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Analysis and Forecasting of the COVID-19 Epidemic Curve

Mohan Bansal*, Sumit Mohanty†, Anju Das†, Prateek Jain*
*VIT-AP University, Amaravti, AP, 522237, India
{mohan.bansal, prateek.jain}@vitap.ac.in
†CMR Institute of Technology, Bengaluru, Karnataka,560037, Inida
{sumit.h, anju.d}@cmrit.ac.in

***Abstract*—Corona Virus Disease 2019 (COVID-19) has emerged as a supreme challenge for the whole world as well as India. As of now approximately 6.5 million people died in the world. However, the major setback to the world was in 2021 as a result of the second and third waves of COVID-19, which were caused by a different variation of COVID-19 than the first variant. The governments and health sectors were not aware of the subsequent possible waves due to the lack of data analysis competency and improper forecasting models. Hence finding an inflection point of this epidemic curve for COVID-19 infection and death is very imperative to understand different waves and variants instigating these waves. Similarly predicting the epidemic curve for the future is vital to make the government and the systems aware of the impending situation and make them prepare accordingly. Hence this work attempts to demonstrate conditions for finding inflection points and intervals which helps in finding the number of waves and the variants of COVID-19. Simultaneously the forecasting of the number of infections in forthcoming wave is also done using the auto-regressive integrated moving average model to identify the number of waves in India. The prediction of the two months data was compared with actual data for proper analysis.**

***Index Terms*—COVID-19, Coronavirus Disease, Inflection Point, Epidemic Curve, Trend Analysis, Forecasting, ARIMA (Autoregressive Integrated Moving Average) Model.**

I. Introduction

Corona Virus Disease 2019 (COVID-19) is caused by SARS-Cov2 (Severe Acute Respiratory Coronavirus-2), a novel pathogenic virus. This disease is considered as a global health issue right from its genesis because of its severe contagious nature and the severity of its effect on the human body [1].

This SARS-COV2 was reported first in Wuhan, China. Initially, China, USA and European countries were acting as an epicentre of this diseases, whereas gradually countries like Brazil, India, South Africa and other African countries became the epicentres of this disease [2]. he COVID-19 has severely affected to Asian and Europian countries, and people's social and economic lives have been greatly disrupted [3]. WHO (World Health Organization) declared COVID-19 as a global pandemic on March 11, 2020. Many countries have imposed nationwide lockdown to avoid infection to their citizens. Standard Operating Procedure (SOP) and guidelines have been released by governments, mostly suggesting keeping social distance, quarantining the patients, and staying home as much as possible.

COVID-19 first phase was a wake-up call for researchers, scientists and scholars. It challenged the whole world to prepare, improvise and review the strategies and policies for facing the subsequent waves of COVID-19 [4]. Developed countries like the US and UK have already gone through three different waves and more than three different mutants. But developing countries like Brazil, India and South Africa have also gone through the deadly second and third waves of COVID-19. Now even each country has different variants and different mutants each affecting in different ways of severity [5]. India has suffered more than 4 lakh death at the end of COVID-19 second wave. Accurate data-based modelling and prediction of the number of cases in future are required to enable India for early stage strategic planning to deal with the next surge of COVID-19 cases due to the next mutant [6].

The paper is organized in such a manner that the prior related work for the forecasting of epidemic curve is discussed in Section II. The proposed methodology for the analysis of the COVID-19 epidemic curve is represented in Section III. The autoregressive integrated moving average (ARIMA) model for modelling the epidemic curve and future prediction of the time series data is presented in Section IV. The results and discussions on the analysis and forecasting of the COVID-19 epidemic curve is given in Section V. Finally, the paper is concluded in the last section following the results and discussion.

II. Prior Work on Forecasting of Epidemic Curve

Proper analysis of the available data and the informative model is required to predict future cases as well as to prepare for mitigating the effects of the any upcoming waves of COVID-19 in India [4]. Stochastic methods-based models have been used to identify parameters crucial for transmission and impact on spread and risk of COVID-19 [7]. Parameter based exponential growth models are also extremely popular where one or two parameters are used to find the growth rate of COVID-19 infection [8]. Ding et.al. [9] proposed a model where the effect of the count of infected individuals was removed from the growth curve to design a model which can predict the growth rate of COVID-19 with a better accuracy than the models built on basic cumulative data of infected individuals.

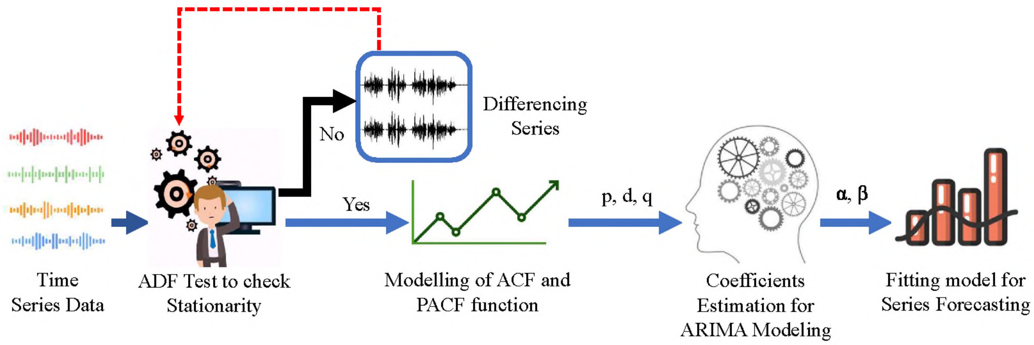

Fig. 1. Representation of proposed framework of ARIMA model.

Based on the demographic and the infected individual's count, in later stages complex machine learning-based modelling are applied for getting better accuracy in prediction and detection of new wave and variant of COVID-19 [10]. The Artificial Intelligence based approach is used for diagnosis and combating of the COVID-19 viruses [11], [12]. In China, the investigated modelling approaches were used for predicting infected cases and the number of deaths [13]. Gaining knowledge about the epidemic curve, the inflection points and other related factors are very essential to get the exact tracking of future waves and variants of COVID-19 [14]. Based on the complex network theory, an SEIR dynamic model of the COVID-19 epidemic with a latency period is developed by Maher et.al. [15]. Qibin et.al. [16] predicted inflection point and the COVID-19 outbreak size for different countries using data of cumulative reported cases by using the Four Parameters Logistic Model (FPLM) for modelling growth parameter.

The methods discussed above mostly rely on the number of confirmed COVID-19 cases only for curve fitting and prediction. Further, these methods are difficult to generalize for different countries to track the new variant and wave of COVID-19. Hence this paper proposes an approach to find the inflection point of the epidemic curve based on both the confirmed cases count and death count. Additionally, a simplified and universal approach of the second derivative plot is used for confirming the new waves and variants based on local maxima and minima. Finally, an Auto-Regressive Integrated Moving Average (ARIMA) based time series model is used to train and forecast the number of COVID-19 cases in future along with the prediction of inflection points, new wave and new variant which occuring in future.

III. Analysis of the COVID-19 Epidemic Curve

Here first the epidemic curve for the number of COVID-19 infected cases and mortality cases are plotted to analyse the historical data. The data-set is collected from the Johns Hopkins Coronavirus Resource Center [17] for the analysis and forecasting of the COVID-19 epidemic curve. The epidemic curve is a graphical representation of the number of cases of a disease or health event over time, in a population, place, over a given period. Later a second derivative plot is done to find the local maxima and minima so that inflection interval and points can be found. The second derivative method used here is very simple to find the inflection interval which in result becomes useful in tracking new waves. Similarly from the same curve only the information of difference of variants and mutants of COVID-19 can be found easily. Further these epidemic curves of India are compared with those of other countries. Later on concepts on ARIMA based modelling are discussed which is helpful in modelling the epidemic curve till now. This modelling is used over the time to forecast the epidemic curve for August, 2021 onwards, in terms of the number of infected cases which is helpful for preparation to encounter the pandemic in our country.

The representation of the proposed framework of the methodology is presented in Fig. 1 in terms of important steps and methods used in this paper. First part of this flow chart discusses plotting of the epidemic curves of the US, UK and India. The data of these countries are readily available in Johns Hopkins Data and readily available data reduces the effort of data exploration, therefore focus can be put more on the analysis part of data. Further the main focus is given to India as the authors belong to India and this country suffered a lot during the second wave. The same analysis can be done for data of any other countries as the analysis part is focused more. The next part describes the process of finding the Inflection point and inflection intervals by the essential second derivative condition. Second derivative plot for all the three countries calculated by the difference method is used for analysis in this step. Based on the inflection point and inflection interval calculation the past COVID-19 waves are tracked in the next step. Even the nature of variants responsible for these waves are also preconceived in this step. In the end step the data of the epidemic curve is used to train an ARIMA model. The number of future cases for India is predicted using this ARIMA model which helps in finding future Inflection points along with tracking of new variants and waves of COVID-19.

A. Finding the Inflection Point by Second Derivative Method

The point of inflection, also known as the inflection point, is the point at which the function's concavity changes [18]. It denotes a change in function from concave up to concave down or vice versa. In other terms, an inflection point is the point at which the rate of change of slope changes from decreasing to increasing or vice versa. A curve is considered to be concave up if it opens up in an upward direction or bends up to form a cup shape. Concave down describes a curve that bends down or resembles a cap [19]. If $f(t)$ is a continuous and differentiable function, then $f(t)$ is said to be concave up at a point $t = t_0$, if second derivative of the function $f''(t) > 0$ at t_0 and concave down if $f''(t) < 0$ at $t = t_0$. The inflection point lies between the concave up and concave down function at a point when the second derivative of the function is zero. i.e. the inflection point at a point $t = t_0$, if $f''(t) = 0$ at t_0. The function $f(t)$ describes the evolution of the confirmed case of COVID-19 through time. The first derivative function $D(t)$ for the time period $\Delta(t)$ can be described mathematically in equation (1).

$$D(t) = \frac{f(t + \Delta t) - f(t)}{\Delta t}. \tag{1}$$

The second derivative $SD(t)$ can be used to find the inflection point, that can be compute mathematically and it is represented in equation (2).

$$SD(t) = \frac{D(t + \Delta t) - D(t)}{\Delta t}. \tag{2}$$

IV. Modeling the Epidemic Curve and Training for future Prediction using ARIMA

A time series is a collection of measurements taken at regular intervals. The next phase is forecasting, which involves predicting the series' future values. A forecasting methodology known as Auto Regressive Integrated Moving Average (ARIMA) [20] is based on the idea that past values of a time series can predict future values on their own. The ARIMA model is defined by the three terms p, q, and d. Where p denotes the Auto Regressive (AR) model order, i.e. the number of lags of the time series to be used as predictors, and q signifies the Moving Average (MA) model order, i.e. the number of lagged forecast errors to be included in the ARIMA Model. The value of d is the smallest differencing required for the series to become stationary.

An ARIMA model combines the Auto Regressive (AR) model and Moving Average (MA) model. A pure AR model [21] is one which is determined only by the lags it generates. A pure MA model [22], is only determined by the lagged forecast errors $e(t)$. The 'lag-p' of the time-series is represented by $y(t-p)$, the intercept term is represented by c, the coefficient of the 'lag-p' is represented by α_p and the forecast error coefficient of the 'lag-q' is represented by β_q in the below mentioned equation (3).

$$\begin{aligned} y(t) &= c + \alpha_1 y(t-1) + \alpha_2 y(t-2) + \cdots + \alpha_p y(t-p) \\ &\quad + e(t) + \beta_1 e(t-1) + \beta_2 e(t-2) + \cdots + \beta_q e(t-q). \end{aligned} \tag{3}$$

In ARIMA model, The first aim is to determine the AR model order (p), minimal differencing (d), and MA model order (q). A thematic diagram for the procedure of the series forecasting using ARIMA modelling is shown in Fig. 1. The right order of differencing is the minimum differencing required to construct a near-stationary series that roams around a particular mean and the Auto Correlation Function (ACF) plot achieves zero quickly is the proper order of differencing. The null hypothesis (H_0) of the Augmented Dickey-Fuller (ADF) test [23] is that the time series is non-stationary. The time series is presumed to be static, if the P-value is less than threshold (0.05), therefore H_0 is rejected.

Model selection is the process of fitting multiple models on a given dataset and choosing one over others. The Akaike's Information Criterion (AIC) and the Bayesian information criterion (BIC) are the most popular in selecting model order for forecasting. AIC and BIC are two ways of scoring a model based on its log-likelihood and complexity. The information criteria's (IC) (4) are defined for logistic regression as follows:

$$IC = mk - 2\mathcal{L}. \tag{4}$$

where $\mathcal{L}$ is the log likelihood, m is the total number of parameters in the model which is equal to $(p+q+d+1)$, and

$$k = \begin{cases} 2, & \text{for AIC} \\ \ln(n), & \text{for BIC} \end{cases}. \tag{5}$$

The lower AIC and BIC values are considered as a best fitted model. The lower AIC may get by higher log likelihood $(\mathcal{L})$ or less number of parameters (m). On the other hand, the lower BIC may get by lower AIC or by fitting model with less number of samples (n) depicted in equation (5).

V. Results and Discussion

This section depicts the inflection point of the epidemic curve based on both the confirmed cases and the mortality count. In addition, new waves and variants based on local maxima and minima are confirmed using a divided difference method of the second derivative plot. Finally, a time series ARIMA model is utilized to train and forecast the number of COVID-19 cases.

A. Analysis of COVID-19 data: US, UK and India

The analysis of the COVID-19 cases for US, UK and India are done in this section. The number of waves can be easily identified by visualizing the data of the above countries. The epidemic curves represented graphically for the confirmed cases and the mortality cases are shown in Fig. 2(a) and Fig. 2(b). Fig. 2 shows the total number of confirmed cases and the mortality cases till the last week of July, 2021. The curves for the US, UK and India are plotted in the red, black and blue colors respectively. It can be clearly observed that the US is a highly infected country around the globe as shown in Fig. 2(a). The mortality rate in the US is also very high depicted in Fig. 2(b). The graph of confirmed cases and mortality cases of India is gradually increasing towards the graph of the US. The daily incidences of positive cases and mortality cases due to COVID-19 of the US, UK and India are presented in Fig. 3. It shows that the situation of the US and UK were under control in spite of two major spikes, but the condition of India was out of control during the second wave. These spikes are useful to find the number of waves and the variants.

Further inflection points and intervals are the essential conditions to find the waves. The second derivative plot is utilized to find out the inflection points of the epidemic curve. This curve is also helpful to confirm the waves and variants based on local maxima and minima. The second derivative is computed by using the divided difference formula, in which $\Delta t = 30$ samples difference is computed for the smooth plot of the second derivative.

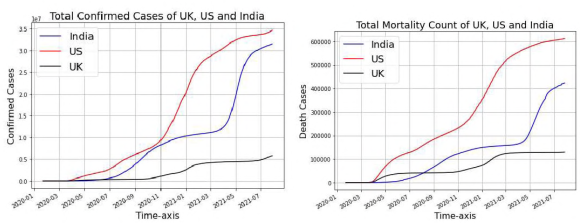

Fig. 2. (a) Total confirmed COVID-19 positive cases and (b) Mortality cases of three countries (India,US and UK)

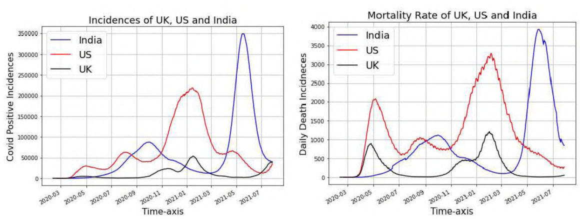

Fig. 3. (a) Daily incidences of COVID-19 positive and (b) Daily incidences of death cases due to COVID-19.

These Inflection points can be found from the essential conditions of the second derivative. Therefore Fig. 4 represents the plot of the second derivative for UK, US and India, which gives complete information on the number of waves of COVID-19, each country has passed through. There were four maxima on May, 2020, August, 2020, January, 2021 and May, 2021, and four minima on June, 2020, September, 2020, March, 2021 and June 2021 for the US. Similarly there were three maxima on April, 2020, November, 2020, and January, 2021, and three minima on July, 2020, December, 2020, and February, 2021 for the UK. It can be clearly observed that the red line completes 3 complete inflection intervals (one set of concave up and concave down below and above zero line) and black line completes 3 complete inflection intervals. Accordingly the US has already passed through 4 different waves and UK has passed through 3 different waves. But the nature of the curves in each inflection interval is different in which implies that different mutants of COVID-19 are responsible for each wave. However, for India two maxima occurred on September, 2020 and May, 2021, respectively and two minima occurred on December, 2021 and end of June 2021. So the second derivative curve of India as seen in blue color shows only two complete inflection interval. Hence it can be inferred that India has encountered two complete wave of COVID-19.

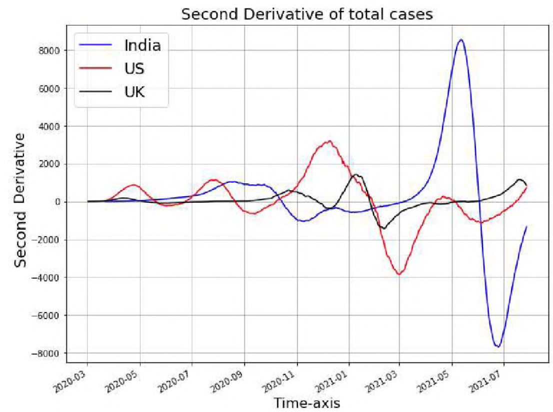

Fig. 4. Second derivative of the UK, US and India Confirmed cases.

B. Forecasting of the epidemic curve in India using ARIMA Model

The overall number of cases in India were over 31.5 million during prediction time, with a mortality rate of total 4.24 lacs till the end of July, 2021. The graph for the total confirmed cases and the death cases from mid-January, 2020 to the end of July, 2021 is shown in Fig. 5. The confirmed cases graph is plotted in the red color and its data is mentioned at the left side of the plot on the y-axis. The death cases graph is plotted in the blue color and its data is mentioned at the right side of the plot on the y-axis. The graph reveals that after March, 2021 the total confirmed cases and death cases rapidly climbed. However, incidents began to decline in mid-May, 2021, as the Indian government implemented a lockdown in the first week of May, 2021. There were around 4 Lakh active coronavirus cases, with up to 30.8 million persons having recovered during the prediction time.

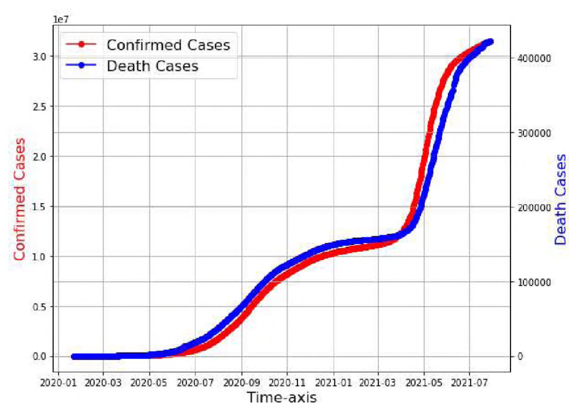

Fig. 5. Total confirmed COVID-19 positive cases and mortality cases in India till May 2021

ARIMA is a forecasting technique whose purpose is to directly model autocorrelation in a series. The ARIMA model is a very powerful tool for the time series forecasting [24], [25]. This model is widely used for the stock market prediction [26]. This model is defined by three parameters (p, d, and q), with p defining the AR model's order and q defining the MA model's order. The smallest value of d is responsible for differencing, which makes the series stable, and d = 0 if the time series is already stationary.

The appropriate order of differencing is the smallest amount of differencing necessary to build a near-stationary series that roams about a certain mean and the Auto Correlation Function (ACF) plot quickly hits zero. The time series is non-static, according to the null hypothesis of the Augmented Dickey-Fuller (ADF) test. The time series is presumed to be static, if the P-value is less than threshold (0.05).

The Augmented Dickey-Fuller (ADF) test is used to assess a time series is stationary [27]. The null hypothesis of the ADF test accepts the time series as non-stationary. There are two parameters to check the H_0 of the ADF test. The ADF test statistic is the first, while the P-value is the second. If the ADF test statistics (τ) is more negative and the test's P-value is less than threshold value, in such case H_0 is rejected, and it implies that time series is stationary. If the P-value is greater than 0.05, then H_0 is accepted, and it implies that the time series is non-stationary.

The ADF test is applied to the total confirmed case time series data to check the stationarity of the series. The computed ADF test statistic and the P-value of the original time-series are $\tau = 1.4657$ and 0.997 respectively. As a result, the P-value is very high (> 0.05) and the ADF test statistic is positive. This shows the week evidence against the null hypothesis indicating the series is non-stationary. In this case, minimal differencing is required to create a stationary series. A first-order differencing is done on the series and applied to the ADF test. The computed ADF test statistic and the P-value of the first order time-series are $\tau = -3.424$ and 0.010 respectively. As a result, the P-value is less than the threshold value (0.05) and the ADF test statistic is negative shows strong evidence against the null hypothesis indicating the series is stationary. Therefore, the first parameter (d=1) of the ARIMA model is computed as the stationary signal is achieved in one difference. Now, it's time to calculate the p and q parameters of ARIMA model. When it comes to select model order for forecasting, the AIC and BIC are the most commonly used criteria. The model parameters with the lowest AIC and BIC values are regarded to be the best fit. The AIC and BIC values are computed for various combinations of p and q as shown in Table I and Table II respectively. The lowest AIC value reached for p=3 and q=2 or 3 and the the lowest BIC value achieved for p=3 and q=2 are depicted in Table 1 and 2 respectively. The model is tested for both scenarios (3,1,3) and (3,1,2) based on the least AIC value for q =2 and q=3 with p=3.

Everything is now available to fit this model after finding the (p, d, q) parameter values, and coefficients are estimated by fitting the model orders. Table III depicts the model summary for p=3, d=1, and q=3, which contains a wealth of information. The coefficients weights of the model are present under 'coef' column. It can be noticed here that the coefficient weight of the third term of the MA (MA3) is less than the coefficient weight of the other AR and MA terms. The P-value in '$P > |z|$' column is high in MA3 compare to the P-value in the other AR and MA terms. For significance, the P-value should be less than 0.05. The MA3 term has a low coefficient value and a high P-value, indicating that it is not relevant parameter for model fitting. So, without the MA3 term, the model redesigned. By fitting the model with parameters p=3, d=1, and q=2, it can be observed that BIC is lowered and AIC is the approximately same as the previous case in Table III. All of the AR and MA terms had P-values of less than 0.05, which is extremely significant. Finally, for the series forecasts, the computed ARIMA model orders (3, 1, 2) and coefficients are employed.

The built model is applied for the series forecasting on the COVID-19 infected cumulative positive confirmed cases for 600 samples(Jan, 2020-Sep, 2021). The plot for the forecasting on the COVID-19 positive confirmed cases is shown in Fig. 6(a). Fig. 6(b) depicts the Actual plot for the cumulative positive confirmed cases. Fig. 6(a) and Fig. 6(b) compares the actual with the forecast one and its exactly in the confidence level of 95%. The actual and predicted plots are shown by the colours orange and blue, respectively. In the grey shaded zone,

TABLE I
AIC VALUES AT DIFFERENT MODEL ORDER FOR D=1, ARIMA(P,1,Q)

AR order (p)		MA Order (q)				
		0	1	2	3	4
	0	14111	13419	12911	12589	
	1	11619	11619	11621	11616	11618
	2	11619	11588	11551	11480	11491
	3	11621	11571	11471	11471	11491
	4	11614	11550	11472	11510	

TABLE II
BIC VALUES AT DIFFERENT MODEL ORDER FOR D=1, ARIMA(P,1,Q)

AR order (p)		MA Order (q)				
		0	1	2	3	4
	0	14119	13432	12928	12610	
	1	11632	11637	11643	11642	11649
	2	11637	11610	11557	11510	11525
	3	11643	11597	11501	11506	11530
	4	11640	11580	11506	11549	

TABLE III
ARIMA MODEL RESULTS

Model Parameters	ARIMA(3,1,3)		ARIMA(3,1,2)	
AIC	11471.988		11471.583	
BIC	11586.511		11501.791	
	Coeff	$P > \|Z\|$	Coeff	$P > \|Z\|$
Constant	5.701e+04	0.003	5.701e+04	0.005
AR1	2.3946	0.000	2.5043	0.000
AR2	-1.8137	0.000	-2.0305	0.000
AR3	0.4178	0.000	0.5251	0.000
MA1	-1.7200	0.000	-1.8564	0.000
MA2	0.6883	0.001	0.9240	0.000
MA3	0.1106	0.245	-	-

the predicted plot for the next two months is displayed in blue. The grey colored region indicates that the true values will fall within the 95% confidence interval. It can be observed from Fig. 6(b), that the number of cases are increased consistently based on the forecasting of the time series data.

This prediction is done in the assumption of without imposing any lockdown. So looking at the forecasting and review of the precautionary actions, proper preparedness of health care, vaccinations, and timely imposing of the lockdown the upcoming 3rd phase was countered.

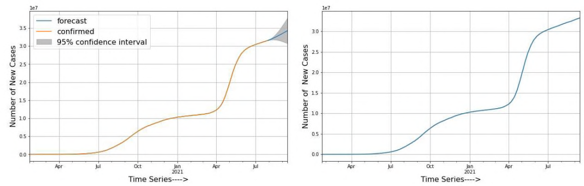

Fig. 6. (a) Forecasted data of the COVID-19 positive cases and (b) Actual cases of the COVID-19 positive cases

VI. Conclusion

This study shows the importance of finding inflection interval, prediction of inflection point which is normally ignored to evaluate a pandemic like COVID-19 specifically when it is highly contagious and depends on different factors for spreading. This inflection point of epidemic curves of US and UK interprets that these countries have passed through more than three different waves of COVID-19 . India has also gone through deadliest 2nd wave as per the calculation of inflection point. This calculation is required to predict the time of 2nd wave and the increased severity of it. Likewise, the forecasting of future epidemic curve in terms of infected cases are also done in this paper. It showed another future wave of COVID-19 during and its severity in terms of a greater number of infected cases. The calculation was done without taking the consideration of Lockdown effects and Vaccination. Therefore Government and healthcare system took proper inference from this to prepare thoroughly to fight the further waves of COVID-19. This forecasting recommended Government for accelerating the vaccination process and increasing manpower in terms of health workers. It proposed healthcare system to arrange proper number of hospital beds, facilities, enough oxygen and doctors and advises to Pharma sector also for production of enough medicines and vaccines.

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