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# IMPACTS OF QUANTIFYING SOCIAL DISTANCING MEASURES ON MPC PERFORMANCE FOR SIR-TYPE SYSTEMS.

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***Abstract*— Currently, there has been a sharp increase in epidemic control research as a result of recent epidemic outbreaks. Several strategies aiming to minimize the Epidemic Final Size and/or to keep the Infected Peak Prevalence under a specific value were proposed.**

**However, not many strategies focused on analyzing the impact of applying quantified measures instead of continuous control action. This analysis is a crucial aspect since policymakers design their non-pharmaceutical intervention based on a discrete scale of intensity, from mask-wearing to hard lockdown.**

**In this work, we present a quantized-input non-linear Model Predictive Control strategy to manage non-pharmaceutical interventions during an epidemic outbreak. The impact of quantifying the social distancing measure is computed through several simulations based on a COVID-19 epidemic model and considering different quantization levels of the non-pharmaceutical intervention. Finally, the control performance in each quantization level is evaluated with the computation of four epidemic indices.**

***Keywords*— Epidemiological models, Model predictive control, Non-pharmaceutical interventions, Discrete control actions.**

## I. INTRODUCTION

Since the appearance of SARS-CoV-2 (Weiss and Navas-Martin, 2005), humanity has had to face different global challenges in terms of health care and economy through epidemic control strategies (Alamo *et al.*, 2021a,b). This kind of pathogen will reappear recurrently, due to zoonotic interaction with other species (Lamers and Haagmans, 2022; Zhou *et al.*, 2020). Thus, the emergence of novel human pathogens could potentially lead to worldwide pandemics similar to the COVID-19 outbreak, in the near future (Akter *et al.*, 2021). These worldwide pandemics could have an uncontrolled exponential spread and, as we saw with COVID-19, cause a global collapse of the healthcare system and economy (Abbasi, 2020; Brodeur *et al.*, 2021). To counteract these new pathogens, policymakers require tools to keep infectious diseases under control. In the absence of a vaccine or medical treatments, one of the main ways to lessen the disease transmission is by implementing Non-Pharmaceutical Interventions (NPIs), mainly Social Distancing (SD) measures such as mask-wearing, stay-at-home, the banning of gatherings, amount other (Flaxman *et al.*, 2020).

Several works have been made in the literature to control epidemic outbreaks by using social distancing measures (Köhler *et al.*, 2021; Morato *et al.*, 2020; Péni *et al.*, 2020; Péni *et al.*, 2022; Pataro *et al.*, 2021; Carli *et al.*, 2020), being the optimal control technique one of the most commonly used. The vast majority of these proposals are based on continuous control actions instead of discrete ones, while common NPIs applied by policy-makers are clearly discrete, covering no more than four or five possible severities. This fact, not only turns most of the control techniques unpractical in real scenarios but also suboptimal.

In Köhler *et al.* (2021), the authors formulate a robust Non-linear Model Predictive Controller (NMPC) to manage the COVID-19 outbreak in Germany. The approach is based on manipulating the transmission rate on the (well-known) SIDARTHE model (Giordano *et al.*, 2020). The control action is considered as a continuous variable taking values between 0 (hard lockdown) and 1 (no intervention). No quantization or discrete levels of SD are considered in the NMPC formulation. In Morato *et al.* (2020), a Model Predictive Controller (MPC) is proposed to manage social distancing in Brazil. The authors present an optimal on-off SD strategy, thus allowing authorities to consider two possible discrete levels of control action: the existence or the absence of SD policy. For these two possible discrete levels, the authors formulate a dwell-time restriction to avoid too frequent shifts between these two control inputs. In Péni *et al.* (2020), the authors presented an NMPC with logic constraints to manage the COVID-19 pandemic in Hungary. Similarly, to Carli *et al.* (2020), the authors consider a control input quantization by applying fixed levels of SD measures.

In this work, we analyze the quantization of control inputs under MPC strategies, to manage the SD measures in general epidemic models. For this, we formulate an NMPC that considers different levels of quantization for the SD measures, which can be obtained by a variety of combinations of the different measures of social distancing, such as: closing public spaces, schools, and universities; banning public transportation; wearing face mask; closing non-essential businesses, among others. To evaluate the controller performance, we simulate the control technique on the so-called SLPIAHRD model, which was proposed in Péni *et al.* (2020) and contains the following population compartments: susceptible, latent, pre-symptomatic, infected-symptomatic, asymptomatic-infected, hospitalized, recovered, and deceased.

The controller performance is assessed through the next four indexes: the Epidemic Final Size ($EFS$, total fraction of infected individuals at the end of the pandemic outbreak), the Infected Peak Prevalence ($IPP$, which corresponds to the maximal fraction of infected individuals over the total epidemic time), the Social Distancing Index ($SDI$, which we proposed as an index to measure the SD severity and side effects), and finally the Herd Immunity Time ($HIT$, time required to achieve the herd immunity value). The obtained results are far from trivial, and we present an extensive interpretation of them, emphasizing the importance of considering quantization/discretization in the control input of optimal control strategies.

The work is organized as follows: Section I presents the between-host dynamical model and the epidemic performance metrics. The control strategy for epidemiological management is presented in Section II. In this section, a non-linear MPC with quantized control actions is presented. After that, the results and discussion are presented in Section IV. Finally, some remarks are given in Section V to conclude this work.

## II. BETWEEN-HOST DYNAMICAL MODEL

Having a model that represents the dynamics and interaction between susceptible, infected, and recovered populations is necessary for the application of model-based predictive controllers. Here, we work with the SLPIAHRD model - an extended, compartmentalized, and control-oriented epidemiological model - presented in Péni *et al.* (2020). The population is divided into eight compartments: $S$ represents the susceptibles, i.e. people who are vulnerable to contracting the disease, $L$ (latent) stands for those who have already contracted the disease but have not yet shown symptoms and are not yet contagious, and $P$ is the pre-symptomatic compartment, which represents persons who are infected but have not yet shown any symptoms. The infected individuals are moved then to the asymptomatic ($A$) and symptomatic ($I$) compartments when the incubation period has passed. Those in compartment $A$ will always recover, however, the more serious cases in compartment $I$ could need to be hospitalized and transferred to compartment $H$. Eventually, patients in $H$ may recover ($R$) or die ($D$).

The dynamical systems consist of eight ordinary differential equations, describing the evolution of the population in each stage over time.

$$\begin{aligned}
\dot{x}_S &= -\beta[x_P + x_I + \delta X_A]X_s, \qquad (1)\\
\dot{x}_L &= \beta[x_P + x_I + \delta X_A]X_s - \alpha x_L,\\
\dot{x}_P &= \alpha x_L - p x_P,\\
\dot{x}_I &= qp x_P - \rho_I x_I,\\
\dot{x}_A &= (1-q)p x_P - \rho_a x_A,\\
\dot{x}_H &= \rho_I \eta x_I - h x_H,\\
\dot{x}_R &= \rho_I(1-\eta)x_I + \rho_A x_A + (1-\mu)h x_H,\\
\dot{x}_D &= \mu h x_H
\end{aligned}$$

where the time dependence was omitted for the sake of simplicity. Model parameters are shown in Table 1. This kind of extended model could be represented by grouping its different compartments into the three main categories of the SIR model: Susceptible, Infected/Infectious, and Removed. In such a way, we have that *Susceptible* is given by $S$, while *Infected* is given by $\{L, P, I, A, H\}$, and *Removed* is given by $\{R, D\}$. Considering that there are no additional flows out of the traditional ones, we can make the stability analysis presented in Sereno *et al.* (2022), which allows us to properly define the control objectives that the controller will be required to achieve (see Subsection III.A.

Table 1. Parameters of the SLPIAHRD model (Péni and Szederkényi, 2021)

| Parameter | Value | Meaning |
|---|---|---|
| $\alpha^{-1}$ | 2.5 (days) | Latent period |
| $p^{-1}$ | 3 (days) | Pre-symptomatic infectious period |
| $\beta$ | 1/3 | Transmission rate |
| $\delta$ | 0.75 | Relative transmissibility of asymptomatic |
| $q$ | 0.6 | Probability of developing symptoms |
| $\rho_I^{-1} = \rho_A^{-1}$ | 4 (days) | Infectious period |
| $\eta$ | 0.076 | Hospitalization probability of symptomatic cases |
| $h^{-1}$ | 10 | Average length of hospitalization |
| $\mu$ | 0.145 | Probability of fatal outcome, given hospitalization |

The time-varying reproduction number of the SLPIAHRD model is given by,

$$\mathcal{R}(\cdot) = \beta(\cdot)\left(\frac{1}{p} + \frac{q}{\rho_I} + \frac{\delta(1-q)}{\rho_A}\right), \qquad (2)$$

which directly depends on the (assumed) time-varying parameter $\beta$ that is affected by the SD measures. The effect of any intervention (from mandatory mask-wearing to hard lockdown) can be quantified by scaling factors of the transmission rate $\beta$. From Péni *et al.* (2020), the boundedness of the transmission rate parameter is $0.067 \le \beta \le 1/3$, where $\beta_{min} = 0.067$ correspond to the strictest SD measure (note that no real-life SD is able to zero the transmission rate), and $\beta_{max} = 1/3$ represents the absence of SD measures.

### A. Epidemic Indexes

Here, we define the four epidemic indexes that are considered to assess the controller performance in the management of the epidemic outbreak. The performance indexes are as follows:

*Infected Peak Prevalence* ($IPP$)

The first epidemic-severity index, the *IPP*, is defined as:

$$IPP \equiv \max_{t\in[0,\infty)} I(t). \qquad (3)$$

A high $IPP$, a large number of infected individuals in a given time, could overwhelm the healthcare capacity and consequently limit the capacity to take care of patients.

*Epidemic Final Size* (*EFS*)

Let $S_\infty \equiv \lim_{t\to\infty} S(t)$, thus, the second epidemic-severity index, the $EFS$, is defined as:

$$EFS \equiv 1 - S_\infty. \qquad (4)$$

A high $EFS$ means a high total number of infected individuals at the end of the epidemic, and consequently a higher number of deaths. Further information about the computation of $EFS$ is given in Sereno *et al.* (2022).

*Social Distancing Index* ($SDI$)

In order to consider the undesirable outcomes and side effects of the SD measures (i.e., psychological stress, economic damages, among others), the third epidemic-severity index, the $SDI$, is defined as:

$$SDI \equiv \int_0^{\infty}(\mathcal{R}_0 - \mathcal{R}(t))dt = \int_{t_i}^{t_f}(\mathcal{R}_0 - \mathcal{R}(t))dt. \quad (5)$$

A high $SDI$ means longer and harder interventions, causing social fatigue and economic issues.

*Herd Immunity Time* ($HIT$)}
As shown in Sereno *et al.* (2022), a standard SIR-type model has a unique asymptotically stable set, define as $\mathcal{X}_s^{st}$, which is reached when $S \in [0, S^*]$ and $I = 0$, being $S^*$ the herd immunity value defined as:

$$S^* \equiv 1/\mathcal{R}_0. \quad (6)$$

Once $S(t)$ goes below the herd immunity value, $S \leq S^*$, the infected population can no longer increase, and therefore the system monotonically converges to the asymptotically stable set $\mathcal{X}_s^{st}$. So, the fourth epidemic-severity index, the $HIT$, is defined as the period of time required for the susceptible population to go below the herd immunity value, $S^*$, since the start of the epidemic outbreak, $t = 0$.

## III. Epidemic Control Strategy

### A. Control Objectives

Considering the epidemiological indexes presented above, the control objectives for the MPC formulation are established as follows:

*Epidemic control objective*: Bringing the $EFS$ as near as possible to $1 - S^*$, while maintaining $IPP \leq I_{max}$.

*Social control objective*: Minimizing $SDI$, provided that the Epidemic Control Objective was achieved.

### B. Quantized Control Action

The transmission rate parameter is quantized through the equation,

$$\beta(t) = \beta_{max} - v(t)\Delta\beta, \quad (7)$$

with

$$\Delta\beta = \frac{\beta_{max} - \beta_{min}}{n},$$

where $n \in \mathbb{I}$ represents the number of possible SD measures, and $v(t) \in \mathbb{I}_{[0,n]}$ is the control integer input describing the severity of the SD measure. Notice from Eq. 7 that $v = 0$ corresponds to the absence of SD measures, while $v = n$ corresponds to the hardest lockdown. This way, from Eqs. 7 and 2, the integer control input $v(t)$ sets a discrete value from $\beta$, allowing us to select a specific reproduction number, as stated in Table 2. Figure 1 shows a schematic plot of $\mathcal{R}(t)$ corresponding to an illustrative example of an intervention scenario when the number of possible SD measures is $n = 4$. $t_i$ and $t_f$ stand for the initial and final time of intervention, respectively.

Table 2. Levels of SD measures, when $n = 4$.

| $v(t)$ | $\beta(t)$ | $\mathcal{R}(t)$ | SD measure |
|---|---|---|---|
| 0 | $\beta_0$ | $\mathcal{R}_0$ | no SD measure |
| 1 | $\beta_1$ | $\mathcal{R}_1$ | addition of mask-wearing |
| 2 | $\beta_2$ | $\mathcal{R}_2$ | addition of university/school closure |
| 3 | $\beta_3$ | $\mathcal{R}_3$ | addition of stay-at-home measures |
| 4 | $\beta_4$ | $\mathcal{R}_4$ | hardest lockdown (all available measures) |

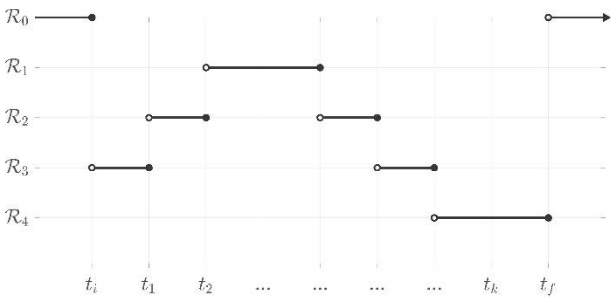

Figure 1. Schematic plot of $\mathcal{R}(t)$ for an illustrated intervention scenario.

### C. MPC Formulation

The system (1) together with (7) is discretized to obtain the general form $x_{k+1} = F(x_k, v_k)$, $k \in \mathbb{I}_{0:\infty}$, where $F(\cdot)$ is the discrete-time version of the non-linear function corresponding to the dynamical model (1). $x_k$ stand for the state vector at the sampled time $k$ ($x_k \equiv x(kT_s)$, $T_s > 0$ is the sampling time), and $v_k$ stands for the input such that $v(t) = v_k$, $t \in [kT_s, (k+1)T_s]$, $k \in \mathbb{I}_{0:\infty}$. We define $t_i$ and $t_f$ as the initial and final time of intervention, respectively. In such a way, for $t \in [t_i, t_f]$ the MPC computes the optimal SD measure.

This subsection is dedicated to the non-linear model predictive controller formulation. This formulation is based mainly on the dynamic analyses conducted in Sereno *et al.* (2022), and the analysis made in the previous subsections. Here, we mainly focus on designing an MPC formulation that explicitly considers control actions in a quantized way, i.e., discrete levels of SD interventions.

The cost function to be minimized online by the MPC is given by:

$$V_N(x; v) = \sum_{j=0}^{N-1} r\|v_j\|^2 + q\,\|S_j - S^*\|^2, \quad (8)$$

where $N$ stands for the control horizon, $r$ and $q$ are positive constants that stand for input, and state penalization, respectively. $x = x_k = (S_k, L_k, P_k, I_k, A_k, H_k, R_k, D_k)$ is the current state at time $k$ and $v \equiv \{v_0, v_1, \cdots, v_{N-1}\}$ is the predicted control sequence, with $v_j \in \mathbb{I}_{[0,n]}$, for $j \in \mathbb{I}_{0:N-1}$. In general, $N$ is assumed to be much smaller than the period of intervention, $(t_f - t_i)/T_s$, and the controller is executed up to the final time of intervention, $k_f = t_f/T_s$ (then, no control action is implemented).

The optimization problem to be solved at each sampling time $k$ (for all $k$ such that $kT_s \in [t_i, t_f]$) is then given by:

$$\min_{v} V_N(x; v) \quad (9)$$

s.t.

$$\begin{aligned} &x_0 = x_k, \\ &x_{j+1} = F(x_j, v_j), && j \in \mathbb{I}_{0:N-1}, \\ &x_j \in \mathcal{X}, && j \in \mathbb{I}_{0:N-1}, \\ &v_j \in \mathbb{I}_{[0:n]}, && j \in \mathbb{I}_{0:N-1}, \\ &H_j \leq H_{max}, && j \in \mathbb{I}_{0:N-1}, \end{aligned}$$

constraint $H_j \leq H_{max}$ stands for the available healthcare capacity $H_{max}$, associated with the availability of beds in the healthcare system. $F(x_j, v_j)$ is the predictive model in discrete-time version of the system (1), for $j \in \mathbb{I}_{0:N-1}$. The optimization problem is applied through a receding horizon control strategy. Note that the use of quantized control actions leads to the use of mixed-integer nonlinear programming strategies to solve (9).

## IV. SIMULATION

In this section, different levels of quantization for SD intervention are tested through several simulation scenarios. These simulations were run on a laptop computer with an i7-4510U processor (2 cores, 4 threads, 2.0-3.1 GHz) and 16GB RAM, using the software MATLAB R2021a and CasADi version 3.5.5 (Andersson *et al.*, 2019). To solve the mixed-integer non-linear problem (9), the BONMIN solver was used.

All simulations were performed for a period of 1 year, with a sampling time $T_s = 5$ days, and $H_{max}$=0.002 was selected as a maximum healthcare capacity (percentage of the total population). Although different levels of quantization were considered, the minimal and maximal intervention severity was set as: $\beta_{min}$=0.067 ($\mathcal{R}_n = 0.44$) and $\beta_{min}$=1/3 ($\mathcal{R}_0 = 2.2$). According to these values, the herd immunity threshold is given by $S^* = 1\,/\mathcal{R}_0 = 0.4545$. Model simulation was set as stated in Péni and Szederkényi (2021), the state space is normalized between [0, 1], the initial state is given by $L(0) = 2.0408 \times 10^{-5}$, $P(0) = 5.1020 \times 10^{-6}$, $I(0) = 2.0408 \times 10^{-7}$, and $A(0) = 1.0204 \times 10^{-7}$ and $S(0) = 1 - L(0) - P(0) - I(0) - A(0)$. The control horizon of the NMPC is selected to be $N = 30$ days, while the penalties $r$ and $q$ are selected to be $10^{-3}$ and $\$10^3$, respectively. This tuning was selected to prioritize the epidemic control objective, in contrast to the social control objective. The initial and final time of intervention was selected as $t_i = 15$ and $t_f = 285$ days, respectively. In such a way, the controller has a time window of 9 months to apply the corresponding interventions to achieve the control objectives (IIIA).

For comparison purposes, a single-intervention strategy (consisting of a 2 months hardest lockdown strategy, were $v(t) = n$, from $\tau_i = 60$ to $\tau_f = 120$ days, i.e. $\mathcal{R}(t) = \mathcal{R}_n$), and an absence-intervention strategy (uncontrolled epidemic, were $v(t) = 0$, $\mathcal{R}(t) = \mathcal{R}_0$, for all $t$) are also simulated and plotted in all figures. Figures 2 to 5 show the temporal evolution of Susceptible, Total Infected, Hospitalized, and Deceased individuals, respectively, while Fig. 6 shows the SD severity, i.e., $\mathcal{R}(t)$. As can be seen, the MPC controller with quantized inputs performs well on average for all possible levels of quantization. The epidemic control objective is achieved for all the simulated levels of quantization, that is, the susceptible population remains close to the optimal value $S^*$, and as we can see in Table 3, the obtained $EFS$ values are quite similar in all cases and close to the optimal value $EFS = 1 - S^* = 0.5455\$$. However, one can see that the On-Off strategy (when $n = 2$) performs slightly better than the others. There is a variety of proposals in the literature that account for this On-Off implementation, but without accounting for the *Epidemic Control Objective* proposed in this article. Instead, they consider just a control objective consisting in minimizing the infected population over time (Morato *et al.*, 2020; Bisiacco and Pillonetto, 2021; Bin *et* al., 2021), so resulting in strategies with significantly large values of $EFS$.

As we can observe in Table 3, the On-Off strategy produces a larger $SDI$ and, in consequence, further social and economic fatigue. From Table 3 is noteworthy that the $HIT$ (in months) decreases as the level of quantization increases, suggesting that more levels of quantization enlarge the controllability of the system, allowing the con-

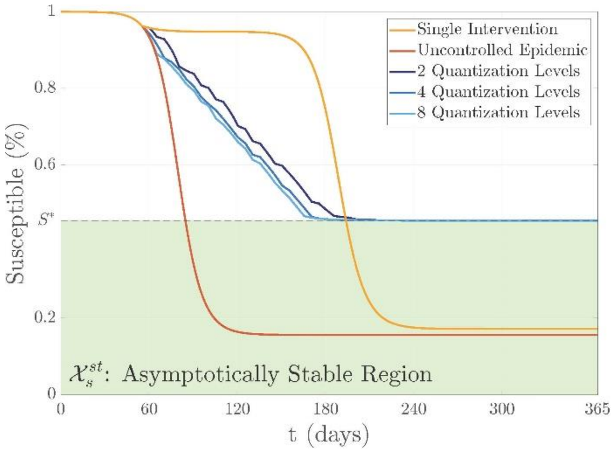


Figure 2. Fraction of susceptible population for SLPIAHRD model.

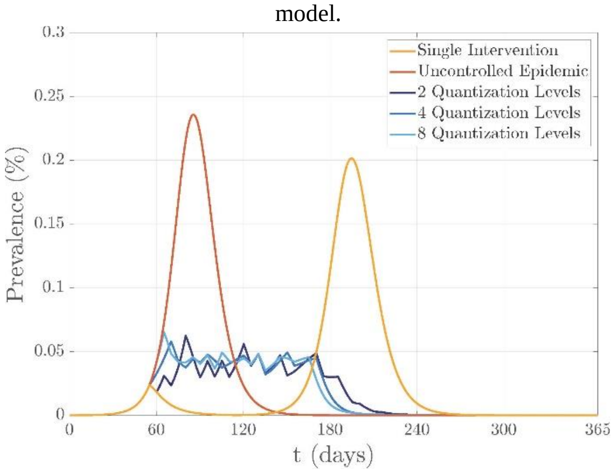


Figure 3. Fraction of total infected population for SLPIAHRD model ($L + P + I + A + H$).

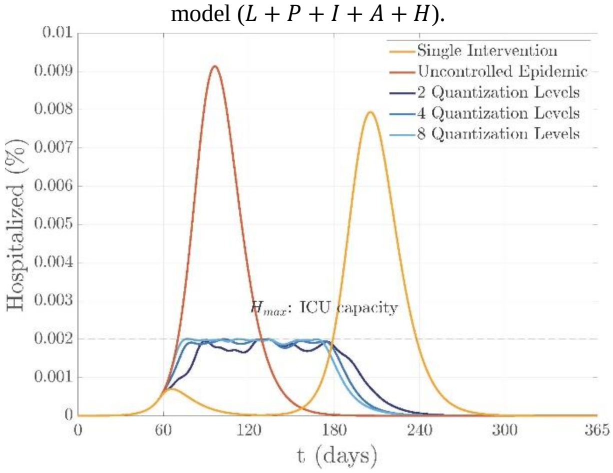


Figure 4. Fraction of Hospitalized population for SLPIAHRD model. Black horizontal-dashed line represents the maximum healthcare capacity.

Table 3. Performance indexes for the SLPIAHRD model

| Quantization levels | Performance index | | | |
|---|---|---|---|---|
| | $EFS$ | $IPP$ | $SDI$ | $HIT$ |
| 2 | 0.5455 | 0.0437 | 38.72 | 10.67 |
| 4 | 0.5456 | 0.0413 | 37.55 | 9.333 |
| 6 | 0.5457 | 0.0376 | 36.26 | 8.333 |
| 8 | 0.5458 | 0.0459 | 35.20 | 8.667 |
| 10 | 0.5459 | 0.0431 | 35.40 | 8.500 |
| 12 | 0.5461 | 0.0451 | 34.40 | 8.667 |

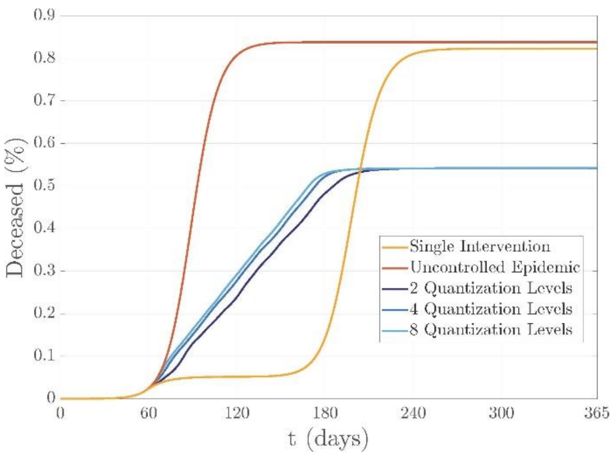


Figure 5. Fraction of Deceased population for SLPIAHRD model.

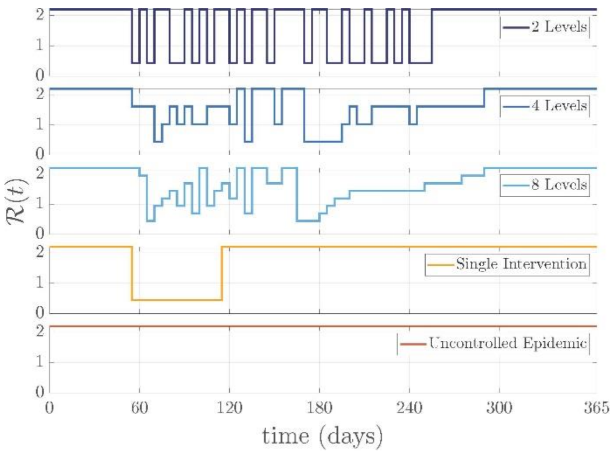


Figure 6. Reproduction number as a control action for SLPIAHRD model.

troller to converge faster to the asymptotically stable set $\mathcal{X}_s^{st}$. No significant difference can be observed for the $IPP$ index, presumably because the controller always tries to operate at the edge of hospital capacity, $H_{max}$. The higher the number of SD levels, the more the controller can operate on the edge of the constraint, which can be seen in detail in Fig. 7a and 7b. In addition, all quantization levels are able to maintain the hospitalized individuals under the $IPP$ restriction, $H_j \leq H_{max}$, see Fig. 4. Finally, Fig. 5 shows that the controller strategy achieves a lower value of the deceased individuals than the single-intervention and absence-intervention strategies, suggesting that this objective is not a trivial one (or one consisting in just applying an intuitive strategy).

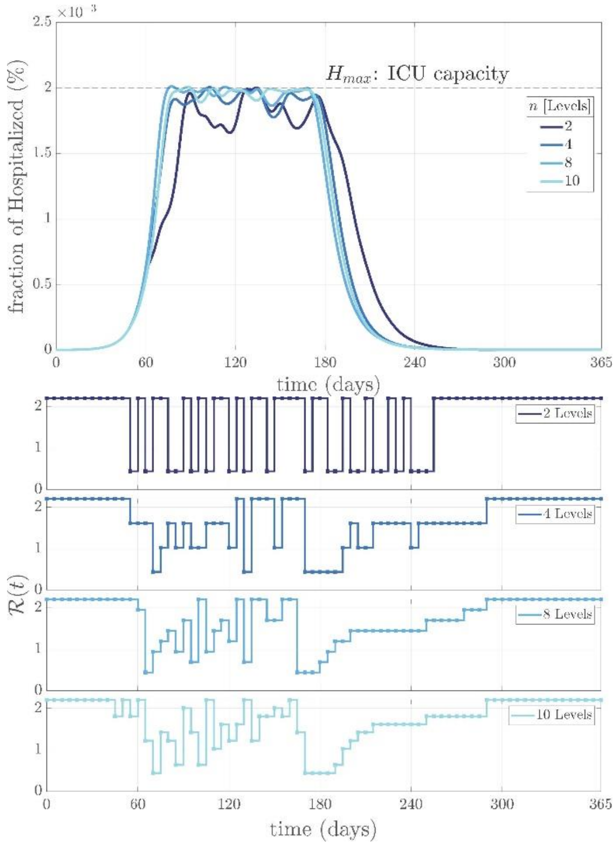


Figure 7. (a) Hospitalized population behaviour vs changes in quantization NPI levels. (b) Control action pattern with respect to different quantization levels.

## V. CONCLUSIONS

A quantized input analysis for model predictive control applied to the COVID-19 pandemic was presented in this paper. First, we consider a well-posed formulation of the optimal control problem for the MPC strategy, based on the results in Sereno *et al.* (2022). Then, an input quantization process is made to evaluate the control performance based on different levels of quantization. The transmission rate parameter was selected to conduct this quantization process and through it, different levels of SD interventions were performed and associated with different levels of the reproduction number. Four different epidemic severity indexes were stated to evaluate the controller performance under quantized level variations. A single intervention and an absence-intervention strategy were also simulated to compare with the proposed MPC strategy. The epidemic control objective is achieved for all simulated quantization levels. It is important to mention that less quantization levels produce more social and economic fatigue. Otherwise, a strategy more like a fast periodic switching policy, between the absence and hardest intervention, could numerically achieve slightly better performance on the $EFS$ index. Accounting for the social control objective, the $SDI$ is minimized better when we have the availability to implement more levels of SD interventions. So, policymakers could achieve less social and economic fatigue by considering more social distancing measures apart from the traditional ones. As a future work, a robustness analysis of the impact of quantifying social distancing measures may add further value to the research.

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