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Hybrid control strategy for SEIARM model of COVID-19 outbreak

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Abstract

In recent years, the global spread of COVID-19 has posed a significant challenge, impacting nearly every country. A newly identified virus variant, exhibiting significantly higher transmissibility, has recently emerged. A comprehensive understanding of the transmission dynamics and the application of focused control measures are necessary for managing and containing its spread. Non-Pharmacological Interventions (NPIs) remain a key component of the main strategies for stopping the spread. In the SEIARM model of COVID-19 transmission, this research presents a novel control strategy to limit the number of affected people. By integrating the concepts of PID and Sliding Mode Control (SMC), the suggested approach guarantees resilience to changes in model parameters brought on by the sliding mode control method. The effectiveness of this method in handling the newly mutated virus is examined, and its performance is compared against open-loop, PID, and SMC controllers.

Subject Classification: *34H05, 37N35, 37N25.*

Keywords: *COVID-19, Sliding mode control, PID Control, Non-pharmacological interventions.*

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1. Introduction

After the first COVID-19 case was documented in Wuhan, China, in 2019, the virus quickly spread throughout the world. Recently, mutated variants have further complicated containment efforts in many regions. As of this writing, the World Health Organization (WHO) reports that COVID-19 has affected several countries, with over 773 million confirmed cases and over 699 million deaths [1]. The virus's extensive spread has led to severe social and economic repercussions globally. The outbreak soon escalated into an international health crisis, prompting WHO to declare it a pandemic in March 2020. In response, various measures were implemented to curb case numbers, including curfews, social distancing, gathering restrictions, and management of healthcare resources, particularly intensive care units (ICUs). A primary concern for governments was preventing ICU saturation. Numerous non-pharmacological interventions (NPIs), such as the closure of universities and non-essential businesses, were enacted across countries to control the virus's spread [2]. To better understand and predict COVID-19 transmission, many epidemiological models have been developed [3-6]. Understanding transmission rates and evaluating the efficacy of NPIs depend heavily on accurate modeling. Control theory has been applied to develop optimal policies for NPIs, particularly under specific constraints. For instance, [7] presents an optimal control strategy for minimizing person-to-person contact and virus transmission. In [8], a time-constrained intervention is proposed to reduce the peak epidemic load in the SIR model. The dynamics of infectious disease transmission, contact tracing, and hospitalization strategies are discussed in [9], while [10] reviews optimal quarantine strategies for containing the virus. The SEIHRD model in [11] proposes a control approach to maintain hospital admissions within capacity. Additionally, [12] investigates optimization techniques to lessen the pandemic's socioeconomic effects. A predictive control strategy utilizing on-off NPIs for social distancing is proposed in [13], while a Bang-Bang controller is examined in [14] for ICU capacity management. Reference [15] offers an NPI optimization approach aimed at minimizing intervention duration, considering healthcare system limits. Nonlinear control techniques for infectious diseases, without factoring in model uncertainties, are explored in [16-18] and [19]. Since the initial smallpox dynamic model was introduced in 1760, mathematical modeling has been vital in understanding infectious disease transmission and control [20]. A significant advancement was the SER model, developed to study plague dynamics in India [21]. Modeling of infectious disease outbreaks has since evolved significantly, with the basic SIR model categorizing individuals as susceptible, infected, and recovered or deceased [22]. As more data has become available, models have adapted, incorporating additional population categories for greater accuracy. Controlling diseases like COVID-19 presents unique challenges due to the latent period, during which infected individuals may not realize they are contagious. This incubation phase facilitates inadvertent transmission. This feature of disease dynamics is captured by the SEIR model, which categorizes people as susceptible, exposed, infected, recovered, or died

[23-24]. Reference [25] uses Support Vector Machine (SVM) to predict confirmed, deceased, and recovered COVID-19 cases based on global time-series data from January to April 2020. The model aims to support real-time forecasting for better resource planning and policy-making, addressing the lack of multi-model comparisons and uncertainty analysis in existing literature. In [26], a descriptive analysis of COVID-19 cases in India is provided, with an emphasis on characteristics such as age, gender, travel history, and mode of transmission. The study finds no significant link between age and infection, but identifies a notable relationship between gender and transmission type (imported vs. local). In [27], a sliding mode controller based on Chebyshev Neural Networks is designed for uncertain nonlinear systems with constrained unknown nonlinearities and mismatched uncertainties. Various nonlinear controllers have been devised for different COVID-19 transmission models [28-33].

This paper introduces a novel PID Sliding Mode Controller to manage COVID-19 spread. The SEIARM model, recognized as one of the most comprehensive available [28], is utilized. By integrating PID control with Sliding Mode Control, the proposed method effectively addresses parameter uncertainties in the COVID-19 model, enhancing robustness. Key contributions and advantages of this work include:

- A new nonlinear SEIARM model for COVID-19 is employed in designing the proposed controller.
- A novel PID-based sliding mode control (SMC) strategy is introduced.
- The proposed method's performance is evaluated against new COVID-19 variants, addressing parameter uncertainties.
- Simulation results confirm that the proposed approach ensures hospital ICU bed capacity will not be exceeded, even with a 10% rise in disease transmission rate.
- The proposed controller can be tailored to individual countries based on their population and healthcare infrastructure.
- The theoretical validation confirms the stability of the proposed method.

2. Mathematical model

The purpose of this part is to present the issue statement and simulate the COVID-19 virus's transmission. First, the importance of precise modeling and implementing quarantine measures at the community level will be discussed.

A. *Statement of the problem*

The COVID-19 virus spreads rapidly, presenting significant challenges for any country. Patients infected with the virus require specialized hospital care, and the availability of such facilities is both limited and finite. If the number of cases surpasses the capacity of healthcare facilities within a specific time period, it can result in critical outcomes, including hospital bed saturation, a spike in sudden deaths, diminished efficiency of healthcare workers, and widespread public dissatisfaction due to the lack of medical resources. Thus, it is crucial for each country to adopt an effective strategy to manage and control this challenge. In this paper, a strategy is developed to prevent the saturation of hospital resources, ensuring that $I(t) \leq I_{\max}$. Here, $I(t)$ represents the number of infected individuals, and $I_{max} = 6.87e^4$ denotes the maximum capacity of healthcare facilities, specifically indicating the number of beds available in hospital intensive care units. This capacity is determined by each country's health authorities. The primary objective is to regulate the spread of the disease to ensure that hospital ICU beds do not become overwhelmed, meaning the number of patients should remain below I_{max}. To achieve this, the only effective solution is the implementation of a structured quarantine policy by the government, which can prevent the rapid transmission and widespread outbreak of the virus. In this context, $u(t)$ represents the percentage of quarantine measures and social restrictions, quantified as a percentage.

Determining the appropriate quarantine percentage presents numerous challenges. The level of quarantine should adjust over time based on the number of infected individuals. Imposing a high quarantine rate can lead to significant issues, such as economic stagnation and the disruption of political, economic, and cultural activities. Conversely, a low quarantine rate may result in a lack of healthcare resources, an increase in the number of patients, reduced energy and efficiency among medical staff, and a rise in mortality rates. Therefore, the quarantine rate must be dynamically adjusted based on the prevailing conditions to effectively manage these challenges. An effective and robust control strategy is crucial for managing COVID-19 outbreaks. In the upcoming sections, a detailed model of COVID-19 and a robust control approach will be introduced.

B. *COVID-19 Model*

Numerous models, including SI, SIS, SIR, SEIR, SIRD, and SEIRD models, have been developed since the COVID-19 pandemic began in late 2019. This article employs the SEIARM model, which is regarded as one of the most comprehensive models available. The SEIARM model encompasses six essential variables, dividing the population into five distinct categories: Susceptible individuals $S(t)$, Exposed individuals $E(t)$, Symptomatically infected individuals $I(t)$, Asymptomatically infected individuals $A(t)$, and Recovered individuals $R(t)$. The research indicates that virus transmission in a reservoir, such as a seafood market $M(t)$, plays a significant role, which is modeled here. The equations governing the COVID-19 disease dynamics are defined as (1) [28]:

$$
\begin{aligned}
{}^{d}/_{dt}\, S(t) &= \Lambda - \mu S(t) - \lambda(t) S(t)\big(1 - u(t)\big) \\
{}^{d}/_{dt}\, E(t) &= \lambda(t) S(t)\big(1 - u(t)\big) - K_1 E(t) \\
{}^{d}/_{dt}\, I(t) &= (1 - \theta)\omega E(t) - K_2 I(t) \\
{}^{d}/_{dt}\, A(t) &= \theta \rho E(t) - K_3 A(t) \\
{}^{d}/_{dt}\, R(t) &= \tau_a A(t) + \tau I(t) - \mu R(t)
\end{aligned} \tag{1}
$$

$$\frac{d}{dt}M(t) = \varrho I(t) + \varpi A(t) - \nu M(t)$$

Where:

$$\lambda(t) = \frac{\eta\big(I(t)+\psi A(t)\big)}{N} + \eta_w M(t) \tag{2}$$
$$K_1 = (\theta\rho + (1-\theta)\omega + \mu)$$
$$K_2 = (\tau + \mu)$$
$$K_3 = (\tau_a + \mu)$$

Table 1 lists all of the model system's parameters in detail. The initial conditions are set as $S(t_0) = S_0 = 13e^8$ and $E(t_0) = E_0 = 1e^7$. With a starting population size of $N(0) = 1.4$ billion, the numbers shown in Table 1 correspond to the population of China.

Table 1
Values and descriptions of the model's parameters.

Parameter	Value	Description
Λ	$\mu \times N(0)$	The rate of hiring (per day)
η	0.134	Rate of contact
μ	1/ (76.79 × 365)	Natural mortality rate (per year)
ψ	0.0002	Transmissibility multiple
η_w	0.0000000080082	Disease transmission coefficient
θ	0.41003	The proportion of asymptomatic infection
ω	0.0000213	Incubation period of I
ρ	0.480322	Incubation period of A
τ	0.000033	Rate of recovery of I
τ_a	0.59	Rate of recovery of A
ϱ	0.0101	Transmission of the virus to M by I
ϖ	0.1314	Transmission of the virus to M by A
N	1.4	Total human population N billion
ν	0.5	Removal rate of virus from M

3. Proposed Controller

Proportional-Integral-Derivative (PID) control and sliding mode control are the two control methods that are combined in the suggested controller. As a linear control mechanism, the PID controller creates the required control law without requiring the system's dynamic equations. Fig. 1 shows a schematic illustration of the suggested controller.

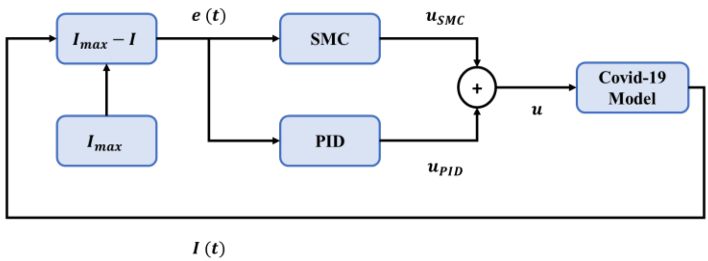

Figure 1
Schematic of the proposed controller

The error signal of the controller will be defined as follows:

$$e(t) = I_{max} - I(t) \tag{3}$$

The PID controller law will be obtained as (4)

$$u_{PID} = e(t)\left(k_P + k_I \int dt + k_D \frac{d}{dt}\right) \tag{4}$$

Then, the first and second derivatives of error signal (3) to time can be given by (5) and (6):

$$\frac{d}{dt}e(t) = \frac{d}{dt}I_{max} - \frac{d}{dt}I(t) \tag{5}$$

$$\frac{d^2}{dt^2}e(t) = \frac{d^2}{dt^2}I_{max} - \left((1-\theta)\omega\frac{d}{dt}E(t) - K_2\frac{d}{dt}I(t)\right) \tag{6}$$

By placing the relations (1) in (6) we will have (7):

$$\frac{d^2}{dt^2}e(t) = \frac{d^2}{dt^2}I_{max} - \left((1-\theta)\omega\left(\lambda(t)S(t)\big(1-u(t)\big) - K_1E(t)\right) - K_2\frac{d}{dt}I(t)\right) \tag{7}$$

A sliding mode surface is defined as (8)

$$\sigma(t) = C_1\frac{d}{dt}e(t) + C_2\int e(t) \tag{8}$$

Where C_1 and C_2 are positive and constant parameters. After designing the sliding surface (8), its derivative should be computed in accordance with the sliding mode control rules; this is provided in (9)

$$\frac{d}{dt}\sigma(t) = C_1\frac{d^2}{dt^2}e(t) + C_2e(t) \tag{9}$$

In this article, active switching (because of increase the more robustness) is used to find the sliding mode control law:

$$\frac{d}{dt}\sigma(t) = -C_3\sigma(t) - C_4 sign\big(\sigma(t)\big) \tag{10}$$

Where C_3 and C_4 are constant and positive parameters. By placing (9) in (10) we have:

$$C_1\frac{d^2}{dt^2}e(t) + C_2e(t) = -C_3\sigma(t) - C_4 sign\big(\sigma(t)\big) \tag{11}$$

Now, by placing equation (7) in (11) and simplifying it, the sliding mode control law will be obtained as (13):

$$C_1\left(\frac{d^2}{dt^2}I_{max}-\left((1-\theta)\omega\left(\lambda(t)S(t)\big(1-u(t)\big)-K_1E(t)\right)-K_2\frac{d}{dt}I(t)\right)\right)$$
$$+C_2e(t)=-C_3\sigma(t)-C_4sign\big(\sigma(t)\big) \tag{12}$$

$$u_{SMC}=1-{}^{1}\!\Big/\big(\lambda(t)S(t)\big)\left({}^{1}\!\big/(1-\theta)\omega\left(\frac{C_2}{C_1}e(t)+\frac{C_3}{C_1}\sigma(t)+\frac{C_4}{C_1}sign\big(\sigma(t)\big)\right.\right.$$
$$\left.\left.+\frac{d^2}{dt^2}I_{max}+K_2\frac{d}{dt}I(t)\right)+K_1E(t)\right) \tag{13}$$

In this paper, the control law proposed will be obtained by combining two equations (4) and (13):

$$u=u_{PID}+u_{SMC} \tag{14}$$

Stability proof: to prove the control law in (13), the Lyapunov function is defined in (15):

$$V(t)=0.5\,\sigma(t)^2\geq 0 \tag{15}$$

By taking derivate from both sides of (15), we can obtain (16):

$$\frac{d}{dt}V(t)=\sigma(t)\frac{d}{dt}\sigma(t) \tag{16}$$

Now, by placing (7) in derivative of sliding surface (9) and replacing in (16), will be obtained (17):

$$\frac{d}{dt}V(t)=\sigma\left(C_1\left(\frac{d^2}{dt^2}I_{max}-\left((1-\theta)\omega\left(\lambda(t)S(t)\big(1-u(t)\big)-K_1E(t)\right)-\right.\right.\right.$$
$$\left.\left.\left.K_2\frac{d}{dt}I(t)\right)\right)+C_2e(t)\right) \tag{17}$$

By replacing the control law (13) in (17) and simplifying it, we will have:

$$\frac{d}{dt}V(t)=\sigma(t)\left(-C_3\sigma(t)-C_4sign\big(\sigma(t)\big)\right) \tag{18}$$

$$\frac{d}{dt}V(t)=-C_3\sigma(t)^2-C_4|\sigma(t)|\leq 0 \tag{19}$$

Equation (19) guarantees the closed-loop system's stability [].

The parameters of the proposed controller are specified in Table 2.

Table 2

The controller parameters' values.

Parameter	Value
$\boldsymbol{k_P, k_I, k_D}$	8, 17, 5
$\boldsymbol{C_1, C_2}$	2, 10
$\boldsymbol{C_3, C_4}$	10, 50

4. Simulation results

In this paper, the results are derived from statistical data collected in China. The findings are presented in two sections: 1. A performance comparison among open-loop, PID, Sliding Mode Control (SMC), and the proposed controllers. 2. A performance comparison of PID, SMC, and the proposed controllers in relation to emerging COVID-19 variants.

4.1. *Performance survey of controllers against normal COVID-19 model*

The rate of disease outbreaks is influenced by the percentage of quarantine implemented. Despite the difficulties associated with quarantine measures in many countries, it is crucial to evaluate how various quarantine rates will impact society. The controller can be utilized in two configurations: open loop and closed loop. Open loop control involves applying a fixed quarantine percentage to the system. A quarantine rate approaching 100% is often impractical due to the economic burdens it imposes. Furthermore, maintaining a high quarantine rate is only viable for a limited duration, as prolonged lockdowns can lead to significant and lasting harm to society. Conversely, a quarantine rate near 0% facilitates the rapid spread of the virus, resulting in increased transmission and mortality rates. The dynamics of the COVID-19 virus outbreak model have been analyzed and compared across open-loop, PID, Sliding Mode Control (SMC), and the proposed controllers. The open loop controllers are considered as 0%, 50%, and 100% of quarantine rate ($u(t) = [0\ 0.5\ 1]$).

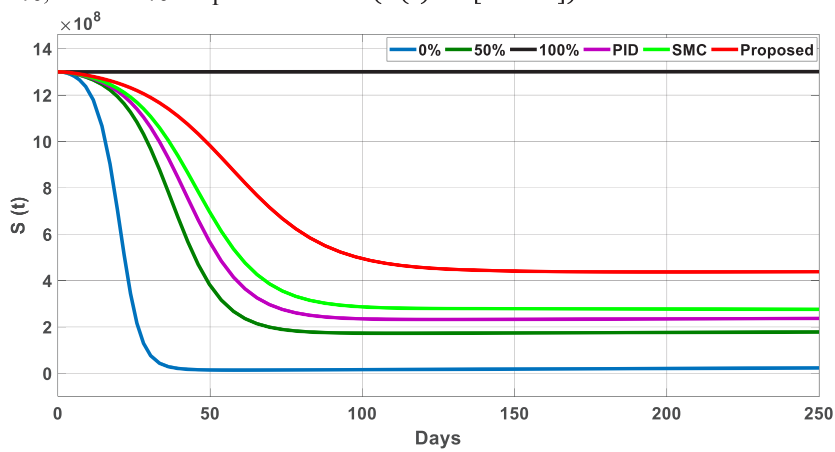

Figure 2

Performance of Susceptible Behavior.

Figures 2 and 3 illustrate the dynamics of susceptible and exposed individuals, respectively. As shown in Figure 2, an increase in the percentage of individuals under quarantine correlates with a higher number of susceptible individuals within the population, signifying that fewer people are becoming infected and remaining in the susceptible group. At the outset of the outbreak, the entire community is susceptible. However, with the enforcement of stricter quarantine measures, interpersonal interactions diminish, thereby reducing disease transmission. Consequently, the number of susceptible individuals increases as fewer individuals contract the virus. Similarly, Figure 3 demonstrates that the number of exposed individuals declines with the implementation of stricter quarantine measures and reduced social interactions.

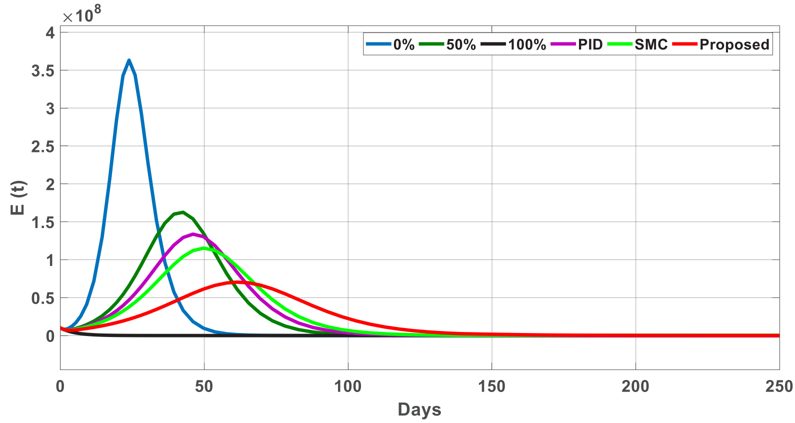

Figure 3

Performance of Exposed Behavior.

Data on asymptomatic and symptomatic illnesses, as well as the rate of disease transmission through locations like seafood markets, are shown in Figures 4, 5, and 6. Both kinds of illnesses can be considerably reduced by enforcing stricter quarantine regulations. But it's important to keep in mind that more stringent quarantines could have serious consequences, such as social and economic upheavals. Figures 4 and 5 show that the number of sick and asymptomatic persons decreases as quarantine procedures grow stricter. This research proposes a unique controller to control the COVID-19 virus's spread. This approach combines two control strategies: proportional-integral-derivative (PID) control and sliding mode control (SMC). The performance of this new approach is compared with that of open-loop, PID, and SMC controllers. The results indicate that the proposed method effectively reduces virus transmission, resulting in a lower number of infected individuals, as demonstrated in Figure 4. Furthermore, the proposed method outperforms both the SMC and PID controllers. As previously discussed, the controllers are designed based on I_{Max} and applied to the model. The primary objective of this article is to utilize the proposed method to prevent the saturation of hospital resources by ensuring that fewer individuals become infected within a specified timeframe.

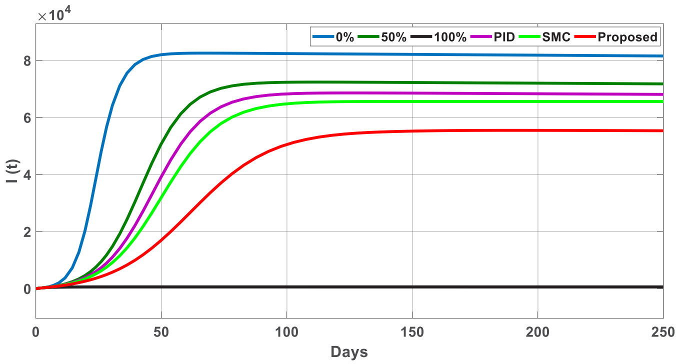

Figure 4
Performance of symptomatic infection behavior.

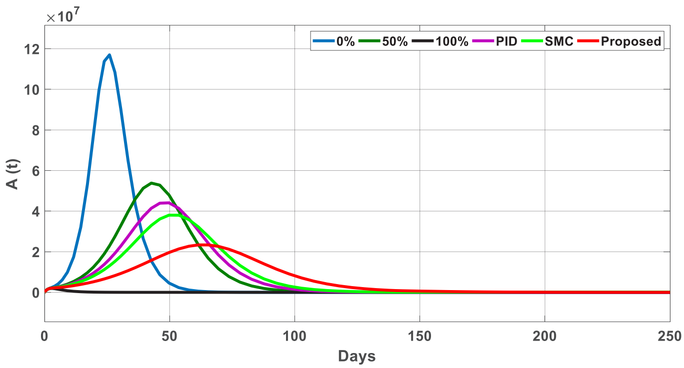

Figure 5
Performance of asymptomatic infection behavior.

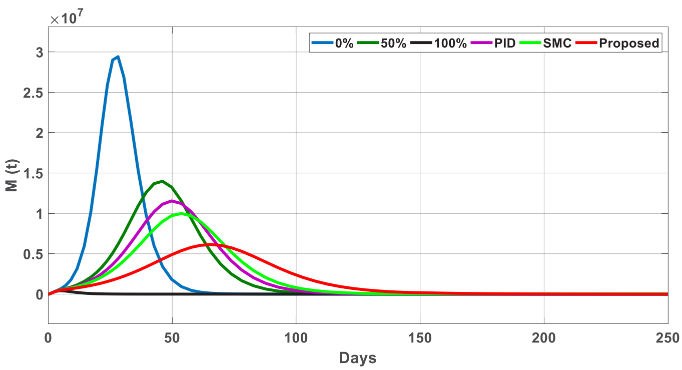

Figure 6
Performance of Place or seafood markets behavior.

The performance of the mentioned methods in relation to I_{max} is illustrated in Figure 7. As shown in this figure, the linear PID controller demonstrates suboptimal performance in decision-making. In contrast, the proposed controller outperforms both PID and SMC controllers, effectively managing the quarantine levels and maintaining the number of COVID-19 infections consistently below the capacity of hospital facilities (I_{max}). Figure 8 presents the control signals for the various methods evaluated. The proposed method has achieved superior performance by implementing an appropriate percentage of quarantine at each time interval.

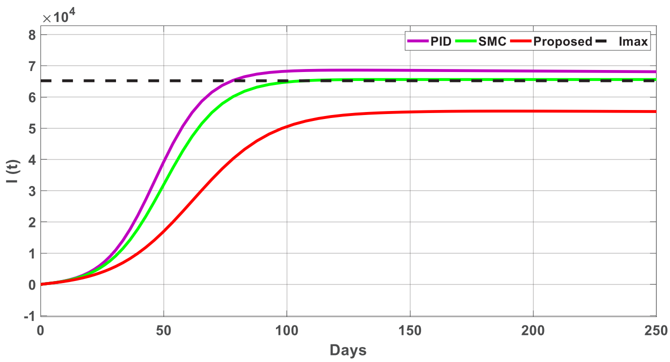

Figure 7
Performance of maximum Infected (symptomatic) behavior.

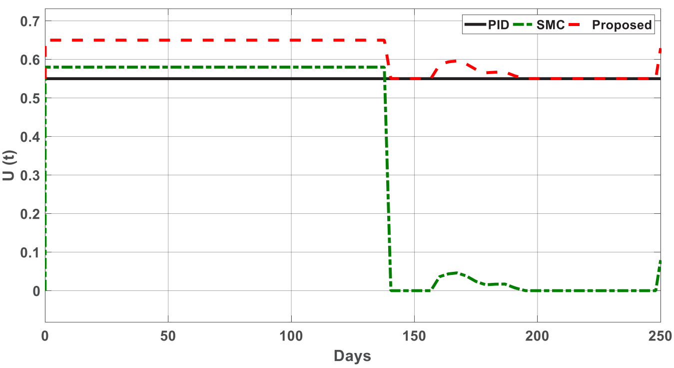

Figure 8
The controller signals.

4.2. *Performance survey of controllers against normal COVID-19 model*

In recent years, the COVID-19 virus has undergone various mutations, leading to the emergence of new variants in different regions worldwide. These mutated viruses exhibit significantly higher transmission rates, resulting in rapid dissemination within communities. The effectiveness of the suggested controller in controlling this novel viral variation is assessed in this part, which also addresses the modifications associated with the new coronavirus as uncertainties within the suggested system model.

The following are the model's real parameters: rate of contact $\mathfrak{U} = 0.134$, and coefficient of disease transmission $\mathfrak{U}_w = 0.0000000080082$. In contrast, the new parameters of the model are defined by: contact rate $\mathfrak{U} = 0.1474$, In contrast, the new parameters of the model are defined by: contact rate $\mathfrak{U}_w = 8.8090e - 09$.

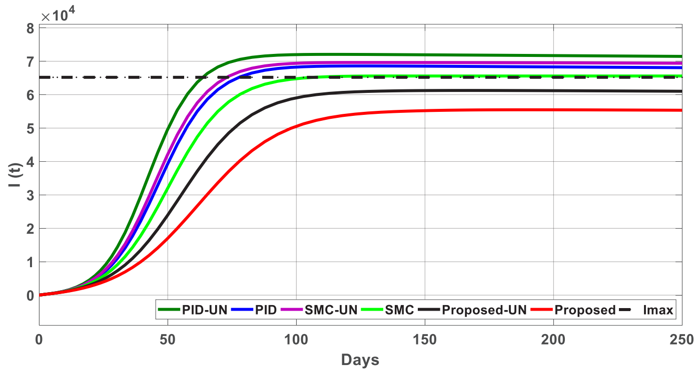

Figure 9
Performance of maximum Infected (symptomatic) behavior (against the novel virus).

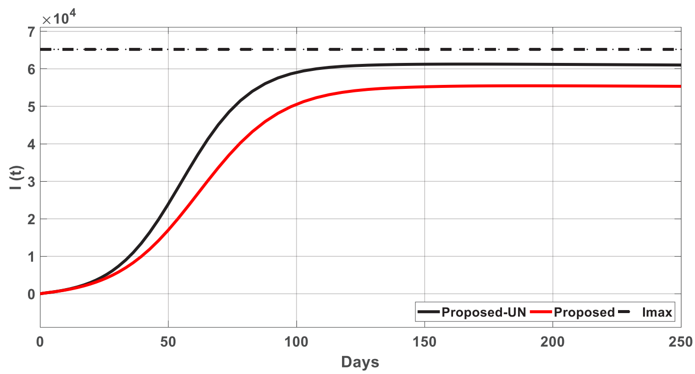

Figure 10
Maximum performance Behavior that is infected (symptomatic) (suggested approach).

Figure 9 shows how well the suggested controller performs when compared to alternative approaches. The PID and SMC controllers were unable to effectively control the mutated virus, leading to a number of patients that exceeded the capacity of available hospital facilities, signaling a saturation of healthcare resources due to the rise in infections. In the figures, "UN" represents the controller's performance against the mutated virus, highlighting the impact of uncertainty. The efficiency of the suggested approach in both normal and mutant viral scenarios is further illustrated in Figure 10. The suggested approach continuously satisfies the key design objective, guaranteeing that the number of sick people stays below the hospital capacity level, as shown in Figure 10.

5. Conclusion

This article proposes a hybrid controller that combines two linear PID controllers with a nonlinear Sliding Mode Control (SMC) strategy. The spread of COVID-19 is simulated using the SEIARM model. This innovative controller is specifically tailored for a new COVID-19 model. The performance of open-loop, PID, and SMC controllers is evaluated under two conditions: normal and mutant virus strains. Simulation results indicate that the proposed method achieves a slower rate of disease spread than the other approaches, demonstrating its effectiveness in significantly reducing both the number of infected and exposed individuals. A reduction in exposed individuals naturally leads to fewer infections.

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