system was trained on data from all regions and was only somewhat tuned to Slovenia.

(2) The data and the resulting model do not contain the information on vaccination, as it was not available in the tested period.
(3) The data and the resulting model do not contain the information on the Delta or newer variants, as it was not available in the tested period.
(4) The model does not predict what would happen with a different implementation of the NPI (e.g., stricter testing of students/teachers).
(5) The study uses costs available from the literature and might not fit best Slovenian specifics.
(6) The study does not use social costs, which are certainly important but difficult to set in a justifiable manner.

Because of these limitations, it is not recommended that this study be used as a basis for future policies. For such purpose, we strongly recommend performing new experiments tailored to the problem we try to address.

Comparing best AI-proposed measures with the actual ones by humans reveals a well-known phenomenon that humans cannot on their own consider all possibilities and propose best actions. Although demonstrated only on a couple of cases here, in our opinion that is a fairly general conclusion valid not only for COVID-19 NPIs. In most cases it should still be the human's role to make final decisions, but humans should take advantage of AI assistance when possible.

In summary, school closing and masks in general represent important NPIs, and the decision to use them in peak infection cases when vaccinations are not available or sufficient, seems reasonable. However, unlike the school closing, the masks can be replaced with other NPIs. Furthermore, vaccinations in particular render NPIs less important – if no new variant of COVID-19 appears.

Acknowledgement

First, we would like to acknowledge all other authors who contributed to the development of the presented AI system: Erik Dovgan, David Susič, Carlo De Masi, Tea Tušar, Matej Cigale, Matej Marinko, Aljoša Vodopija, Anton Gradišek.

Second, we want to acknowledge XPRIZE, the organizer of the $500K Pandemic Response Challenge competition and their sponsor Cognizant, who made the development of the system possible.

Finally, we acknowledge the financial support from the Slovenian Research Agency (research core funding No. P2-0209).

REFERENCES

[1] 2021. Business closures and partial reopenings due to covid-19 could cost the u.s. trillions. https://news.usc.edu/178979/business-closures-covid-19-pandemic-united-states-gdp-losses/.

[2] Thomas Hale, Sam Webster, Anna Petherick, Toby Phillips and Beatriz Kira. 2020. Oxford covid-19 government response tracker, blavatnik school of government. (April 2020). https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

[3] Vito Janko, Gašper Slapničar, Erik Dovgan, Nina Reščič, Tine Kolenik, Martin Gjoreski, Maj Smerkol, Matjaž Gams and Mitja Luštrek. 2021. Machine learning for analyzing non-countermeasure factors affecting early spread of covid-19. *International Journal of Environmental Research and Public Health*, 18, 13. ISSN: 1660-4601. DOI: 10.3390/ijerph18136750. https://www.mdpi.com/1660-4601/18/13/6750.

[4] Gideon Meyerowitz-Katz and Lea Merone. 2020. A systematic review and meta-analysis of published research data on covid-19 infection-fatality rates. *International Journal of Infectious Disease*, 101, (December 2020), 138–148. An optional note.

[5] Reščič Nina, Janko Vito, Susič David, De Masi Carlo, Vodopija Aljoša, Marinko Matej, Tušar Tea, Dovgan Erik, Gradišek Anton, Cigale Matej, Gams Matjaž and Luštrek Mitja. 2021. Finding efficient intervention plans against covid-19. In ETAI 2021 (exact name will be given for the camera ready version). (September 2021).

[6] Md Z Sadique, Elisabeth J Adams and William J Edmunds. 2008. Estimating the costs of school closure for mitigating an influenza pandemic. *BMC public health*, 8, 1, 1–7.