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Plausible explanation for the third COVID-19 wave in India and its implications

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ABSTRACT

Recently some of us used a random-walk Monte Carlo simulation approach to study the spread of COVID-19. The calculations were reasonably successful in describing secondary and tertiary waves of infection, in countries such as the USA, India, South Africa and Serbia. However, they failed to predict the observed third wave for India. In this work we present a more complete set of simulations for India, that take into consideration two aspects that were not incorporated previously. These include the stochastic movement of an erstwhile protected fraction of the population, and the reinfection of some recovered individuals because of their exposure to a new variant of the SARS-CoV-2 virus. The extended simulations now show the third COVID-19 wave for India that was missing in the earlier calculations. They also suggest an additional fourth wave, which was indeed observed during approximately the same time period as the model prediction.

1. Introduction

The COVID-19 pandemic confronted humanity with the largest global public health crisis of recent times. In addition to causing a significant loss of life, it has presented multifaceted challenges to communities worldwide. For example, it strained global health and food systems, led to political uncertainty, and severely affected socio-economic growth. To date, the World Health Organization (WHO) has reported more than 600 million confirmed cases of COVID-19, with nearly 6.5 million deaths. Most countries have endured waves of attack, depending on the SARS-CoV-2 mutations that have evolved in various regions over time (Tracking SARS-CoV-2 variants). To mitigate rampant disease spread, many countries have gone through partial to complete lockdown phases over extended time periods (COVID-19 lockdowns by country). Not surprisingly, the pandemic also motivated an unprecedented amount of COVID-19-related research, much of which was aimed towards predicting spatio-temporal patterns pertaining to the spread of the disease. Such studies, performed mainly through the analysis of bountiful data acquired since the start of the pandemic (Brainard, 2020), have provided invaluable guidance towards disease containment strategies and a preparation for similar future challenges.

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For India (with a population of nearly 1.4 billion), the first case of COVID-19 was reported as early as Jan 30, 2020 (Andrews et al., 2020). Not long after, the government announced a stringent 21 day nationwide lockdown on March 24 (Chandrashekhar, 2020), with severe mobility restrictions imposed on its population. The lockdown period was then extended well into the summer (Mave et al., 2022; Tripathi, 2020). Despite the partial effectiveness of the lockdown (Salvatore et al., 2020), a rapid increase in the number of cases led to the first wave of infections for India, that peaked at close to 100,000 cases/day in mid-September (WHO). Towards the end of this wave, by February 2021, more than 10 million cases were reported. For a brief period the disease appeared to be contained, with daily cases dropping to around 10,000/day. However, this respite was short-lived. Apprehensions regarding a second wave were confirmed soon after, mainly through SARS-CoV-2 variants belonging to the lineage B.1.1.7 and B.1.617, named Alpha and Delta, respectively. The latter were detected between October and December 2020 (Kunal et al., 2021; Tracking SARS-CoV-2 variants). The second wave was absolutely devastating (Samarasekera, 2021), with a surge in cases beginning around mid-March 2021 (WHO), peaking at more than 400,000 cases/day in May. By the end of June, nearly 400,000 COVID-19 related deaths were officially reported in the country. The second wave tapered off rather slowly, hovering around 40,000 reported daily cases for around two months. This feature, despite a seemingly robust vaccination rollout that was initiated earlier that year (Press Release, Ministry of Health and Family Welfare, 2021), may be attributed to the gradual reopening of public places, the occurrence of several post-lockdown mass gatherings (Kamal, 2021) and the neglect of personal protective measures because of "prevention fatigue". Nevertheless, the large-scale impact of the second wave inspired targeted modelling studies using serological surveys (Fei et al., 2022; Song et al., 2021) that were used to gain further insight into COVID-19 infection attack and fatality rates. It also raised apprehensions of future possible waves, similar to those observed in other countries. This led to several modelling studies that aimed to forecast possible third and fourth waves for India (Mandal, Arinaminpathy, Bhargava, & Panda, 2021; Rajeshbhai, Dhar, & Shalabh, 2022; Agrawal, Kanitkar, & Vidyasagar, 2021; Mohan et al., 2022; Ghosh & Ghosh, 2022). Although some of these studies were called into question during the time (Sharma, 2021; Business Today, 2022), the third wave did appear at the end of December 2021 (WHO), driven primarily by the Omicron (B1.1.529) variant (Tracking SARS-CoV-2 variants).

In context of the above, this study extends earlier work done by some of us, which used two-dimensional random walk Monte Carlo simulations (Mahapatra & Triambak, 2022; Triambak & Mahapatra, 2021) to investigate the spread of COVID-19. The first version of the simulations (Triambak and Mahapatra, 2021) showed that imposing mobility constraints on the random walkers reproduced observed power-law exponents (Triambak et al., 2021) in COVID-19 growth curves, that were attributed to successful containment/mitigation strategies (Maier & Brockmann, 2020). Next, the model was extended to study its forecasting ability in terms of secondary and tertiary waves of infections (Mahapatra & Triambak, 2022). Mahapatra & Triambak (2022) showed that, given a first wave, the number of successive infection waves in a country depend on the population density, the intermixing rate, and most importantly the timing and duration of the control interventions imposed on/followed by the population. The simulations were shown to make satisfactory predictions of disease trajectories for countries such as Serbia, South Africa, the USA and India. For the case of India, although the simulations correctly predicted the relative intensity of the second wave, as well as the time of its occurrence - they did not show the third wave, which was ongoing during the time the work by Mahapatra & Triambak (2022) was published. Since this wave was mainly driven by the Omicron variant, it was speculated if a large number of reinfections or the waning of vaccine-induced immunity could cause this additional wave (Mahapatra and Triambak, 2022). Such speculation was contrary to earlier studies, which showed that the reinfection probability was relatively insignificant for previous SARS-CoV-2 variants (Deng et al., 2020; Tang, Musa, Zhao, & He, 2021). However, Omicron was declared as a variant of concern (Centers for Disease Control and Prevention, 2021), based on evidence of increased transmissibility and a reduction in vaccine effectiveness. A more recent study showed that a history of SARS-CoV-2 infection or vaccination only offered an effective protection against Omicron for approximately 20% of the population (Klaassen et al., 2022). We investigate this aspect in greater detail herein, using the random-walk Monte Carlo approach.

2. The random walk Monte Carlo method

Our simulation approach has already been discussed extensively before (Mahapatra & Triambak, 2022; Triambak & Mahapatra, 2021). We recapitulate the method briefly for completeness. The population of a country is described as N points on a 2-dimensional region of unit area (1 km^2). The simulations start with one point in an infected (I) state and $N-1$ points representing susceptible (S) individuals. As time progresses the points execute random walks on the plane, and the spread of the disease is through contact interactions between infected and susceptible points. A separation distance of ≤ 2 m between individuals is taken as the 'contact' distance. Such a first-principles-based approach implicitly incorporates both an SIR (susceptible, infected, recovered) compartmentalization of the population, as well as its stochastic motion. The latter is usually incorporated in a Kermack–McKendrick model through the partial differential equations (Noble, 1974)

$$\frac{\partial I}{\partial t} = \beta IS - \mu I + D_I\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right)I, \tag{1}$$

$$\frac{\partial S}{\partial t} = -\beta IS + D_S\left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}\right)S, \tag{2}$$

where S and I are the susceptible and infective population densities, β is the transmissibility coefficient, μ is the recovery rate, and $D_{S,I}$ are diffusion constants. Critical parameters in our simulations are l, the step-size (or jump-length) taken by each random walker; the transmission coefficient β; and the recovery rate μ. The speed of infection growth depends on the jump distance l for each point, taken as a multiple of the mean separation $\langle r \rangle$ between the random walkers, with $\langle r \rangle = \sqrt{1/N}$ (Mahapatra & Triambak, 2022; Triambak & Mahapatra, 2021). Each time-step corresponds to one random jump by all N individuals, and is taken as one day.

Previous work (Mahapatra & Triambak, 2022) showed that the growth trajectory of the infection could be tracked in terms of the SIR populations, considering $1/\mu = 35$ days and $\beta = 0.3$, used for time periods when effective control interventions are in place or followed, as evident in reported data from the World Health Organization (WHO). In this work we show that a different recovery rate ($\mu = 1/14$ day^{-1}) is required when one considers reinfection by a different variant (such as Omicron). It is assumed that a fraction of the R population can get reinfected after a post-recovery time duration of two weeks. The total number $N = N_S + N_I + N_R$ is conserved at all times.

2.1. *The Indian scenario*

The simulated SIR data for India in Fig. 3 of the previous work of by Mahapatra and Triambak (2022)) showed the number of infectious agents $N_I \rightarrow 0$, with full recovery beyond Day 500 (Day 1 being April 22, 2020). In this time period N_S remained roughly constant at a very small value, which implied the stoppage of infection spread. This model did not yield a third-wave, which clearly *did occur*, peaking at the end of January 2022 (WHO). A conceivable explanation for this discrepancy is that the simulations of Mahapatra & Triambak (2022)) did not take into account a post-second-wave increase in the number of susceptibles N_S (and hence an increase in N_I). This could be due to either long-range dispersal (Hallatschek & Fisher, 2014) of a previously protected population and/or a significant number of reinfections for recovered individuals who lost immunity and became re-susceptible.[2] We investigate both aspects in this work. The former is quite plausible for a country such as India, whose rural population constitutes around 65% of the total population (The World Bank). Additionally, the first lockdown resulted in a large-scale migration of workers from urban cities back to their villages in rural India (Iyengar & Jain, 2021; Slater & Masih, 2020; Triambak & Mahapatra, 2021), which were not as severely affected as the urban centers during the first wave (Shil et al., 2022). Therefore, one cannot rule out that a fraction of the rural population in India may have been shielded from the pandemic until the end of the second wave, when migration flows from these regions to urban areas (and vice-versa) were reinitiated. As we show later, taking this aspect into consideration does yield a third wave in our simulations. However, its predicted intensity is significantly smaller than the one observed. It is more likely that the dominant contribution to the third wave is through reinfections, because of SARS-CoV-2 variants such as Omicron. As mentioned previously, it is now accepted that reinfections occur more easily with the Omicron variant (Klaassen et al., 2022; Update on Omicron), whose relative risk of reinfection is significantly higher than the Delta variant (Ferguson et al., 2021). While the possibility of reinfections was mentioned in passing (Mahapatra & Triambak, 2022), the earlier simulations assumed N_R to be completely immune to the disease. This is evidently not the case for Omicron. We discuss both the mobility and reinfection aspects below, under Methods-I and II, respectively.[3] Their combined effect is discussed in Method III. Unless mentioned otherwise, all our simulations were averaged over five runs. The simulations were carried out as before (Mahapatra & Triambak, 2022), with $N = 10$k and a combination of jump parameters $l = \langle r \rangle$ and $1.8\langle r \rangle$. The latter jump length was used for days beyond 150, with an assumed $\beta = 0.3$ from Day 150 to Day 310.

3. Results and discussion

3.1. *Method-I: Assigning mobility to a previously protected population*

The previous simulations for India (Mahapatra & Triambak, 2022) allowed the complete S population to be mobile from Day 1 onward. Consequently, as the disease spread, this fraction dropped to insignificant levels around Day 550. This did not yield a third wave for India, as the number of contact interactions between I and S state individuals became negligible. In contrast, data reported from the World Health Organization(WHO) clearly show a third-wave peak around Day 650 (c.f. Fig. 2). We first investigated if the third-wave was caused by the post-second-wave relaxation of mobility constraints on a population fraction (f) that was previously isolated from the disease. Since the disease spread can only occur through contact interactions in our model, the simplest way to incorporate this was to assume that the fraction f of the random-walkers were completely immobile until the end of the second wave, around Day 550. As these protected S points covered zero area, this

[2] This latter number increases with the number of recoveries.

[3] Similar investigations were performed within the framework of a deterministic model (Mandal et al., 2021), to forecast the third wave in India.

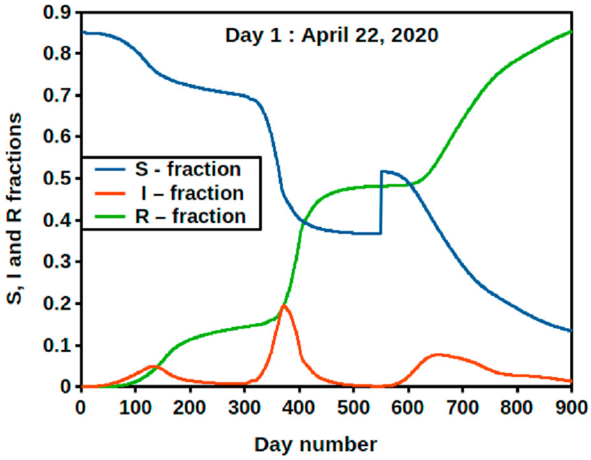

Fig. 1. Simulated *S*, *I* and *R* data with 15% of the population being immobile till Day 550. Making this fraction mobile after Day 550 results in a corresponding increase in *S* fraction. A broad, third-wave structure starting from Day 600 is clearly observed. Results shown in each case are averaged over 10 runs.

approach ensured that probability of their contact with the *I* points was small during this time, yet allowing for random interactions.

We carried out simulations for different *f* fractions of 5%, 10% and 15%. The $f = 0.15$ results are shown in Figs. 1 and 2. It is clear that unlike our previous work, the new simulations lead to a substantial increase in the *S*-fraction around Day 550, which, in turn increases the *I* population, even with a small number of infected individuals available at that time. Furthermore, the results clearly show a broad, third-wave structure for the *I*-fraction after Day 600, that extends beyond Day 900. Next, we matched our results with scaled data from the WHO (c.f. Fig. 2). The latter show that the third wave ends around Day 700, with the daily reported cases dropping to near minimal levels. To incorporate this in our simulations, we used a reduced transmissibility coefficient, $\beta = 0.3$ (Mahapatra and Triambak, 2022), between days 620 and 700, for effective control interventions that may have been followed by/imposed upon the population beyond Day 600. This results in a third-wave peak near Day 620, but with a much reduced intensity compared to reported data. A similar analysis based on lockdown/release, adjusting both the transmission rate and the basic reproduction number R_0, was carried out by Mandal et al. (2021). Their results also indicate a similarly reduced and broad third-wave intensity.

Although not shown here, the magnitude of the third wave depends on the chosen value of *f*, and decreases with smaller *f* values. The location of the peak depends on the date on which the protected population is rendered mobile and also the subsequent date on which the control interventions (i.e. $\beta = 0.3$) are imposed. Interestingly, the simulations also predict an additional peak around Day 800. These results are shown in Fig. 2. The appearance of this fourth wave agrees with the earlier observation (Mahapatra & Triambak, 2022) that applying control interventions on a growth curve results in additional peak structures. To check the possibility of a fifth wave, we applied a further intervention beyond Day 800. However no additional structure is evident, as shown in Fig. 2.

3.2. Method-II: Incorporating reinfections

Unlike Method-I, here the entire population is mobile at all times. However, all individuals in the *R* state are no longer immune to the disease. A randomly selected fraction f_R of the *R* population was assumed to be prone to reinfection. After a time period (δt) of two weeks, the points belonging to this subset become susceptible to reinfection (and therefore become a part of N_S). In this context, reinfection can be either from the same variant that caused the previous infection, or from a new mutated version such as the Omicron variant, which presumably drove the third wave for India.

For the former, we carried out four sets of simulations with $f_R = 0.005$, 0.01, 0.015 and 0.05. In all these simulations the reinfections were introduced right at the beginning, since they are from the same variant responsible for the first and second waves. The results of these simulations, including only the first two waves (up to Day 500)[4] are shown in Fig. 3. The extracted second-wave to first-wave peak intensity ratios were in range 5.5:1 to 6.5:1, changing rapidly from $f_R = 0.005$ to $f_R = 0.015$. These values are not consistent with the relative intensity ratio determined from reported WHO data (WHO), which is about 4:1. Therefore, one can rule out such reinfections with reasonable confidence, which agrees with earlier independent findings (Deng et al., 2020; Tang, Musa, Zhao, & He, 2021).

[4] Additional third and fourth-wave peaks show up around days 630 and 760. We do not discuss these, because the second to first-wave peak intensity ratios obtained are discordant with reported data.

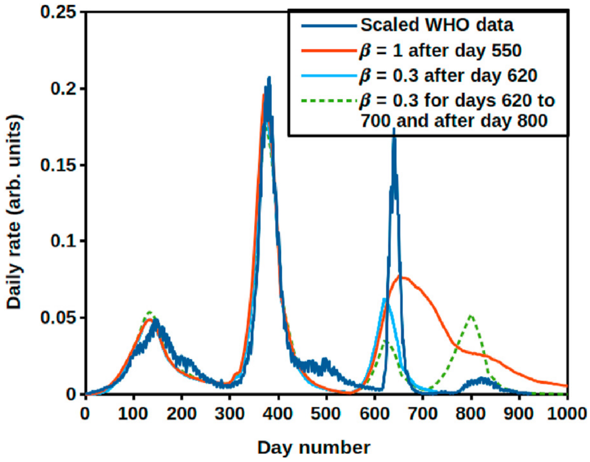

Fig. 2. Simulated daily rates for India, from results shown in Fig. 1 (Method-I). The results obtained both including and excluding interventions applied beyond Day 550 are shown. Reported WHO data, scaled to match the intensity of the second wave (Mahapatra & Triambak, 2022), are shown for comparison. The scale-factor is simply the ratio of the peak-height (maximum value) in the simulated second wave to its corresponding value from WHO reported data.

If a different variant causes the reinfection, a different recovery rate μ is not unexpected. Guided by clinical reports on Omicron (Masson, 2022), we repeated the above simulations using a shorter recovery period of 14 days (instead of 35 days) for the reinfections. Since the reinfections only come into play after the new variant is dispersed among the population, this implies that reinfections ought to be incorporated after the second-wave for India. Following this logic, we introduced reinfections from Day 450 in our simulations. This assumption resulted[5] in a third wave starting around Day 600, which is consistent with observations (WHO).

Fig. 4 shows the results of our simulations for various values of f_R, together with those obtained with no control interventions ($\beta = 1$) beyond the second-wave peak. For $\beta = 1$, the simulations yield a broad third-wave structure between days 600 and 900, similar to the results from Method-I (c.f. Fig. 2). Applying interventions (with $\beta = 0.3$) between days 620 and 700, as previously (under Method-I), produces a narrower third-wave peak between days 600 and 700. We note that the intensity of the third wave depends strongly on the value of f_R used. In all cases a strong peak emerges around Day 770, indicating a fourth wave that is also consistent with the predictions from Method-I.

Simulated S and I fractions for $f_R = 0.05$ (introduced at Day 450) are shown in Fig. 5. This value of f_R yields a rapid increase in the susceptible population, to nearly 100% within a short span of time. This induces the strong third and fourth waves around Day 620 and 770. The intensities of these peaks may be compared to the one generated in Fig. 2, from Method-I.

3.3. Combination of methods I and II

It is evident that our random-walk Monte Carlo simulations require the presence of extra susceptible agents after the second wave, to describe the observed third COVID-19 wave in India. The susceptible fraction could arise from reinfections or a relaxation of mobility constraints on a protected fraction of the population. Thus far we had treated these effects separately. However, in a more realistic scenario the two effects can take place together, particularly in a large and diverse country such as India. We investigated this aspect using different combinations of the immobile fraction (that later become mobile) with a fixed reinfection fraction, $f_R = 0.015$. This value of f_R was chosen because recent work (Klaassen et al., 2022) showed that the effective protection against reinfection with the Omicron variant was approximately 20%. This implies that about 80% of the recovered/immune population would be susceptible to reinfection by Omicron. Our simulations show that the S-fraction rises to this value (similar to Fig. 5) on using $f_R = 0.015$ around Day 450. These simulations were performed as before (Methods I and II), and their results are shown in Fig. 6. It was evident that when a fraction of the recovered population (f_R) become susceptible again (because of their reduced immunity towards the new variant), this dominantly contributes to the third-wave peak and its corresponding intensity. For example, when 15% of the susceptible and protected population is eventually rendered mobile (with no reinfection, as shown in Fig. 2), the extracted third-wave intensity is much smaller than the one obtained with simulations that incorporated a 1.5% reinfection fraction.

It is important to note that a consistent theme in all our simulations is the predicted fourth-wave peak around Day 770. Although not shown here, other simulations that were performed with a smaller value of $\beta = 0.2$ (for the 'control-intervention

[5] The simulations also show that shifting the introduction of reinfection to Day 500 and beyond does not produce any observable effect. On the other hand, starting the reinfections earlier brings the resulting third wave closer to the second-wave peak.

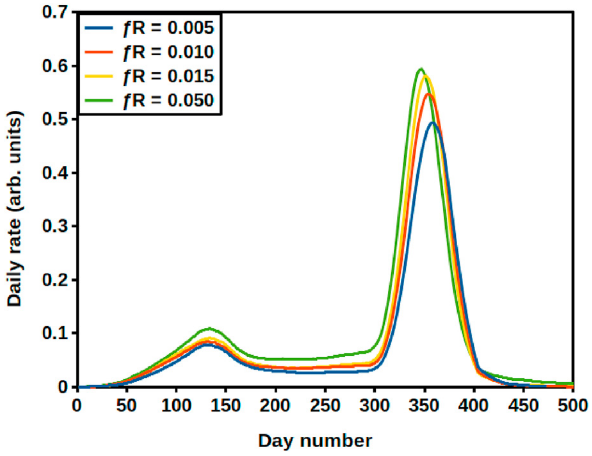

Fig. 3. Simulated first and second wave intensities for different reinfection fractions f_R. The second-to-first-peak intensity ratios in all cases are larger than 5.

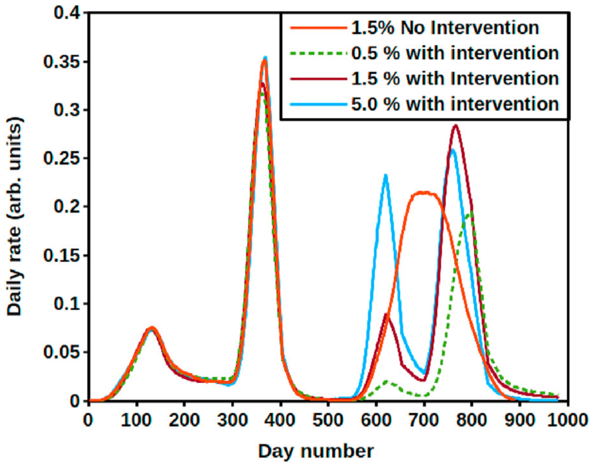

Fig. 4. Simulated daily rate data obtained with and without interventions, with reinfection starting at Day 450. There are two interventions with $\beta = 0.3$ for the window between days 620 and 700, and beyond Day 800. Data shown in each case are averaged over 10 runs.

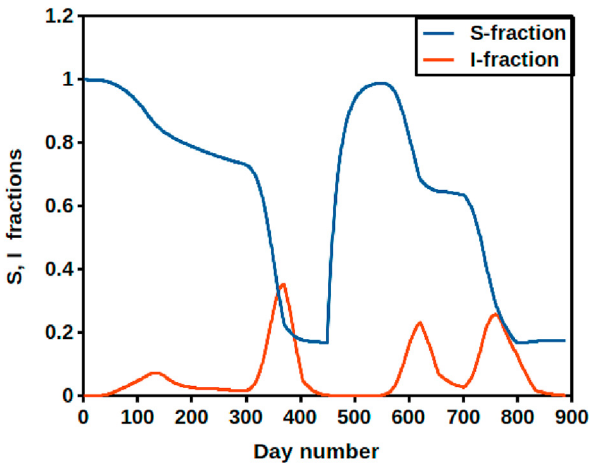

Fig. 5. Simulated S and I state data obtained with a reinfection fraction $f_R = 0.05$, and the two interventions ($\beta = 0.3$) mentioned in the caption of Fig. 4. One can see the S fraction rises rapidly, resulting in fairly intense third and fourth waves.

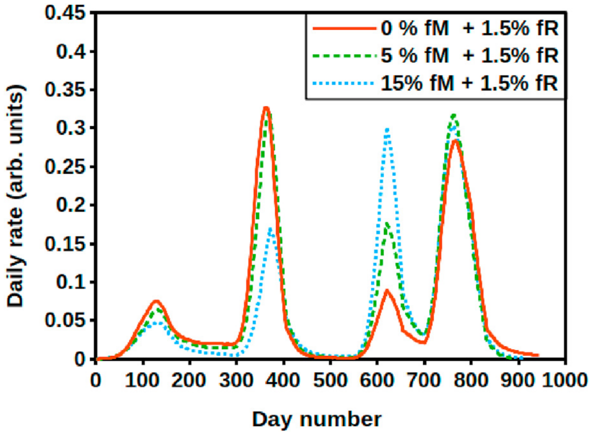

Fig. 6. Simulated daily infection rates with the combined effects of reinfection and mobility. These results are for a fraction $f_R = 0.015$ of the R population, with different mobile fractions $f_M = f$, that acquire mobility after Day 550.

time windows') and independently used different values for δt (four and six weeks) yielded very similar results for the location of the fourth-wave peak.

4. Conclusions

In conclusion, this work extends earlier investigations of COVID-19 spread as a contact process, using a first-principles random-walk Monte Carlo approach. Previous work (Mahapatra & Triambak, 2022) based on this approach assumed all random walkers under consideration to be mobile, with no possibility of reinfection. The calculations were used to model secondary and tertiary waves of COVID-19 infection in countries such as India, South Africa, the USA and Serbia. Despite being reasonably successful in replicating observed multiple waves of infections, these calculations did not predict the observed third wave for India.

In this paper we report results from more extended simulations, carried out to predict the trajectory of COVID-19 infection waves for India. The simulations included previously-disregarded susceptible individuals from a shielded fraction of the population, as well as recovered cases being prone to reinfection, particularly from new variants of the virus. The new simulations show a third wave for India, peaking around Day 620, which is reasonably close to the observed peak reported by the World Health Organization (WHO). The simulations also consistently predict a significant fourth wave starting around Day 770, from April 22, 2020. This corresponds to a peak around Day 810, June 01, 2022. Based on this work, other waves of similar intensity seem improbable. Our results may be compared with a recent statistical prediction (Rajeshbhai, Dhar, & Shalabh, 2022) of a fourth-wave peak in the range August 15 – August 31, 2022, and an independent modelling study (Mandal, Arinaminpathy, Bhargava, & Panda, 2021) that was used to forecast a third wave, albeit with no mention of a fourth wave for India. A comparison of our simulation results with reported data shows that the magnitude of the observed fourth wave is considerably smaller than the model predictions (Fig. 2). This discrepancy could be because of a large number of unreported COVID-19-positive cases during this time. According to the guidelines posted by the Indian Council of Medical Research (ICMR) in January 2022, COVID-19 testing of exposed, asymptomatic patients was no longer deemed necessary. Furthermore, individuals were recommended (ICMR Advisory, 2022) to upload the results of all COVID-19 home self-tests at the ICMR COVID-19 data portal. It is possible that a large fraction of positive home test results were not voluntarily uploaded on the portal.

The strength of the present approach lies in the fact that it is a first-principles simulation that includes stochastic effects of human mobility at the fundamental level. Consequently, it predicts the profile of an epidemic without fitting any reported data. However, the simulation approach is statistics-limited, because of the low number of individuals (points) considered. It also relies on accurately recorded initial numbers to tune the calculations. Despite this, the simulations are flexible, and allow for changes in disease type and timing, as well as varying mobile populations of susceptible (S), infected (I), and recovered (R) individuals.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: S. Triambak reports financial support was provided by National Research Foundation.

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