

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
 Maths 2020; 5(2): 95-101
 © 2020 Stats & Maths
www.mathsjournal.com
 Received: 04-01-2020
 Accepted: 07-02-2020

Gaurav Kumar
 Head, Analytics
 Future Generali India Insurance
 Company Ltd. PGDM, Indian
 Institute of Management
 Lucknow, Uttar Pradesh, India

Dynamics of COVID-19 outbreak & lockdown effectiveness in India

Gaurav Kumar

Abstract

On 11 March 2020, WHO declared Novel Coronavirus Disease (COVID-19) outbreak as a pandemic and reiterated the call for countries to take immediate actions and scale up response to treat, detect and reduce transmission to save people's lives.

As a result, across globe, nations have taken steps to implement social distancing to reduce the transmission rates.

On 24 March 2020, India implemented a 21-day nationwide lockdown. As on 2 April 2020, according to the Ministry of Health & Family Welfare, India, a total of 2069 COVID-19 cases, have been reported in 29 states/union territories. These include 155 who have been cured/discharged, 1 who has migrated and 53 deaths. Hospital isolation of all confirmed cases, tracing and home quarantine of the contacts is ongoing.

This study aims at laying down a theoretical base by way of developing a mathematic model of the pandemic as well as analyzing the effectiveness of the current lockdown and recommendations for an effective containment.

Keywords: COVID-19, lockdown, outbreak, quarantine, social distancing, epidemic model

1. Introduction

December 2019, the first case of respiratory disease caused by a novel coronavirus was identified in Wuhan City, Hubei Province, China. The outbreak of the disease is ongoing worldwide and the World Health Organization named it coronavirus disease 2019 (COVID-19) on 11 February 2020. In India, the first case was reported on 31st January 2020 and the number of reported confirmed COVID-19 cases per day has increased day by day.

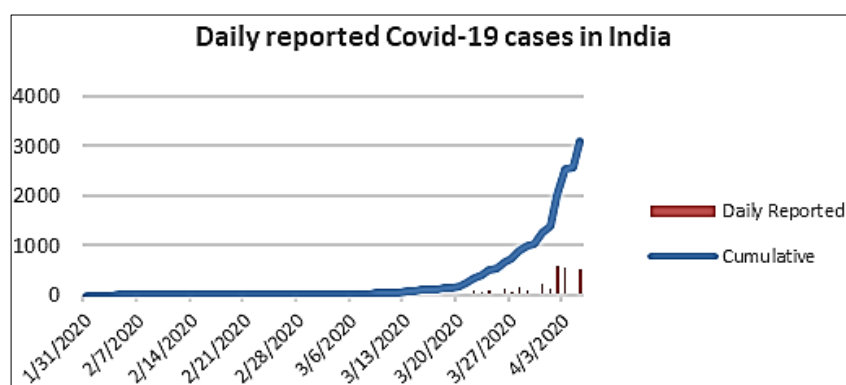


Fig 1: Outbreak of COVID-19 cases in India

As seen in Figure 1, the number of newly reported cases per week has increased and a serious outbreak in India is the outcome which forced national authorities to implement Lockdown and quarantine measures across the country. The purpose of this study is to give a prediction of the epidemic peak of COVID-19 in India, as well as, effectiveness and sensitivity of control measures, which might help to act appropriately & proactively to reduce the epidemic risk.

Corresponding Author:
Gaurav Kumar
 Head, Analytics
 Future Generali India Insurance
 Company Ltd. PGDM, Indian
 Institute of Management
 Lucknow, Uttar Pradesh, India

The epidemic data as shown in Figure 1 would have mainly twofold uncertainty. The first one is since asymptomatic infected people could spread the infection. The second one is due to the lack of opportunity for the diagnostic test as sufficiently simple diagnostic test kits have not been developed yet and the diagnosis in the early stage in India and has yet to achieve scale given a population of over 1.3 Bn.

2. Epidemic model

The progress of an infectious micro-parasitic disease is defined qualitatively in terms of the level of pathogen within the host, which in turn is determined by the growth rate of the pathogen and the interaction between the pathogen and the host's immune response. The abundance of the parasite grows over time & during this early phase the individual may exhibit no obvious signs of infection and the abundance of pathogen may be too low to allow further transmission—individuals in this phase are said to be in the exposed class. Once the level of parasite is sufficiently large within the host, the potential exists to transmit the infection to other susceptible individuals; the host is infectious. Finally, once the individual's immune system has cleared the parasite and the host is therefore no longer infectious, they are referred to as recovered. This fundamental classification (as susceptible, exposed, infectious, or recovered) solely depends on the host's ability to transmit the pathogen. This implies that the disease status of the host is irrelevant—it is not important whether the individual is showing symptoms; an individual who feels perfectly healthy can be excreting large amounts of pathogen. This disease profile can be mathematically modeled as SEIR (susceptible-exposed-infectious-recovered), however, it is mathematically simpler and justifiable at the population scale to ignore the exposed class, reducing the number of equations by one and leading to SIR dynamics.

The SIR model (Kermack and McKendrick, 1927) ^[1] is one of the simplest compartmental models, and many models are derivatives of this basic form. The model consists of three compartments: S for the number of susceptible, I for the number of infectious, and R for the number of recovered or deceased (or immune) individuals. This model is reasonably predictive for infectious diseases which are transmitted from human to human.

The variables (S, I, and R) represent the number of people in each compartment at a time. To represent that the number of susceptible, infected and recovered individuals may vary over time (even if the total population size remains constant), we make the precise numbers a function of t (time): $S(t)$, $I(t)$ and $R(t)$. For a specific disease in a specific population, these functions may be worked out in order to predict possible outbreaks and bring them under control.



Fig 2: SIR Compartment model with transition rates

The dynamics of an epidemic, for example the COVID-19, is much faster than the dynamics of birth and death, therefore, birth and death is omitted in the model. The SIR system without vital dynamics can be expressed by the following set of ordinary differential equations:

$$\frac{dS}{dt} = -\frac{\beta IS}{N}, \quad (1)$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I, \quad (2)$$

$$\frac{dR}{dt} = \gamma I \quad (3)$$

β is a parameter controlling how much the disease can be transmitted through exposure. It is determined by the chance of contact and the probability of disease transmission. γ is a parameter expressing how much the disease can be recovered in a specific period. The ratio, β/γ , is called *basic reproductive ratio* R_0 , which if >1 leads to epidemic.

3. Deploying the model to Indian scenario

A major challenge in the application of epidemic models is the determination of model parameters. In this case, recent relevant research by Rajesh Singh and R. Adhikari ^[2], turned out to be extremely helpful. Their research titled "Age-structured impact of social distancing on the COVID-19 epidemic in India" ^[2], provides necessary parameters, namely, R_0 and γ , which is computed based on case data, age distribution and social contact structure of India ^[3]. R_0 hence is taken as 2.1 and γ as 1/7, yielding β as 0.3. These parametric values established the model for India as below:

$$\frac{dS}{dt} = -\frac{0.3IS}{N}, \quad (4)$$

$$\frac{dI}{dt} = \frac{0.3IS}{N} - 0.1428I, \quad (5)$$

$$\frac{dR}{dt} = 0.1428I \quad (6)$$

Isolation or quarantining as well as lockdown of regions are some of the oldest, yet most effective, means of disease control. Even for the COVID-19 epidemic these strategies are adopted globally. Two strategies have been witnessed to control the outbreak:

1. Strict Lockdown, Testing & Social Distancing, Ex: China, Philadelphia, France, South Korea
2. Mild Lockdown & BAU, Ex: Germany, Sweden

This study aims at analyzing the effectiveness of the current lockdown period of 21 days and attempts to provide a theoretical base to decide upon duration & strictness required to control the outbreak.

The Lockdown scenario can be modelled by an effective decrease in transmission rate, β and Quarantine can be modelled by introducing two more parameters, detection rate, quarantine period and another variable capturing the Quarantine class. The Quarantine scenario, however, is ignored given the large population, limited quarantine facility and for mathematical simplicity. This model was implemented and solved in R using *ODE* function in the package *deSolve*. The program was ultimately deployed on a shiny server with a user-interface in the form of an output on a web browser. This facilitated easy study of model's dynamics & sensitivity towards parameter shifts, the latter being the simulation of the Lockdown control measure.

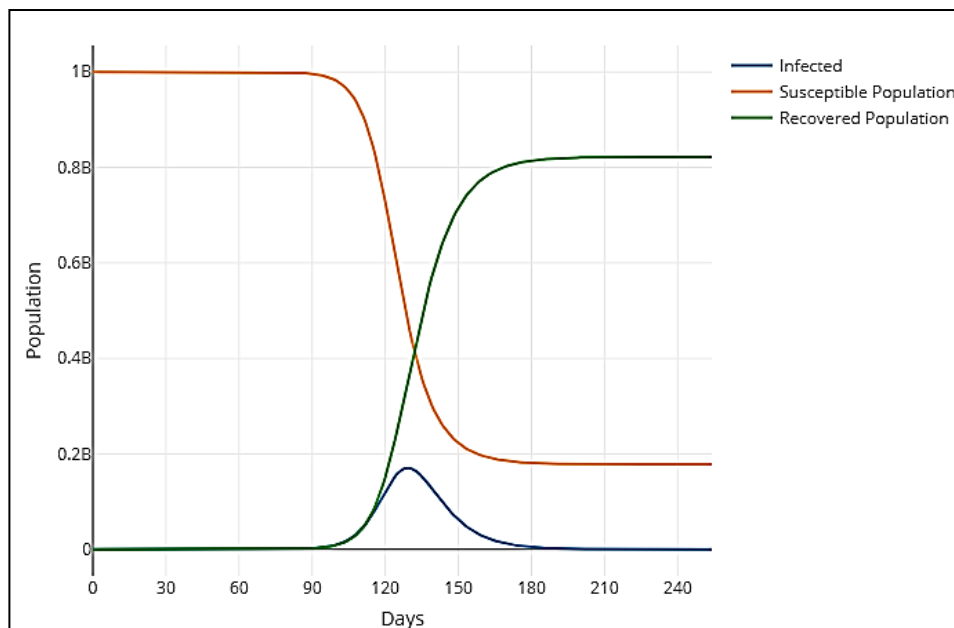


Fig 3: SIR Model Dynamics

4. Simulation approach

We model the COVID-19 epidemic with following parameters, initials and assumptions.

Table 1: Parameters & Initial Boundary Conditions

Particulars	Value	Remarks
Beta	0.3	Rajesh Singh and R. Adhikari
Gamma	1/7	Rajesh Singh and R. Adhikari
$S(t=0)$	$1-(1e-09)$	
$I(t=0)$	$(1e-09)$	
$R(t=0)$	$(1 -S-I)$	
Population	1 Bn	
Start Date	25th Jan 2020	

The model was implemented & solved in R and the results were dynamically plotted. The dynamics of the outbreak was analyzed by varying the transmission rate, β , lockdown period, and lockdown count of the same. Considering the administrative constraints and flow of normal life, a break of 7 days is considered if multiple lockdowns are implemented. Further to this, the strictness of implementation of lockdown was simulated by assigning a Lockdown β for the Lockdown period which is at least 1/3rd of the 'normal steady-state' β . Same is enabled to vary over a range to analyze the impact on the outbreak.

The simulation model has been implemented on live server and is also made accessible via web for seamless access to anyone interested to study the outbreak behavior.

The start date of the simulation has been chosen as 25th Jan, 5 days prior to the first reported case.

To mathematically or logically account for the very low number of tests conducted in initial period, though gradually increasing, the model assumes no lockdown for about 11 weeks from the date of start. This takes care of the offset or lag which arises in comparing the actual trend with the predicted curve.

5. Simulation findings

The model was back-tested with the actual data for a period of over 10 weeks daily time-series and excellent results were obtained. The goodness of fit of the prediction was also tested yielding very good fit & following results.

Correlation was performed with the *cor.test* function in the native *stats* package in R and the results were as below:

- $t = 38.247$
- $df = 73$
- $p\text{-value} < 2.2e-16$
- Alternative hypothesis: true correlation is not equal to 0
- 95 percent confidence interval: 0.962 to 0.985
- Sample estimates: cor 0.976

The prediction of the outbreak $I(t)$, under various parametric assumptions and lockdown scenarios are produced in the figures below. Actual reported cases for India is also added as dotted trace for comparison.

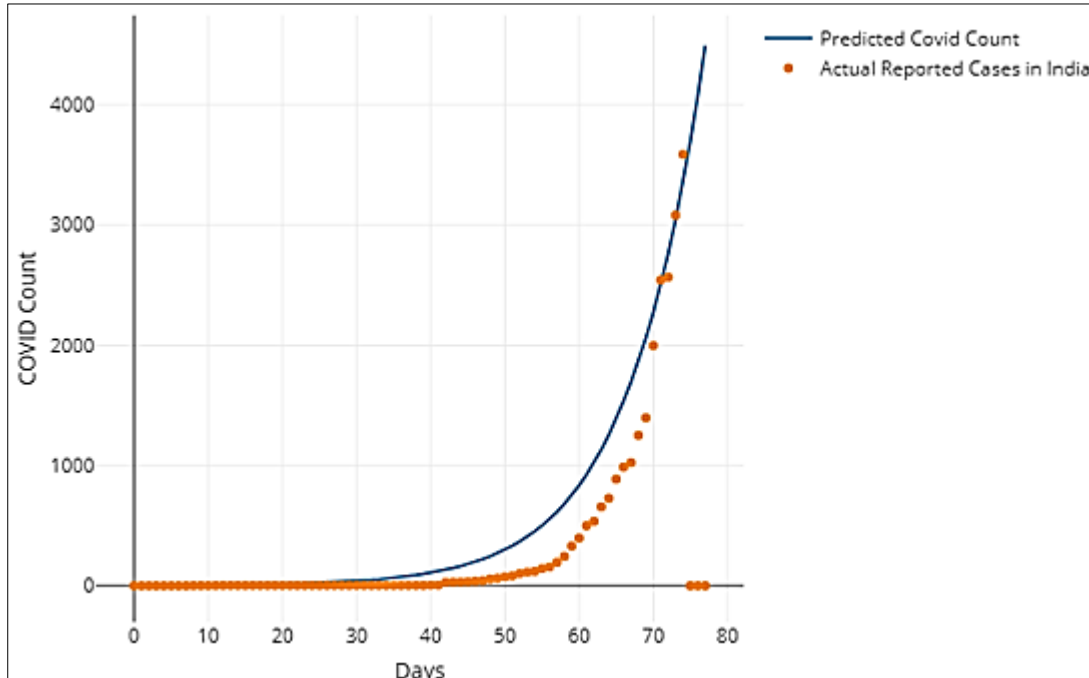


Fig 4: Model Prediction vs Actual

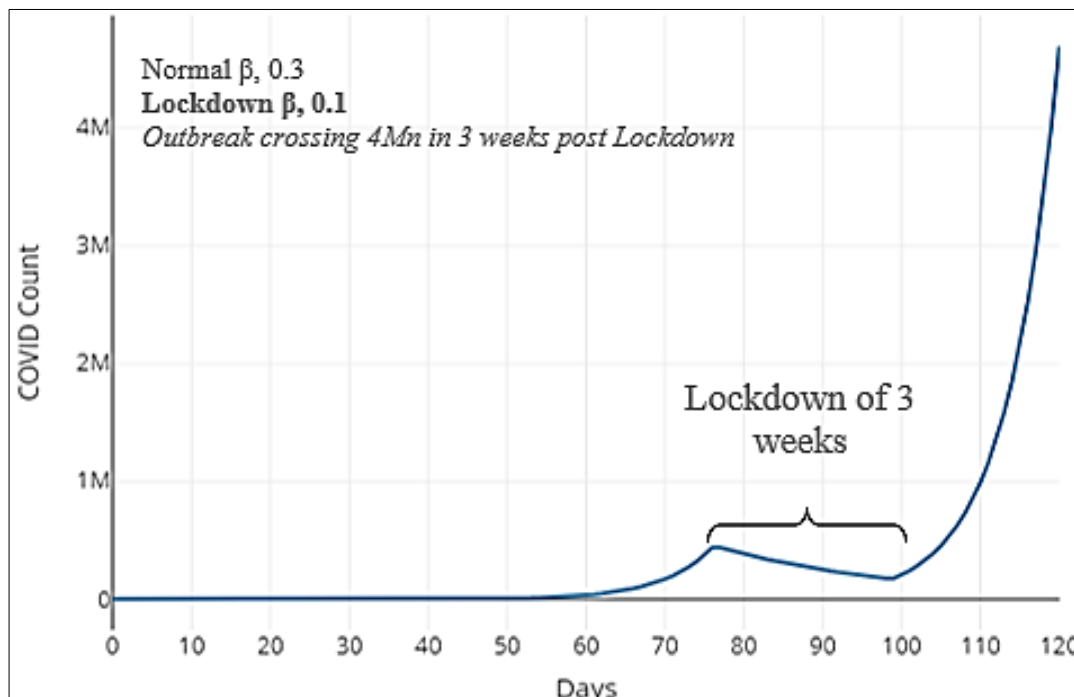


Fig 5: Immediate resurgence of Infection after 1 Lockdown of 3 weeks

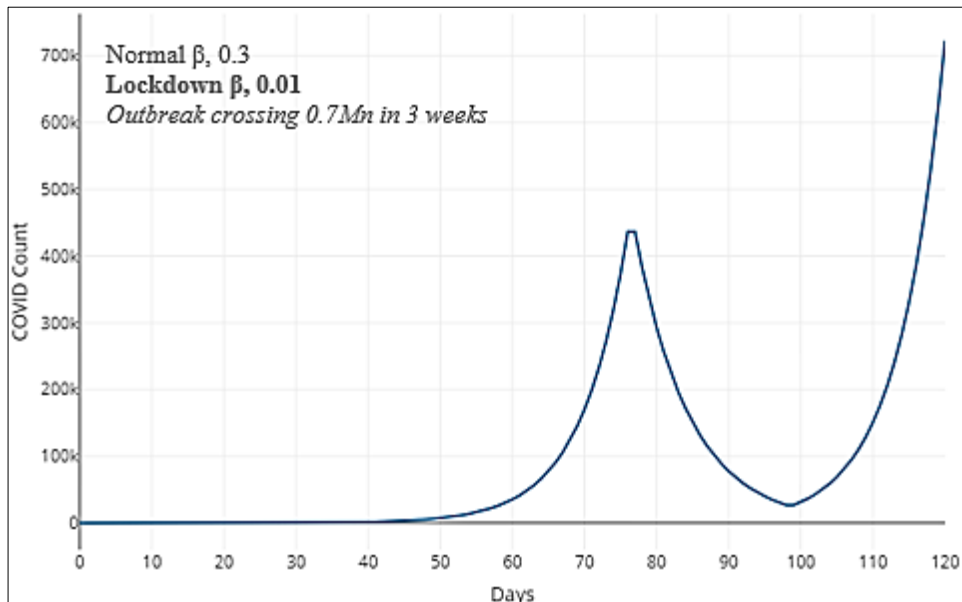


Fig 6: Subdued resurgence with strict Lockdown of 3 weeks

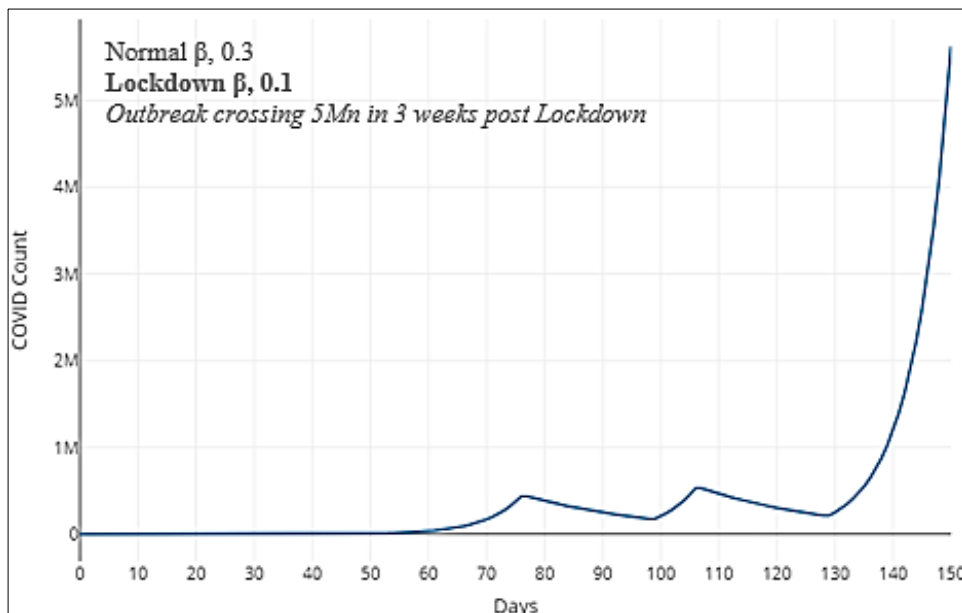


Fig 6: Subdued resurgence with strict Lockdown of 3 weeks

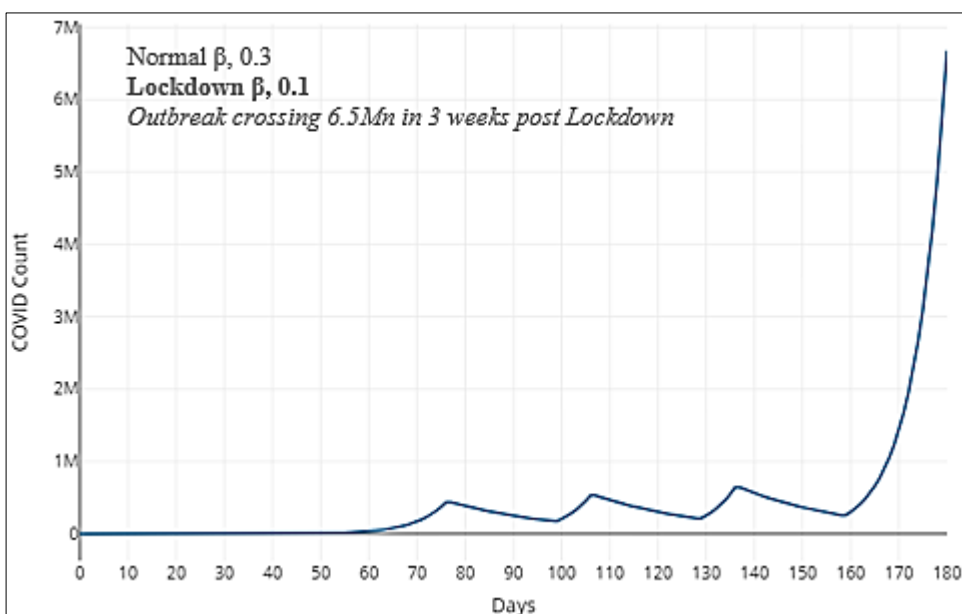


Fig 7: Resurgence after 2 Lockdowns of 3 weeks with 1 week gap

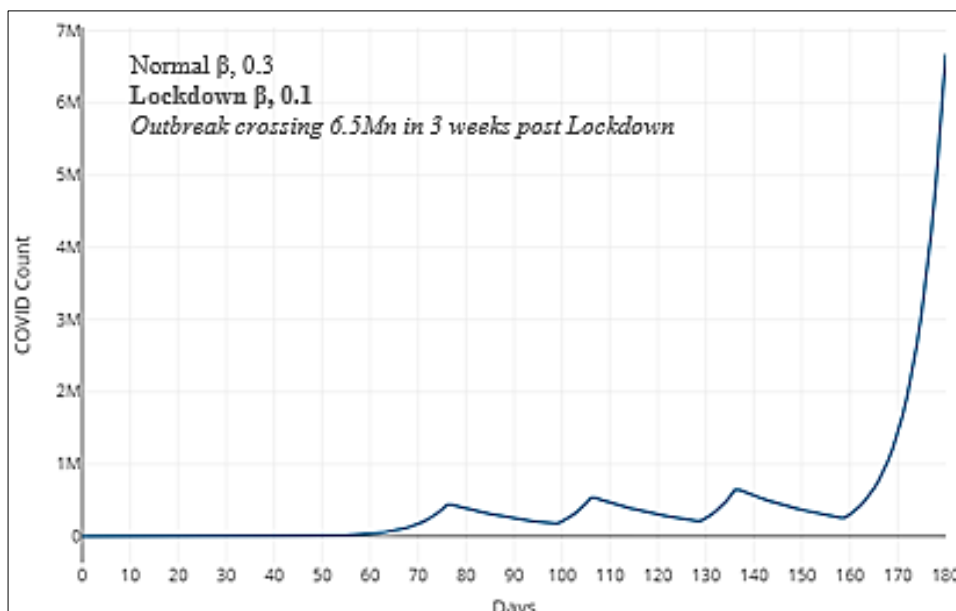


Fig 8: Resurgence after 3 Lockdowns of 3 weeks & 1 week gap

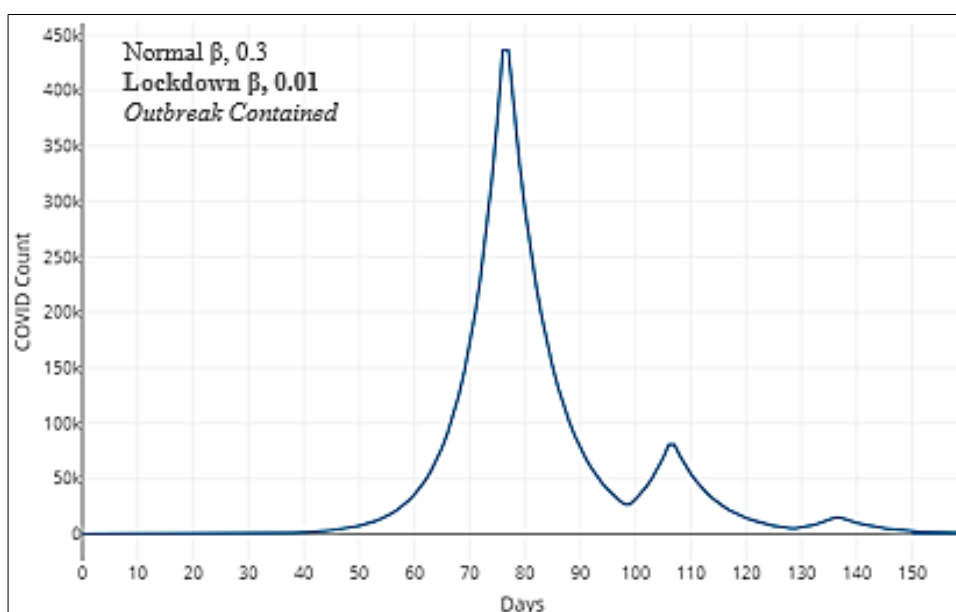


Fig 9: Complete flattening after 2 Lockdowns of 3 weeks & 1-week gap with "Strict implementation"

Figures 4-10 exhibit the model dynamics under different scenarios and parametric assumptions. Figure 5 shows the outbreak crossing 4 Mn infection counts in just 3 weeks once lockdown is lifted. Figure 6 shows for a more stringent lockdown over same period, note that β in this case is reduced by $1/10^{\text{th}}$ to 0.01, simulating a very stringent Lockdown (Curfew), this condition dramatically reduces the outbreak and the count after 3 weeks reduced to 0.7 Mn. However, the outbreak still resurges exponentially. In the Subsequent figures, Figure 7 & 8, the simulation shows if the number of lockdowns is increased to 2 or 3, even then the outbreak resurges, notable is the strictness of lockdown. In both the cases of Figure 7 & 8, a moderate lockdown is implemented.

In Figure 10, it becomes evident that a combination of 2 intermittent Lockdowns is extremely effective provided, it is "strictly implemented", β in this case assumed at 0.01.

1. Conclusion

In this paper classic SIR epidemic model was implemented using relevant parameters for India which were computed in recent research [2]. The Model's prediction was back tested for the goodness of fit and a very satisfactory fit was obtained. The model was simulated by incorporating the control measures of Lockdown and the sensitivity of Lockdown scenario was studied. The study clearly shows effectiveness of a strict lockdown measure, which might be intermittent so as not to extremely hamper the social & business functioning. The simulation also shows one Lockdown of 3 weeks duration will mostly be ineffective, also supported by the fact that the outbreak's actual breadth and depth is unknown given the low count of tests performed. A tabular finding is also presented in the Appendix A and the model is made open to public at the link provided in the Appendix B. Given the large population and extremely diverse demographic factors, like, population density, social contact structure & age-profile, it makes sense to implement the model for each state or major region for sharper analysis and decision making.

Appendix**A. Table of key Simulation findings**

Scenario	Normal β	Lockdown β	γ	No. of Lockdowns	Lockdown Period	Peak Count at Day 150
1	0.3	NA	1/7	0	NA	170 Mn
2	0.3	0.1	1/7	1	21	160 Mn
3	0.3	0.1	1/7	2	21 + 21	5.6 Mn
4	0.3	0.1	1/7	3	21+21+21	0.4 Mn
4	0.3	0.01	1/7	3	21+21+21	221
5	0.3	0.01	1/7	2	21+21	0.1 Mn

B. Model URL

<http://blackstrat.in/analytics/covid/>

C. Data sources

John Hopkins CSSE, GitHub repository at <https://github.com/CSSEGISandData/COVID-19>

Conflicts of interest

The author declares that he has no conflicts of interest.

Acknowledgment

This research & underlying study was motivated and supported by Dr. Shreeraj Deshpande, COO at Future Generali India Insurance Company Limited.

References

1. William Ogilvy Kermack AG. McKendrick and Gilbert Thomas Walker, A contribution to the mathematical theory of epidemics Proc. R. Soc. Lond. A115700-721
2. Rajesh Singh R. Adhikari, Age-structured impact of social distancing on the COVID-19 epidemic in India, arXiv:2003.12055 [q-bio.PE]
3. Prem K, Cook AR, Jit M. Projecting social contact matrices in 152 countries using contact surveys and demographic data, PLoS Comp. Bio 13, e1005697
<https://www.worldometers.info/coronavirus>,
4. Kato F, Tainaka K, Sone S. *et al.*, Combined effects of prevention and quarantine on a breakout in SIR model. Sci Rep. 2011; 1:10
<https://doi.org/10.1038/srep00010>
5. Wang, Xingyuan, Zhao, Tianfang, Qin, Xiaomeng. Model of epidemic control based on quarantine and message delivery. Physica A: Statistical Mechanics and its Applications. 458. 10.1016/j.physa. 2016; 04:009.
6. Kuniya T. Prediction of the Epidemic Peak of Coronavirus Disease in Japan, J. Clin. Med. 2020; 9:789.
7. Matt J. Keeling and Pejman Rohani, Modeling Infectious Diseases in Humans & Animals
8. Cantó B, Coll C, Sánchez E. Estimation of parameters in a structured SIR model. Adv Differ Equ, 2017, 33.
<https://doi.org/10.1186/s13662-017-1078-5>