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The COVID-19 Pandemic Dynamic in India in the Spring and Summer of 2021

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Abstract

The sharp increase in the number of new COVID-19 patients in India in the second half of April 2021 has caused alarm around the world. A detailed analysis of this pandemic storm is still ahead. We present the results of anterior analysis using a generalized SIR-model (susceptible-infected-removed). The final size of this pandemic wave and its duration were predicted. The obtained theoretical results were compared with the real pandemic dynamics in the summer of 2021 and showed that the COVID-19 pandemic could be a problem for mankind for a very long time.

Keywords: ***COVID-19 pandemi; Epidemic dynamics in India; Mathematical modeling of infection diseases; SIR model; Parameter identification; Statistical methods.***

1. Introduction

The daily number of new laboratory-confirmed COVID-19 cases in India exceeded 400,000 in the end of April 2021. This huge figure is frightening, but if we take into account the population of India, the number of new cases per capita is not yet higher than the maximum for some other countries, including Ukraine. It is very important to assess the growing trends in the number of new cases and the ability of the Indian medical system to cope with the huge number of patients and deaths.

Any mathematical modeling of the epidemic dynamics will be of particular value if we make an accurate long-term forecast of its duration and number of diseases using statistics data sets obtained immediately after the outbreak. Many authors are trying to predict the Covid-19 pandemic dynamics in many countries and regions [1]-[72]. We will not analyze these studies in details and only note that the correct mathematical simulation of the Covid-19 pandemic is very difficult for at least two reasons.

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First, data on the number of cases are clearly incomplete immediately after the epidemic outbreak, there are quite long hidden periods [67], [70], [73]-[77]. In particular, first COVID-19 cases probably have appeared already in August 2019 [67], [70]. The reason is the large number of asymptomatic patients and the lack of skills to detect a new disease. It must be noted that large discrepancy between registered and actual number of cases occurred even for later periods of Covid-19 pandemic [72], [78]-[80].

The second reason for the limited accuracy of long-term forecasts is the constant changes in the conditions of the pandemic (quarantine measures, social behavior, virulence of the pathogen, etc.). Therefore, a prediction made using statistics for a certain time period is not suitable for other periods of time. To solve this problem a generalized SIR-model and the methods of its parameter identification was proposed in [70], [81], [82]. Since the new pandemic wave in India is not the first one, we will use the generalized SIR-model and the method of direct parameter identification (without calculations of the previous epidemic waves) [83]. Corresponding results for the first Covid-19 epidemic waves in mainland China, USA, Germany, the UK, the Republic of Korea, Austria, Italy, Spain, France, the Republic of Moldova, Qatar, Ukraine, the city of Kyiv and for the world are already published in [65], [67], [69]-[72], [81], [82], and showed rather good accuracy. In this article we will apply the same approach to the case of India.

2. Data

We will use the data set regarding the accumulated numbers of confirmed COVID-19 cases in India (V_j) from Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) [84]. The values V_j and corresponding time moments t_j (measured in days) are shown in Table 1.

3. Generalized SIR Model and Parameter Identification Procedure

The classical SIR model for an infectious disease [85-87] was generalized in [70], [72], [81] to simulate different epidemic waves. We suppose that the SIR model parameters are constant for every epidemic wave, i.e. for the time periods: $t_i^* \le t \le t_{i+1}^*, \; i = 1, 2, 3, \dots$. Then, for every wave we can use the equations, similar to [85]-[87]:

$$\frac{dS}{dt} = -\alpha_i SI \qquad (1)$$

$$\frac{dI}{dt} = \alpha_i SI - \rho_i I \qquad (2)$$

$$\frac{dR}{dt} = \rho_i I \qquad (3)$$

Here, t is time and S is the number of susceptible persons (who are sensitive to the pathogen and **not protected**); I is the number of infectious persons (who are sick and **spread the infection)**; and R is the number of removed persons (who **no longer spread the infection),** at the moment of time t. It must be noted that *I(t)* is not the number of active cases. People can be ill (among active cases), but isolated. In means, that they don't spread the infection anymore. There are many people spreading the infection but not tested and registered as active cases. The use of number of active cases as *I(t)* in some papers a principal mistake which may lead to incorrect results. Parameters α_i and ρ_i are supposed to be constant for every epidemic wave.

Table 1: Cumulative Numbers of Laboratory Confirmed Covid-19 cases in India Vj According to JHU, [84].

Day in cor-res-pon-ding month t_j	**Number of cases, V_j**						
	March 2021	April 2021	May 2021	June 2021	July 2021	August 2021	September 2021
1	11124527	12303131	19557457	28307832	30458251	31695958	32857937
2	11139516	12392260	19925517	28441986	30502362	31726507	32903289
3	11156923	12485509	20282833	28574350	30545433	31769132	32945907
4	11173761	12589067	20664979	28694879	30585229	31812114	32988673
5	11192045	12686049	21077410	28809339	30619932	31856757	33027621
6	11210799	12801785	21491598	28909975	30663665	31895385	33058843
7	11229398	12928574	21892676	28996473	30709557	31934455	33096718
8	11244786	13060542	22296081	29089069	30752950	31969954	33139981
9	11262707	13205926	22662575	29182532	30795716	31998158	33174954
10	11285561	13358805	22992517	29274823	30837222	32036511	33208330
11	11308846	13527717	23340938	29359155	30874376	32077706	33236921
12	11333728	13689453	23703665	29439989	30907282	32117826	33264175
13	11359048	13873825	24046809	29510410	30946147	32156493	33289579
14	11385339	14074564	24372907	29570881	30987880	32192576	33316755
15	11409831	14291917	24684077	29633105	31026829	32225513	33347325
16	11438734	14526609	24965463	29700313	31064908	32250679	33381728
17	11474605	14788003	25228996	29762793	31106065	32285857	33417390
18	11514331	15061805	25496330	29823546	31144229	32322258	33448163
19	11555284	15320972	25772440	29881772	31174322	32358829	33478419
20	11599130	15616130	26031991	29935221	31216337	32393286	-
21	11646081	15930774	26289290	29977861	31257720	32424234	-
22	11686796	16263695	26530132	30028709	31293062	32449306	-
23	11734058	16610481	26752447	30082778	31293062	32474773	-
24	11787534	16960172	26948874	30134445	31371901	32512366	-
25	11846652	17313163	27157795	30183143	31411262	32558530	-
26	11908910	17636186	27369093	30233183	31440951	32603188	-
27	11971624	17997113	27555457	30279331	31484605	32649947	-
28	12039644	18376421	27729247	30316897	31528114	32695030	-
29	12095855	18762976	27894800	30362848	31572344	32737939	-
30	12149335	19164969	28047534	30411634	31613993	32768880	-
31	12221665	-	28175044	-	31655824	32810845	-

In [70], [72], [81] the set of differential equations (1)-(3) was solved with the use of initial conditions:

$$I(t_i^*) = I_i,\ R(t_i^*) = R_i,\ S(t_i^*) = N_i - I_i - R_i$$

$$N_i = S + I + R$$

and by introducing the function $V(t)=I(t)+R(t)$, corresponding to the number of victims or the cumulative confirmed number of cases. For many epidemics (including the COVID-19 pandemic) we cannot observe dependencies $S(t), I(t)$ and $R(t)$ but observations of the accumulated number of cases V_j corresponding to the moments of time t_j provide information for direct assessments of the dependence $V(t)$. The corresponding analytical formulas for this exact solution; the saturation levels $S_{i\infty}$; $V_{i\infty}=N_i-S_{i\infty}$ (corresponding the infinite time moment) and the final day of the *i-th* epidemic wave (corresponding the moment of time when the number of persons spreading the infection will be less than 1) can be found in [70], [72], [81].

The exact solution depends on five parameters - $N_i, I_i, R_i, \nu_i, \alpha_i$. The values V_j, corresponding to the moments of time t_j can be used to find the optimal values of this parameters providing the maximum value of the correlation coefficient r_i [88]. The details of this approach can be found in [90], [91]. It was successfully used in [65], [67], [69]-[72], [81]-[83], [89]-[91] to simulate the COVID-19 pandemic dynamics and other phenomena. The exact solution [70], [72], [81] allows avoiding numerical solutions of differential equations (1)-(3) and significantly reduces the time spent on calculations. The new algorithm proposed in [92] allows estimating the optimal values of SIR parameters for the *i-th* epidemic wave directly (without simulations of the previous waves) with the use of only two independent parameters N_i and ν_i.

4. Results

The optimal values of parameters and other characteristics of the severe COVID-19 pandemic wave in India are calculated and listed in Table 2. We have used the number *i=2* and the time period: T_{c2} - April 10-23, 2021 for SIR simulations of this wave. Corresponding values of V_j and t_j are listed in Table 1. The value of the correlation coefficient r_i = 0.999959712033103 is very high (see Table 2), nevertheless we are not satisfied with the convergence procedure by isolation of the maximum of this parameter. Probably new simulation with the use of fresher datasets could fix this problem. The estimate of the average duration of the infection spread in India $\tau_i = 1/\rho_i \approx 35$ days is significantly higher than in Ukraine in the end of March 2021, [72].

Unfortunately, the estimations of the pandemic duration in India are very pessimistic (4,434 days or 12.1 years after April 30, 2021). If we suppose that the end of the epidemic corresponds the moment when the number of persons spreading the infection is less than 20, the calculations yield the middle of January 2023. Probably a strict quarantine and vaccination could change this sad trend, but it looks that some new cases of COVID-19 will appear if not always, then for a very long time. The very long duration of the epidemic in India and the large number of cases increase the likelihood of new mutations in the coronavirus, which can make existing vaccines ineffective and pose a threat to all mankind.

Table 2: The COVID-19 Pandemic Storm in India. Optimal Values of SIR Parameters and Other Characteristics, [93].

Characteristics	***i=2***
Time period taken for calculations T_{ci}	April 10-23, 2021
I_i	1,388,033.10466357
R_i	11,836,652.8953364
N_i	43,000,000
V_i	7,965,355.17869963
α_i	3.58639081028928e-09
ρ_i	0.0285668766135785
$1/\rho_i$	35.0055770368917
r_i	0.999959712033103
$S_{i\infty}$	645,561
$V_{i\infty}$	42,354,439
Final day of the epidemic wave	June 23, 2033

Knowing the optimal values of parameters, the corresponding SIR curves can be easily calculated with the use of exact solution [70], [72], [81] and compared with the pandemic observations before and after T_{c2}. The results are shown in Figs. 1 and 2 by blue lines: $V(t)=I(t)+R(T)$ – solid; dashed ones represent the number of infectious persons multiplied by 5, i.e. $I(t)\times 5$; dotted lines show the derivative $(dV/dt)\times 100$ calculated with the use of formula:

$$\frac{dV}{dt} = \alpha_i SI \qquad (4)$$

Equation (4) follows from (2) and (3) and yields an estimation of the real daily number of new cases. Red "Circles" and "stars" correspond to the accumulated numbers of cases registered during the period of time taken for SIR simulations T_{i2} and beyond this time period, respectively (all taken from Table 1). Fig. 1 demonstrates that these values are in good agreement with the theoretical blue solid line. After May 1, 2021, significant discrepancies are visible in Fig. 2.

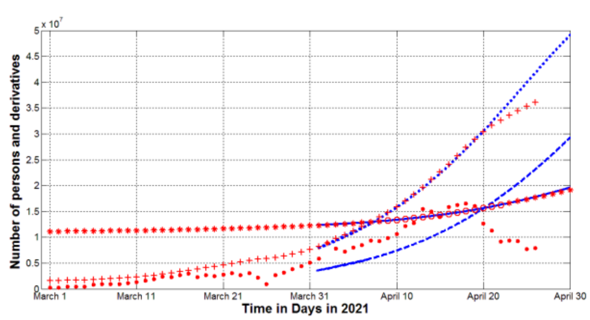

Fig. 1. The COVID-19 epidemic dynamics in India in the spring 2021.

(The results of SIR simulations are shown by blue lines. Numbers of victims *V(t)=I(t)+R(t)* – solid; numbers of infected and spreading *I(t)* multiplied by 5 – dashed; derivatives *dV/dt* (eq. (4)) multiplied by 100 – dotted. Red markers show the real number of cases and its derivatives: "circles" correspond to the accumulated numbers of cases taken for calculations (during period of time T_{c2}); "stars" – number of cases beyond T_{c2} (all the values from Table1); "crosses" – the first derivative (6) multiplied by 100; "dots"- the second derivative (7) multiplied by 1000).

The blue dotted line in Fig. 2 shows that the daily number of the new cases could start to diminish after May 10, 2021, but the number of people spreading the infection *I(t)* could have its maximum only in the end of May, 2021. We can also compare the theoretical curve (4) with the average daily number of new cases which can be calculated with the use of smoothing registered V_j values [70], [81], [82]:

$$\bar{V}_i = \frac{1}{7}\sum_{j=i-3}^{j=i+3} V_j \qquad (5)$$

and its first derivative:

$$\left.\frac{d\bar{V}}{dt}\right|_{t=t_i} \approx \frac{1}{2}\left(\bar{V}_{i+1} - \bar{V}_{i-1}\right) \qquad (6)$$

(see, e.g., [70], [81], [82]). The red "crosses" in Figs. 1 and 2 represent the results of calculations of the first derivatives (6) and are in a good agreement with the theoretical dotted line for moments of time before April 22, 2021.

After this period, we can see a significant discrepancy, but the time moments corresponding to the maximum values of the daily numbers are very close. The maximal value of derivative (6) was achieved approximately one week before the maximum of the theoretical value (4). After two weeks, both the theoretical estimation (4) and the average recorded value (6) decreased approximately twofold. It must be noted that the SIR simulation predicted the onset of the pandemic wave before the daily number of new cases in India began to decline (corresponding preprint [93] was posted on May 3, 2021).

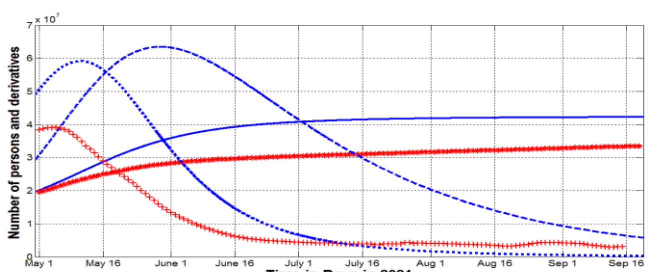

Fig. 2. The COVID-19 epidemic dynamics in India in the summer of 2021.
(The results of SIR simulations are shown by blue lines. Numbers of victims *V(t)=I(t)+R(t)* – solid; numbers of infected and spreading *I(t)* multiplied by 5 – dashed; derivatives *dV/dt* (eq. (4)) multiplied by 100 – dotted. Red markers show the real number of cases and its derivatives: "stars" – number of cases V_j from Table1; "crosses" – the first derivative (6) multiplied by 100).

5. Discussion

Rather large differences between the real (6) and theoretical (4) values of the first derivative after April 22, 2021 can be the result of the convergence problem mentioned above. There are also two other reasons. The first is related to changes in the epidemic dynamics. This is evidenced by the sharp changes in the second derivative of the average number of reported cases, which can be estimated using formulas:

$$\left.\frac{d^2\overline{V}}{dt^2}\right|_{t=t_i} \approx \overline{V}_{i+1} - 2\overline{V}_i + \overline{V}_{i-1} \qquad (7)$$

and (5) (see, e.g., [70], [81], [82]).

So, we can talk about a new wave of pandemic in India, which may be weaker than the one we saw in April 2021 due to the sharp decrease in the second derivative (7) after April 20, 2021 (see red dots in Fig. 1). The second reason for discrepancies between formulae (4) and (6) may be the large number of unregistered cases (observed in many countries [72], [78]-[80], [94]). Estimates for Ukraine made in [72], [94] for different epidemic waves showed that the ratio of real number of cases to registered ones varies from 4 to 20. Similar estimates can be made for the case of India.

The theoretical results presented in Table 2 and Figs. 1 and 2 were posted already in May 2021, [93]. The course of the epidemic allows us to compare its real dynamics in May-September 2021 with the theoretical predictions (see Fig. 2), where SIR curves were based on dataset for the time period: T_{c2} - April 10-23, 2021 and optimal values of the parameters shown in Table 2. First of all the predicted saturation level $V_{i\infty}$ = 42,354,439 looks too high (compare the blue solid line and red "stars" in Fig. 2). But after mid-July 2021, the average daily number of new cases (6) began to exceed the theoretical estimate (4) (compare the dotted blue line and red "crosses" in Fig. 2), which may indicate the beginning of a new epidemic wave. This is exactly the picture we observed in Ukraine and Israel [95], where the sharp increase in the number of cases was not prevented by the high level of vaccination in Israel and the probable presence of natural immunity in Ukraine [94].

As of September 1, 2021 the daily number of new cases per million was 30.696 in India. This figure is much lower than the corresponding values in the United States 503.381 and worldwide 81.926, [84]. This fact allows increasing the number of tests per registered case without very high costs. The recent average figure for India is approximately 16, [84]. Estimates presented in [96] show that if this figure exceeds 520, the epidemic can be brought under full control. This is evidenced by the experience of Australia, Hong Kong and China. Unfortunately, this is the only way to stop the pandemic. Recent statistical analysis has shown that existing vaccines can significantly reduce the likelihood of death from coronavirus, but do not prevent new cases [96].

6. Conclusions

SIR simulations and statistical methods can provide effective tools in order to predict and control the COVID-19 pandemic dynamics. In particular, the moment corresponding to the maximum of the daily number of new cases was predicted quite accurate before it happened. The comparison of this characteristic with the theoretical estimation allows us to warn in a timely manner about the emergence of a new epidemic wave.

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