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Day Level Forecasting for COVID-19 Pandemic Spread in SAARC Countries

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Abstract

The COVID-19 is declared a global epidemic by the World Health Organization (WHO). Till now there is no effective medicine and vaccine is not available to treat COVID-19 and the genetic mutation capability of COVID-19 is very aggressive. Day-level knowledge of COVID-19 spread distribution is essential to measure the nature of the virus. The aim of this paper is two folds. Firstly, we compare the forecasting performance of three models namely Simple Exponential Smoothing (SES), Moving Average (MA) and Weighted Moving Average (WMA) for South Asian Association for Regional Cooperation (SAARC) countries. Secondly, the best forecasting model is used to predict the day level number of infected case for SAARC countries. In this study we consider the daily infected case from March 08, 2020 to May 18, 2020. The empirical analysis showed that the SES model give beter forcasting performance for all of the SAARC countries based on graphical comparison as well as Mean Absolute Percentage Eorror (MAPE), Mean Absolute Deviation (MAD), Mean Square Error (MSE). The one month aheah forecast result of infected case for Bangladesh, India, Pakistan, Bhutan, Nepal, Maldives and Afghanistan will be 71702, 246726, 90926, 26, 1339, 1490, 2152 and 17934 respectively. Besides these we also shows the growth rate of the infected case based on Exponential and logarithmic scale. Having access to skilful daily updated forecast value of infected case could help better informed decision on how to manage the spread of COVID-19.

Keywords and Phrases: Simple Exponential Smoothing, Moving Average, Weighted Moving Avearge, Daily forecast, SAARC

AMS Classification: 97K80, 62P10, 92-02.

1. Introduction

A growing infectious disease causes rapid spread, threatening the health of a huge number of people and therefore needs urgent action to avoid the disease at the grass-roots level (Lin et al., 2017). The new coronavirus (COVID-19) spread rapidly in China in late 2019 and infected a great number of people. It is spreading with astounding speed. Currently, the local outbreak has already been largely controlled while the new coronavirus is rapidly spreading in other regions around the world (Li et. 2020; Huang et al. 2020; Dong et al. 2020). People of all ages are susceptible to COVID-19. The common symptoms include sore throat, cough, malaise, fever, diarrhea, breathing difficulties. In severe cases, pneumonia, organ failure, severe acute respiratory syndrome, and death occur, especially patients with elderly and multiple disorders (Chen et al. 2020; Singhal 2020; Goyal et al. 2020). COVID19's incubation time lasts for 2 weeks. The disease can still be contagious during the time of the latent infection. Usually, infection is transmitted by symptomatic and asymptomatic patients via large droplets produced during coughing and sneezing (Rothe et al. 2020; Peng et al. 2020).

Currently, the United States is at the forefront of the latest pneumonia outbreak. The World Health Organization (WHO) declared a new outbreak of pneumonia as a global pandemic. The new coronavirus has posed a serious threat to the country's public safety worldwide, because of its immense spreading ability and potential harm. Work on national and foreign epidemics as well as the movement towards future growth has become a hot button topic of the latest research (Li et al. 2020). The coronavirus pandemic has already affected countries and regions in southern Asia. The situation in the countries of the South Asian Association for Regional Cooperation (SAARC) Countries is very rapidly deteriorating. It covers 21% of the global population and 4.21% of the global economy. In SAARC countries, Nepal was the first country to report the COVID-19 case on 5 January 2020. At least one COVID-19 case was recorded in every SAARC country as of 29 March 2020. The latest numbers present a pronounced jump in the COVID-19 case. It was going very badly for most of the SAARC countries. It could down the economic growths, supply chains, and public health systems. COVID-19's drastic impacts on our daily lives and the economy have contributed to considerable scientific interest in this novel coronavirus. At this moment, many critical questions on this pandemic are still unresolved (Stübinger 2020). In addition to medicine, microbiology, and bioinformatics, the COVID-19 outbreak also attracts interest in the area of epidemiology and statistics. These disciplines especially focus on time series analysis and model forecasting (Zhao et al. 2020; Fong et al. 2020). Effective countermeasures can also be taken in the field of risk control and communication with the guidance of a precise forecast of the further development path. Surprisingly, the current coronavirus forecasting literature considers only individual, country-specific time series in its model. There is no previous study of day level forecasting of the SAARC countries. There are two ways to predict the future number of observation namely, model based prediction and data based prediction. Since our data size is limited so in our study we choose data based forecasting models. So, the aim of this paper is to compare the performance of different models for forecasting the daily infected case and to forecast the infected case by the most suitable model for SAARC countries. The rest of this paper is as follows: section 2 presents the methods and materials, section 3presents the results and discussions and finally section 4 presents the conclusions and policy recommendations.

2. Methods and Materials

2.1. Data description

Data on the affected individuals at a daily level can provide insights into the transmission of COVID-19. WHO, China's National Health Commission and Johns Hopkins University have created an online database for the COVID-19 cases. Hence, the research goals to gain insights such as improvements over time in many affected cases and predict the current number of affected cases (confirmed cases, recovered cases, and deaths). This research also aims to examine the increase in overtime cases at the level of SAARC countries. The data comprises the date of the

DD/MM/YYYY observation, country of observation, the cumulative number of infected cases till that date.

2.2 Forecasting Models

2.2.1 Exponential Smoothing

The exponential smoothing technique is considering as one of the popular forecasting methods for short-term predictions. Exponential smoothing introduces the concept of constructing a forecasted value as the average figure from differently weighted data points for the average calculation. Different exponential methods such as Simple Exponential Smoothing (SES) uses only one smoothing constant, double exponential smoothing or Holt exponential smoothing uses two smoothing constants and triple exponential smoothing or Holt-Winters exponential smoothing accordingly uses three smoothing constants. Simple Exponential Smoothing (SES) is a smoothing time series data based on the exponential window function (Cadenas et al. 2010; Nazim and Afthanorhan 2014). Elmousalami and Hassanien (2020) used these three models to forecast the day level forecasting the COVID-19 confirmed, death, and recovered cases internationally.

For a data set with T observations, we calculate our predicted value, $\hat{Y}_{t+1}$, which will be based on y_1 through y_t as follows:

$$\hat{y}_{t+1} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + ... + \alpha(1-\alpha)^{t-1} y_1 \quad (1)$$

where $0 < \alpha \leq 1$. It is also common to come to use the *component form* of this model, which uses the following set of equations.

$$\hat{Y}_{t+1} = l_t$$

$$l_t = \alpha y_t + (1-\alpha)l_{t-1} \quad (2)$$

When α is closer to 0 we consider this *slow learning* because the algorithm gives historical data more weight. When α is closer to 1 we consider this *fast learning* because the algorithm gives more weight to the most recent observation.

2.2.2 Moving Average (MA)

A moving average (MA) tests the data points by averaging the data points array. It relies on assuming future observations that are close to previous recent observations. The next point moving average is identical to the mean of the latest K observation. With K rising, the majority of forecasts depend on past data. MA can be determined from the following formula (Box et al. 1970; Yang et al. 2018).

$$MA = (y_1 + y_2 + ... + y_t)/n \quad (3)$$

Here, MA, y, k, and n are moving average, observed data value, number of pints period, and number of data points, respectively.

2.2.3 Weighted Moving Average (WMA)

Similar to the moving average (MA), a weighted moving average (WMA) is an update of Moving average (MA) model by assigning weights to data points as follows (Hunter 1986; Lowry et al. 1992):

$$WMA = y_1 w_1 + y_2 w_2 + ... + y_t w_t \quad (4)$$

Here, WMA, w, t, n are weighted moving average, weights, number of pints period, and number of data points, respectively.

The forecasting performance was carried out by the following criteria mean absolute deviation (MAD), mean square error (MSE), mean absolute percentage error (MAPE). Mathematically, this can be represented as:

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{5}$$

Here, n = total summation of cases, i = number of the case and $\hat{y}_i$ = predicted outcome of the time series model and y_i = the actual outcome.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[y_i - \hat{y}_i\right]^2 \tag{6}$$

$$MAPE = \frac{1}{n}\left(\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{\hat{y}_i}\times 100\right) \tag{7}$$

Here, n = total number of cases, i = number of the case and $\hat{y}_i$ = predicted outcome of the model and y_i = actual outcome.

3. Results and Discussions

Among the SAARC countries, the first covid-19 infected case found in Nepal on January 05, 2020, in Sri Lanka on January 27, 2020, in India on January 30, 2020, in Afghanistan on February 14, 2020, in Pakistan on February 26, 2020, in Bhutan on March 06, 2020, in Maldives on March 07, 2020 and lastly infected case was identified in Bangladesh on March 08, 2020. Although Nepal confirmed the first infected case on January 05, 2020 but up to March 07, 2020 it's confirmed only one infected case. Similarly, India confirmed 34, Pakistan confirmed 6, Bhutan and Sri Lanka confirmed 1, Maldives confirmed 2 and Afghanistan confirmed only 4 infected cases. So, in our analysis we consider the data from March 08, 2020 to May 18, 2020. The comparison of the number of infected case and percentage of total infection of each SAARC countries at different time periods are given in Figure 1.

Total number of infected case at different time **Percentage of total infection at different time**

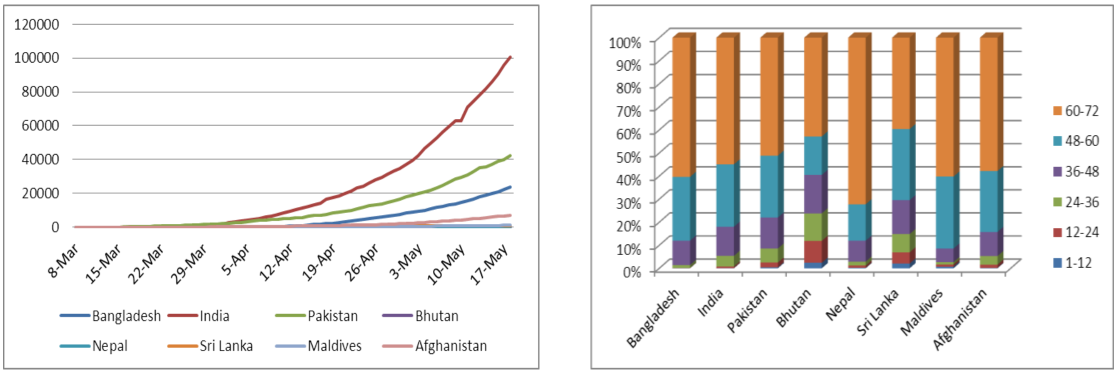

Figure 1: Graphical representation of infected case for SAARC countries

Figure 1 indicates that number of infected case from March 08, 2020 to first 12 days is higher in Pakistan (307) and lower in Bhutan (1) and Nepal (1). The other SAARC countries Bangladesh, India, Sri Lanka, Maldives and Afghanistan showed the total number of infected case as 14, 169, 51, 13 and 22 respectively. The percentage of total infected case occur at 0.05%, 0.16%, 0.72%, 5.55%, 0.26%, 5.14%, 1.17% and 0.31% in Bangladesh, India, Pakistan, Bhutan, Nepal, Sri Lanka, Maldives and Afghanistan respectively at first 12 days. The next 12 i.e. first 24 days also showing the similar trend. The number of infected case is becoming higher in India and lower in Bhutan within first 36 days. The figure showing the at the first 48 days the infected case increases slightly in India, Pakistan and Bangladesh, moderate increase observed in Sri Lanka and Afghanistan. The number of infected case in Bangladesh, India, Pakistan, Bhutan, Nepal, Sri Lanka, Maldives and Afghanistan became 10929, 49400, 22049, 7, 82, 771, 573 and 3224 respectively which covers 45.78%, 49.23%, 52.34%, 38.88%, 21.86%, 77.72%, 51.80% and 45.58% of total infected case of these SAARC countries respectively which indicates that the maximum percentage of total infected case observed in Pakistan, Sri Lanka and Maldives within first 60 days. From 60 days to 72 days the infected case sharply increases in case of India, Pakistan and Bangladesh and it reached to 100328, 42125 and 23870 respectively. The maximum percentage of total infected case observed in Nepal (78.13%), Bhutan (61.11%), Afghanistan (54.41%), Bangladesh (54.21%) and India (50.76%). From Figure 1 we observed that most of the SAARC countries confirmed maximum percentage of total infection within first 60 and 72 days.

The initial spread of the COVID-19 infected case, many methods have been proposed and applied to predict future numbers, either based only on data analysis or on health models (Buizza 2020, Fanelli and Piazza 2020). This work falls into first category. The comparison of forecasting performance is carried out by graphical view and also some standard measure such as Mean Absolute Deviation (MAD), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE). For the MA model, we consider 5 days moving average and for the WMA model, we consider the weights 0.0, 0.0, 0.15, 0.30, and 0.55. It is mentionable that from first to 72, the infected case is higher after 45 days so we give more weight to the later cases. For SES model, the alpha is designed to be equal to 1 based on a genetic algorithm. Based on different parameters, the three forecasting models have accurately matched the reported data of the infected cases. Figure 2 presents the forecasting performance of these three models with an actual data for SAARC countries.

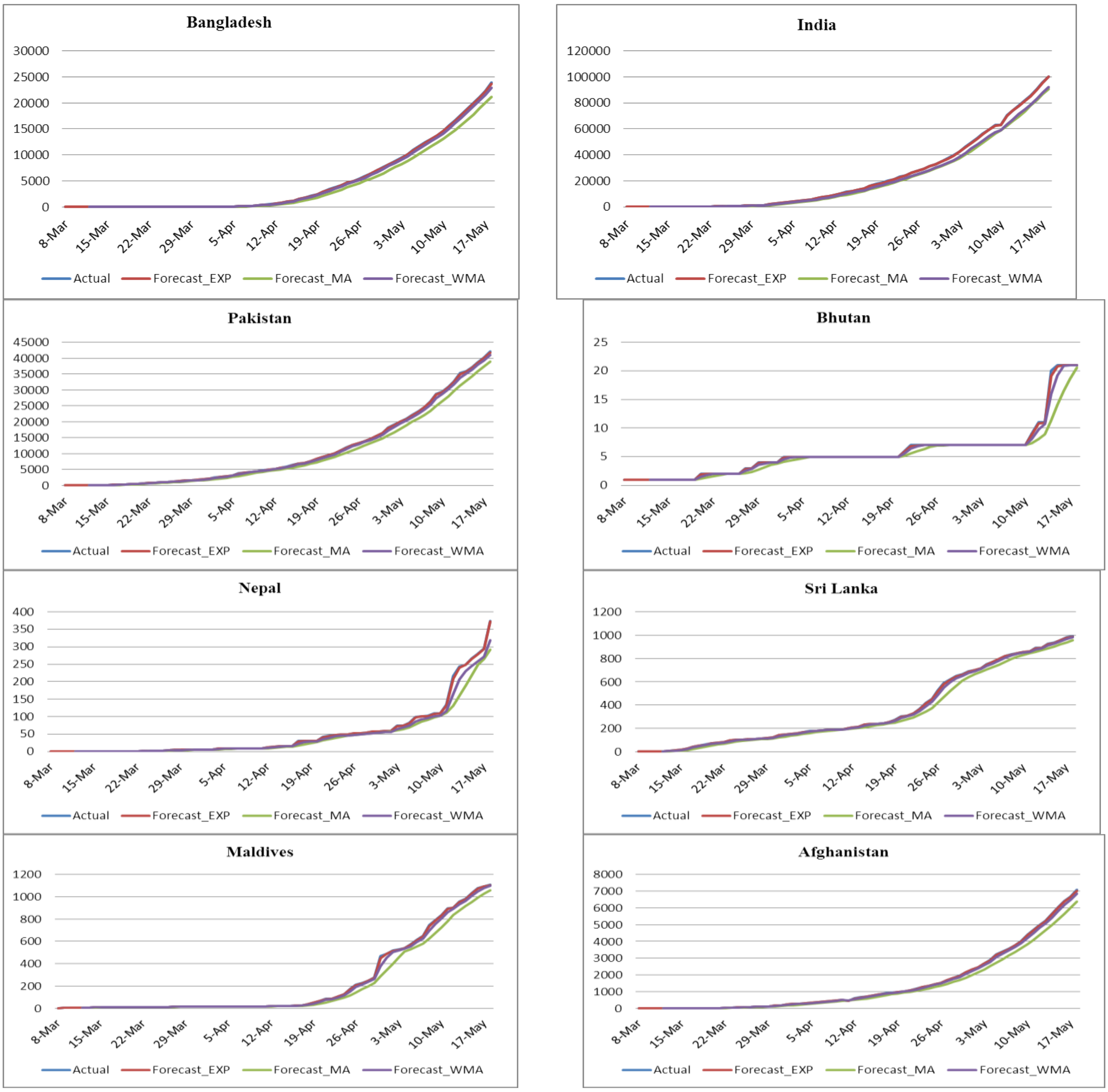

Figure 2: Forecasting performance of the three models for infected case in SAARC countries

Table 1: Forecasting evaluation of three models for infected case in SAARC countries

Country	Model	MAD	MSE	MAPE		Country	Model	MAD	MSE	MAPE
Bangladesh	SES	55.59	7376.30	2.84%		India	SES	73.521	17546.9	1.09%
	MA	462.03	489691.4	21.51%			MA	1256.8	506910	16.65%

	WMA	144.32	47063.63	7.28%			WMA	934.84	303671	12.18%
Pakistan	SES	49.06	6467.23	1.23%		Bhutan	SES	0.0107	0.0010	0.28%
	MA	793.19	137783	19.07%			MA	0.1935	0.1561	5.01%
	WMA	288.92	188326.3	7.29%			WMA	0.067	0.0341	1.72%
Nepal	SES	0.1050	0.097	0.362%		Sri Lanka	SES	1.578	5.116	1.24%
	MA	1.726	16.203	6.06%			MA	27.238	1415.25	15.43%
	WMA	0.6191	3.07640	2.23%			WMA	9.622	188.79	6.20%
Maldives	SES	1.441	11.075	0.79%		Afghanistan	SES	6.440	107.12	1.09%
	MA	24.177	2225.72	13.07%			MA	107.26	29526.3	17.59%
	WMA	9.0316	397.45	4.94%			WMA	40.079	4100.7	6.81%

From Table 1, the forecasting models for the infected cases produce the means absolute percentage error (MAPE) from the range 21.51% to 2.84% for Bangladesh. The SES model presents the lowest MAPE for Bangladesh and also other measures mean absolute deviation (MAD) and mean square error (MSE) is minimum for the SES model. The three forecasting models have successfully fit the recorded data for the infected case for Bangladesh. Figure 2 also confirms the superiority of the SES model for forecasting the infected case for Bangladesh. So, results indicate SES is the most reliable model for forecasting infected COVID-19 cases for Bangladesh. For India, the SES model shows the MAPE is ranging from 16.65% to 1.09%. The SES model also produces minimum MAD and MSE whereas the WMA model produce moderate MAPE, MAD and MSE and MA model produce highest MAPE, MAD and MSE. So, the result from Table 1 also suggests that SES model is the most reliable model for forecasting the infected case for India. The graphical representation from Figure 2 also confirms the performance of the SES model for forecasting the infected COVID-19 case in India. The MAPE for Pakistan for forecasting the confirmed case are ranging from 19.07% to 1.23%. In the case of the SES model where WMA and MA model show higher MAPE. The MAD and MSE also show minimum value for SES model. The Graphs also confirm the closeness of the SES model with actual data. The similar results are visible for other SAARC countries such as Bhutan, Nepal, Sri Lanka, Maldives, and Afghanistan. Therefore Figure 2 and Table 1 show that the SES model is the most suitable model for forecasting the COVID-19 infected case for all of the SAARC countries.

Therefore, the empirical results indicate that Single Exponential Smoothing (SES) is the most suitable technique for forecasting infected cases of COVID-19 for all of the SAARC countries. The one month ahead forecasting results for infected case is given in Figure 3.

Figure 3 indicates that the number of infected case will be expected to be increased up to more than 71702 cases for Bangladesh on June 18, 2020. The forecasting value indicates that one month ahead the infected case for India will be 246726. The infected case of Pakistan will reach to 90926 on the following date. For Bhutan, the number of infected cases is increasing gradually and it will reach 26. The infected case for Nepal is almost constant up to March 23 and later it is increasing slowly, the total infected case will be 1339. In Sri Lanka, the infected case is increasing not so high speed and it will reach to 1490 on June 18, 2020. Based on our model the total infected case for Maldives and Afghanistan will be 2152 and 17934 respectively on June 18, 2020. For more convenient we also present the forecasting value for every 10 days for these eight SARRC countries in Table 2.

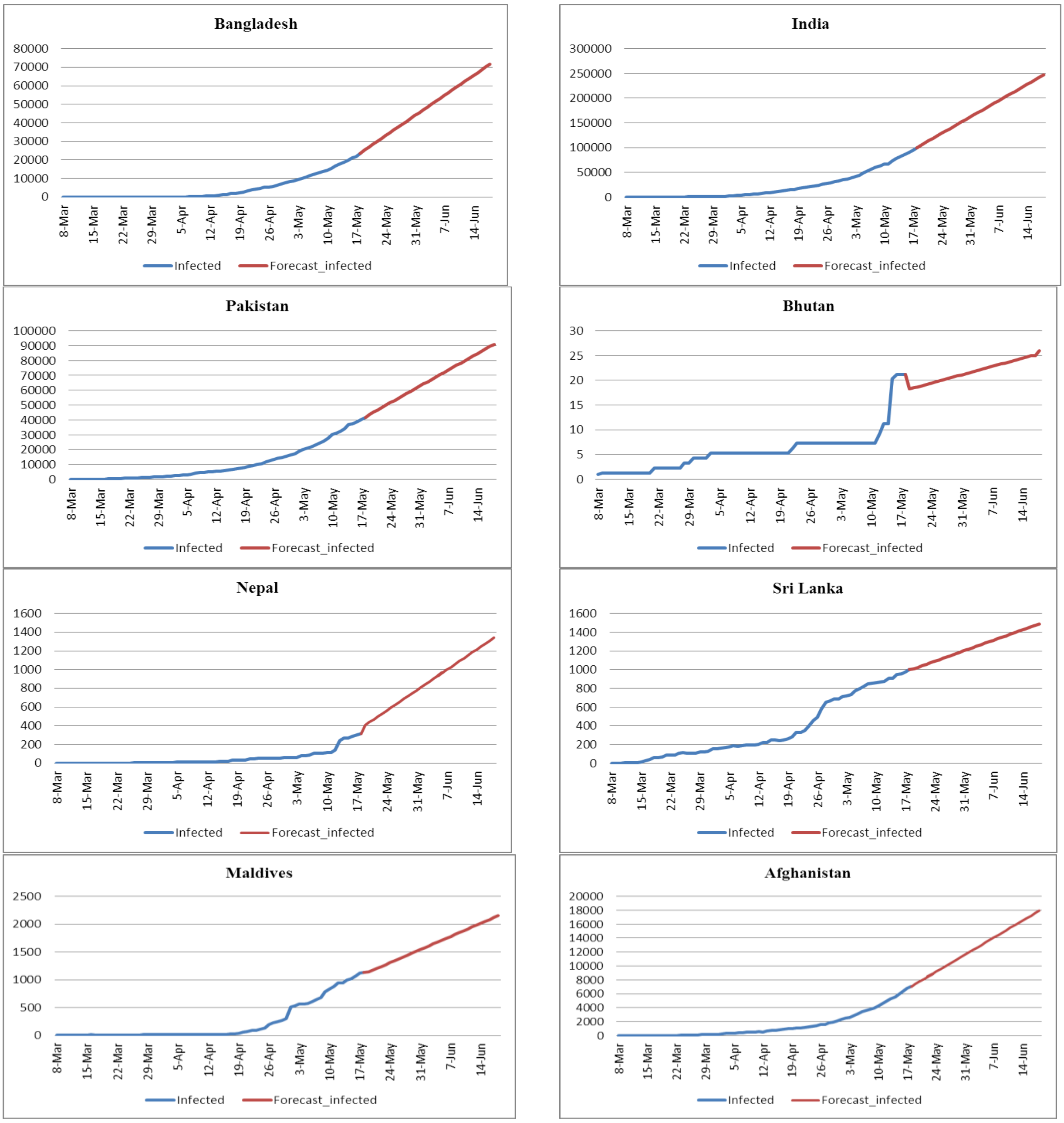

Figure 3: One month ahead forecast value for infected case in each SAARC countries

Table 2: Forecasting value for infected case in every 10 days for SAARC countries

Country	**Bangladesh**	**India**	**Pakistan**	**Bhutan**	**Nepal**	**Sri**	**Maldives**	**Afghanistan**

						Lanka		
10 days	39291	147392	57802	20	686	1153	1444	10568
20 days	54725	194694	73575	23	997	1313	1781	14076
30 days	71702	246726	90926	26	1339	1490	2152	17934

Now we forecast the infected case per thousand of total population for SAARC countries. Here we consider the total population for the year 2020 of these eight countries and forecast the one month ahead infected case per thousands of total population is given in Figure 4.

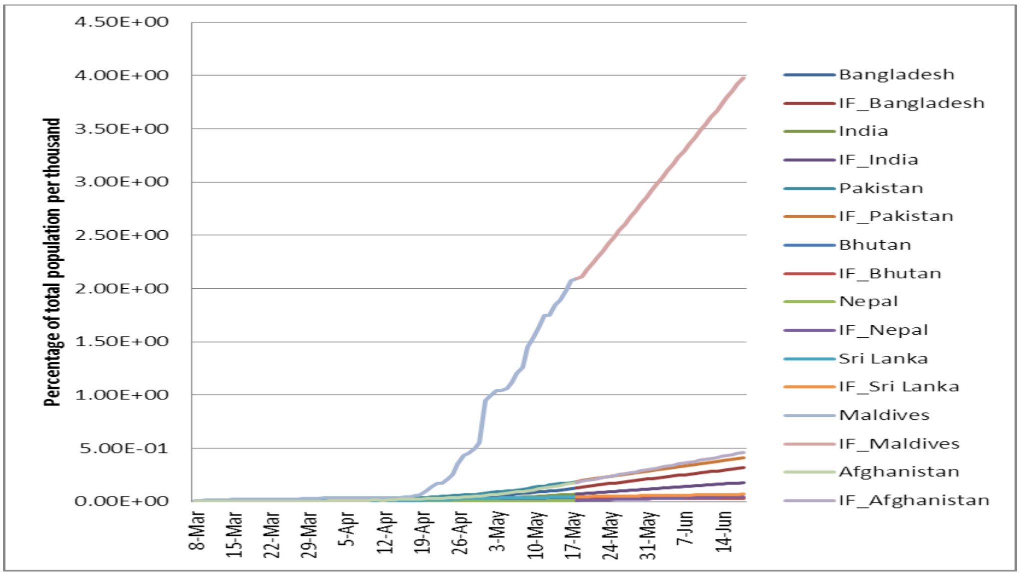

Figure 4: The infected case per thousand of total population

Figure 4 indicates that the infected case per thousand of total population will reach for Bangladesh (0.3179), India (0.1787), Pakistan (0.4116), Bhutan (0.0329), Nepal (0.0459), Sri Lanka (0.0695), Maldives (3.9808) and Afghanistan (0.46606) on June 18, 2020. This figure indicates that for Maldives the percentage of total population the infected will reach maximum and in Bhutan it will reach minimum.

Besides these, we also try to predict the infected case based on the exponential scale and logarithmic scale for SAARC countries. The mathematical models for explaining and analyzing the dynamics of COVID-19 spreading can be developed for these countries. The number of daily new infected cases and the daily growth rate of the infected cases are proportional to the existing cases. The daily growth rate can be modeled by the following equation:

$$\Delta N_d = E * P * N_d \tag{8}$$

$$N_{d+1} = N_d + \Delta N_d = (1 + E * P) N_d \tag{9}$$

Here, ΔN_d = number of infected cases on a given day, N_{d+1} = expected number of infected cases in the next day, E = average number of people someone infected is exposed to each day, P = the probability of each exposure becoming an infection, N_d = number of the coming days. We can measure the growth factor as follows:

$$GF = \frac{\Delta N_d}{\Delta N_{d-1}} \tag{10}$$

Here, GF = growth factor of the infected cases, ΔN_d = number of new infected cases on a given day and ΔN_{d-1} = number of new infected cases in the previous day. The growth factor for SAARC countries is given in Figure 8.

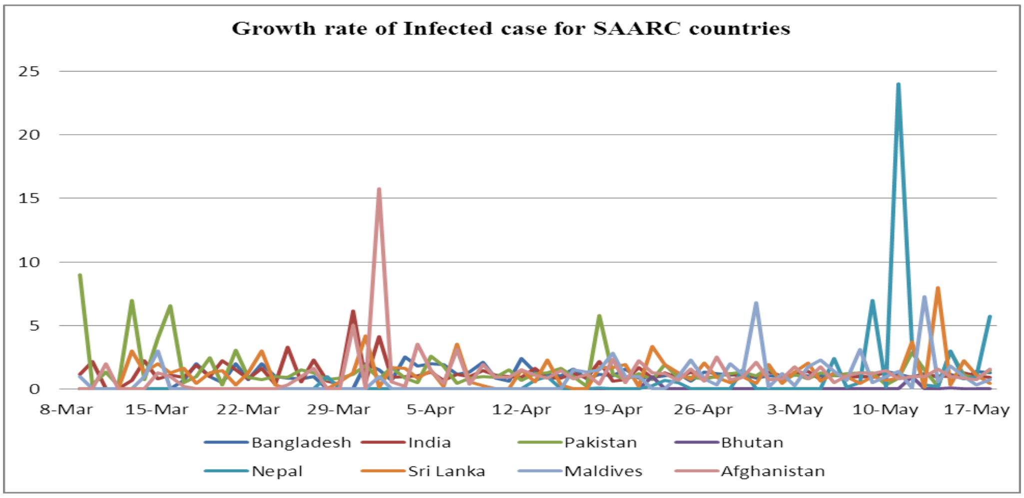

Figure 5: Growth factor of infected case for SAARC countries

The growth factor of the infected cases for the SAARC countries is shown in Figure 5. The growth rate first-time increased in Bangladesh on March 14, 2020, and after that, it fluctuated from March 17, 2020 to March 28, 2020. Higher fluctuated growth was observed from March 30, 2020 to April 12, 2020 and later from April 14, 2020 to April 23, 2020 where the growth rate increased gradually from 0.88 to 1.58. The maximum growth rate for Bangladesh was 2.5. In India higher fluctuated growth was observed from March 6, 2020 to April 16, 2020 and later it also showed less fluctuated up to the following time period. The maximum growth factor was observed from March 9, 2020 to March 10, 2020 in case of Pakistan. The growth rate first-time increased for Bhutan on April 22, 2020. There was no growth rate from March 6, 2020 to April 21, 2020 for Bhutan. The growth rate slightly fluctuated from April 13, 2020 to April 23, 2020 in case of Nepal. The growth rate was ranges from 1 to 0.67 between these time periods and later it also showing higher fluctuated. In case of Sri Lanka the highest growth rate observed 4.2 on March 30, 2020. The growth rate was fluctuated from March 29, 2020 to April 22, 2020. For Maldives the highest growth rate observed 3 on March 15, 2020 later the growth rate reduce to 1 and after April 16, 2020 the growth rate increases to around 3. The growth rate first time increased for Afghanistan on March 11, 2020. The highest growth rate observed 15.75 on April 1, 2020. After that, the growth fluctuated below 5 from April 4, 2020 to May 18, 2020.

A logarithmic function is the inverse of the exponential function. In this paper we add exponential and logarithmic trend line for these eight countries and predict the population based on these two trend line which was reported on Figure 6.

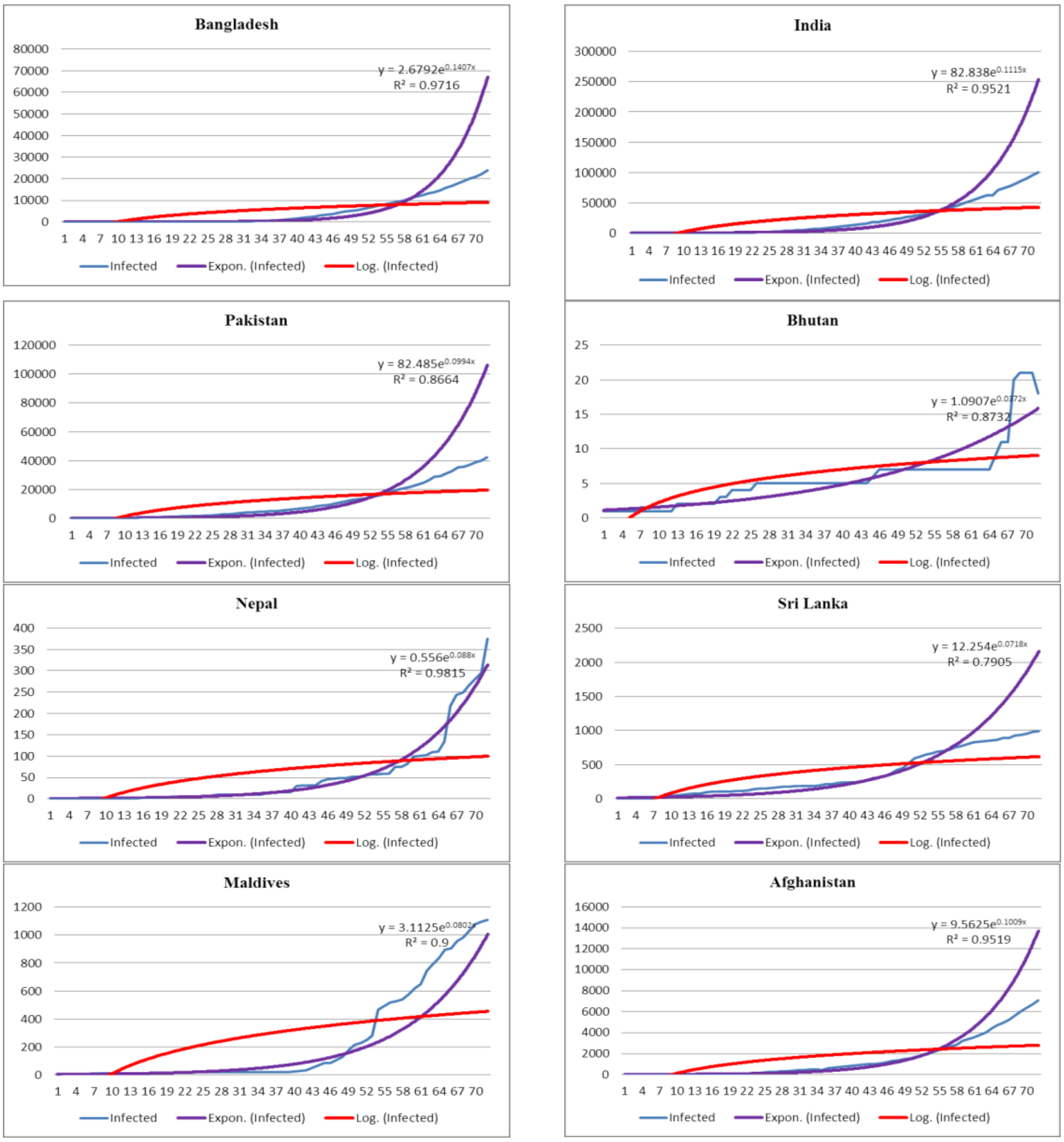

Figure 9: The infected case with exponential and logarithmic scale for SAARC countries.

The anticipated growth can be interpreted via the current exponential function, depending on the exponential graph indicated in Figure 6. The accuracy of the exponential models based on R-square is 97.16%. On average, the number of infected cases in Bangladesh will doubled 10 fold per 16 days, depending on the exponential formula. The logarithmic scale graph showed that the cases increased from 10 to 100 in cases of Bangladesh over 30 days and increased from 100 to 1000 over 9 days.

For India, the accuracy of the exponential model is 95.21 percent. On average, the number of infected cases in India will doubled 10 fold per 7 days. The logarithmic scale graph showed the cases increased from 10 to 100 over 7 day and from 100 to 1000 over 8 days.

For Pakistan, the R-square of the exponential formula is 86.64 percent. On average, the number of infected cases in will doubled 10 fold per 14 days. The logarithmic scale graph showed that the cases increased from 10 to 100 over 8 days and from 100 to 1000 over 10 days for Pakistan.

For Bhutan, the value of R-square is 87.92 percent. The number of infected case will doubled 10 fold from beginning to 62 days.

For Nepal, the value of R-square is 98.15 percent. Based on exponential scale the number of infected case will doubled 10 fold in 35 days. The logarithmic scale showed the cases increased from 10 to 100 over 35 days in Nepal.

For Sri Lanka, the exactness of the exponential formula on the R-square is 79.05 percent. On average, the number of infected cases in Sri Lanka will doubled 10 fold per 45 days and next 10 fold around 9 days. The logarithmic scale graph showed the cases increased from 10 to 100 over 11 days and from100 to 1000 over 40 days.

For Maldives, the accuracy of the exponential model based on R-square is 97.01 percent. On average, the number of infected cases in Maldives will doubled 10 fold per 44 days and next 10 fold around 12 days. The logarithmic scale graph showed the cases increased from 10 to 100 in cases of over 40 days and from 100 to 1000 over 23 days.

For Afghanistan, the exactness of the exponential formula based on the R-square is 95.19 percent. On average, the number of infected cases in Afghanistan will doubled 10 fold per 14 days, depending on the exponential formula. The logarithmic scale graph showed that the cases increased from 10 to 100 in cases of Afghanistan over 8 days and from 100 to 1000 over 24 days. From the above exponential and logarithmic scale we found that the number of infected case will increase sharply in India, Pakistan, Bangladesh and Afghanistan accordingly.

4. Conclusion and Policy Recommendation

COVID-19 is reported as a global epidemic and it is spreading day by day around the globe. Day-level knowledge of COVID-19 spread distribution is very important to take proper initiative for upcoming days. In order to forecast the infected case firstly, we compare the forecasting performance of our used models namely Simple Exponential Smoothing (SES), Moving Average (MA) and Weighted Moving Average (WMA) for SAARc countries. Secondly, the best forecasting model is used to predict the day level number of infected case for SAARC countries. In this study we consider the daily infected case from March 08, 2020 to May 18, 2020. The empirical analysis showed that the SES model give beter forcasting performance for all of the SAARC countries based on graphical comparison as well as some standard measure for forecasting evaluation. The one month aheah the infected case for Bangladesh, India, Pakistan, Bhutan, Nepal, Maldives and Afghanistan will be 71702, 246726, 90926, 26, 1339, 1490, 2152 and 17934 respectively. The forecast based on exponential model indicate that the population will double 10 fold within 7 days in India, 14 days in Pakistan and 16 days in Bangladesh.

India is the most populated country in southern Asia. On average, the COVID-19 infected person transmitting the virus to another 1.7 people in India, while it was 2.73, 2.34, and 2.14 for Iran, Italy, and China, respectively. Indian governments mandated the complete lockdown of India on 22 March 2020. Among all SAARC countries India, Pakistan, and Bangladesh are at more risk. The infected cases and death cases are increasing day by day. The mortality is also very high than the WHO's estimation in India, Pakistan, Bangladesh, and Afghanistan. India's mortality rate is 12% which is very alarming.

As most of the SAARC country's healthcare system is not up to standard, it will be very difficult to control this epidemic. Depending on this interpretation and modeling, this study suggests that all SAARC countries must be obliged to maintain quarantine, maintain stringent lockdown, avoid public gatherings, social distancing, closing of educational institutions, and maintain personal hygiene. The number of COVID-19 infected individuals will grow sharply over the next three weeks. All necessary facilities are available for limited accessibility, including daily necessities and drug store. Special phone lines can be assured to answer the queries related to COVID-19 awareness which would be responsible for the flattening of the curve. Mandatory quarantine for suspected and confirmed cases, as well as the use of mask and hand sanitizer would be helpful to minimize the number of COVID-19 cases.

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