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An optimal control policy in fighting COVID-19 and infectious diseases

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ABSTRACT

When an outbreak starts spreading, policymakers have to make decisions that affect the health of their citizens and the economy. Some might induce harsh measures, such as a lockdown. Following a long, harsh lockdown, the recession forces policymakers to rethink reopening. To provide an effective strategy, here we propose a control strategy model. Our model assesses the trade-off between social performance and limited medical resources by determining individuals' propensities. The proposed strategy also helps decision-makers to find optimal lockdown and exit strategies for each region. Moreover, the financial loss is minimized. We use the public sentiment information during the pandemic to determine the percentage of individuals with high-risk behavior and the percentage of individuals with low-risk behavior. Hence, we propose an online platform using fear-sentiment information to estimate the personal protective equipment (PPE) burn rate overtime for the entire population. In addition, a study of a COVID-19 dataset for Los Angeles County is performed to validate our model and its results. The total social cost reduces by 18% compared with a control strategy where susceptible individuals are assumed to be homogeneous. We also reduce the total social costs by 26% and 22% compared to other strategies that consider the health-care cost or the social performance cost, respectively.

1. Introduction

According to World Health Organization (WHO), the first death due to SARS-COV-2 infection was reported on January 11, 2020, in China Wuhan [1]. The origin of the virus remains uncertain. By the end of April 2022, close to 519 million people had been infected worldwide by the COVID-19 virus, and over 6 million people have died (JohnHopkinsCenter[2]). The virus spread between nations quickly, and it became a global concern.

Currently, many countries are practicing community-based measurements to mitigate the spread of the virus. The policymakers and governments have tried to control the epidemic based on the limited medical resources that makes a delay in the infection peak, providing more time to produce a vaccine [3]. As a result, the closure of many businesses has been implemented, which leads to some economical loss. It raises the question: "what are the alternative interventions with the lowest negative economic impact?"

When a *Susceptible* person makes a contact with a contagious individual, he/she may become *Exposed*. It will take some time till the symptoms appear. A person might become *Infectious* before being symptomatic. Finally, that person will be *Removed* either through death or recovery with temporary immunity. As their names indicate, SEIR models or SIR models are mathematical models used to describe individuals transitioning between these stages. For classical references on virus dynamics refer to [4–7].

Several studies in the existing literature propose a lockdown and exit strategy using a SIR model. [8] proposed an optimal lockdown strategy using a SIR model where a homogeneous susceptible individuals is considered. [9] introduced a classical epidemiology model to reduce the burden of infections on health-care sector where the individuals is divided into different age classes. [10] investigated a SIR model that considers social activity level and the capacity of health-care sector to find the optimal lockdown strategy. However, we propose an optimal lockdown strategy that investigates a trade-off between the burden of infections on health-care sector and financial loss of economic activity level of people who follow social distancing. Moreover, we consider a non-homogeneous of susceptible population where the ratio of susceptible individuals who have high-risk behaviors or low-risk behaviors is estimated.

Other models investigate the impact of individuals' propensities in the SIR model. [11] incorporated individuals' emotions in the epidemiology model to estimate the ratio of individuals who have switching behaviors during the pandemic where fear function of individuals is determined. [12] investigated individuals' memory performance in terms of learning information and forgetting information during the pandemic in order to estimate the final disease function. [13] studied human behaviors into the SIR model by dividing the individuals into two groups. One group

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of individuals have physical contact and spread the infections in the society. The second group of individuals spread disease information in the society using the social media. [14] considered the impact of contact tracing, social distancing, and case isolation on the number of infections using a classical epidemiology model. [15] introduced an automated system that warns individuals who have faced others who have tested positive using their cell phones. [16] studied COVID-19 symptoms model using mobile data that supports public health decisions in selective lockdown strategies. After a pandemic, governments implement a set of non-pharmaceutical interventions (NPIs) to reduce the spread of the virus in the society. [17] investigated these restrictions on economic activity for 59 countries. [18] proposed an approach to estimate the effectiveness of the dynamic quarantine policy by including time-related variables and socioeconomic factors in a causal analysis. However, we determine the optimal activity level based on the real-time fear sentiment that integrates the limited health-care sector and the social performance to provide a lockdown and exit strategy during the pandemic. The proposed model also considers the efficiency measures such as the speed of learning in the health care system during the pandemic.

Social media offer a platform for sharing disease information [19]. People can share their sentiment with all people in the Twitter, while other platforms such as Instagram and Facebook have limitations to share sentiment with all groups of society. People currently use the microblogging platform Twitter with over 300 million monthly users, to share their ideas and feelings about a wide range of subjects. Government agencies such as the Centers for Disease Control and Prevention (CDC) and the World Health Organization (WHO) have used Twitter's potential to update people about disease information. Using Twitter data to understand real-time individuals' behavioral responses to an event is a well-accepted tool. For instance, during the Ebola virus (EV) outbreak in 2014 [20], during the spread of influenza in 2009 [21], during the Syndrome outbreak in 2015 [22] and the Zika virus epidemic [23] researchers used the Twitter dataset. Tweets that demonstrate public sentiment regarding the outbreak are related to emotions of fear, anger, and surprise.

Some studies such as [24–26] have been introduced deep learning language models on Twitter to monitor global sentiment during the COVID-19 pandemic. [27] considered a sentiment analysis to understand negative emotion of individuals during the COVID-19 pandemic using Twitter data. A real-world tool to curb COVID-19 fake news using Twitter data is proposed by [28]. A comprehensive review of sentiment analysis in fighting the pandemics is studied by [29]. [30] investigated human behaviors during pre-lockdown and post-lockdown weeks using online social media networks. [31] predicted the sentiment of individuals from the outbreak of the disease to the distribution of vaccines using Twitter data. [32] proposed the CrystalFeel algorithm to detect the emotional intensity of four emotions in terms of joy, anger, sadness, and fear. [33] studied sentiments regarding COVID-19 from tweets for tourism sectors, sub-domains hospitality, and healthcare sectors using a deep learning approach. [34] classified public sentiment to find correlations between real-life events and sentiment changes during the COVID-19 pandemic.

In this research work, for the first time, we propose a mathematical model that considers positive and negative attitudes about the current pandemic to estimate the ratio of individuals who have high-risk behaviors or low-risk behaviors. Additionally, we estimate PPE demand over time during the pandemics using a fear-sentiment analysis. To address the above questions on the control strategy of pandemic, we propose an optimization model that minimizes the social costs during the pandemic. The goal is to minimize the burden of infections on the health care system and the financial loss of economic activity level during lockdown. In order to estimate the growth of infection and economic activity cost, the SIR model under individual behavior factors are considered. Our contributions include the following epidemic management features:

- We investigate a state-space model using the real-time temporary sentiment to obtain the final sentiment information. We apply individuals' posts on Twitter based on emotion and user interest that reflect public sentiment in real-time regarding the current global outbreak.
- We consider an information system that consists of learning and forgetting information. This model considers the impact of individuals' propensities on the pandemic.
- In the proposed policy, the population is divided into two groups based on individuals' propensities. We estimate the percentage of individuals with high-risk behavior and the percentage of individuals with low-risk behavior.
- We suggest an online control strategy using a data-driven method that provides real-time health data such as the percentage of individuals who want to wear a mask. Other methods for estimating mask usage for the entire population, such as conducting a survey, are inefficient. For example, a survey can be conducted once, and it is expensive to repeat the study. Therefore, we propose an online platform using fear-sentiment information to estimate mask usage over time for the entire population. Hence, the demand for personal protective equipment (PPE) products can be estimated by the proposed strategy that helps domestic manufacturers to respond to the shortage of PPE items.
- We propose an optimal lockdown policy that minimizes the financial loss associated with social performance and the stress on the health care system. The proposed control policy also considers the efficiency measures such as the speed of learning in the health care system during the pandemic.

The next section shows details of our proposed optimal control strategy that considers an online disease information system to minimize the financial loss during the pandemic. In Section 3, we will show how our optimization model can be implied to real data. As an example, we consider LA County. Section 4 summarizes our main findings and discusses possible directions for future study.

2. The proposed control strategy of pandemic

Several stages are needed to propose an optimum control strategy using real data. The first stage is to use the real data to extract the individual's sentiments about an epidemic by Twitter data. Using these sentiments, we run a time series method to forecast the future public sentiments. We estimate the rate of population who will change their behavior and switch, and lastly the rate of infected population using an SIR model. Finally, an optimization model is proposed that minimize the social cost including the health cost and the financial loss that incurs by decreasing economic activities.

2.1. The disease information

Within a routine day, each person makes both local and global communications. Each individual has a unique understanding of the epidemic and chooses different precautions to protect themselves from the virus. They receive information about the disease from both their local and global networks. Local networks such as home or their neighborhoods, global network such as social media [35]. Based on the amount of disease information that individuals acquire, they change their behavior during the epidemic.

We develop a statistical technique for predicting and tracking sentiment polarity and individuals' behaviors from social media during health emergencies such as COVID-19. The disease information system is characterized through the definition of input or observed information, state variables, and output information [36]. The observed information are external entities that are added into the system and can serve as control noise or inputs. State variables are unobserved information that evolve through time following a given state equation and also depending on the values of the observed information. Lastly, output information results from the realization of the state plus noise factors and represent the observable outcome of the information system [37]. We run a state-space model which is a flexible framework with time-varying parameters to forecast the temporary sentiment polarity over time.

Suppose $y_1,\ldots, y_n$ is a series of fear-sentiment observations at time n and $p_1,\ldots, p_n$ refer to the unobserved states at time n that depend on the observation sets. The main idea behind state-space approach is to predict the state variables that depend on the observed sentiment information. The following equations show the observation equation and the state equation, respectively [37]:

$$y_n = \upsilon_n p_n + \varepsilon_n;\ \ \varepsilon_n \sim N(0, h_n) \tag{1}$$

$$p_{n+1} = k_n p_n + \varepsilon_n';\ \ \varepsilon_n' \sim N(0, \psi_n) \tag{2}$$

where the error terms ε_n and ε_n' are assumed to be independent of each other. Let ψ_n and h_n denote the covariance matrices of the error terms, υ_n and k_n are the ones that define how the observations relate to the state and how the state evolves over time.

Memory cells can store and retrieve the disease information. The disease information is being forgotten over time. [38] studied the learning and forgetting information process. If a represents the degree of learning and b denotes the rate of forgetting of information, then after n time periods, memory performance, z, can be measured by the following formula.

$$z = a \cdot n^{-b}; 0 < a, b < 1. \tag{3}$$

An individual is able to learn new information by $\alpha_0\ p_{n+1}$, while the past information is being forgotten by $(1 - \alpha_0)f_n$. Finally, the final sentiment, f, is [12] calculated as follows,

$$f_{n+1} = \alpha_0 p_{n+1} + (1 - \alpha_0)f_n, \tag{4}$$

where $\alpha_0 = a \cdot n_f^{-b}$ is the memory performance over the longest memory epoch n_f.

2.2. The individual with low-risk behavior

When facing a pandemic different individuals have different responses. Some might self isolate most of the time, some might keep some of their social activities and some never follow any social distancing rules. In fact a wide range of rationale is involved. It could be because of the type of the job that a person has, like social workers, medical personnel and cab drivers, but here in this study we are considering the impact of fear sentiment. Behavior of individuals heavily depends on the amount of fear sentiment which they receive [12].

As mentioned above, we denote the individuals with low-risk behavior by S^L, where superscript L stands for low-risk. [39] introduce the idea of using satellite equations. A satellite equation is an equation that is added to a model to calculate new quantities without changing the original model. To calculate the fraction of population with low-risk behavior we use a "satellite" equation (see the excellent article by [39]). We use the "Model E+" introduce by [39] as our primary model to describe the pandemic. Model E+ is a simple model and uses only one parameter that needs to be estimated. This parameter is β_n with Poisson distribution and will be used for calculating the average susceptible individuals infectious contact, $\beta_n I_n$. Policy makers can use the simple model to make decision during the outbreak crisis.

Model E+ (6) suggests that we can calculate the contact rate in week n by Eq. (5). We determine several past observations of contact rate using Eq. (5), then we use a linear regression (see [40]) to fit the contact rate for the remaining periods. Once we calculate the contact rates using Eq. (5), we can plug it in Model (6) and produce the outbreak.

$$\beta_n = -\frac{1}{I_n} ln(1 - \frac{I_{n+1}}{1 - \sum_{i=1}^{n} I_n}). \tag{5}$$

As mentioned above, I_n is the fraction infectious in week n and can be calculated using real data.

Now we simulate the pandemic using the real data. By assuming that $S_0 = 1$, i.e. initially everyone is susceptible, then the Model $E+$ is used as follows,

$$I_{n+1} = S_n(1 - e^{-\beta_n I_n}) \tag{6a}$$

$$S_{n+1} = S_n - I_{n+1} \tag{6b}$$

where I_n denotes the fraction of individuals who are infectious throughout the week n and S_n denotes the fraction of individuals who are susceptible at the beginning of week n respectively.

The only parameter of the above model that needs to be specified to produce the pandemic is the contact rate in week n which is denoted by β_n. According to Poisson distribution when the expected number of events in a unit time is λ and events occur independently, then the probability that an event does not occur is $exp(-\lambda)$. Susceptible individuals on average make $\beta_n I_n$ infectious contact, therefore the probability that no new infectious case happens in week n is $exp(-\beta_n I_n)$, therefore the number of new infectious cases in week $n + 1$ will be calculated by Eq. (6a) above.

Now we have the fraction susceptible in each week, we finally calculate the probability that an individual wants to have low-risk behavior by the next satellite equation [11],

$$S_n^L = S_n \frac{exp\left(f_n\theta\right)}{1 + exp\left(f_n\theta\right)}, \tag{7}$$

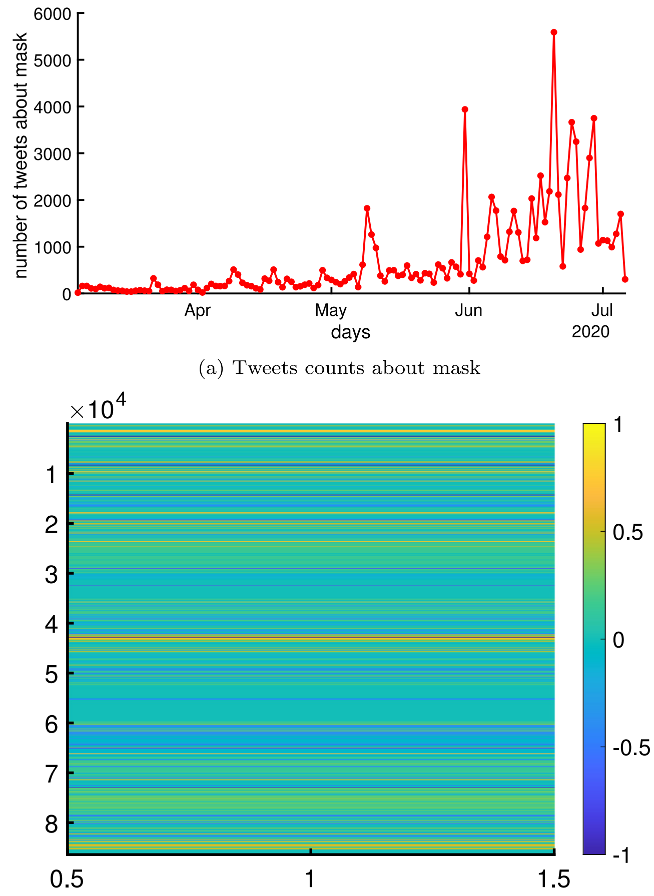
where θ is a coefficient to amplify the final sentiment and S_n^L is the percentage of susceptible individuals with low-risk behavior. The ratio $exp\left(f_n\theta\right)/\left(1 + exp\left(f_n\theta\right)\right)$ is the rate at time period n at which susceptible individuals choose to have low-risk behaviors. This is equivalent to the PPE burn rate for the entire population.

2.2.1. Estimating mask usage over time

Face masks combined with other preventive measures, such as self-quarantine and frequent hand-washing, help slow the spread of the virus [41]. The Disease Control and Prevention (CDC) recommends community face masks for the public, while the N95 and surgical masks are needed by health care providers. Modeling and tracking public sentiment can provide key information for decision making to control the pandemic.

The number of tweets related to masks in California from March 5th to July 6th, 2020 is 86,365. Daily number of tweets related to masks is shown in Fig. 1(a). Before May 30, 2020, our analysis showed a very small number of tweets related to mask followed by a steady increase starting June 1, 2020. We analyzed tweets about masks for negative, neutral, and positive polarity. Fig. 1(b) shows an analysis of tweets sentiment polarity about masks.

COVID-19 is a global pandemic that mostly spreads by asymptomatic or pre-symptomatic patients because individuals often



(a) Tweets counts about mask

(b) Sentiment scores for mask Tweets

Fig. 1. Tweets related to mask from March 5th to July 6st, 2020.

do not know if they are infected with the COVID-19. Therefore, it is difficult to determine the percentage of infected individuals by the classical SIR model when almost everyone is susceptible. To address the issues, we calculate the susceptible population based on individuals' propensities that considers the susceptible individuals with high-risk and low-risk behaviors. By estimating the susceptible individuals with low-risk behaviors, we are also able to calculate the percentage of individuals who want to wear mask.

2.3. Optimal threshold between health care system and economic activity

Another major open question, affecting the decisions of policy makers, is how to calculate the relation between health care system and economic activity using the actual number of COVID-19 infections. To address this issue, we introduce an optimization formulation (Problem 1) to obtain the optimal activity level during lockdown that minimizes the financial loss and the stress of health care system.

Problem 1. The proposed optimal strategy for the COVID-19 pandemic

$$\text{Min}C(u) = \sum_{n=1}^{T} e^{-rn}\left(c_1 e^{-c_2 n}\hat{I}_n + \omega_1(1-u_n^* - \omega_2)^2 S_n^L\right) \tag{8a}$$

$$\hat{I}_n = u_n^*\gamma\, I_n(1-I_n) \tag{8b}$$

$$0 \le u_n^* \le 1 \tag{8c}$$

The first term in the right hand side of Eq. (8a) is the stress in the health care system that determines by proportional to $\hat{I}_n$, a factor c_2 that is the efficiency level or the speed of learning related to the health care sector, and a coefficient c_1 that shows the burden of new infections on the health care system which is calibrated by the damage of the pandemic on economic about the U.S. of 13 trillion dollars corresponding to 61% of the annual U.S. GDP [8]. We assumed that a half of year (182 days) is needed for the health care system for preparation to manage the pandemic.

$$c_1 \int_0^{182} e^{-rn} e^{-c_2 n}\hat{I}_n \, dn \ = 365(0.61) \tag{9}$$

The relation between the activity level (social performance) and financial loss during the pandemic is considered in the second term in the right hand side of Eq. (8a) where ω_1 and ω_2 are the scaling and shift parameter [11].

The constraint Eq. (8b) is a possibly time-varying infection rate that reflects government policy such as the activity level. By increasing activity level u_n^*, the percentage of infection goes up that causes a burden on the health care sector. Let γ denote the growth rate of the percentage of infected individuals [20,42]. The last constraint is the optimal activity level u_n^* which is limited between 0 and 1.

Using the proposed algorithm, by forecasting the temporary public sentiment, first we calculate the final sentiment using the rate of learning and forgetting information. We determine the percentage of infected persons and the percentage of susceptible persons using the SIR model. Then, we determine the percentage of individuals who have high fear and follow low-risk behavior. The percentage of people who wear a mask is also determined by the ratio of individuals who have high fear and want to wear a mask. Finally, we solve an optimization model to find optimal threshold of activity level and the financial loss during the epidemic. All our experiments are conducted on a computer with a 2.50 GHz processor, 8 GB RAM and 64-bit Windows 10 Professional operating system. The model was coded in Julia and we solved the NIP models using non-linear Optimizer in Julia. The CPU run-time in seconds of the proposed model for the test case is about 4s.

2.4. Formulating the proposed model in the form of a stage-by-stage algorithm

The proposed optimal control strategy for the pandemics can be summarized as the following stage-by-stage algorithm:

Step1: Initialization: N, T, $I(0)$, $S(0)$, and input parameters.

Step2: Sampling the temporary sentiment during the pandemic from Twitter.

Step3: Run a time-series method based on a state-space framework Equations ((1) and (2)) to predict the temporary public sentiment using the Tweeter samples.

Step4: Determine the final sentiment (FS) at period n which are calculated from Eqs. (3) and (4), respectively.

Step5: Calculate the contact rates of infected individuals β_n using Eq. (5). Then, solve the SIR model using Eqs. (6a) and (6b).

Step6: Determine the ratio of individuals with low-risk behavior from Eq. (7). This is equivalent to the PPE burn rate for the entire population.

Step7: Determine the optimal control strategy by solving an optimization model using Eqs. (8) and (9). The structural parameters, including the interest rate, medical resources parameters (costs and the speed of learning), the ratio of infected individuals, the ratio of susceptible individuals, and the ratio of individuals

Table 1
The model parameters.

Parameter	Description	Value
θ	Coefficient to amplify the FS	10
a	The degree of learning	0.5
b	The rate of forgetting information	0.5
n_f	The sum of memory portions	7 days
c_1	A coefficient (the burden of new infections on the health care sector)	265 [8]
c_2	The speed of learning for the health care service	$-ln(0.5)/182$ [8]
r	An interest rate	0.0001
ω_1, ω_2	Scaling and shift parameter for financial loss performance	0.2, 0.3
γ	The growth rate of infection	0.5
$I(0)$	Initial infection rate	$1/N$
$S(0)$	Initial susceptible rate	$(N-1)/N$
N	Population(LA County)	10,000,000

with low-risk behavior should be given as the input data of the proposed model.

Step8: If n has reached the last time step of the study period, go to the next stage. Otherwise, increment n ($n = n + 1$) and go back to stage 2.

Step9: Outputs: the optimal activity level $u^*(n)$; the number of susceptible individuals with low-risk behavior $S^L(n)$; the number of susceptible individuals with high-risk behavior $S^H(n)$; the number of infected individuals $I(n)$. The flowchart of the proposed model is shown in Fig. 2.

3. Experimental results

3.1. COVID-19 dataset

Twitter is a valuable platform for analyzing and tracking public sentiment where millions of users share their feelings. We carried out an experimental study of the proposed model by Tweet dataset in California. We are continuously gathering the dataset since March 5, 2020 until July 6, 2020. The data that were obtained from [24,43] were used to evaluate the framework. The authors used the sentiment intensity analyzer from python Natural Language Toolkit (NLTK) library package [44] to automatically classify the COVID-19 tweets into a specific emotion category in terms of negative, natural, and negative attitude. They used the compound score which is a normalized score. Each file of the dataset has about 200 thousand rows, and each row contains tweet id, date/time, location, text, sentiment (polarity and subjectivity), user id, and user verified. The subjectivity analysis that is a measurement of opinion or fact in a text ranging from 0 to 1 is also included in the dataset. The polarity of the sentiments is distributed across the scale between [-1,0), 0, and (0,+1] that shows negative, natural, and positive polarity, respectively. We used the samples from [43] which contain neutral, negative, and positive attitudes about the current pandemic to determine the temporary fear-sentiment information. More details about the sentiment data can be found in [24,43]. Fig. 3 represents the number of neutral, negative, and positive tweets. Other datasets related to the COVID-19 pandemic such as the number of confirmed cases in LA County can be also found in the USAFactsdataset [45].

Based on Eqs. (1) and (2), we run a time-series analysis to predict the range of temporary sentiment over time. Fig. 4 predicts the temporary sentiment information over 100 simulated runs using time-series method in a state-space framework.

3.2. Results

3.2.1. Optimal control evaluation of disease

The list of input parameters used for the SIR model is presented in Table 1. Using the range of temporary sentiment, we solve a SIR model to determine the percentage of infected individuals $I(n)$, the percentage of susceptible individuals with high risk behaviors $S^H(n)$, and the percentage of susceptible individuals with low-risk behavior $S^L(n)$. Lastly, we obtain the optimal activity level that minimizes the financial loss during the pandemic. Fig. 5 presents the contact rate of detectable infected individuals over time in LA County which is calculated using Eq. (5).

We now can determine the number of susceptible and infected individuals using Model E+ Eq. (6). The number of infected individuals in LA County over 40 weeks is shown in Fig. 6. The result shows a comparison on infected individuals between prediction and true values. This method is found to be the best fitting and makes less error in prediction . Therefore, due of a complex nature of pandemic models, a more accurate prediction model is proposed which is a simple and fast method. Note that we are not proposing a new SIR model to control the disease here. We are merely using this model as part of our optimization model to estimate the number of individuals who have low risk behavior and wear mask. Policy makers can use the simple model to make decision during the outbreak crisis. Using Eq. (5), we determine several past observations of contact rate, then we use a linear regression to fit the contact rate for the remaining periods [40]. The root mean square error (RMSE) is applied to evaluate the fitness of model from the actual observation data where the RMSE is 14%. The susceptible individuals on average $\beta_n I_n$ infectious contact will vary by time, so it makes more sense to estimate the intensity by an online prediction method based on a non-homogeneous Poisson process (NHPP), as another future work [46,47]. An agent-based simulation model based on the human trajectory can be also considered to estimate the average infectious contact $\lambda = \beta_n I_n$ between agents during the pandemics, these properties can be explored in future study.

In this study, we consider the susceptible individuals under two types of behaviors. One group is the percentage of susceptible individuals with risky behaviors, while other group is the percentage of susceptible individuals with low-risk behaviors. Individuals will change their behaviors during the pandemic based on the final sentiment information which they receive. The total number of susceptible individuals is shown in Fig. 7(a) and the number of susceptibles with low-risk behavior is shown in Fig. 7(b).

During the COVID-19 crisis, the information of suppliers and demands was unavailable [48]. This kind of disruption damages

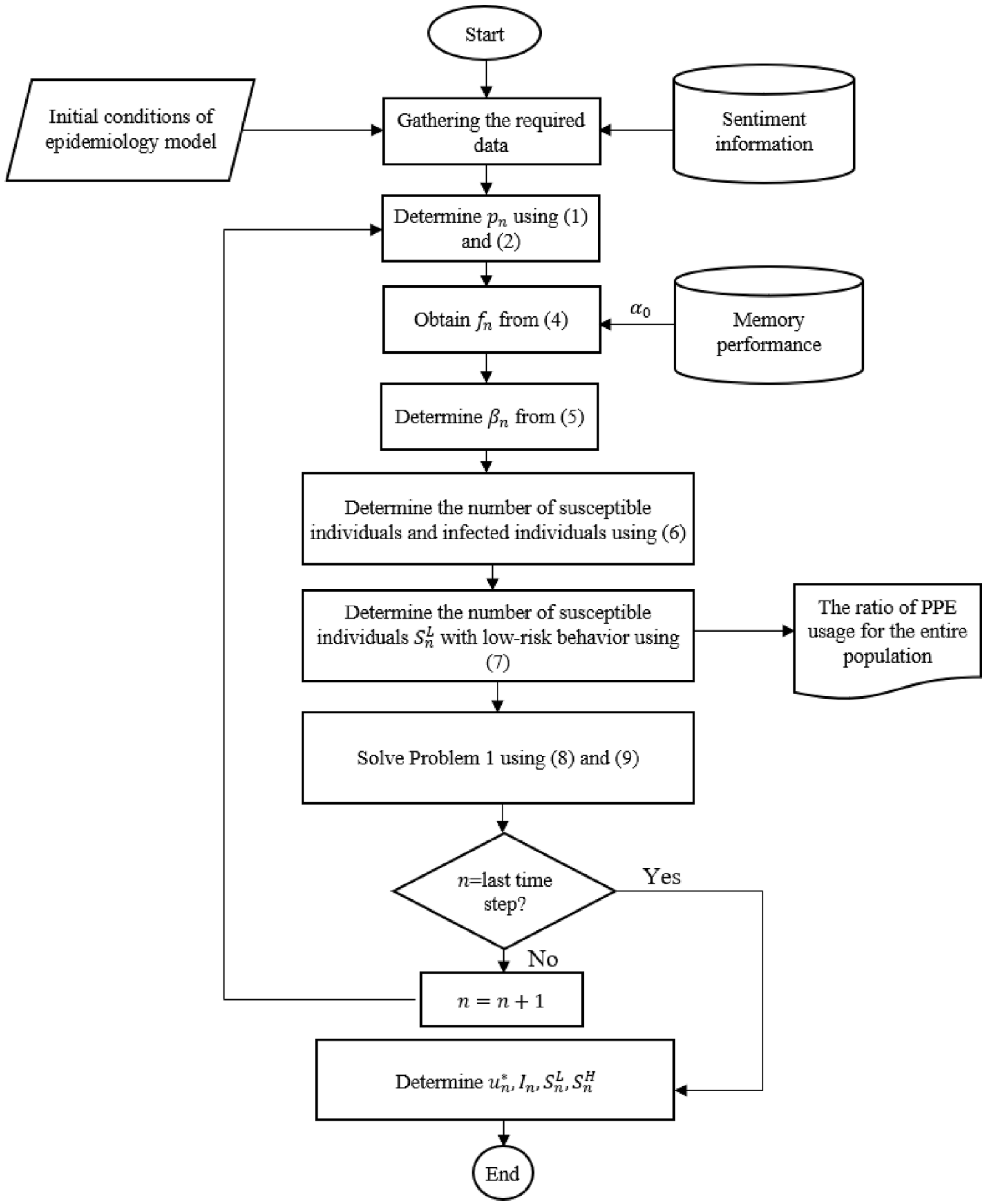


Fig. 2. Flowchart of the proposed model.

the capability of manufacturers to produce medical. Using our model, we can estimate the PPE burn rate during the pandemic. In the supply chain resilience, firms can manage their inventories of PPE products based on the actual demand projections for medical items. Suppliers can take advantage of the activity level information to manage supply chain risk and disruption in directing the flow of goods to demand nodes during the pandemic. Moreover, the transit system needs to estimate the actual trips in order to design the fleet during the epidemic. As Fig. 7(b) represents the percentage of susceptible with low-risk behaviors increases at the first of the epidemic, because the individuals have high fear. However, it goes down at the peak of the COVID-19 pandemic and finally it increases during the remaining time periods of the pandemic.

The health care sector and medical professionals are facing challenges like never before due to the COVID-19 pandemic. We solve an optimization model based on Eq (8) that minimizes the total cost in terms of the stress of health care system and the financial loss associated with social performance. Prediction of the pandemic duration can help the policy makers to forecast the end time of lockdown to avoid consequent social-economic damages as well. The optimal activity level during lockdown is determined using the provided information by solving the SIR model. A 3.2 trillion dollars gross state product as of 2019 is

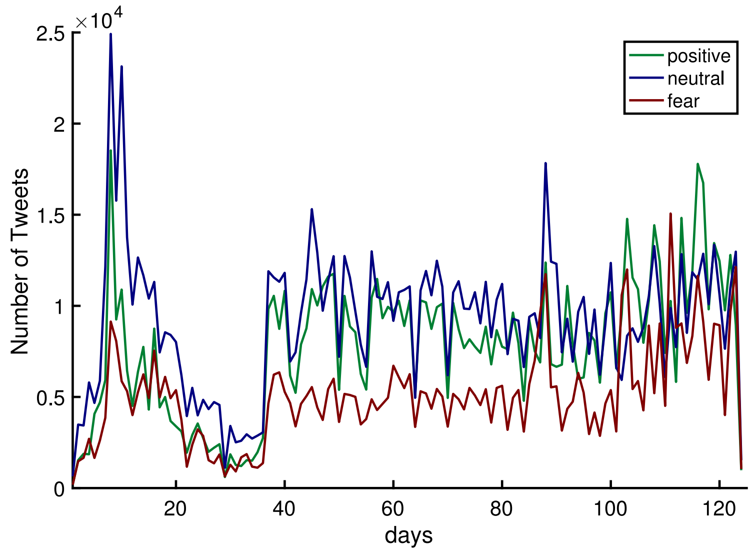


Fig. 3. Temporary sentiment from March 5th to July 6st, 2020 (Source: Twitter).

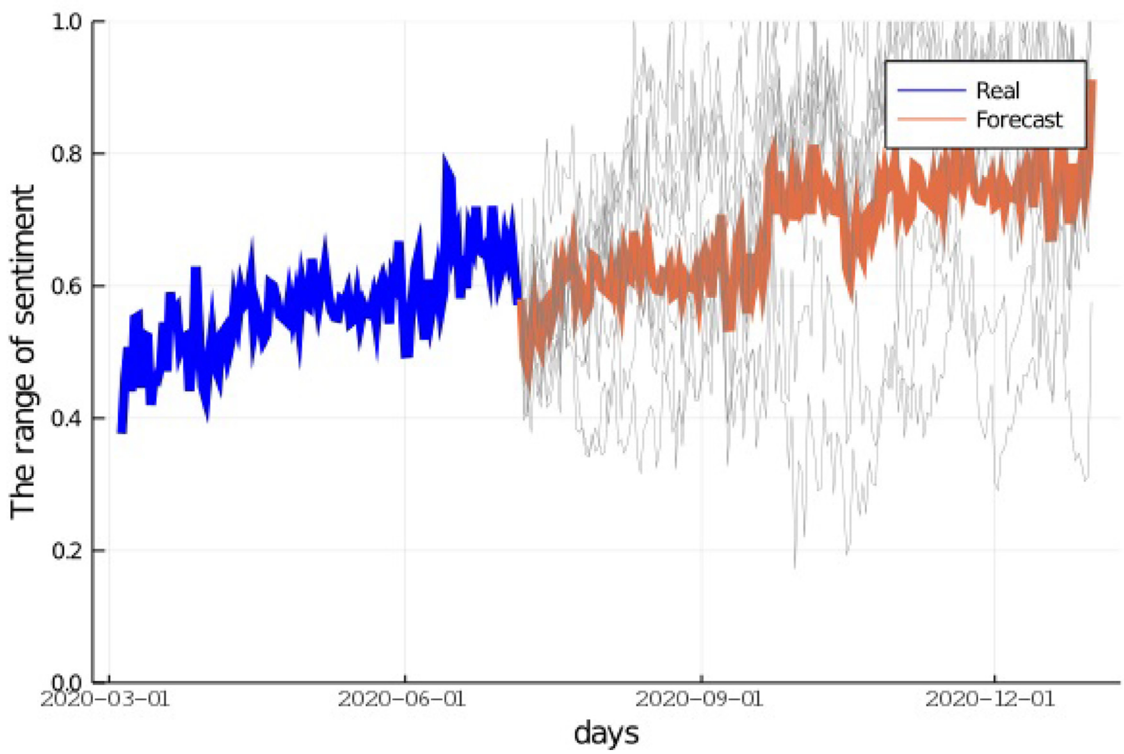


Fig. 4. Historical temporary sentiment and forecasting over 100 simulated runs..

showed in the California state that uses to estimate the percentage damage during the pandemic [49]. Base on (9), the burden of new infections on the health care sector is calibrated by the damage of the pandemic on economic in the California state.

This study explores the determinants of switching behaviors in the social activity level. The impact of heterogeneous susceptible (who have low-risk behavior S^L and wear a mask) on the social costs is also considered in Eq. (8). Fig. 8(a) shows the impact of the speed of learning in the healthcare sector on the optimal activity level during the epidemic in LA County. The results show that the optimal activity level is decreased until 0% during weeks 18 through 24. The activity level is dropped until 40% when the performance of health-care sector goes up. Likewise, a sensitivity analysis on γ (between 0.1 and 0.7) and the optimal activity level that reflects the stress of health care system during the pandemic is shown in Fig. 8(b). The result shows that the optimal activity level reduces by increasing γ. Therefore, the vulnerability threshold of health-care sector during the pandemic can be estimated by the proposed strategy.

In order to show the improvement of the proposed strategy, we compare the total cost when the susceptible individuals are assumed to be homogeneous. In this scenario, we have to consider the total susceptible individuals $S_n = S_n^H + S_n^L$ instead of the susceptible individuals with switching behaviors S_n^L in the second term of Eq. (8a). The total social cost based on the proposed strategy is $121,800,000 per week while it is $147,700,000 per week

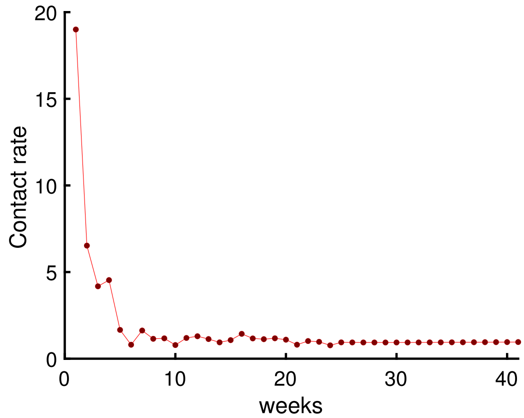


Fig. 5. The contact rates of detectable infected individuals over time in LA County..

when a homogeneous of susceptible individuals is considered. Therefore, using the proposed control strategy, the total social cost reduces by 18% in compared with a control strategy under homogeneous individuals.

Different strategies have implemented by many countries to control the COVID-19 pandemic. Some countries try to reduce the burden of infections on health-care sector by having a complete lockdown of their population that may not be sustainable for long [9]. For example, a complete lockdown in Canada had a deep impact on economy in Canada where the jobless rate rose to 13.7% in May 2020, the highest it has been since 1976 [50]. Other countries such as Sweden decided not to have a lockdown during the COVID-19 crisis, where the death rate goes up to 10 times higher than Nordic countries [51]. We compare the proposed optimal activity level with the above policies by replacing Eq. (10) instead of Eq. (8a) in Problem 1.

$$\mathrm{Min}C(u) = \sum_{n=1}^{T} e^{-rn}\left(\eta * c_1 e^{-c_2 n}\hat{I}_n + (1-\eta) * \omega_1 (1-u_n^* - \omega_2)^2 S_n^L\right) \quad (10)$$

We define a weight η to differentiate the health care cost and the financial loss of social distancing in Eq. (10). The results of the activity level under different weights are summarized graphically in Fig. 9. The blue line represents an optimal activity level by considering the similar weight of health-care cost and social distancing cost. We increase the weight of health-care cost to find the activity level which is shown by green line. Otherwise, we consider another scenario which is demonstrated by red line where the weight of social distancing cost is increased.

Based on Fig. 9, the optimal activity level is decreased until 0% during weeks 18 through 24 when the weight of costs is $\eta = 0.5$. However, the activity level is reduced until 0% during weeks 5 through 35, when the weight of healthcare sector is changed from $\eta = 0.5$ to $\eta = 0.8$. We also change the weight of social performance from $\eta = 0.5$ to $\eta = 0.8$. The results shows that the activity level is decreased until 50% when the weight of health care cost is less than the weight of financial loss under social distancing. The optimal total social cost per week is \$62,153,568, while it is \$84,132,501 and \$80,614,202 when we increase the weight of health-care sector and social performance, respectively. Therefore, the proposed optimal lockdown strategy can help countries to avoid the damage of the pandemic.

3.2.2. Online social distancing monitoring

Wearing a mask helps prevent the spread of COVID-19, especially those at high-risk. In this study, we use the tweets about fear-sentiment to estimate mask usage over time for the entire population. Fig. 10 shows susceptible individuals with low-risk behavior and want to wear a mask. We prove that our sentiment analysis approach for Twitter generated time series is validated, because analysis of such data showed that 73% of people in LA County wear mask on July 2, 2020; this agrees with the results of [52]. The New York Times investigated a survey of a national sample of 250,000 adults on July 2, 2020 and the result indicates that the percentage of adults endorsing face mask wearing on July 2, 2020 is about 77% [52]. Therefore, not only the proposed online strategy mitigates the pandemic, but also provides real-time health data based on individuals' propensities.

3.2.3. The sensitivity analysis of learning and forgetting disease information

The individuals communicate by sharing their sentiment to each other where their individual's brains store and retrieve the disease information during the pandemic. The individual's brain can make lots of daily decisions about whether to store facts and events. Some of experiences will be stored in the brain for a few seconds or minutes and finally forgotten. However, some of experiences and facts will be remained for a few days, while others will be ingrained for many years or even a lifetime. If individuals decide to remember the disease information, the brain makes connections between the cells, which alters their structure, and is what allows individuals to retain memories. We determine the final sentiment with regards to the learning and forgetting factors for individuals.

We calculate the individual's memory performance measure based on Eq. (3). A sensitivity analysis of the final sentiment by changing the forgetting factor of individual's memory between 0.1 and 0.9 is shown in Fig. 11(a). As a result, the rate of the final sentiment goes up by decreasing the rate from 0.9 to 0.1. Therefore, the number of susceptible individuals with low risk behaviors increases by changing the rate from 0.9 to 0.1. Similarly, we analyze the relation between the longest memory epoch n_f and the final sentiment as shown in Fig. 11(b). By decreasing the longest memory epoch, the number of susceptible individuals with low risk behaviors increases, because the individuals have more fear sentiment due to the shortest memory epoch for reminding the disease information. We compare the number of susceptible individuals with high fear by changing the rate of forgetting information b between 0.1 and 0.9.

Fig. 11(c) shows a sensitivity analysis on the forgetting sentiment information and the number of individuals who have low-risk behaviors. The low-risk behaviors during the pandemic has also affected by the longest memory epoch n_f. Thus, we analysis the relation between the longest memory epoch n_f and the number of susceptible individuals who have high fear as shown in Fig. 11(d). Individuals will have higher risk to be infected when the longest memory epoch n_f goes up.

4. Conclusions

This paper presents an optimal strategy model for pandemics that considers the interaction of individuals to obtain the temporary sentiment information and the final sentiment information. A fear information function based on the final sentiment information is calculated to find the number of susceptible individuals with high fear and low fear. Then, we applied the SIR model for COVID-19 to determine the percentage of infected persons and the percentage of susceptible persons by determining individuals' propensities. We prove our results with real survey that was conducted to estimate mask usage. Our results showed that 73% of people in LA county in the first week of July 2020 have always wearing a mask, this agrees with the results of the survey. Lastly, we solved an optimization formulation to find trade-off

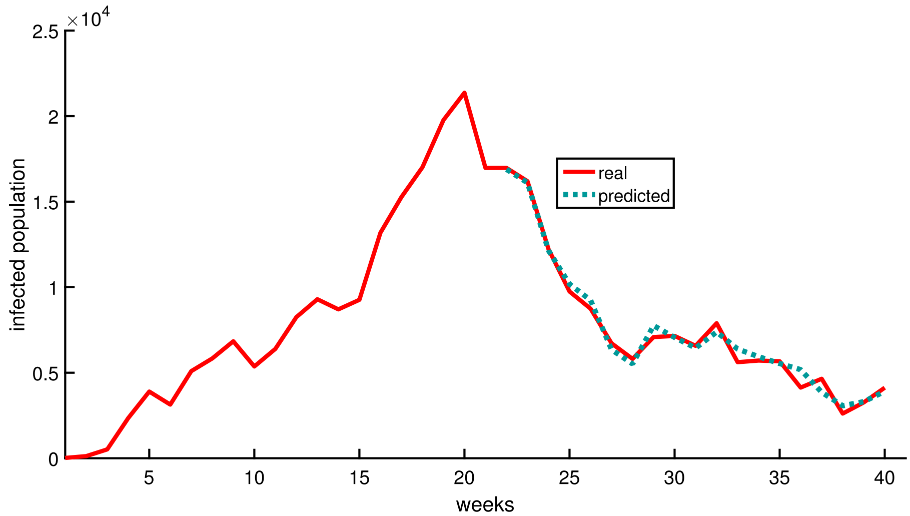


Fig. 6. The number of infected individuals over time in LA County..

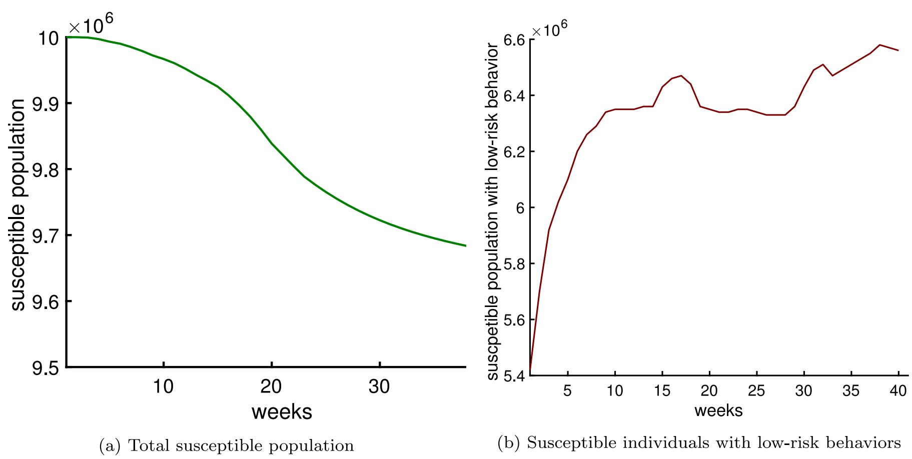
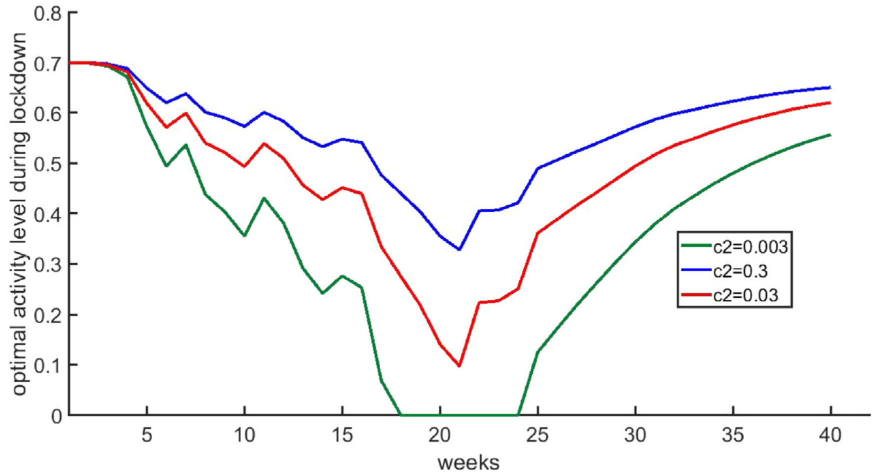


Fig. 7. Susceptible individuals.

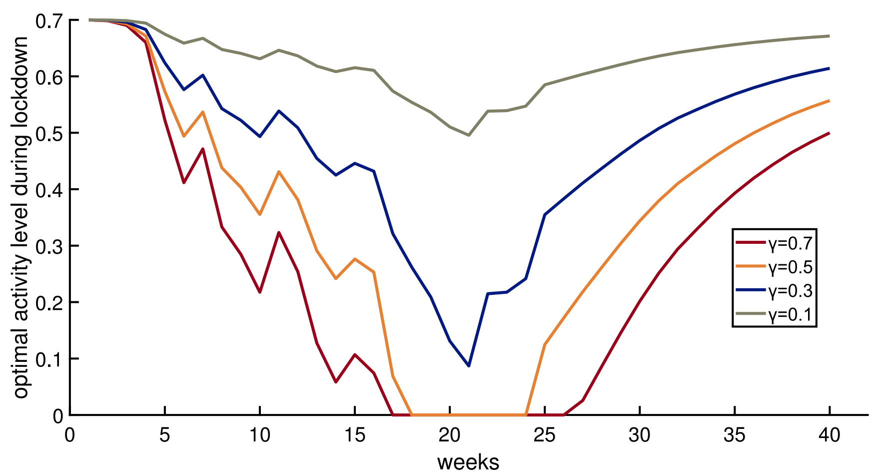
between social performance and limited medical resources. We proposed optimal lockdown and exit strategy during an epidemic for each state or territory that helps the policy makers during the pandemic. The total social cost under the proposed control strategy reduces by 18% in compared with a control strategy with homogeneous susceptible individuals. We also reduced the total social costs by 26% and 22% in compared to other strategies that consider the health-care sector or the social performance, respectively. Hence, the proposed policy can monitor the human behaviors during epidemic in order to control the stress of health care sector.

The proposed model can be extended in the future research works, as below:

- An actual demand price function for medical (PPEs) items by modeling the elasticity of demand and individuals' willingness to pay to avoid risks can be investigated in the future study. This competitive system can solve the demand issue and excess inventory buildup where small and medium companies can compete with large manufacturers to pivot their operations to produce PPE products.
- Public and private sectors put in their best efforts to balance between the supply and the demand of PPE products. By estimating the consumption vector of PPE products, a resilient supply chain for domestic firms [53,54] under the objective of maximizing social benefit can be considered in the future research [55].
- After the COVID-19 pandemic, many countries have to rethink their offshoring strategies for the PPE market [56]. The net demand for each traded PPE item can be determined by the consumption vector of the PPE item. Hence, an international trade resilience policy to balance between trade surplus and the budget deficit can be investigated in the future study [57,58].
- The proposed model helps us to understand the impact of epidemic on transport modes and travel patterns of individuals. Using this information, we can solve the challenges of the last mile delivery, multi-tiered delivery, and delivery on demand during the pandemic. The service providers can control customer demands during the pandemic by predicting the percentage of individuals who have participated social distancing. Hence, an agent-based simulation model based on the human trajectory during the pandemic would be highly valuable as another direction of the future work.
- By estimating human behaviors during the pandemics in each region, an optimal allocation of vaccination and PCR tests can be considered as another future work [59].



(a) Optimal activity level under different speed of learning in the health care system



(b) Optimal activity level under the growth rate of infected individuals

Fig. 8. Sensitivity analysis.

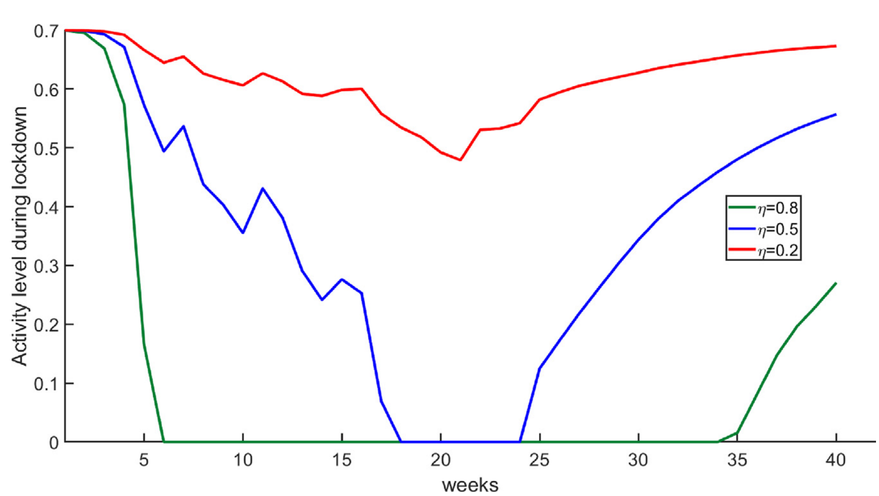


Fig. 9. A comparison of activity level under different control strategies..

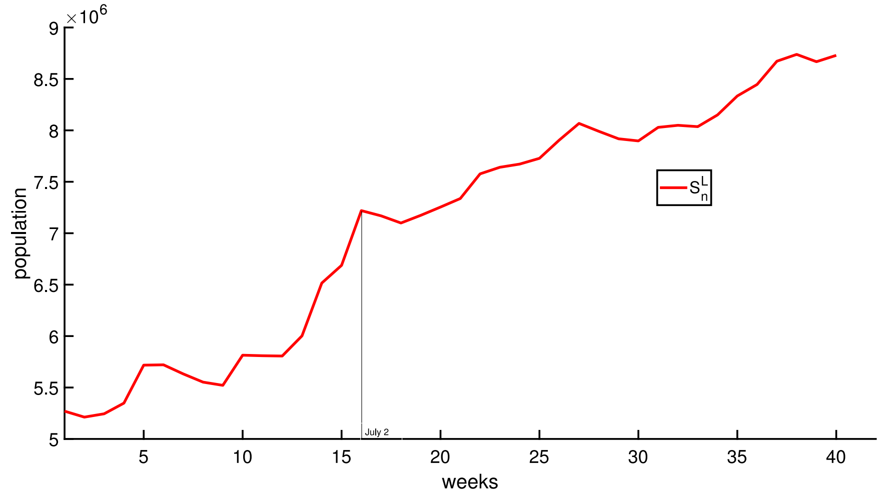


Fig. 10. Susceptible individuals with low-risk behavior and wear a mask..

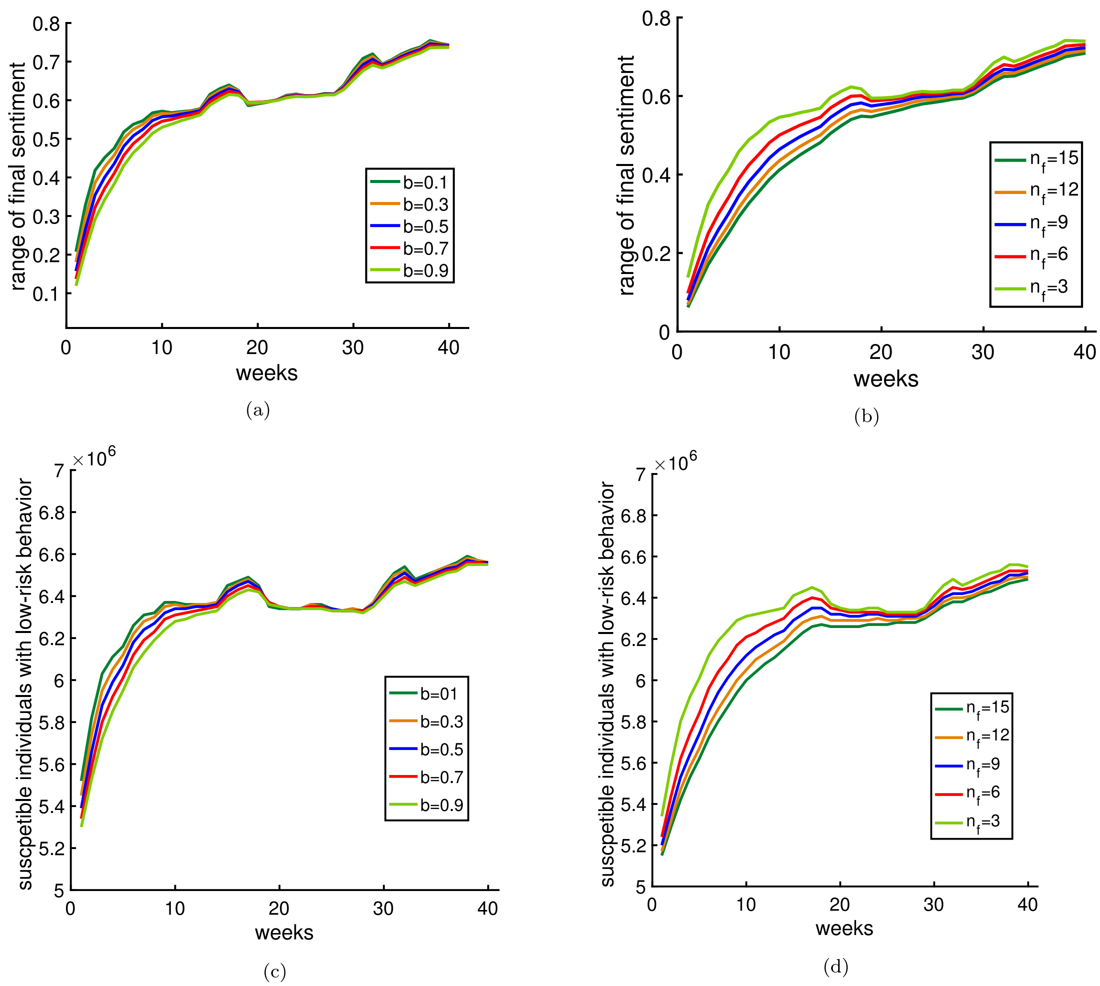


Fig. 11. (a) Final sentiment (FS) under different rate of forgetting information(LA County). (b) A sensitivity analysis on the longest memory epoch n_f and the final sentiment (FS). (c) A sensitivity analysis on the forgetting sentiment information and the susceptible individuals with high fear. (d) A sensitivity analysis on the longest memory epoch n_f and the susceptible individuals with high fear.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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