As COVID-19 in some countries has increasingly become more severe, there have been significant efforts to develop models that forecast its evolution there. These models can help to control and prevent the outbreak of these infections. In this paper, we make long-term predictions based on the number of current confirmed cases, accumulative recovered cases, and dead cases of COVID-19 in some countries by the modeling approach. We use the SIRD (S: susceptible, I: infected, R: recovered, D: dead) epidemic model which is a nonautonomous dynamic system with incubation time delay to study the evolution of COVID-19 in some countries. From the analysis of the recent data, we find that the cure and death rates may not be constant and, in some countries, they are piecewise functions. They can be estimated from the delayed SIRD model by the finite difference method. According to the recent data and its subsequent cure and death rates, we can accurately estimate the parameters of the model and then predict the evolution of COVID-19 there. Through the predicted results, we can obtain the turning points, the plateau period, and the maximum number of COVID-19 cases. The predicted results suggest that the epidemic situation in some countries is very serious. It is advisable for the governments of these countries to take more stringent and scientific containment measures. Finally, we studied the impact of the infection rate $\beta$ on COVID-19. We find that when the infection rate $\beta$ decreases, the cumulative number of confirmed cases and the maximum number of currently infected cases will greatly decrease. The results further affirm that the containment techniques taken by these countries to curb the spread of COVID-19 should be strengthened further.

1. Introduction

In December 2019, an outbreak of a typical pneumonia occurred in Wuhan City, the capital of Hubei Province, China. In the subsequent weeks, this virus spread throughout China. Estimating trends in the spread of any infection over time may provide information and insight into the epidemiological situation and determine if outbreak control strategies have a significant effect [1, 2]. Such approaches may provide decision-makers with scenarios of the expected potential future progress and help to quantify risks and direct mitigation strategies [3]. The cause of COVID-19’s outbreak has been reported in [4–6]. Hellewell and Abbott [7] developed a stochastic transmission model, parameterising to the COVID-19 outbreak. In this paper, we use the classical infectious diseases model, i.e., the SIRD compartment model, to investigate the tendency of COVID-19 in some foreign countries. Dhanwant and Ram-anmaranathan [8] employed a SIR approach to forecast the outbreak of COVID-19 in India by using the SciPy platform. Elhia et al. [9] optimized the SIR epidemic model with time variation and control measures of H1N1 data in Morocco. Kumar [10] studied the age-structured impact of India by using a SIR model. Vattay [11] forecasted the outcome and estimated the epidemic model parameters of SIR from the fatality time series. Bagal [12] estimated the parameters of the SIR model of COVID-19 cases in India during containment periods. Jess and Charles [13] established a SIRD model. Zifeng Yang et al. [14] used the modified SEIR and AI to predict the epidemics trend of COVID-19 in China. Yu Chen et al. [15] used a time-delayed dynamical model to study the outbreak of the epidemic. Liangrong Peng et al. [16] proposed a generalized SEIR model to analyze this epidemic. Based on the public data of the National
Health Commission of China from January 20th to February 9th, 2020, they reliably estimated key epidemic parameters and made predictions on the infection point and possible ending time for 5 different regions. Zhihua Liu et al. [17] modeled COVID-19 in China and they used the early reported data of cases to predict the cumulative number of reported cases to a final size. Qianying Lin et al. [18] used a conceptual model for the COVID-19 outbreak. Peter Song et al. [19] studied an epidemiological forecast model. Analysis and prediction of COVID-19 were investigated in some foreign countries [20–22]. Prediction of NACP and the plateau phases of COVID-19 in China was investigated [23, 24]. Treatment and prognosis of COVID-19 were studied in [25, 26]. The containment strategy of COVID-19 was discussed [27]. Cartocci et al. [28] proposed a time-varying SIRD model distributed by age and sex groups. The model provided insights and additional information on the dynamics of COVID-19 in Italy. Mohammadi et al. [29] introduced a fractional-order SIRD model with Caputo derivative. They researched the stability of the model and the existence and uniqueness of the nonnegative solution. Zhicheng Zheng et al. [30] constructed a SIRD model by considering the factors of lockdown and riot. They concluded that reducing mobility and increasing social distance were the most effective measures to end the epidemic earlier. Deivosita and Debasis [31] provided a modified SIRD model to analyze data of COVID-19. The parameters of the SIRD model were estimated by different methods [32, 33]. Nisar et al. [34] discussed a fractional-order SIRD mathematical model and computed the basic reproduction number through the next-generation matrix. Jahanshahi et al. [35] introduced variable memory indexes in the SIRD model and defined a fractional-order SIRD model by a time-dependent function. Pacheco and Lacerda [36] proved with the SIRD model that the approach of quantifying the different rates by means of function estimation was very robust and consistent. Jason et al. [37] predicted the peak number by using the SIRD model. Vishnu et al. [38] researched the Gaussian model, SIRD, SEIRD, and the latest SEIHIRD techniques used for the prediction of epidemics. Lounis and Raeii [39] used the SIRD model to estimate the basic reproduction number and the peak of the COVID-19 epidemic in Algeria. Ananthi et al. [40] predicted the infection spread and recovery rate of the epidemic by simulating the model and checked the vulnerability. Gupth et al. [41] used the SIRD compartment model for parameter estimation and prediction of COVID-19. Al-Raeei [42] applied the SIRD model for estimating the basic reproduction number of COVID-19. Thus, the SIRD model is the basic model suitable for COVID-19.

We study the development of the epidemic through a nonautonomous SIRD epidemic model with time delay. Here, we choose the delayed nonautonomous model for two reasons. Firstly, susceptible people will not become infected immediately after being exposed to the virus. The virus has an incubation period. After the incubation period, the patient will show symptoms and be diagnosed as an infected person. Therefore, we have introduced an incubation delay in the paper. Secondly, the cure rate and death rate change with time. If they are taken as constants, the errors of the model will increase. Taking the cure rate and death rate as the functions of time can clearly observe their real changes. From their changes, we can also see the country’s attitude to fight the epidemic during this period of time. So it is more reasonable to take them as the functions of time. Hence, we think that the nonautonomous SIRD epidemic model with a time delay can more accurately reflect the development of the epidemic. Using the finite difference method, we find that the cure and death rates in some countries may not be constant and may be piecewise functions. Based on the data released by the Worldmeter [43], the parameters of the model are accurately estimated, so as to simulate the long-term development of the epidemic. We make the long-term prediction of number of current susceptible, confirmed, accumulative recovered, and dead cases of COVID-19 in some countries. We can estimate the turning points and the end times of COVID-19 and the maximum number of current confirmed, recovered, and dead cases.

The structure of this paper is as follows: in Section 2, the SIRD model is introduced. Parameter estimation of the SIRD model is presented in Section 3. In Section 4, the long-term predictions of some countries, as well as the ones after strengthening prevention and control measures, are presented. The conclusion and discussion are presented in Section 5.

2. SIRD Model Building

This section introduces the nonautonomous time-delayed epidemic model of COVID-19 in some countries. The SIRD model is a compartmental model describing how a disease spreads among the population. It is a set of general equations that explain the dynamics of an infectious disease. The subjects of the SIRD model are susceptible, infected, recovered, and dead cases. The population under study is presumed to be invariant. Obviously, \( S(t) + I(t) + R(t) + D(t) = N \). In the model, natural birth and death rates are not considered. We use the following symbols to mark the number of people in each category:

(i) \( S(t) \): susceptible, representing the number of people who do not have infectious diseases at time \( t \) but are likely to have infectious diseases in the future

(ii) \( I(t) \): infected, representing the number of people who get infectious diseases at time \( t \)

(iii) \( R(t) \): recovered, representing the cumulative or total number of the recovered groups at time \( t \)

(iv) \( D(t) \): dead, representing the cumulative or total number of the dead groups at time \( t \)

In this paper, the highlights of the model lie in the following.

Firstly, time delay is introduced to describe the virus incubation period. Infected cases go through an incubation period of \( r \) days before showing significant symptoms. Once symptoms appear, the infected person will seek treatment and be transformed into the confirmed case. Many works did not consider the effect of the incubation delay. But actually, this delay is long, even up to more than 20 days, and its effect on the dynamic is crucial. So, we have to introduce it into the model and consider its effect on the dynamics and stability.
In this paper, we take the mean value, 4 days, as the incubation delay.

Secondly, according to the data issued by the Worldometer, we find that perhaps the cure and death rates in some countries may not be constant and may be piecewise functions. The death rates may increase continually. The reason is that the medical resources and treatment measures have been saturated. The cure rate in some countries has increased slightly, while the cure rate in other countries has decreased, which may be caused by the rapid increase in the number of infected cases. By the finite difference method, we obtain accurately the cure and death rate functions. It is very crucial for the long-term predictions of COVID-19 in these countries. The partial results of cure and death rates are displayed in Figure 1.

Through analysis, we can get the nonautonomous time-delayed dynamic model of COVID-19 in some countries as follows:

\[
\begin{align*}
\frac{dS}{dt} &= -\frac{\beta S(t-\tau)I(t-\tau)}{N}, \\
\frac{dI}{dt} &= -(\gamma(t) + \mu(t))I + \frac{\beta S(t-\tau)I(t-\tau)}{N}, \\
\frac{dR}{dt} &= \gamma(t)I, \\
\frac{dD}{dt} &= \mu(t)I.
\end{align*}
\]

(1)

In the above model, \(\beta\) represents the rate of transmission for the susceptible to the infected. In model (1), we take the values of the incubation delay \(\tau\) as the mean value, 4 days. \(\gamma(t)\) represents the cure rate of the infected cases. \(\mu(t)\) represents the death rate of the infected cases. According to the model, \(\gamma(t)\) is approximately equal to the number of newly cured cases per day divided by the current number of infected cases on the present day, \(\mu(t)\) nearly equals the number of new deaths per day divided by the current number of infected cases on the present day. From equation (1), we obtained the following expressions:

\[
\gamma(t) = \frac{R(t+1) - R(t)}{I(t)}, \quad \mu(t) = \frac{D(t+1) - D(t)}{I(t)}.
\]

(2)

3. Estimation of Parameters in the Delayed SIRD Model

Due to the colder weather, this epidemic in some countries has become more severe. Since the time periods of the outbreaks in different countries are different, the time periods we choose are also different. We choose the data from September 15th to November 15th as the research data for France and Russia; the data from October 1st to November 15th as the research data for Italy and Germany; the data from September 15th to November 20th as the research data for Hungary and Canada; the data from September 10th to November 20th as the research data for Iran; the data from September 1st to November 20th as the research data for Ukraine; the data from October 31st to November 20th as the research data for Japan, Turkey, and USA; the data from October 17th to November 20th as the research data for Pakistan; the data from September 20th to November 20th as the research data for Lithuania; and the data from October 15th to November 20th as the research data of Uganda. For all of these countries, we choose the first day’s data as the initial function. In the SIRD model, the parameters to be estimated are \(\beta\). By the finite difference method, we get \(\gamma(t)\) and \(\mu(t)\). We estimate \(\gamma(t)\) and \(\mu(t)\) by calculating the average value separately. The values of \(\gamma(t)\) and \(\mu(t)\) are displayed in Tables 1–3. Analyzing Tables 1–3, we find that France, Italy, Hungary, Ukraine, Lithuania, and Uganda have very low cure rates. Canada and Japan have relatively high cure rates. Hungary, Canada, Iran, Japan, Turkey, and Pakistan have higher death rates.

Based on the least square method, we use the Lsqnonlin function built in MATLAB to carry out parameters inversion and get the optimal parameters. The reason why we use the Lsqnonlin function is that it is a relatively advanced tool in MATLAB, and when it is adopted for parameter estimation, the result is perfect. We choose the selected data of the first day as the initial functions of \(S(t), I(t), R(t),\) and \(D(t)\) in DDEs (1). Here, we also give some results of parameter estimations and fitting curves in Figures 2 and 3. The blue dots are the real data for parameter estimations. The red solid curves are the fitted evolution curves of COVID-19 in model (1). Here, we use relative error and R-squared to evaluate the results of the parameter estimations of the models. Results of the model evaluation are shown in Figures 4 and 5 and Table 4 and 5. By observing Figures 4 and 5, we find that some countries have large relative errors for infected cases. This is related to our method, the accuracy of data statistics, and the irregularity of the data or nonsmoothness of the evolution curves. Due to the unknown real initial functions and the imperfect estimations of cure and death rates, our method has results with limited precision and cannot be consistent with actual data very much. Some countries may have inaccurate statistics, which may also cause certain errors. These errors may also be related to the adjustment of national prevention and control policies, the will of people, and the changes in climate. However, by observing Tables 4 and 5, we find that the real data and the fitting data are in good agreement. It indicates that our method is effective and powerful. Based on the official data, we get the parameter inversion results shown in Table 6.

4. Long-Term Prediction

4.1. Long-Term Predictions Based on Model (1). The parameters \(\beta\) obtained in Section 3 are substituted into equation (1), and the numerical method is carried out to simulate the evolutions of \(S(t), I(t), R(t),\) and \(D(t)\). In Figures 6 and 7, we make long-term predictions of COVID-19 in some countries based on this model. Based on the predicted results, it is obvious that the situation of COVID-19 in France, Italy, Germany, Hungary, Pakistan, Lithuania, Uganda, and USA will develop very seriously. Almost everyone can eventually get infected. The government should...
Figure 1: Curves of cure and death rates of different countries. (a) Cure rate of France. (b) Death rate of France. (c) Cure rate of Italy. (d) Death rate of Italy. (e) Cure rate of Germany. (f) Death rate of Germany. (g) Cure rate of Russia. (h) Death rate of Russia.
Table 1: Cure and death rates.

|      | France   | Italy     | Germany   | Russia   |
|------|----------|-----------|-----------|----------|
| $\gamma$ | 0.001002 | 0.01430 (t < 39) | 0.04391 | 0.02630 (t < 41) |
| $\mu$  | 0.0001708 (t < 39) | 0.0000464 (t < 20) | 0.0004299 (t < 31) | 0.0007853 |

Table 2: Cure and death rates.

|      | Hungary  | Canada    | Iran      | Ukraine  | Japan   |
|------|----------|-----------|-----------|----------|---------|
| $\gamma$ | 0.01167 | 0.083577 | 0.04598 | 0.01333 (t < 64) | 0.08185 |
| $\mu$  | 0.0006237 (t < 29) | 0.001199 | 0.004038 (t < 41) | 0.0006148 | 0.001072 |

Table 3: Cure and death rates.

|      | Turkey   | Pakistan | Lithuania | Uganda   | USA     |
|------|----------|----------|-----------|----------|---------|
| $\gamma$ | 0.04375 | 0.04995 (t < 16) | 0.01441 | 0.009446 (t < 21) | 0.01606 |
| $\mu$  | 0.001911 | 0.001150 | 0.0004279 | 0.0004418 (t < 21) | 0.0003115 |

Figure 2: Continued.
Figure 2: Fitting curves of the current susceptible, infected, recovered, and dead cases. (a) France. (b) Italy. (c) Germany. (d) Russia. (e) Hungary. (f) Canada. (g) Iran. (h) Ukraine.
Figure 3: Fitting curves of the current susceptible, infected, recovered, and dead cases. (a) Japan. (b) Turkey. (c) Pakistan. (d) Lithuania. (e) Uganda. (f) USA.
Figure 4: Continued.
Figure 4: Relative errors of real data and fitting data in some countries. Relative errors in (a) France, (b) Italy, (c) Germany, (d) Russia, (e) Hungary, (f) Canada, (g) Iran, and (h) Ukraine.

Figure 5: Continued.
strengthen the prevention and control of the current situation. The situations in Russia, Canada, Iran, Ukraine, Japan, and Turkey are significantly better. They have a relatively low infection rate. Compared with France and Italy, these countries have taken better epidemic prevention measures, but isolation and containment measures still need to be further strengthened. The epidemic of France, Russia, Ukraine, Turkey, Lithuania, Uganda, and USA will last longer and the plateau period will come later. France, Italy, Hungary, Pakistan, Uganda, and Lithuania have a relatively large proportion of death due to their low cure rate. Iran has a relatively large proportion of death due to its high death rate.

4.2. Impact of Infection Rate $\beta$. Obviously, if the containments are strengthened more effectively, the infection rates will decrease. In Figure 8, we make the long-term predictions for the reduction of infection rates $\beta$. Here, we choose some countries with severe epidemic to make predictions to investigate the impact of $\beta$. According to Figures 6–8, we find that the cumulative number of confirmed cases and the maximum number of currently infected cases have decreased significantly due to better containments corresponding to the smaller $\beta$. It will decrease the medical cost of COVID-19 significantly there. The results further affirm that the containment measures taken by these countries to curb the spread of the disease were efficient and need to be strengthened further. The results also indicate containment will be very effective and helpful. But the dead proportions will remain nearly the same due to the saturation of their medical measures and resources. If containment is strengthened, the time of the turning point will be delayed and so will the arrival time of the plateau period.

Figure 5: Relative errors of real data and fitting data in some countries. Relative errors in (a) Japan, (b) Turkey, (c) Pakistan, (d) Lithuania, (e) Uganda, and (f) USA.
### Table 4: Model evaluation.

|        | France | Italy | Germany | Russia | Hungary | Canada | Iran |
|--------|--------|-------|---------|--------|---------|--------|------|
| $S$    | 0.994310 | 0.992955 | 0.992410 | 0.995583 | 0.997262 | 0.990909 | 0.995913 |
| $I$    | 0.993874 | 0.987677 | 0.971390 | 0.982330 | 0.993040 | 0.971657 | 0.950614 |
| $R$    | 0.992237 | 0.994642 | 0.998596 | 0.997516 | 0.985735 | 0.983678 | 0.994399 |
| $D$    | 0.997578 | 0.993619 | 0.989594 | 0.992414 | 0.996345 | 0.991078 | 0.999008 |

### Table 5: Model evaluation.

|        | Ukraine | Japan | Turkey | Pakistan | Lithuania | Uganda | USA |
|--------|---------|-------|--------|----------|-----------|--------|-----|
| $S$    | 0.997894 | 0.993132 | 0.995558 | 0.987388 | 0.980322 | 0.998340 | 0.991034 |
| $I$    | 0.992513 | 0.956707 | 0.979797 | 0.973321 | 0.972250 | 0.988288 | 0.975948 |
| $R$    | 0.998063 | 0.998454 | 0.994549 | 0.991874 | 0.937519 | 0.902473 | 0.997076 |
| $D$    | 0.995915 | 0.976341 | 0.999446 | 0.996198 | 0.974676 | 0.974414 | 0.975776 |

### Table 6: SIRD model (1) parameter inversion.

|        | France | Italy | Germany | Russia | Hungary | Canada | Iran  | Ukraine | Japan | Turkey | Pakistan | Lithuania | Uganda | USA |
|--------|--------|-------|---------|--------|---------|--------|-------|---------|-------|--------|----------|-----------|--------|-----|
| $\beta$ | 0.03798 | 0.09518 | 0.12299 | 0.04965 | 0.13032 | 0.07969 | 0.03795 | 0.14103 | 0.06194 | 0.08758 | 0.07781 | 0.04042 | 0.03972 |

### Figure 6: Continued.
Figure 6: Continued.
Figure 6: Long-term predictions of COVID-19 in some countries based on the delayed nonautonomous SIRD model. (a) France. (b) Italy. (c) Germany. (d) Russia. (e) Hungary. (f) Canada. (g) Iran. (h) Ukraine.

Figure 7: Continued.
Figure 7: Long-term predictions of COVID-19 in some countries based on the delayed nonautonomous SIRD model. (a) Japan. (b) Turkey. (c) Pakistan. (d) Lithuania. (e) Uganda. (f) USA.
Figure 8: Continued.
5. Conclusion

SIRD epidemic models are classical and effective mathematical models of infectious diseases. In this paper, the SIRD model is used to describe the development of COVID-19 in some countries. Through the analysis of the recent data, we find the cure and death rates in these countries are piecewise functions but not constant. We estimate them by the finite difference method. And, after substituting them into the SIRD model, we estimate the infection rate $\beta$ through the recent data. Finally, we simulate delayed SIRD model (1) with the above parameters to make the long-term predications of COVID-19 in the countries, i.e., under the same measures and conditions. We also consider the effect of the strengthened containment, i.e., smaller $\beta$. The analysis of the recent data indicates that the countries' prevention and control measures can affect the development significantly. If these countries strengthen their prevention and control, the cumulative number of infections and the maximum number of currently infected cases will decrease significantly. Therefore, from the results, intervention measures are more effective in containing the spread of COVID-19 in these countries. However, if the rate of interaction between members
of the population remains uncontrolled, the number of infected cases would increase. This will be facilitated by the existence of asymptomatic people that will transmit the disease to others in the population. This paper does not predict the second wave of epidemics since we estimate the parameters of nonautonomous DDE systems with strong determinacy, which cannot be subject to larger fluctuations. This is the feature and limitation of this method. However, the second wave of epidemics is often associated with climate change, change of governments’ prevention and control policies, and people’s willingness to contain the epidemic. The variation of these factors can induce larger random disturbance of the DDE, making it less deterministic. Therefore, it is difficult for us to accurately predict the second wave. Finally, we hope that the governments will impose the strictest and most scientific and effective containment measures, so as to quickly conquer COVID-19.

Data Availability

The data used to support this study were obtained from the following website: https://www.worldometers.info/coronavirus/.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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