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Optimal Control Strategies for Assessing the Impact of Medical Masks on COVID-19 Dynamics: Global Perspectives and Societal Well-Being

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Abstract

The pandemic crisis caused by the spread of the COVID-19 variants elicited how urgent is to establish a robust mathematical model for effective policy decision-making. To investigate the effectiveness of control measures like medical masks on the transmission dynamics of COVID-19, more sophisticated mathematical models can be employed. The purpose of this study is to investigate the effectiveness of control measures, e.g., medical masks use on the transmission dynamics of COVID-19. In this work, we have established a model that includes medical masks use in order to study its ability to flatten the epidemic curve, taking into account demographic rates (birth and death rates). The model was used to formulate an optimal control study with the objective function of minimizing the number of infected individuals and relative cost of the interventions associated with medical masks use. The aim is to reduce the transmission of the virus in order to keep the healthcare services below full capacity and to reduce the total cumulative infected. The model was used to assess the importance of mask usage in society by evaluating its impact on the spread of the virus in Norway, the United States and India. Medical mask use during COVID-19 significantly reshaped social norms while presenting diverse effects on individual well-being, blending cultural, psychological, and health-related impacts.

Keywords

Optimal Control, Medical Mask, COVID-19, Well-Being, Social Factors

1. Introduction

The highly contagious disease coronavirus (COVID-19), has indeed caused a significant number of deaths and infections globally since it was first identified in late 2019. The pandemic has had a profound impact on public health, economies, and societies worldwide. The emergence of novel variants of the COVID-19 virus has indeed created a crisis in the healthcare sector. The rapid spread of these variants has put significant pressure on healthcare systems worldwide. The increased transmissibility has led to a surge in cases, overwhelming hospitals and healthcare facilities in many regions. The need for additional resources, such as hospital beds, medical equipment, and healthcare workers, has been a challenge for many countries. The pandemic has highlighted the need for advanced modeling tools that can aid in projecting epidemic trends, exploring intervention scenarios, and estimating resource needs (Aguas et al., 2020; Agarwal, Nieto, & Torres, 2022).

The COVID-19 pandemic has had a staggering toll, with reported deaths between January 1, 2020, and December 31, 2021, reaching 5.94 million globally. However, estimates suggest that the true number of deaths attributable to the pandemic during this period is approximately 18.2 million worldwide. The competitive interactions among these variants, driven by their co-transmission, have significantly influenced the dynamics of the pandemic. This global crisis has stretched healthcare and socio-economic infrastructures to unprecedented levels, presenting not only a health emergency but also a significant policy challenge. The response to the pandemic varies widely across nations, reflecting diverse approaches to governance and crisis management. From swift action to hesitation, and from evidence-based decisions to ideological influences, the pandemic response serves as a unique natural experiment in policy-making and crisis management on a global scale (Wang et al., 2022; Riley, Xie, & Khurshid, 2021).

Mathematical and computational models have played a crucial role in understanding the spread of the virus, predicting its impact, and informing decision-making processes (Rachah, 2018). Advanced modeling tools, such as epidemiological models, can simulate and forecast the transmission dynamics of infectious diseases like COVID-19. These models take into account various factors, including population demographics, disease characteristics, and intervention strategies, to project epidemic trends and evaluate the effectiveness of different control measures (Rachah, Torres et al., 2015; Adi-Kusumo, 2017; Rachah et al., 2017; Duncan, Scott, & Duncan, 1994). By using these models, policymakers and public health officials can explore various intervention scenarios, such as the implementation of social distancing measures or mask mandates. They can estimate the potential impact of these interventions on reducing transmission, hospitalizations, and mortality rates. Moreover, advanced modeling tools can help estimate resource needs, such as hospital beds, intensive care unit capacity, and medical supplies. By projecting the number of infections and severe cases, these models can assist in planning and optimizing resource allocation to ensure healthcare systems can adequately respond to the demands imposed by the pandemic.

Amidst the COVID-19 pandemic, epidemiological models have assumed an unprecedentedly vital role, surpassing even previous health crises. These models have been instrumental in forecasting the trajectory of the pandemic, evaluating the impact of health interventions, and anticipating potential side effects. Moreover, in the absence of robust decision-support tools, particularly during the initial phases of the pandemic, epidemiological models emerged as the primary resource guiding political decision-making processes (Eubank et al., 2020; Holmdahl & Buckee, 2020). In France, the scientific committee tasked with advising public policy during the COVID-19 pandemic heavily relied on epidemiological models as their primary reference. The assessments and recommendations provided by this committee in mid-March prompted the French government to implement a series of measures aimed at curbing social interactions (Manzo, 2020).

One commonly used model is the Compartmentalized SEIR model, which divides the population into different compartments based on their disease status (susceptible individuals (S), exposed individuals (E), infected individuals (I), and recovered individuals (R)). For the COVID-19 pandemic, several models have been used to estimate the number of individuals that need to be hospitalized, aiming to help policy-makers ensure the health system does not overload (Rachah, 2022; Agarwal et al., 2022; Wang et al., 2020).

While compartmental modelling of contagious diseases and healthcare logistics has the ability to well describe the real dynamics, optimal control theory can be applied to find the optimal strategies for administering interventions during the COVID-19 pandemic. Optimal control theory is a mathematical framework that aims to find the best control actions to optimize a given objective function, subject to constraints and system dynamics (Rachah & Torres, 2017; Khatua, Kar, Nandi, Jana, & Kang, 2020). In the context of COVID-19, optimal control theory can help identify the optimal timing and dosage of interventions such as lockdown measures, testing strategies, contact tracing, vaccination campaigns, and resource allocation. Applying optimal control theory to COVID-19 can provide policymakers with valuable guidance on designing effective intervention strategies. It can inform decisions on when and how to implement various measures, considering factors such as transmission dynamics, healthcare capacity, and societal impact.

Different COVID-19 control measures have been applied around the world. The most important in applying strategies or measures, is they must be timely applied, in order to achieve the desire impact. Wearing face masks has been shown to help minimize the viral load and reduce the transmission of COVID-19. Face masks act as a physical barrier that can block respiratory droplets containing the virus from being released into the air and inhaled by others. Respiratory droplets are one of the primary modes of transmission for COVID-19, particularly through close contact or in enclosed spaces with poor ventilation. When an infected individual breathes, talks, coughs, or sneezes, respiratory droplets containing the virus can be expelled into the surrounding environment. Wearing a mask can help prevent these droplets from being released into the air, protecting others from potential exposure (Froese, Prempeh et al., 2022; Cooper, Mondal, & Antonopoulos, 2020). Masks have been widely advocated as a precautionary measure against COVID-19 transmission due to their demonstrated efficacy in reducing droplet dispersion in laboratory settings. However, during the initial stages of the pandemic, the utilization of masks exhibited significant variability across countries. Despite this, studies assessing the effectiveness of face masks in mitigating COVID-19 transmission have yielded promising results. Research indicates that wearing masks, particularly higher quality ones such as respirators, along with mask mandates, generally resulted in a reduction in COVID-19 transmission within the studied populations (Aravindakshan, Boehnke, Gholami, & Nayak, 2022; Lyu & Wehby, 2020; Howard et al., 2021).

The extensive adoption of medical masks during the COVID-19 is prompted diverse shifts in societal norms and interactions, reflecting unique cultural and socioeconomic landscapes. While instrumental in curbing virus transmission, prolonged mask use also presented varied impacts on individual well-being, influencing social dynamics and posing both physical and psychological challenges (Betsch et al., 2020).

This paper investigates the impact of medical mask use on the transmission dynamics of COVID-19 pandemic using a SEIR compartmental model in Norway, the United States, and India. We present the formulation of the model including face masks use, birth and death rates in the three countries. Then, we show the numerical simulation of the COVID-19 transmission dynamics for different rates of masks use. Then, the model was used to formulate an optimal control study, with the aim to minimize the number of active infected individuals and the relative cost associated with application of medical masks in order to keep the healthcare services below full capacity. The widespread adoption of medical masks amid COVID-19 led to substantial shifts in social norms and had multifaceted effects on individual well-being, amalgamating cultural, psychological, and health-related influences.

2. Model Formulation

Using a model capable of suggesting efficient, up-to-date, and practical control measures for the disease is essential as the impact of not doing so can have unpredictable consequences. Face masks wearing was one of the control measures that was applied in several countries. It can be included within the SEIR model by adding a new parameter u which describes the wearing of masks to obtain the following system of differential equations:

$$\begin{aligned}
\frac{\mathrm{d}S}{\mathrm{d}t} &= \mu-(1-u)\beta SI-\mu S, \\
\frac{\mathrm{d}E}{\mathrm{d}t} &= (1-u)\beta SI-\alpha E-\mu E, \\
\frac{\mathrm{d}I}{\mathrm{d}t} &= \alpha E-\gamma I-\mu I, \\
\frac{\mathrm{d}R}{\mathrm{d}t} &= \gamma I-\mu R.
\end{aligned} \tag{1}$$

The model divides the population into different compartments based on their disease status:

- Susceptible (S): The individuals who are susceptible to the disease.
- Exposed (E): The individuals who are infected but not yet infectious. They have been exposed to the virus and are in the incubation period.
- Infectious (I): The individuals who are currently infected and can transmit the disease to susceptible individuals.
- Recovered (R): The individuals who have recovered from the disease and are now immune or removed from the susceptible population.

These differential equations describe the flow of individuals between the compartments over time. The first equation represents the rate of change of susceptible individuals, which depends on the effective contact rate and the number of infected individuals. The second equation represents the rate of change of exposed individuals, considering the transmission from susceptible individuals and the movement from exposed to infectious. The third equation represents the rate of change of infectious individuals, considering the movement from exposed to infectious and the recovery rate. The fourth equation represents the rate of change of recovered individuals, which depends on the recovery rate.

The parameters β, α and γ represent the transmission rate, the incubation rate and the recovery rate, respectively. The model takes into account the demographic changes in the population by including the natural birth rate and death rate μ. Parameters values of the model were described in **Table 1**. The parameter u describes the wearing of mask. The initial states S_0, E_0, I_0 and R_0 were described in **Table 2**. The parameter values were obtained using numbers provided by reports done by Norwegian Institute of Public Health (FHI) (NIPH, 2020), and Wintachai and Prathom's paper on stability analysis done in USA and India (Wintachai & Prathom, 2021). An Illustration of the model is given in **Figure 1**.

3. Numerical Simulation

The numerical resolutions of the system of differential Equations (1) for different values of the parameter u of masks use are given in **Figures 2-4**.

- When $u = 0$, none face masks wearing is applied.
- When $u = 1$, a total use of face masks is applied.

The numerical simulation was done using the software Python 3.9.10. The Python packages used in solving the system of differential equations of the model and plotting the results were: NumPy, Scipy, and Matplotlib (Virtanen et al., 2020; Harris et al., 2020; Hunter, 2007).

Figure 2 shows the ability of masks use to flatten the curve on infective individuals and delay it by applying two levels of masks use in Norway and then reducing the transmission of the virus. An application of masks wearing at the rate $u = 0.2$ decreases the peak to the half and delay it to happen at day 130 instead of day 80 when $u = 0$. By wearing masks at rate $u = 0.3$, the number of infections

Table 1. Parameter values from Norway, the United States and India.

Parameter	Norwegian value	U. S. value	Indian value
β	0.32	0.462	0.462
α	0.25	0.0870	0.462
γ	0.157	0.0696	0.0696
μ	2.829×10^{-5}	3.178×10^{-5}	3.178×10^{-5}

Table 2. Initial states from Norway, the United States, and India.

Parameter	Norwegian value	U. S. value	Indian value
S_0	0.994	0.97286	0.994
E_0	2.813×10^{-4}	0.00805	2.813×10^{-4}
I_0	1×10^{-4}	0.001	1×10^{-4}
R_0	5.569×10^{-3}	0.01809	5.569×10^{-3}

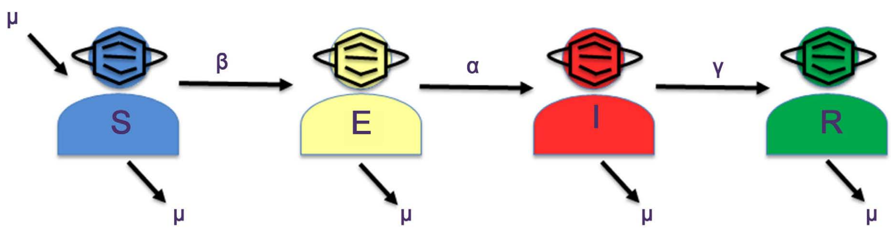

Figure 1. Schematic presentation of the model with facemask use.

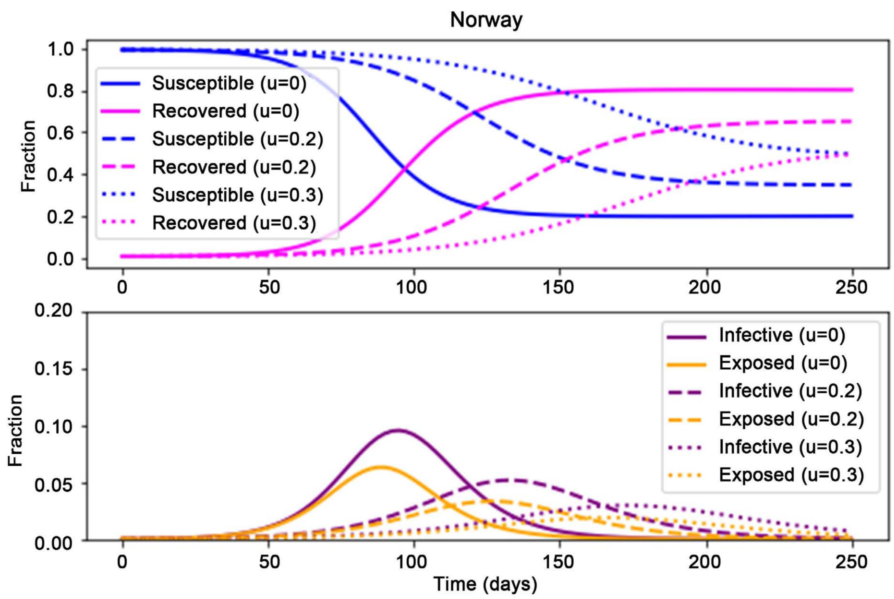

Figure 2. Various levels of masks use applied for the COVID-19 pandemic in Norway.

was reduced, leading to flattened epidemic curve. The results are confirmed by applying masks wearing at the rates $u = 0.4$ and $u = 0.6$ in the United States (**Figure 3**) and the rates $u = 0.3$ and $u = 0.5$ India (**Figure 4**) and show the ability

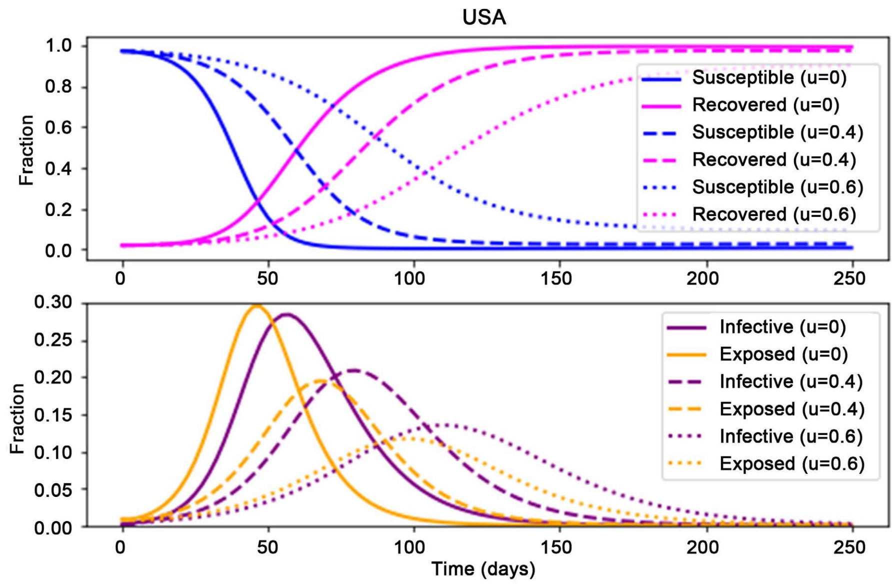

Figure 3. Various levels of masks use applied for the COVID-19 pandemic in USA.

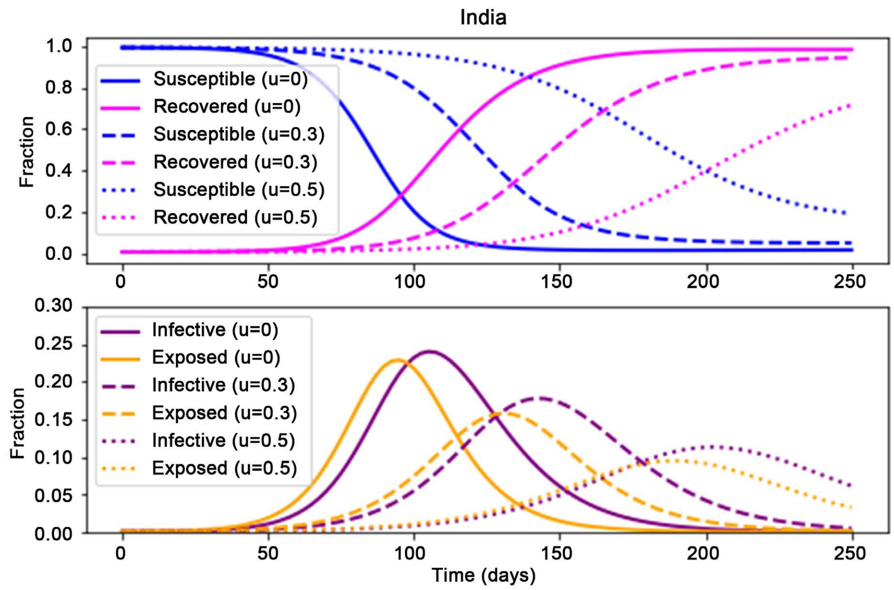

Figure 4. Various levels of masks use applied for the COVID-19 pandemic in India.

of increasing the rate of masks use to reduce the overall number of infections, leading to a slower increase in cases over time. As a result, the healthcare system is better able to manage the number of patients, and the peak of infections can be delayed. Delaying the peak allows more time for hospitals and healthcare facilities to prepare, secure resources, and improve treatment protocols, leading to better outcomes for patients. The application of different rates of masks use depends on the spread of the virus, which is different from one country to another. The basic reproduction number is a critical parameter used to measure the spread of the virus. It represents the average number of new infections generated by one infectious individual in a susceptible population. It provides insights into the transmission potential of an infectious disease and helps assess the spread of the disease within the population.

- If R_0 is greater than 1, each infected person, on average, spreads the virus to more than one other person, indicating the virus is likely to spread exponentially.
- If R_0 is less than 1, each infected person, on average, spreads the virus to fewer than one other person, suggesting the virus will eventually die out in the population.

The mathematical formulation of R_0 is given by:

$$R_0 = \frac{\beta\alpha}{(\mu+\alpha)(\mu+\gamma)}$$

The application of masks wearing at different levels depends on R_0 which is equal to 2.037 in Norway, 4.66 in India, and 6.63 in the United States. In Norway, the R_0 of COVID-19 is 2.037, it means that, on average, each infected person will infect two other individuals, leading to exponential growth in the number of cases. However, if the R_0 can be reduced below 1 through measures like wearing masks, social distancing, and vaccinations, the spread of the virus can be slowed or controlled. The basic reproduction number can change based on various factors, including the characteristics of the virus, the behavior of the population, and the effectiveness of control measures in place. Estimating R_0 is an important tool for public health officials to understand the potential impact of an infectious disease outbreak and to guide the implementation of appropriate interventions to mitigate its spread.

4. Optimal Control through Masks Use

COVID-19 control continues to be a significant challenge in many countries worldwide. Despite efforts to mitigate the spread of the virus, several factors contribute to the ongoing struggle in controlling the pandemic. Covid-19 control measures must be timely applied, in order to have the desire impact. Face masks use was one of the measures applied around the world. However, economical, social and environmental constraints are imposed to Covid-19 control measures. The ideal situation would be a minimization of active infected individuals with the lowest cost possible. The numerical simulation of the model showed an application of constant masks wearing which may lead to an outbreak that peaks before receding. In this section we study an optimal masks wearing policy using the control variable $u(t)$ that changes over time and check its ability to flatten the curve of infected individuals in case of available healthcare constraints as is showed in **Figure 5**.

The formulation of the optimal control policy of the virus is based on the model (1) by using a control variable $u(t)$ for the masks use (instead of fixed parameter) with the objective of minimizing active infected individuals with the lowest cost possible. The study includes two constraints: (i) constraint on the number of infected individuals that must stay below a specific percentage of the

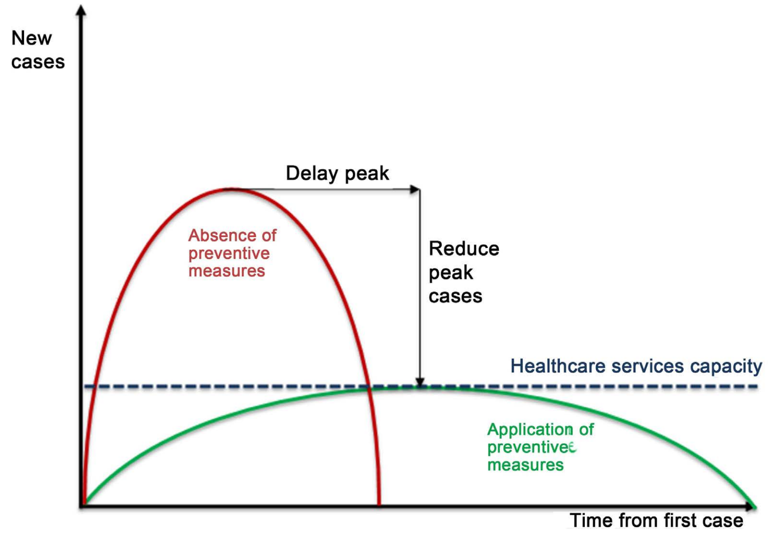

Figure 5. Schematic presentation of flattening the epidemic curve.

population in order to keep healthcare below full capacity; (ii) constraint on the maximum achievable masks wearing is 0.8.

The formulation of the optimal control problem consists of minimizing the number of symptomatic infectious individuals and the costs needed to control the disease given by the following objective function

$$J(u)=\int_0^{t_f}\left[C_0 I(t)+\frac{C_1}{2}\delta^2(t)\right]\mathrm{d}t, \tag{2}$$

subject to (i), (ii), and

$$\begin{aligned}\frac{\mathrm{d}S(t)}{\mathrm{d}t}&=\mu-(1-u(t))\beta S(t)I-\mu S(t),\\ \frac{\mathrm{d}E(t)}{\mathrm{d}t}&=(1-u(t))\beta S(t)I(t)-\alpha E(t)-\mu E(t),\\ \frac{\mathrm{d}I(t)}{\mathrm{d}t}&=\alpha E(t)-\gamma I(t)-\mu I(t),\\ \frac{\mathrm{d}R(t)}{\mathrm{d}t}&=\gamma I(t)-\mu R(t).\end{aligned} \tag{3}$$

In the objective function (2), C_0 is the constant weight for the compartment of infectious individuals I, and $u\in\mathcal{U}_{ad}$ the admissible control set given by

$$\mathcal{U}_{ad}=\left\{\delta: u \text{ is measurable}, u^{\mathrm{lb}}\le u(t)\le u^{\mathrm{ub}}, t\in[0,t_{end}]\right\}.$$

where u^{lb} and u^{ub} are the lower and upper bounds for the control policies respectively. In the quadratic term of (2), the constant C_1 is a measure of the relative cost of the interventions associated with the control u, and the square of u reflects the severity of the side effects of the face mask use.

4.1. Numerical Experiments

The numerical resolution of the optimal control problem was done using the software Python 3.9.10. The Python packages used in finding the numerical resolution and plotting the results were: NumPy, and Matplotlib (Harris et al., 2020; Hunter, 2007). The optimal control problems were solved using the GEKKO Python package, which solves large-scale mixed-integer and differential algebraic equations with nonlinear programming solvers (such as IPOPT) (Beal, Hill, Martin, & Hedengren, 2018).

For the objective function, we used $C_0 = 100$ and $C_1 = 50$. The main objective of the optimal control problem is to flatten the curve of infected individuals and also reduce the cost associated with the control measures such that an overload in the healthcare system is avoided. The control variable u(t) represents the control policy of the population using face masks and is kept within the limits $u^{lb} = 0$ and $u^{ub} = 0.8$.

4.2. Optimal Use of Masks in Norway

Figure 6 shows the numerical resolution of the optimal control problem, where we assume a number of infected individuals has to be less than 2% of the population ($I < 0.02$) in order to reply to the need of Norwegian healthcare below full capacity.

The obtained results showed a completely flat tend infection curve, by applying a high policy enforcement at day 52 and smoothly reduces until day 180. The more restrictive policy at day 52 corresponds to the beginning of the original epidemic period.

4.3. Optimal Use of Masks in the United States

In the numerical resolution of the optimal study of masks wearing in the United States, a requirement of number of infected individuals has to be less than 5% of the population ($I < 0.05$) was included in the study, in order to keep the healthcare services to be below full capacity.

As showed in **Figure 7**, the strategy follows high policy enforcement from day 10 until around day 220 when the use of face masks becomes less and less restrictive reaching its minimum of 0 at the end. The obtained results showed a completely flattened curve by following the optimal trajectory of face masks use.

4.4. Optimal Use of Masks in India

The optimal study on the masks use in India, an assumption of number of infected individuals has to be less than 3.5% of the population ($I < 0.035$) was included in the study, in order to keep the healthcare services to be below full capacity.

Figure 8 shows that by applying a high policy enforcement of wearing masks from day 52 until around day 225, the overall number of infections is reduced, leading to a flattened infection curve.

5. Impact on Social Factors and Well-Being

Medical mask use during the COVID-19 pandemic has significantly impacted

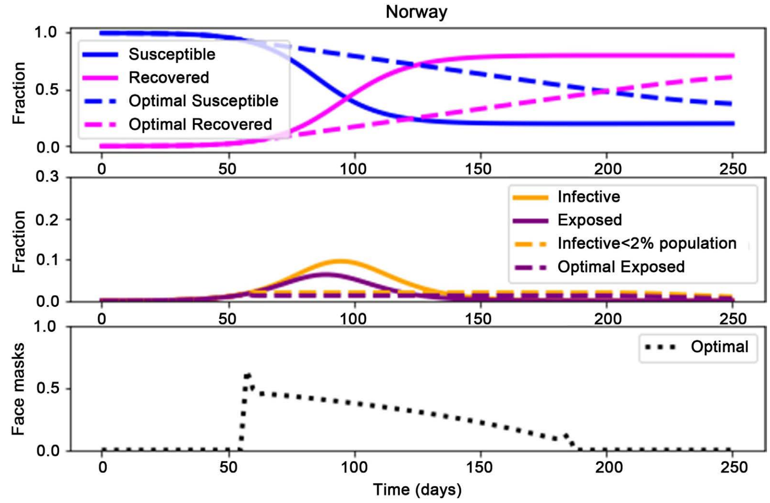

Figure 6. Numerical resolution of the optimal control policy in Norway.

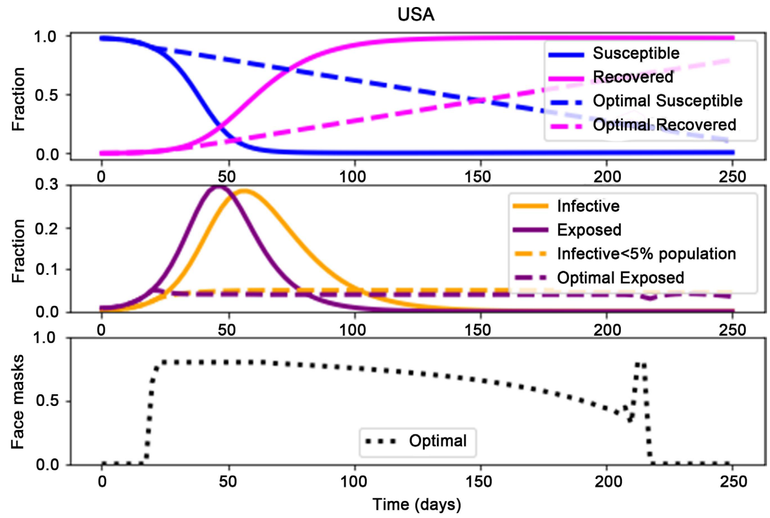

Figure 7. Numerical resolution of the optimal control policy in the United States.

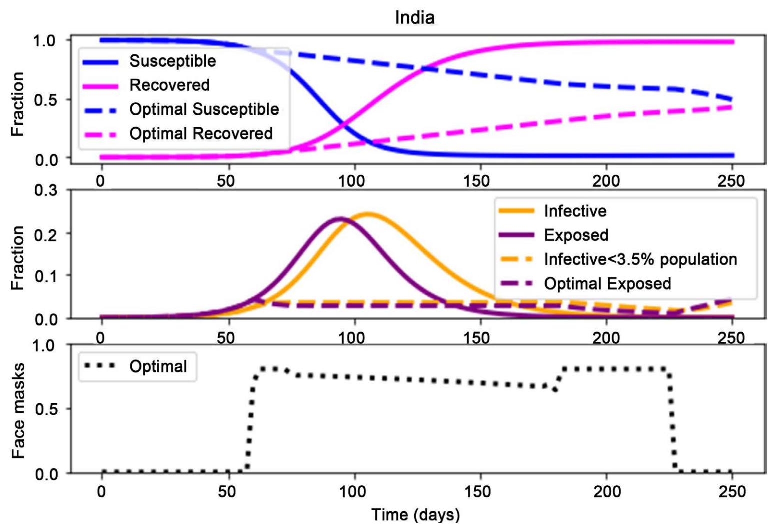

Figure 8. Numerical resolution of the optimal control policy in India.

various social factors and individual well-being, influencing societal norms, interpersonal interactions, and mental health.

5.1. Social Factors

Medical mask use during the COVID-19 pandemic has significantly impacted various social factors, reshaping societal norms, interactions, and perceptions. The widespread adoption of masks has instigated a shift in cultural practices, normalizing the act of wearing masks in public settings. This has led to a collective understanding and acceptance of mask-wearing as a responsible behavior to safeguard public health. Moreover, the visibility of masks in daily life has influenced social perceptions, signifying a shared commitment to protecting oneself and others from viral transmission. The integration of masks into social settings has also introduced changes in communication dynamics, modifying non-verbal cues and altering the way individuals interpret facial expressions and emotions during interactions. As a result, the adoption of masks has not only influenced individual behaviors but has also played a significant role in shaping societal norms and the broader social fabric during these unprecedented times.

5.2. Individual Well-Being

The utilization of medical masks amid the COVID-19 pandemic has carried diverse impacts on individual well-being. While serving as a crucial preventive measure against viral transmission, prolonged mask-wearing has presented certain challenges to individuals' well-being. Physically, wearing masks for extended durations may lead to discomfort, skin irritation, or breathing difficulties for some individuals, impacting their physical comfort and health. Psychologically, the adoption of masks has altered social interactions, hindering non-verbal communication cues and potentially leading to feelings of social disconnect or isolation. This change in facial interactions could contribute to emotional strain, particularly in contexts reliant on visual cues for communication and empathy. Despite these challenges, mask usage has also offered a sense of safety and security, empowering individuals by providing a visible means of protecting themselves and others. Overall, while masks have played a crucial role in curbing virus transmission, their prolonged use has presented a complex mix of physical and psychological impacts on individual well-being, necessitating a delicate balance between public health measures and individual comfort.

6. Global Perspectives on Medical Mask Impact

Medical mask use during COVID-19 has had diverse impacts on social factors and individual well-being across Norway, the United States, and India, reflecting varied societal contexts and responses.

6.1. Norway

In Norway, adherence to mask mandates was generally high, fostering a collective sense of responsibility and unity. This widespread compliance contributed to a normalized societal acceptance of mask-wearing, reducing stigma and reinforcing a shared commitment to public health. The consistent adoption of masks influenced social interactions by introducing a new norm, altering non-verbal communication, and fostering a sense of community vigilance against the virus.

6.2. The United States

The impact of mask mandates in the United States varied significantly due to cultural and political influences. Divergent compliance levels led to fragmented perceptions and societal divisions. The politicization of mask mandates created a complex landscape, contributing to varied adherence rates, pockets of resistance, and conflicts over personal freedoms versus public health measures. This resulted in altered social interactions, with mask-wearing becoming a symbol of individual beliefs and values rather than a unified effort against the virus.

6.3. India

In India, the impacts of mask usage were multifaceted, reflecting the country's diverse cultural and socioeconomic landscape. Compliance varied across regions, influenced by cultural norms, accessibility, and varying policy implementations. In areas where mask usage aligned with cultural practices, compliance rates were higher, whereas regions facing socioeconomic challenges experienced barriers to adherence. This led to varying levels of social acceptance, altering interpersonal interactions, and shaping community perceptions based on regional norms and access to resources.

7. Conclusion

The study employed mathematical modeling to investigate the impact of wearing masks on the spread of the COVID-19 virus in Norway, the United States and India. The model is based on a system of differential equations, which incorporate mask usage and take into account the demographic effects in the three countries. The numerical simulation of the model showed different scenarios of application of masks with several rates in the three courtiers to observe how different mask usage strategies impact the disease spread over time.

Furthermore, optimal control strategies are also employed to minimize the number of infected individuals and related costs of the interventions associated with mask usage, especially in the context of resource limitations. In the optimal control study, two constraints were included: first constraint on the number of infected individuals that must stay below a specific percentage of the population in order to keep healthcare below full capacity, and a second constraint on the maximum achievable masks wearing. The results showed the effectiveness masks usage, haw can help decrease the number of infections, slow down the spread of the virus, and have a positive impact on flattening the infection curve. By wearing masks, the overall number of infections can be reduced, leading to a slower increase in cases over time. As a result, the healthcare system is better able to manage the number of patients, and the peak of infections can be delayed. Delaying the peak allows more time for hospitals and healthcare facilities to prepare, secure resources, and improve treatment protocols, leading to better outcomes for patients.

The effectiveness of wearing masks can vary depending on the type of mask, proper usage, and adherence to other preventive measures. It's essential to follow guidelines issued by health authorities to maximize their benefits and protect both individuals and communities. The application of mathematical modeling and optimal control, are a powerful mathematical tools that can be used to make decisions in this situation. Applying optimal control theory to COVID-19 can provide policymakers with valuable guidance on designing effective intervention strategies. It can inform decisions on when and how to implement various measures, considering factors such as transmission dynamics, healthcare capacity, and societal impact.

Overall, while medical mask use aimed to curb virus transmission, its impacts on social factors and individual well-being were diverse, influenced by cultural, political, and socioeconomic dynamics unique to each country. These differences underscore the complex interplay between health measures and societal responses during the global pandemic.

Economic, social, and environmental constraints play significant roles in shaping COVID-19 control measures and the processes involved in implementing and concluding them. Economically, restrictions such as lockdowns and travel bans can impact businesses, leading to loss of revenue, unemployment, and economic downturns. Socially, measures like social distancing and quarantine can disrupt daily life, strain relationships, and exacerbate mental health issues. Environmentally, the increased use of single-use plastics and disinfectants can contribute to pollution and environmental degradation. Balancing these constraints requires careful consideration of their implications and trade-offs. The procedures for concluding control measures involve assessing their effectiveness, weighing the costs and benefits, and consulting with stakeholders to determine the appropriate timing for easing restrictions based on evolving epidemiological data, vaccination rates, and other relevant factors.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

Adi-Kusumo, F. (2017). The Dynamics of a SEIR-SIRC Antigenic Drift Influenza Model. *Bulletin of Mathematical Biology, 79,* 1412-1425. https://doi.org/10.1007/s11538-017-0290-5

Agarwal, P., Nieto, J. J., & Torres, D. F. M. (2022). *Mathematical Analysis of Infectious Diseases*. Academic Press.

Aguas, R., White, L., Hupert, N., Shretta, R., Pan-Ngum, W., Celhay, O., Moldokmatova, A., Arifi, F., Mirzazadeh, A., Sharifi, H et al. (2020). Modelling the COVID-19 Pandemic in Context: An International Participatory Approach. *BMJ Global Health, 5,* e003126. https://doi.org/10.1136/bmjgh-2020-003126

Aravindakshan, A., Boehnke, J., Gholami, E., & Nayak, A. (2022). The Impact of Mask-Wearing in Mitigating the Spread of COVID-19 during the Early Phases of the Pandemic. *PLOS Global Public Health, 2,* e0000954. https://doi.org/10.1371/journal.pgph.0000954

Beal, L. D. R., Hill, D. C., Martin, R. A., & Hedengren, J. D. (2018). Gekko Optimization Suite. *Processes, 6,* Article 106. https://doi.org/10.3390/pr6080106

Betsch, C., Korn, L., Sprengholz, P., Felgendreff, L., Eitze, S., Schmid, P., & Bohm, R. (2020). Social and Behavioral Consequences of Maskpolicies during the COVID-19 Pandemic. *Proceedings of the National Academy of Sciences, 117,* 21851-21853. https://doi.org/10.1073/pnas.2011674117

Cooper, I., Mondal, A., & Antonopoulos, C. G. (2020). A SIR Model Assumption for the Spread of COVID-19 in Different Communities. *Chaos, Solitons & Fractals, 139,* Article 110057. https://doi.org/10.1016/j.chaos.2020.110057

Duncan, S. R., Scott, S., & Duncan, C. J. (1994). Modelling the Different Smallpox Epidemics in England. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences, 346,* 407-419. https://doi.org/10.1098/rstb.1994.0158

Eubank, S., Eckstrand, I., Lewis, B., Venkatramanan, S., Marathe, M., & Barrett, C. (2020). Commentary on Ferguson, et al., Impact of Non-Pharmaceutical Interventions (NPIs) to Reduce COVID-19 Mortality and Healthcare Demand. *Bulletin of Mathematical Biology, 82,* Article Number 52. https://doi.org/10.1007/s11538-020-00726-x

Froese, H., Prempeh, A. G. A. et al. (2022). Mask Use to Curtail Influenza in a Post-COVID-19 World: Modeling Study. *JMIRx Med, 3,* e31955. https://doi.org/10.2196/31955

Harris, C., Millman, K. J., Van Der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J. et al (2020). Array Programming with NumPy. *Nature, 585,* 357-362. https://doi.org/10.1038/s41586-020-2649-2

Holmdahl, I., & Buckee, C. (2020). Wrong but Useful—What Covid-19 Epidemiologic Models Can and Cannot Tell Us. *New England Journal of Medicine, 383,* 303-305. https://doi.org/10.1056/NEJMp2016822

Howard, J., Huang, A., Li, Z., Tufekci, Z., Zdimal, V., Van Der Westhuizen, H.-M., Von Delft, A., Price, A., Fridman, L., Tang, L.-H. et al. (2021). An Evidence Review of Face Masks against COVID-19. *Proceedings of the National Academy of Sciences of the United States of America, 118,* e2014564118. https://doi.org/10.1073/pnas.2014564118

Hunter, J. D. (2007). Matplotlib: A 2D Graphics Environment. *Computing in Science & Engineering, 9,* 90-95. https://doi.org/10.1109/MCSE.2007.55

Khatua, A., Kar, T. K., Nandi, S. K., Jana, S., & Kang, Y. (2020). Impact of Human Mobility on the Transmission Dynamics of Infectious Diseases. *Energy, Ecology and Environment, 5,* 389-406. https://doi.org/10.1007/s40974-020-00164-4

Lyu, W., & Wehby, G. L. (2020). Community Use of Face Masks and COVID-19: Evidence from a Natural Experiment of State Mandates in the US: Study Examines Impact on COVID-19 Growth Rates Associated with State Government Mandates Requiring Face Mask Use in Public. *Health Affairs, 39,* 1419-1425. https://doi.org/10.1377/hlthaff.2020.00818

Manzo, G. (2020). Complex Social Networks Are Missing in the Dominant COVID-19 Epidemic Models. *Sociologica, 14,* 31-49.

NIPH (2020). Norwegian Institute of Public Health, Corona Report.

Rachah, A. (2018). A Mathematical Model with Isolation for the Dynamics of Ebola Virus. *Journal of Physics: Conference Series, 1132,* Article 012058. https://doi.org/10.1088/1742-6596/1132/1/012058

Rachah, A. (2022). Modeling the Impact of Isolation during an Outbreak of Ebola Virus. In P. Agarwal, J. J. Nieto, & D. F. M. Torres (Eds.), *Mathematical Analysis of Infectious Diseases* (pp. 247-257). Academic Press. https://doi.org/10.1016/B978-0-32-390504-6.00019-X

Rachah, A. et al. (2017). Analysis, Simulation and Optimal Control of a SEIR Model for Ebola Virus with Demographic Effects. *Communications Faculty of Sciences University of Ankara Series A1 Mathematics and Statistics, 67,* 179-197. https://doi.org/10.1501/Commua1_0000000841

Rachah, A., Torres, D. F. M. (2017). Predicting and Controlling the Ebola Infection. *Mathematical Methods in the Applied Sciences, 40,* 6155-6164. https://doi.org/10.1002/mma.3841

Rachah, A., Torres, D. F. M. et al. (2015). Mathematical Modelling, Simulation, and Optimal Control of the 2014 Ebola Outbreak in West Africa. *Discrete Dynamics in Nature and Society, 2015,* Article ID: 842792. https://doi.org/10.1155/2015/842792

Riley, C., Xie, B., & Khurshid, A. (2021). Challenges Encountered in Comparing International Policy Responses to COVID-19 and Their Effects. *Health Research Policy and Systems, 19,* Article No. 134. https://doi.org/10.1186/s12961-021-00783-1

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J. et al. (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods, 17,* 261-272. https://doi.org/10.1038/s41592-019-0686-2

Wang, H., Paulson, K. R., Pease, S. A., Watson, S., Comfort, H., Zheng, P., Aravkin, A. Y., Bisignano, C., Barber, R. M., Alam, T. et al. (2022). Estimating Excess Mortality Due to the COVID-19 Pandemic: A Systematic Analysis of COVID-19-Related Mortality, 2020-21. *The Lancet, 399,* 1513-1536. https://doi.org/10.1016/S0140-6736(21)02796-3

Wang, K., Ding, L., Yan, Y., Dai, C., Qu, M., Jiayi, D., & Hao, X. (2020). Modelling the Initial Epidemic Trends of COVID-19 in Italy, Spain, Germany, and France. *PLOS ONE, 15,* e0241743. https://doi.org/10.1371/journal.pone.0241743

Wintachai, P., & Prathom, K. (2021). Stability Analysis of SEIR Model Related to Efficiency of Vaccines for COVID-19 Situation. *Heliyon, 7,* e06812. https://doi.org/10.1016/j.heliyon.2021.e06812