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New strategy to control covid-19 pandemic using lead/lag compensator

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ABSTRACT

COVID-19 is still the main worldwide issue since the outbreak. Many strategies were implemented such as suppression, mitigation, and mathematical-engineering strategies, to control this pandemic. In this work, a lead/lag compensator is proposed to control an unstable Covid-19 nonlinear system after using some required assumptions. The control theory is involved with the unstable pandemic and other existing strategies until the invention of the vaccine is approved. In addition, the Most Valuable Player Algorithm (MVPA) is used to optimize the parameters of the proposed controller and to determine whether it is a lead or lag compensator. Finally, the simulation results are based on the daily reports of two pandemic cities: Hubei (China), and Lazio (Italy) since the outbreak began. It can be concluded that the lead/lag compensator can effectively control the COVID-19 system.

1. Introduction

Covid-19 has been a worldwide issue since the outbreak. Much research has been conducted to describe the spread of the virus or the virus itself mathematically [1]. Frequently, these kinds of diseases (like SARS) were described using a Susceptible-Exposed-Infectious (SIR) model or a delayed SIR model, which has three dynamic states [2]. Since the viruses are continually developing, researchers have tried to expand their models by using Susceptible-Exposed-Infectious-Recovered (SEIR) or modified SEIR models with four states, to express them precisely [3]. Researchers facing more complicated viruses such as Covid-19 have relied on the Susceptible-Exposed-Infectious-Quarantine-Recovered (SEIQR) model to describe the virus accurately, by adding the quarantine state to the model [4,5].

Many strategies have been implemented to control the spread of the Coronavirus pandemic since the outbreak. The main strategies that have been used to overcome the Covid-19 pandemic since the outbreak, are illustrated below:

- a. Suppression strategy: It is applied to keep Covid-19 cases as low as possible. This strategy succeeded in delaying the outbreak of Covid-19 and was effective whenever control measures were sustained. However, when controls are eased or restricted, Covid-19 is likely to spread and herd immunity seems to not be acquired. The Suppression strategy has the advantage of buying time until a vaccine and/or treatment becomes available. In this strategy, a combination of strong border measures and successful suppression is used to reduce the infected cases around the world. Eventually, the control measures can be relaxed when the cases are reduced to a handful [6].
- b. Mitigation strategy: It is applied to allow the controlled outbreak to prevent the significant overloads on the local healthcare systems and then the World Healthcare System (WHO). Consequently, this leads to gradually allowing the population to develop herd immunity. The success or failure of mitigation strategies depends sensitively on the timing and efficacy of control measures and requires the ability to bring rapidly growing outbreaks under immediate control when needed. This is yet untested even for a combination of national interventions including case isolation, population-wide social distancing, household quarantine and closure of schools (universities). Strategy can be switched from suppression to mitigation. For example, once successful mitigation strategies have been tested in other countries. However, it is not necessary then to apply a suppression strategy owing to the difficulty of switching from mitigation to a suppression strategy [7].
- c. Mathematical-engineering strategy: this strategy can be used with both suppression and mitigation strategies during and after the invention of the vaccine. This strategy depends on control engineering theories that are employed to analyze the Covid-19 system. After that, a controller is designed to compensate for unpredictable nonlinear behavior of the Covid-19 pandemic [8].

Recently, a Sliding Mode Control strategy was used to control the
nonlinear dynamics of Covid-19, with continuity and bifurcation analysis [9]. In addition, a Model Predictive Control was used to handle the behavior of the pandemic with logic constraints [10]. Moreover, a Nonlinear Adaptive Control strategy was implemented to Covid-19 responses, to reduce the number of infected people and control the pandemic [11]. Furthermore, a new strategy was suggested to control this pandemic, using a robust control algorithm with certain data delivered by WHO reports [12]. Eventually, a lead-lag compensator is proposed to overcome the nonlinearity without linearizing the system. Furthermore, the input dataset used in this article was for two cities, Lazio and Hubei for a certain amount of time since the outbreak.

The main objective of this paper is to introduce a new strategy to contain the Covid-19 pandemic. The control theory strategy opens the door to many other ideas for mathematical-engineering solutions (especially control engineering), to overcome the pandemic, along with medical treatments. Moreover, other techniques and methods can be used to produce better results with more accurate and robust controllers. Covid-19 behavior is unpredictable. A control theory Strategy can be used with any other model to describe the pandemic more precisely.

The following paper is organized as follows. The lead/lag compensator is introduced in Section 2 with COVID-19 mathematical description and the Most Valuable Player Algorithm (MVPA). The simulation results are explained in Section 3 to show the potential effects of the control algorithm. In Section 4, the discussion is made, to sum up, the results and the final evaluation of the lead-lag compensator. The conclusion is presented in Section 5.

2. Materials and methods

In this section, a new robust control algorithm is introduced to compensate for the COVID-19 nonlinear system. In addition, the mathematical model of COVID-19 is presented with necessary assumptions and new techniques/methods that are used alongside the proposed control algorithm, to fit the design procedures.

2.1. Covid-19 mathematical model description

In this work, the basic Susceptible-Exposed-Infectious-Recovered (SEIR) model can be developed as a COVID-19 model as follows [12]:

\[
\begin{align*}
\frac{dS(t)}{dt} &= - \beta u(t) S(t) / N, \\
\frac{dE(t)}{dt} &= \beta u(t) S(t) / N - \varepsilon E(t), \\
\frac{dI(t)}{dt} &= \varepsilon E(t) - \gamma I(t), \\
\frac{dR(t)}{dt} &= \gamma I(t).
\end{align*}
\]

(4)

where \(R(t)\) represents Resistant subjects, \(S(t)\) represents Susceptible individuals, \(I(t)\) represents Infectious individuals that have been infected but are not yet infectious. \(N\) represents the total population and \(E(t)\) represents Exposed individuals. The parameter \(\beta\) represents the likelihood of infection per unit in time. \(\varepsilon\) refers to the inverse of the average latency time of the disease and \(\gamma\) represents the inverse of the average time infectious individuals spend, actually infecting people. After some assumptions that are made in earlier work; the control-oriented model of the epidemic is thus [12]:

\[
\begin{align*}
\frac{dE_i(t)}{dt} &= \beta(u(t)) I_i(t) - \varepsilon E_i(t), \\
\frac{dI_i(t)}{dt} &= \varepsilon E_i(t) - \gamma I_i(t), \\
y(t) &= \varepsilon E_i(t).
\end{align*}
\]

(5)

(6)

(7)

Where \(\beta(u(t))\) is functional, a mathematical function depends on function/s but not variable/s. The control action \(u(t)\) is that may contain the doses of the vaccine as a parameter value that can help individuals to recover from the virus. Also, \(I_i(t) = a I(t)\) and \(E_i(t) = a E(t)\), where \(a\) is a certain fraction of officially reported infectious and exposed cases. \(u(t)\) is the model output. In addition, if \(\beta(u(t))\) depends on \(u(t)\) then, the proposed controller is not considered as a suppression or a mitigation controller policy. However, it may contain the vaccine as a cure in part to eliminate this epidemic in the future. In the next subsection, the lead/lag compensator is used to control the COVID-19 system to achieve stability and better performance.

2.2. Lead/lag compensator

From the reported literature of control theories, the lead/lag compensator is a component that is used to control and achieve the desired performance for linear systems. In this work, the lead/lag compensator is used to control a nonlinear system represented by the Covid-19 nonlinear model. Furthermore, this compensator (lead/lag) is used with the general form and the optimization method (MVPA) to decide whether it is a lead, or a lag compensator, based on the optimized parameters. Eq. (8) shows the generalized form of the compensator in the Laplace domain [13]:

\[
C(s) = \frac{\beta(U(S))}{E(S)} = \frac{1 + \tau_S}{1 + \tau_S}.
\]

(8)

Where \(E(S) = Y(S) - R(S)\) measures the error, \(R(s)\) is the input, \(Y(s)\) is
the output, $S$ is Laplace operator and $\tau_1, \tau_2$ are time constants for pole and zero. In addition, in lead compensator $\frac{1}{\tau_1} < \frac{1}{\tau_2}$; while in lag compensator $\frac{1}{\tau_1} > \frac{1}{\tau_2}$. In the next subsection, the Most Valuable Player Algorithm (MVPA) is used to optimize the parameters of the compensator $\tau_1$ and $\tau_2$, and decide whether it is a lead or lag compensator. Moreover, the optimal parameters of the compensator are obtained by using the integral square error (ISE) formula as following [14]:

$$J = \int_0^t e^2(t)dt,$$

where $e(t)$ presents the difference value between the system input and output. Fig. 1 shows the overall block diagram of the Covid-19 nonlinear system interconnection with the MVPA.

**Table 1**

| Countries   | Covid-19 system parameters | MVPA settings | Lead compensator parameters |
|-------------|---------------------------|---------------|----------------------------|
| Hubei (China) | $\epsilon = 0.16 \text{ days}^{-1}$ | $LB = 0.0055$ | $\tau_1 = 17.194$ |
|             | $\gamma = 0.1875 \text{days}^{-1}$ | $UB = 25.813$ | $\tau_2 = 0.0055$ |
| Lazio (Italy) | $\epsilon = 0.16 \text{days}^{-1}$ | $Player_{size} = 20$ | $\tau_2 = 16.697$ |
|             | $\gamma = 0.2375 \text{days}^{-1}$ | $Team_{size} = 4$ | $\tau_1 = 17.194$ |
|             |                             | $Iterations = 40$ | $UB = 25.813$ |

**Fig. 2.** Validated data of China and Lazio outbreak [16].

**Fig. 3.** Open-loop system responses in Hubei and Lazio.
2.3. The Most Valuable Player Algorithm

The Most Valuable Player Algorithm (MVPA) is an optimization method that is based on sport (football, basketball). It depends on competitions between teams and players within teams to obtain the best team and then the best player of the league that would be awarded the MVP trophy. The reasons behind using MVPA are that this method converges faster, optimizing the parameters by passing through many phases, and is more accurate when compared with 13 other well-known optimization methods such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), …, etc. The following steps explain how this player (MVP player) is selected. First, the number of players, teams (initialization) are selected. The skills of the players are present in the parameters of the controller \((\tau_1, \tau_2)\) that need to be optimized. Consequently, the objective function (cost function) is chosen, which is in our case study the ISE. Next, the players improve their skills throughout the MVPA phases [15]. Then, the pre-optimized parameters are computed and applied simultaneously to the controlled system, to find the measured error. After that, the measured error is used to obtain the cost function in the second round and compared to the previous one to find the best cost function. Finally, the previous process is repeated until the optimum parameters are obtained after a certain number of iterations [15]. Table 1 shows the parameters of the COVID-19 system, MVPA settings, and the optimal parameters of the compensator.

After implementing the MVPA it turned out that the compensator is a lead compensator \(\left( \frac{1}{2} < \frac{1}{\tau_2} = \frac{1}{17.197} < \frac{1}{18.097} = 0.0582 < 0.0599 \right)\).

3. Results

In this section, the results of the open and closed-loop system are presented. Fig. 2 shows the input dataset (infected cases) is collected from daily reports in Hubei from Dec 29, 2019, to Jan 23, 2020, and Lazio from Feb 24, 2020, to Apr 14, 2020 [16,17].
The results of the controlled COVID-19 system are presented based on the input dataset of Lazio (Italy). Fig. 9 shows the states of the stabilized system ($I_t(t)$, $E_t(t)$) with initial condition ($I_t(0) = -0.5$ and $E_t(0) = 0.25$).

Fig. 10 presents the states of the system trajectories after applying the proposed lead compensator.

Fig. 11 shows the tracking property of the COVID-19 system under the lead compensator effect which is more accurate compared with the one that used the Hubei input dataset. Fig. 12 shows the phase-plane of the controlled system after implementing the lead compensator which proves the stability of the compensated Covid-19 system. In addition, the figure affirms the definition of the phase plane property that states the trajectory which starts at the stable equilibrium point and ends at the same point whenever time increases to a certain value (or in some cases to infinity).

Fig. 13 shows the control action ($\beta(u(t))$) that jumped at a high point on day 16 due to the increasing number of infected cases at Lazio. Fig. 14 explains the convergence property of the cost function after using MVPA to optimize the parameters of the lead compensator using the ISE cost function.

It is worth mentioning, that an iteration is corresponding to the day unit of the COVID-19 pandemic.

4. Discussion

The aforementioned results show that the lead compensator strategy could work in parallel with other existing strategies (suppression and mitigation), to compensate and reduce the spread of the COVID-19 pandemic. However, this strategy may not be effective without a COVID-19 vaccine, but it could be used alongside vaccine doses in the future. In addition, these results are valid for a certain period for both Hubei and Lazio and can be applied for other places, any time when the required data is available. Furthermore, the results confirm the effectiveness of the lead compensator. Results show the stabilization and the improvement of the performance of the controlled COVID-19 system. Eventually, these results can be compared to recent works as shown in Table 2.

Eventually, the proposed compensator could be used to control the spread of other pandemics in the future when the required data and epidemic model are available.

5. Conclusion

In this article, a lead compensator has been proposed as a control strategy to control the COVID-19 system to control the pandemic. This strategy is argued to bring more engineering solutions to overcome this pandemic. In addition, it can be used alongside suppression and mitigation strategies even with the vaccine. Also, the simulation results have proved the ability of the proposed controller, to compensate the COVID-19 system based on the daily reports from both Hubei-China and Lazio.
Italy. However, the model used is an SEIR model which can be modified to represent the pandemic more accurately. Finally, any updated data or model that represents the spread of the virus (SEIQR model) or the virus itself (within-host model), could be used with the proposed compensator.

CRediT authorship contribution statement

Musadaq A. Hadi: substantial contribution to conception and design, substantial contribution to acquisition of data, substantial contribution to analysis and interpretation of data, drafting the article, critically revising the article for important intellectual content, final approval of the version to be published. Zainab M. Amean: critically revising the article for important intellectual content, final approval of the version to be published.
Table 2
The paper strategy versus exists strategies.

| No. | Nonlinear adaptive control strategy [11]. | Robust control Strategy [12]. | The paper strategy. |
|-----|------------------------------------------|-------------------------------|---------------------|
| 1.  | It was an adaptive controller.           | It was a robust controller.   | It is a lead compensator controller. |
| 2.  | It was designed using Lyapunov analysis using adaptive laws. | It was designed using Lyapunov stability analysis after the system was simplified using the Variable Transformation technique (VTT). | It is simply designed without any further analysis. |
| 3.  | It was a nonlinear controller.           | It was a nonlinear controller. | It is a linear controller. |
| 4.  | It used the adaptation method.           | It used the MVPA optimization method. | It uses the MVPA optimization method with different optimization settings. |
| 5.  | It used two control variables $u_1$ and $u_2$. | It used one control variable with a complex structure as a chattering part (signum) in it. | It uses simple control action which has worked effectively. |

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Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

References

[1] K. Hattaf, N. Yousfi, Dynamics of SARS-CoV-2 infection model with two modes of transmission and immune response, Math. Biosci. Eng. 17 (5) (2020) 5326–5340, https://doi.org/10.3934/mbe.2020288 (Accessed 21 March 2021).
[2] K. Hattaf, A. Lashari, Y. Louartassi, N. Yousfi, A delayed SIR epidemic model with a general incidence rate, Electron. J. Qual. Theory Differ. Eq. (3) (2013) 1–9, https://doi.org/10.14232/ejqtde.2013.1.3 (Accessed 21 March 2021).
[3] H. Youssef, N. Alghamdi, M. Ezzat, A. El-Bary, A. Shawky, A modified SEIR model applied to the data of COVID-19 spread in Saudi Arabia, AIP Adv. 10 (12) (2020) 125210, https://doi.org/10.1063/5.0029698 (Accessed 26 March 2021).
[4] A.A. Mhosen, H. Fadhil AL-Husseiny, X. Zhou, K. Hattaf, Global stability of COVID-19 model involving the quarantine strategy and media coverage effects, AIMS Public Health 7 (3) (2020) 587–605, https://doi.org/10.3934/aph.2020047 (Accessed 21 March 2021).
[5] X. Liu, X. Zheng, B. Balachandran, COVID-19: data-driven dynamics, statistical and distributed delay models, and observations, Nonlinear Dyn. 101 (3) (2020) 1527–1543, https://doi.org/10.1007/s11071-020-05863-5 (Accessed 21 March 2021).
[6] F. Jung, V. Krieger, F. Hufert, J. Küpper, Herd immunity or suppression strategy to combat COVID-19, Clin. Hemorheol. Microcirc. (2020) 1–5, https://doi.org/10.3233/ch-209006 (Accessed 27 December 2020).
[7] James, S. Hendy, M. Plank, N. Steyn, Suppression and Mitigation Strategies for Control of COVID-19 in New Zealand, 2020, https://doi.org/10.1101/2020.03.26.20044677 (Accessed 14 December 2020).
[8] F. Casella, Can the COVID-19 epidemic be controlled on the basis of daily test reports? IEEE Control. Syst. Lett. 5 (3) (2020) 1079–1084, https://doi.org/10.1109/lcsys.2020.3009912 (Accessed 14 December 2020).
[9] T. Pêni, B. Cunak, G. Sezerken, G. Rost, Nonlinear model predictive control with logic constraints for COVID-19 management, Nonlinear Dyn. 102 (4) (2020) 1965–1986, https://doi.org/10.1007/s11071-020-05980-1 (Accessed 21 March 2021).
[10] G. Robith, K. Devika, Dynamics and control of COVID-19 pandemic with nonlinear incidence rates, Nonlinear Dyn. 101 (3) (2020) 2013–2026, https://doi.org/10.1007/s11071-020-05774-5 (Accessed 21 March 2021).
[11] B. Cao, T. Kang, Nonlinear adaptive control of COVID-19 with media campaigns and treatment, Biochem. Biophys. Res. Commun. 555 (2021) 202–209, https://doi.org/10.1016/j.bbrc.2020.12.192 (Accessed 19 March 2021).
[12] M. Hadi, H. Ali, Control of COVID-19 system using a novel nonlinear robust control algorithm, Biomedical Signal Process. Control 64 (2020) 102317, https://doi.org/10.1016/j.bspc.2020.102317 (Accessed 26 December 2020).
[13] M. Haidekker, Linear Feedback Controls, 2nd ed., Elsevier, Radarweg 29, Po Box 1965, 1000 AE Amsterdam, Netherlands, 2020.
[14] H. Ali, M. Hadi, Optimal nonlinear controller design for different classes of nonlinear systems using black hole optimization method, Arb. J. Sci. Eng. 45 (8) (2020) 7053–7055, https://doi.org/10.11648/j.ajes.2020458.1351, https://doi.org/10.3233/ch-209006 (Accessed 27 December 2020).
[15] M. Hadi, H. Ali, Optimal model reference control scheme design for nonlinear strict-feedback systems, Eng. Technol. J. 38 (9) (2020) 1342–1351, https://doi.org/10.30684/etj.v38i9a.1351 (Accessed 27 December 2020).
[16] M. Gatto, et al., Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures, Proc. Natl. Acad. Sci. 117 (19) (2020) 10484–10491, https://doi.org/10.1073/pnas.2004978117 (Accessed 27 December 2020).
[17] Coronavirus, Coronavirus Update (Live): 80,988,457 Cases and 1,769,841 Deaths From COVID-19 Virus Pandemic – Worldometer, Worldometers.info, 2020 [Online]. Available: https://www.worldometers.info/coronavirus/ (Accessed 27 December 2020).