ANALYSIS OF SARSCOV-2 CASES IN NEPAL USING DIFFERENT MODELS

Oat Bahadur Dhakal[1], Roshan Chalise*[1,2] and Raju Khanal [2]

[1]Patan Multiple Campus, Tribhuvan University, Lalitpur, Kathmandu 44700, Nepal

[2]Central Department of Physics, Tribhuvan University, Kirtipur, Kathmandu 44613, NepalEmail: plasma.roshan@gmail.com

ABSTRACT

The world has faced many epidemics during its evolution of human civilization from the influenza epidemic in 1200 BC, to severe acute respiratory syndrome SARSCOV-2 in 2019, each epidemic has become fatal and people have died from thousands to millions. The epidemic pattern of COVID-19 in Nepal is analyzed and predicted using the Exponential, Logistic, SIR (Susceptible Infectious Recovered), and SIRD (Susceptible Infectious Recovered Deceased) models. The cumulative instances of an outbreak rise exponentially at first, described by the exponential model but there is a point of inflection after some time where the curve nearly turns linear which is predicted by the logistic model. The SIR and SIRD models are used to anticipate the number of cumulative cases of COVID-19 for the 400 days based on information supplied by the Ministry of Health and Population. Based on real-time data and data from our simulation, we can conclude that by strengthening the efficiency of social isolation and lockdown, we could significantly reduce the spread of COVID-19 in our country.

1. Introduction

Looking back to history, infectious diseases are the companion of human beings. Even in this modern era epidemic outbreaks are frequent. The different epidemic models have been extensively used for analyzing and forecasting epidemiological tactics together with unfolding of HIV, SARS, Influenza, and SARSCov-2. Mathematical models have helped in describing the quantitative facts estimating the epidemic and providing tips to the authorities in dealing with the outbreak. They use fundamental assumptions and cumulative facts in combination with parameters for numerous infectious illnesses and to identify the parameters to calculate the consequences of various involvements. The modeling also can help to determine which precautions are to be taken in future. COVID-19 is of extreme difficulty as it has hastily spread throughout the globe causing widespread deaths. Like many developing countries with sub-optimal health systems and capacity, Nepal has already suffered significantly.

The Hunan seafood market in China is regarded as the first location where an outbreak of pneumonia without a known cause occurred, attracting international attention. When an outbreak first began, the Chinese government responded quickly with a total lockdown and mass protection. Chinese researchers discovered a novel coronavirus (COV) in patients in Wuhan on January 7, 2020 [1]. This virus is genetically linked to the coronavirus that caused the SARS pandemic in 2003 due to which it was given the name SARS-CoV-2 by the International Committee on Virus Taxonomy (ICTV) on February 11, 2020. When the number of confirmed cases reached 1, 18, 319 with 4, 292 deaths, WHO (World Health Organization) gave the name COVID-19 and notified the disease as worldwide pandemic on March 11, 2020. Canto et al. [2] used a variety of SIRD based approaches and the SEIR

(Susceptible Exposed Infectious Recovered) model to analyze COVID-19 dynamics in Mexico. According to their findings, the largest number of infected cases would be reported on August 15, with a total of 5, 52, 420 infections and 58, 653 fatalities in Mexico on August 1. Crokidakis [3] used the SIQR (Susceptible Infectious Quarantine Recovered) model to analyze data from the Brazilian Department of Health from February 26 to March 25, 2020, to look at the early evolution of the COVID-19. Their results estimated that the basic reproduction number was 5.25 and the epidemic rate is doubled 2.72 days. Using the SIRD model, Chatterjee et al. [4] investigated the course of the COVID-19 outbreak in India, predicted the time for infection peak. Adhikari and Marahatta [5] studied the pandemic of a novel corona virus in Nepal using logistic, SIR, and ARIMA (Autoregressive Integrated Moving Average) model and expected that the total number of confirmed cases to be around 64,000 and the highest number of confirmed cases around 1,500 on the 111th day on July 11 from March 23, 2020. Hamzah et al. [6] forecasted the worldwide COVID-19 outbreaks estimating the total number of confirmed cases and its occurring time. Deep learning models were used by Arora et al. [7] to predict and analyze COVID-19 positive cases in India. The suggested method produces high accuracy for short-term predictions, with daily predictions having an error rate of less than 3% and weekly predictions having an error rate of less than 8%. Qin et al. [8] used social media search index to predict the number of new cases of COVID-2019. In Malaysia, Alsayed et al. [9] estimated the epidemic peak and infected cases for COVID-19 and anticipated the time for peak of new cases to be followed by a 30-day period of uncertainty. Huang et al. [10] investigated the global COVID-19 pandemic forecast trend. With a case study of Wuhan, Ndairou et

al. [11] investigated the mathematical modeling of COVID-19 transmission kinetics. Sarkar et al. [12] used susceptible (S), asymptomatic (A), recovered (R), infected (I), isolated infected (Iq), and quarantined susceptible (Sq), collectively expressed SARIIqSq to predict the cases of COVID-19 in India. They discovered that quarantining susceptible individuals can successfully reduce the basic reproduction number by reducing the contact rate between uninfected and infected individuals. The Gaussian mixture model was used by Singhal et al. [13] to predict the COVID-19 outbreak, the overall number of expected cases and deaths. COVID-19 in Asia was studied by Aviv-Sharon et al. [14] using a generalized logistic growth model. To anticipate the trend of the COVID-19 outbreak in Iran, Ahmadi et al. [15] employed an epidemic projection model and least square error with percentage error. Kuniya [16] predicted the epidemic peak of coronavirus disease in Japan using SEIR model. Bhandary et al. [17] analyzed the pandemic scenario of Nepal during the first phase of lockdown from 23rd January 2020 to 30th April 2020. They recommended keeping social distance and a stay-at-home policy in the COVID-19-affected district, as well as implementing rigorous lockdown. Dmitry [18] estimated the effects of pandemic outbreaks on global supply networks using simulations based on the coronavirus outbreak scenario. They showed how to analyze and forecast the effects of epidemic outbreaks using simulation-based approach. Wangping et al. [19] used extended SIR model to predict and compare the trends of the COVID-19 outbreak in Italy and Hunan, China, with COVID-19 time-series data from January 22 to April 02, 2020. John et al. [20] were unable to predict the COVID-19 epidemic, due to insufficient data input, incorrect modeling assumptions, and a variety of other factors. Gatto et al. [21] investigated the prevalence and behavior of the COVID-19 outbreak in Italy, claiming that a series of mobility and human-to-human interactions

restrictions reduced transmission by 45 percent. Saez et al. [22] used generalized linear mixed models to examine the effectiveness of the Spanish government's response to the COVID-19 outbreak. Ceylan [23] used ARIMA models to estimate the epidemiological pattern of COVID-19 prevalent in Italy, Spain, and France from February 21 to April 15, 2020. In Italy, Spain, Germany, and France, Ding et al. [24] calculated pandemic trends and important epidemic aspects of COVID-19. Using the SEIR model they found the day for maxima of daily new confirmed cases for Italy, Spain, Germany, and France would be on April 16, April 5, April 21, and April 19. Wang [25] used mathematical models to describe applications, limitations, and potentials, implying the mathematical models that have long been employed in epidemiology to generate quantitative data and provide useful guidance for outbreak management and policy creation. Bastos and Cajueiro [26] used two versions of the SIR model to simulate and anticipate the early course of the COVID-19 pandemic in Brazil. In order to determine the epidemic trend in Wuhan, China, Wang et al. [27] used an infectious disease dynamics SEIR model. Giordano et al. [28] introduced SIDARTHE (Susceptible Infected Diagnosed Healed Ailing Recognised Threatened Extinct), a novel model that forecasts the course of an epidemic to aid in the planning of an effective control strategy. Weitz et al. [29] designed and studied an epidemiological intervention model to aid in the maintenance of interactions required for the operation of critical goods and services while lowering the risk of transmission. The termination of social confinement and the danger of COVID-19 re-emergence were investigated by López and Rodo [30]. They recommended that lockdowns be maintained for at least two months to avoid the spread of the disease and the emergence of a 2nd wave of COVID-19 infections. Findings of a stochastic agent-based microsimulation model of the COVID-19 outbreak in France were given by Hoertel et al. [31].

A large number of works are reported on COVID-19 modeling that is based in different countries, however, only a few works [5, 17] are published on forecasting the corona epidemic of Nepal and also use only a few models, so we are interested to consider four models (Exponential Model, Logistic Model, SIR Model, and SIRD Model) and study which one fits best with real data. This work is expected to help decision-makers to estimate the development of epidemic outbreaks and their long-term effects in current and future pandemic crises. In the event of an epidemic outbreak, it can also assist in identifying essential parts of reducing risk, response, and recovery plans.

2. DESCRIPTION OF MODELS

COVID-19 cases and deaths have surged over the world, requiring more attention to future epidemics and global risks. We have undertaken a comparative study of this epidemic in Nepal using the four different models (Exponential Model, Logistic Model, SIR Model, and SIRD Model).

One of the models used is the Exponential Growth Model which uses the following equations:

$$f(x, a, b, c) = a \cdot e^{b(x-c)} \tag{1}$$

where variable 'x' is the time for required data, 'a' is the initial value, 'b' is the growth rate and 'c' is the time for initial data.

A Logistic Function's most general expression is

$$f(x, m, n, p) = \frac{r}{1 + e^{-(x-n)/m}} \tag{2}$$

where 'm' stands for infection speed, 'n' stands for the day with the most infections, and 'p' stands for the total number of infected persons at the end. Due to the dynamics of an epidemic, which is much faster than the birth and death rate, birth and death are often omitted in basic compartmental models.

The following set of ordinary differential equations are used to define the SIR [32] model

$$\frac{d(S)}{dt} = -\beta SI \tag{3}$$

$$\frac{d(I)}{dt} = -\frac{\beta IS}{N} - \gamma I \tag{4}$$

$$\frac{d(R)}{dt} = \lambda I \tag{5}$$

Where SIRD model [33] is appropriate for an influenza-type disease, and helps to identify the population, who are susceptible of being infected, those who are infected, and those who have recovered and deceased. The susceptible population $NS(t)$ decreases through contact with infected, at a rate given by λ, as

$$\frac{d(NS)}{dt} = -\lambda SNI \tag{6}$$

The infected population $NI(t)$ increases through contact with infected (at a rate set by λ, decreases through recovery, at a rate γ, and also decreases through death, at a rate μ:

$$\frac{d(NI)}{dt} = \lambda SNI - \gamma NI - \mu NI \tag{7}$$

The recovered population $NR(t)$ increases as the infected population recover, assuming that all recovered people are immune to being infected a second time in quick succession.

$$\frac{d(NR)}{dt} = \gamma IN \tag{8}$$

The deceased population $ND(t)$ increases through death at a rate μ.

$$\frac{d(ND)}{dt} = \mu IN \tag{9}$$

The fact that the member of all groups together must add up to the total population expressed as:

$$NS + NI + NR + ND = N \tag{10}$$

In order to introduce the effect of social distancing the equations (6) and (7) are modified as

$$\frac{dS}{dt} = -\lambda(1 - Q)SI$$
$$\frac{dI}{dt} = \lambda(1 - Q)SI - \gamma I - \mu I \tag{11}$$

where Q is a function of time, represents the effectiveness of social distancing defined as

$$Q = Q_0 H(t - t_Q), \tag{12}$$

with t in days, t_Q gives the count of number of days passed after social distancing measures are implemented, H is the Heaviside step function:

$$H(t) = \begin{cases} 0 & t < t_Q \\ 1 & t \geq t_Q \end{cases}, \qquad (13)$$

To include the effect of stopped isolation, say after t_{UQ} days (for "un-quarantine"), we modified the function Q as:

$$Q(t) = \begin{cases} 0 & t < t_Q \\ Q_0 & t_Q \leq t < t_{UQ} \\ 0 & t \geq t_{UQ} \end{cases} \qquad (14)$$

3. Results and Discussion

The results of Exponential, Logistic, SIR, and SIRD models are analyzed and compared with the real data of the COVID-19 outbreak in Nepal based on the information released by the Ministry of Health and Population [34], Government of Nepal.

The exponential model represents the uncontrollable spread of infection, but it cannot predict when the epidemic will terminate. It provides the idea that the number of infected cases rapidly increase in the early stages. The total infected population during January 22 to July 23, 2020, along with the prediction using the exponential model is shown in Fig.1.
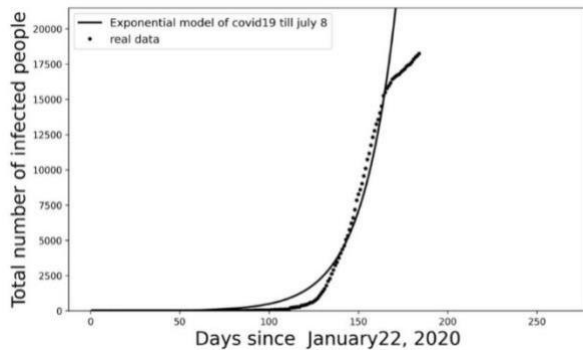

Fig. 1: Total infected cases versus days started from January 22, 2020.

The logistic model is that curve fitting and prediction outcomes heavily depend on past data, and it explains epidemic growth that will terminate in the future. Cumulative infected case of 300 days starting from January 22, 2020, using a logistic model with real data fitted and is shown in Fig. 2. The infection speed of the

epidemic is found to be 9.31 along with the estimated maximum growth rate of confirmed COVID-19 cases on 153 days (June 22, 2020). This calculation was made without assuming the effectiveness of lockdown, and social distancing.

The total assumed population versus the number of days from 23rd March 2020 using the SIR model is shown in Fig. 3. It describes the COVID-19 in such a way that susceptible, infected, and recovered persons were correlated to each other. When the initial date of the model was set to be 23rd March 2020 there were 2 total confirmed cases and 0 deaths. For this prediction, assumed that the total number of suspected persons will be 10,00,000 people among the total population of Nepal. Effective contact rate and recovery rate were considered 0.2 and 1/14 respectively. From the simulation, it is observed that the reproduction number is found to be 2.8. The peak of the infected persons is found at 110 days (which lies in the first week of July) and the curve gets flattened after 200 days. The total number of infected persons is found to be 2,75,135 along with 9,99,997 susceptible and 9,24,974 persons will be recovered up to 26th April 2021.
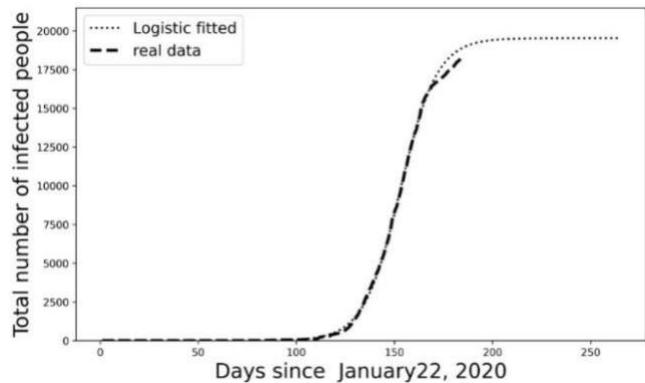

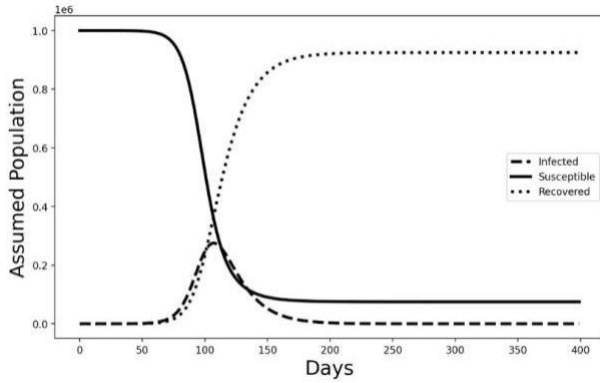**Fig. 2**: Cumulative infected cases versus days started from January 22, 2020.

Fig. 3: Number of the assumed population versus days from March 23, 2020.

Considering the total susceptible population to be 10^6 the number of assumed population versus days (400) from March 23, 2020, without starting lockdown, is shown in Fig. 4. At first, for the formulation of this model before lockdown, the assumed total population to be infected is 10,000,000 along with the data on March 23, 2020. On that day, the total number of cases was 2, deaths were 0, and recovered were 1. The reproduction number is assumed to be 2.4 along with a mortality rate of 0.004. Thus, the result shows that 0.4 % (3,504) of total population will die, 87.6% (8,75,840) recover and 21.9 % (2, 18,887) will be infected after 400 days.
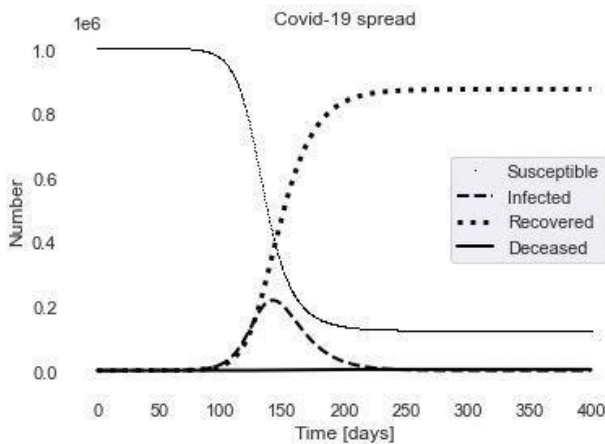
With the initiation of lockdown the nature of the number of population versus days (300) is shown in Fig. 5. As the government of Nepal has implemented lockdown from March 24, 2020, then the SIRD model has to be modified including different parameters such as social distancing, effective lockdown rate, introducing social distancing Q0, and time of lockdown t_Q, which has been assigned to 0.1 and 1. Introducing these parameters and implementing them 0.3 % (3,050) faced death, 76.3 % (7,62,620) recovered and 13.5% (1,34,710) get infected from COVID-19. The number of infected has reduced from 2,18,887 to 1,34,710 and the number of deaths reduced from 3,504 to 3,050 with the introduction of lockdown.

The prediction of future scenario after the Government of Nepal ended the lockdown on July 21, 2020 is depicted in Fig. 6. It describes the total assumed population versus the number of days after the end of lockdown. For this, we have included that R_o =2.1, M = 0.004, p=14, & Q_0 = 0.1, t_Q = 0, t_{UQ} = 120. It was found that 0.3% (3,499) faced deaths, 87.5 % (8, 74,798) recovered and 21.7% (2,16,926) get infected after the end of 400 days. The number of infected has increased from 1,34,710 to 2,16,926 with the implementation of lockdown from March 24, 2020, to July 21, 2020.
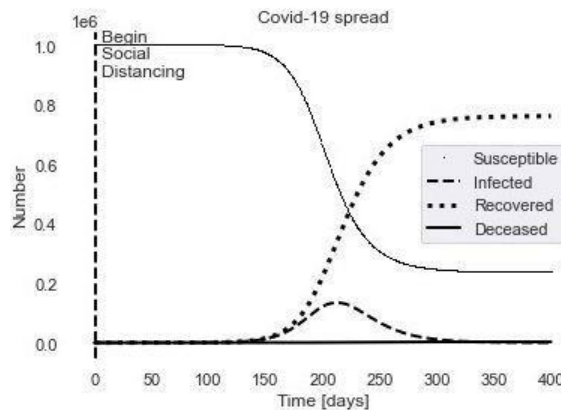

Fig. 4: Number of the assumed population versus days from March 23, 2020, without lockdown effect.

Fig. 5: Assumed population versus the number of days from March 23, 2020, with the initiation of lockdown.
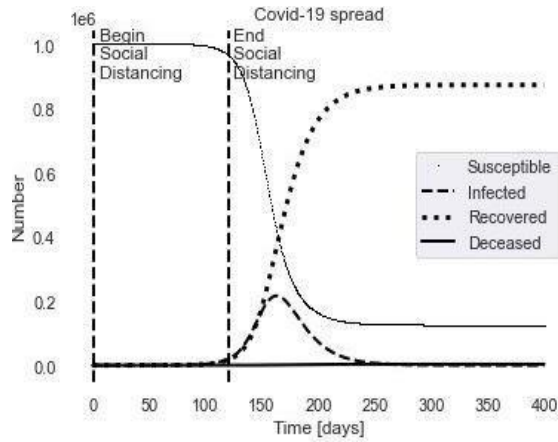
Fig. 6: Total assumed population versus the number of days from March 23, 2020, with lockdown ends on July 21, 2020.

Conclusion

In this work, we used the classic Exponential, Logistic, SIR, and SIRD model to interpret the collected public data on the cumulative numbers of quarantined cases, recovered cases, and death cases from January 22 to July 23, 2020, which are published on a daily basis by the Ministry of Health and Population of Nepal [34]. The logistic model predicts the infection rate for Nepal is 9.31 along with the infection number at 22 June 2020 is 19,529 ±7126. The SIR model predicts the infection peak for Nepal at the end of June 2020 and the total number of infected persons is found to be 2,75,135 along with 9,99,997 susceptible and 9,24,974 recovered persons after the end of 26 April 2021. SIRD model gives an idea of how social distancing (lockdown) helps to decrease the infection rate of COVID-19. As the percentage of the total number of infected persons has decreased from 21.9 % to 13.5 % which is almost 84,177. The death trends have also decreased from 3,503 to 3,050 which are 453 less due to the implementation of lockdown. Widespread social distancing can help to reduce the number of cases and limit the burden of the healthcare system. The earlier the social distancing the lower the number of cases would be. However, slacking off on social distancing could lead to a re- emergence of the virus. Specifically isolating the most vulnerable segments of the population can significantly reduce the overall mortality rate. The models used here are good for prediction and comparative studies. As these results depend heavily on data availability and their authenticity more realistic and continuous modeling has to be carried out as the COVID-19 is not going away easily or quickly, as the models indicate.

References

[1] C. Wang et al., A novel coronavirus outbreak of global health concern, The Lancet 395 (2020) 470-473.https://doi.org/10.1016/S0140-36(20)30185-9.

[2] F. J. A. Canto et al., SIRD-based models of COVID-19 in Yucatan and Mexico, Accessed online (2020) 22pp. https://doi.org/10.13140/RG.2.2.10385.86889

[3] N. Crokidakis, Modeling the early evolution of the COVID-19 in Brazil: Results from a Susceptible–Infectious–Quarantined– Recovered (SIQR) model. Int. J. Mod. Phys. C, 31 (2020) 1-7. https://doi.org/10.1142/S0129183120501351

[4] S. Chatterjee et al., Studying the progress of COVID-19 outbreak in India using SIRD model, Indian J. Phys. 95(2021)1941-1957. DOI: 10.1007/s12648-020-01766-8.

[5] N. P. Adhikari, and S. B. Marahatta, Modeling Early Pandemic of Novel Coronavirus in Nepal, ASTA 1 (2020) 1-5

[6] B. Hamzah et al., CoronaTracker: worldwide COVID-19 outbreak data analysis and prediction. Bull. World Health Organ 1 (2020) 32pp. https://doi.org/10.2471/BLT.20.255695

[7] P. Arora et al., Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India. Chaos, Solitons & Fractals 139 (2020) 110017
https://doi.org/10.1016/j.chaos.2020.110017

[8] L. Qin et al., Prediction of number of cases of 2019 novel coronavirus (COVID-19) using social media search index. Int. J. Environ. Res. Public Health 17 (2020) 2365
https://doi.org/10.3390/ijerph17072365

[9] A. Alsayed, et al., Prediction of Epidemic Peak and Infected Cases for COVID-19 Disease in Malaysia, 2020. Int. J. Environ. Res. Public Health 17 (2020) 4076
https://doi.org/10.3390/ijerph17114076

[10] J. Huang, et al., Global prediction system for COVID-19 pandemic. Sci. Bull. 65 (2020) 1884-1887.
https://doi.org/10.1016/j.scib.2020.08.002

[11] F. Ndairou, et al., Mathematical modeling of COVID-19 transmission dynamics with a case study of Wuhan. Chaos, Solitons & Fractals, 135 (2020) 109846.
https://doi.org/10.1016/j.chaos.2020.109846

[12] K. Sarkar, S, Khajanchi and J. J. Nieto, Modeling and forecasting the COVID-19 pandemic in India. Chaos, Solitons & Fractals139 (2020) 110049.
https://doi.org/10.1016/j.chaos.2020.110049

[13] A. Singhal et al., Modeling and prediction of COVID-19 pandemic using Gaussian mixture model. Chaos, Solitons & Fractals 138 (2020) 110023
https://doi.org/10.1016/j.chaos.2020.110023

[14] E. Aviv-Sharon and A. Aharoni, Generalized logistic growth modeling of the COVID-19 pandemic in Asia. Infect. Dis. Model. 5 (2020) 502-509
https://doi.org/10.1016/j.idm.2020.07.003

[15] A. Ahmadi, et al., Modeling and forecasting trend of COVID-19 epidemic in Iran until May 13, 2020. Med. J. Islam.Repub. Iran 34 (2020) 27
https://doi.org/10.34171/mjiri.34.27

[16] T. Kuniya, Prediction of epidemic peak of Corona disease in Japan, J. Clin. Med. 9 (2020) 789
https://doi.org/10.3390/jcm9030789

[17] S. Bhandary et al., Trend Analysis, Modeling and Impact Assessment of Covid-19 in Nepal, J. Inst. Sci. Technol. 25 (2020) 1-8
https://doi.org/10.3126/jist.v25i2.33715

[18] I. Dmitry, Transportation Research Part E: Logistics and Transportation Review 136 (2020) 101922.

[19] J. Wangping et al., Extended SIR Prediction of the Epidemics Trend of COVID-19 in Italy and Compared With Hunan, China, Frontiers in Medicine 7 (2020) 169.
https://doi.org/10.3389/fmed.2020.00169

[20] P. A. John, et al., Forecasting for COVID-19 has failed, International Journal of Forecasting(2020).
doi:10.1016/j.ijforecast.2020.08.004.

[21] M. Gatto, et al., Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures, PNAS 117 (2020) 10484
https://doi.org/10.1073/pnas.2004978117

[22] M. Saez, et al., Effectiveness of the measures to flatten the epidemic curve of COVID-19. The case of Spain, Sci.Total Environ. 727 (2020) 138761
DOI:10.1016/j.scitotenv.2020.138761

[23] Z. Ceylan, Estimation of COVID-19 prevalence in Italy, Spain, and France, The Sci.Total Environ. 729 (2020)138817.
DOI: 10.1016/j.scitotenv.2020.138817

[24] K. Wang, et al., Modelling the initial epidemic trends of COVID-19 in Italy, Spain, Germany,and France. Plos one 15 (2020)
DOI: 10.1371/journal.pone.0241743

[25] J. Wang, Mathematical models for COVID- 19: applications, limitations, and potentials, J. public health and emergency 4 (2020) 9
https://doi.org/10.21037/jphe-2020-05

[26] S. B. Bastos and D. O. Cajueiro, Modeling and forecasting the early evolution of the Covid-19 pandemic in Brazil, Scientific Reports 10 (2020) 19457
https://doi.org/10.1038/s41598-020-76257-1

[27] H. Wang, et al., Phase-adjusted estimation of the number of coronavirus disease 2019 cases in Wuhan, China. Cell Discovery 6 (2020) 1- 8
https://doi.org/10.1038/s41421-020-0148-0

[28] G. Giordano, et al., Modeling the COVID-19 epidemic and implementation of population- wide interventions in Italy. Nature Medicine 26 (2020) 855-860
https://doi.org/10.1038/s41591-020-0883-7

[29] J. S. Weitz, et al., Modeling shield immunity to reduce COVID-19 epidemic spread. Nature Medicine 26 (2020) 849-854
https://doi.org/10.1038/s41591-020-0895-3

[30] L. López and X. Rodó, The end of social confinement and COVID-19 re-emergence risk. Nature Human Behaviour 4 (2020) 746- 755
https://doi.org/10.1038/s41562-020-0908-8

[31] N. Hoertel, et al., A stochastic agent-basedmodel of the SARS-CoV-2 epidemic in

France. Nature Medicine 26 (2020) 1417-1421

https://doi.org/10.1038/s41591-020-1001-6

[32] W. O. Kermack and A. G. McKendrick, A contribution to the Mathematical Theory of Epidemics, Proc. R. Soc. A 115 (2020) 700-721

https://doi.org/10.1098/rspa.1927.0118

[33] N. T. Bailey, The mathematical theory of infectious diseases and its applications, 2nd edition (1975) London

[34] Ministry of Health and Population, Nepal, https://covid19.mohp.gov.np/