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Analysis of COVID 2019 By Using Weighted Moving Averages

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Abstract

This research analyses and forecasts covid-19 case trends using weighted moving averages (WMA), a time series approach that prioritises recent data. The research examines how WMA can catch short-term patterns. This study examines the trajectory of COVID-19 utilising Weighted Moving Averages (WMA) to estimate short-term trending in case numbers. When compared to older approaches such as Simple Moving Averages (SMA), WMA is more sensitive and accurate in smoothing and predicting daily infections because it prioritises recent data items. The study uses publicly available COVID-19 time series data to assess the effectiveness of WMA in capturing real-world patterns, providing insights for public health planning and action. In order to predict daily case trends, this study uses weighted moving averages (WMA) using COVID-19 time series data. WMA provides better short-term prediction than conventional techniques by focussing on current data. In epidemiology, time series analysis is a useful technique that supports traditional epidemiological models in two ways: forecasting and prediction. Prediction is the process of interpreting historical and present data using a variety of internal and external factors that may or may not be causal. Exploring potential future values based on the model's predictive power and projected future values of internal and/or external effects is known as forecasting. The time series analysis technique has the benefit of being simpler to apply (for more simplistic and linear models like auto-Regressive integrated moving average). Nonetheless, it has a limited predicting time, unlike conventional models such as susceptible-exposed-removed. Its usefulness in predicting stems from its superior accuracy in short-term prediction. It may be used to estimate morality or hospital risk based on new cases, conduct seroprevalence studies, examine the characteristics of emerging variations, and estimate excess morality and its relevance to pandemic conditions.

1. Introduction

Covid-19 is an infectious illness caused by a coronavirus, also known as severe acute respiratory syndrome coronavirus. The disease was initially discovered in the capital of China's Hubei province, Wuhan district, in December 2019, and has since spread over the world, becoming a worldwide pandemic. Since its arrival in India, the number of covid-19 cases has increased. Patients are suffering from respiratory failure due to acute respiratory distress syndrome, which is the leading cause of mortality. Healthcare workers are among the most affected by this pandemic. The covid-19 response team produced a report on the characteristics of those affected in the healthcare area [1].

Various studies are being conducted to discover characteristics of cases with navel coronavirus illness (COVID-19). A significant initiative has also been undertaken in the realm of vaccine development. After 74 days of lockdown in India, the government granted unlock 1 on June 8, 2020, allowing certain sectors of enterprises to operate in a restricted way. India is among the most vulnerable countries, with a relaxed lockdown potentially leading to an increase in new infections. According to numerous analyses, one of the two scenarios may arise as a result of unlocking. The first scenario is that if the number of instances decreases and the growth curve for the number of cases flattens, a positive feedback loop will kick in. The second possibility is that reopening the economy will increase the number of instances, resulting in the cessation of movement. The analysis of the consequence of the unlock condition should be a top priority in research. In the article, we investigated several time series models for predicting positive instances. Then, we used an auto-regressive integrated moving averages model to investigate the unlocking impact and forecast the occurrence of 2019-ncov illness.

The main goal of the article is to identify the effect of unlocking in India by doing a comparative analysis on the forecasts utilising the unlock and lockdown. COVID-19 data, including both positive instances and total In December 2019, a large number of people in province, China, began experiencing significant health problems. This is when the COVID-19 epidemic began. According to the World Health Organisation (WHO), as of June 22,2022, about 545,891,254 cases and 6,343,938 deaths from COVID-19 had been documented. During the early epidemic, to lower incidence and fatality rates, the WHO encouraged self-quarantine and isolation of sick individuals, resulting in the greatest lockdown in history. On June 3, 2020, 188 nations and regions reported more than six million COVID-19 cases [3, 4]. The most prevalent COVID-19 symptoms are fever, respiratory difficulties, exhaustion, and a loss of taste and smell [5, 6]. In severe instances, multiorgan failure, septic syncope, acute respiratory distress syndrome, and blood clots are seen. Although unfavourable effects are often seen after about five days, they can worsen between two and fourteen days [7].

The genetic sequence of COVID-19 was made public on January 11, 2020, prompting a global effort to accelerate vaccine development and prepare for an epidemic. Since then, governments and the global pharmaceutical sector have collaborated in unprecedented ways to advance vaccine research.

By June 2020, businesses, governments, non-governmental organisations, and university research teams had invested tens of billions of dollars in the development of various vaccine candidates and global immunisation campaigns. According to the Coalition for Epidemic Preparedness Innovation, North American organisations contributed around 40% of the COVID-19 vaccine research effort. In February 2020, the WHO announced that it did not expect a COVID-19 vaccine to be ready in less than 18 months. Since its outbreak in China in December 2019, the new coronavirus has infected millions of individuals globally. Covid-19 has a high mutation rate and can spread quickly.

Infected patients with this virus experience significant respiratory problems and may develop serious sickness if they have chronic conditions such as cardiovascular disease or diabetes, have a weakened immune system, or are beyond the age of 14. On March 11, 2020, the World Health Organisation (WHO) designated COVID-19 to be a pandemic. Containing the disease is difficult since an infected individual may not exhibit symptoms for a long period or at all. Currently, no immunisation has been identified to include COVID-19. In this circumstance, the only options for preventing the virus from spreading are social distance, finding positive cases by large-scale testing, and containing sick individuals.

COVID-19 spreads in three stages:
1. Local outbreak: This stage allows for tracking the virus's distribution and determining the source of infection. The instances at this point are largely about relatives or friends, or local exposure.
2. Community transmission: At this point, the source of the infection chain cannot be determined. Infected cases spread by cluster transmission in communities.
3. huge-scale transmission: At this point, the virus spreads swiftly to other parts of the country as a result of uncontrolled human migration on a huge scale.

Because of the huge community effect and ease of dissemination internationally, the national government ordered a lockdown to stop the spread of the coronavirus. As of May 20th, 2020, 4996472 cases had been confirmed, 1897466 patients had recovered, 2328115 fatalities had been recorded, and 2770891 active cases had been discovered globally. The statistical data is gathered, and the number of COVID-19 cases is estimated between January 22, 2020 and May 20, 2020. As no vaccine for the disease has been identified, the objective for this work is to model the spread of the coronavirus and estimate the effect in order to optimise the The government's approach for managing the vast array of public services and resources. Some researchers have been published that use statistical analysis, modelling, and artificial intelligence to control the virus's transmission and highlight its effects in the future days. This early research is based on the limited knowledge available during the outbreak's early stages. Now the infection has spread. Now that the virus has spread on a massive scale, the government must plan for and limit the spread of the contagious disease. Modelling and forecasting the virus's daily spread behaviour can help health systems prepare for the expected number of cases.

Accurate disease forecasting is important because it may influence government policy, containment rules, the health system, and social life. In this context, we investigate the predictive capabilities of the Arums and Prophet forecasting models. The models are extensively used and trusted because they can forecast more accurately. For our research, we use the day-level cumulative instances of COVID-19 globally, as well as the ten most afflicted countries: the United States, Spain, France, Germany, Russia, Iran, the United Kingdom, Turkey, and India.

The remainder of the paper is organised as follows:
Section II provides a literature review. Section III presents a trend analysis of COVID-19 instances. Section IV presents an overview of time series forecasting models. Section V describes the modelling methodology and the dataset utilised for COVID-19. Section VI presents the statistical analysis and development of models. Section VII finishes the paper.

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, has had a far-reaching global impact since it began in late 2019. Monitoring and anticipating the spread of COVID-19 is critical for making informed decisions and implementing public health interventions. Time series analysis is critical for analysing daily case patterns, recoveries, and deaths.

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LITERATURE REVIEW:

1. **Moving averages in covid-19 analysis:**
   - The application of simple moving averages (SMA) and weighted moving averages (WMA) has been instrumental is smoothing daily fluctuations in covid-19 data. Moving average models, while basic, were often as effective as complex machine learning methods for short-term forecasts during the early phases of the pandemic.
2. **Weighted moving average (WMA) overview:**
   - WMA is a forecasting technique where recent data points are given more importance (higher weights).
   - It is widely used in epidemiology to model trends in disease and infections.
3. **Comparison with simple moving average (SMA):**
   - SMA treats all past data equally
   - WMA is superior because it emphasizes recent changes, making it more responsive and accurate for short-term forecasting
4. **Time series forecasting in epidemiology:**
   - Time series forecasting is a statistical technique that deals with analysing Time-ordered data to forecast future values. In the context of epidemiology, it helps track the spread of disease estimate peak periods, and guide health policy disease infection
5. **Applications in COVID-19 Forecasting:**
   - Researchers use WMA to predict daily covid-19 cases count, recoveries, and deaths
   - This method helps in planning and decision-making by health authorities.

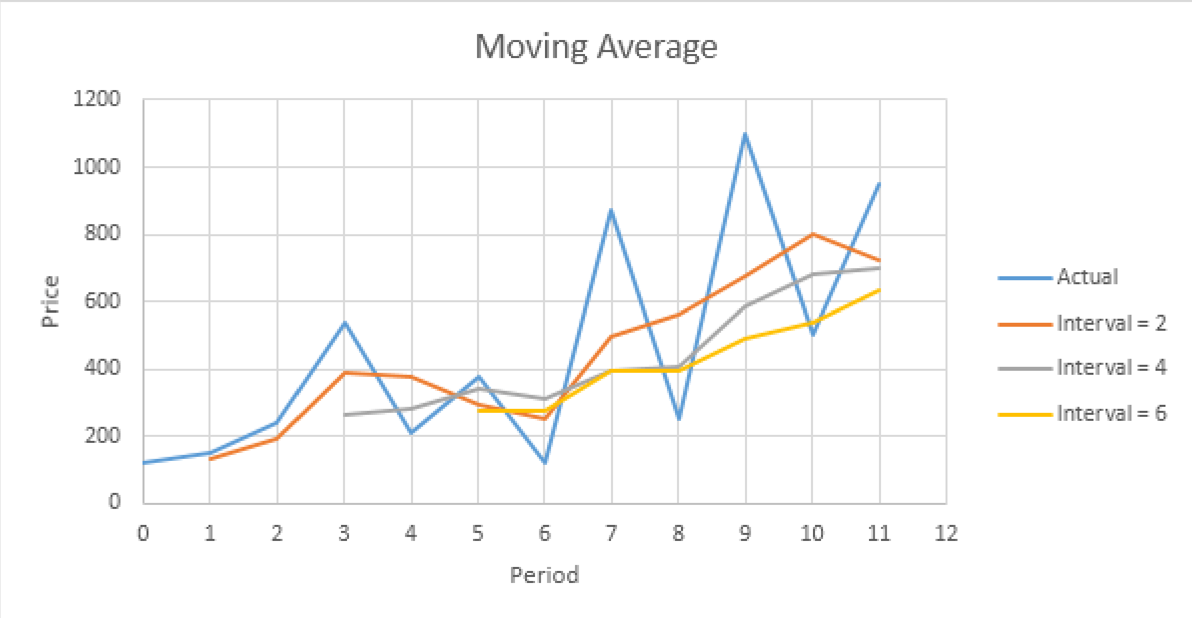
WHAT IS MOVING AVERAGE:

Traders utilise technical indicators to assist them make purchase and sell decisions. Moving averages are one such indicator that helps smooth out daily price movements in order to establish a price trend by creating a constantly updated average price. By calculating the moving average, the impact of random, short-term fluctuations on the price of a stock over a specified time frame is mitigated. basic moving averages (SMAs) take a basic arithmetic average of price over a given time period, whereas exponential moving averages (EMAs) give more weight to current prices over time.

HOW A MOVING AVERAGE (MA) WORKS:

Moving averages are constructed to indicate a stock's trend direction or support and resistance levels. It is a trend-following or lagging indicator since it is based on historical pricing. The moving average's latency increases with the length of the period. A 200-day moving average will have a far larger degree of lag than a 20-day moving average since it includes values from the previous 200 days. 200-day moving average numbers are extensively watched by investors and traders and are seen as major trend indications. Depending on their trading objectives, investors can compute moving averages across a variety of time periods. Shorter moving averages are commonly employed for short-term trends, whilst longer moving averages are more suited for long-term investors.

While it is hard to anticipate a stock's future movement, technical analysis and research can assist develop more accurate predictions. A rising moving average suggests that the security is in an uptrend, whilst a decreasing moving average indicates that it is in a downturn. Similarly, a bullish crossing happens when a short-term moving average crosses above a longer-term moving average, indicating upward momentum. In contrast, a bearish crossover confirms downward momentum when a short-term moving average crosses below a longer-term moving average.



METHODOLOGY:

TYPES OF MOVING AVERAGES

1.SIMPLE MOVING AVERAGE:

A simple moving average is a form of moving average that is calculated by taking the average of prices or values observed over a specified number of days or periods. It serves as a technical indicator in the financial market. The average or SMA values are drawn in a conversation containing asset prices to generate the SMA line as it changes. Using SMA on asset prices inside a specific range allows traders to analyse market movements, detect patterns, and establish entry or exit points. The simple moving average is a technical indicator that calculates the average value of a set of data over a specific time period. If the SMA swings higher, the market is in an uptrend. If the SMA moves downward, the market is in a downturn. Another form of moving average that is frequently compared to SMA is EMA, which gives greater weight to recent prices than SMA.

FORMULA FOR SIMPLE MOVING AVERAGE:

$$SMA = \frac{A_1+A_2+\cdots+A_n}{n}$$

Where: A_n =the price of an asset at period n

n = the number of total periods

2. EXPONENTIAL MOVING AVERAGES:

EMA is another sort of moving average that gives greater weight to the most recent price points, making it more sensitive to new data. When opposed to the SMA, the EMA is more sensitive to recent price movements since it gives equal weight to all price changes within a certain time period. An exponential moving average (EMA) is one form of moving average (MA). This emphasises the importance of the most recent data points. Exponential moving averages are also known as exponentially weighted moving averages. An exponentially weighted moving average reacts more strongly to recent price changes than a simple moving average, which assigns equal weight to all observations across the time.

FORMULA FOR EXPONENTIAL MOVING AVERAGE:

$$EMA_{TODAY} = \left(Value_{TODAY} * \left(\frac{smoothing}{1 + Days}\right)\right) + EMA_{Yesterday} * \left(1 - \left(\frac{smoothing}{1 + Days}\right)\right)$$

Where:

EMA = Exponential moving average

3. WEIGHTED MOVING AVERAGE:

The weighted moving average (WMA) is a technical indicator that traders use to determine trade direction and buy/sell decisions. It prioritises recent data points above previous data points. The weighted moving average is generated by multiplying each data point by a defined weighting factor.

Traders utilise the weighted average technique to produce trading signals. For example, when price action approaches or exceeds the weighted moving average, the single can be used to quit a trade. However, if the price movement drops near or slightly below the weighted moving average, it may indicate a good moment to initiate a trade. When all values in the data set are assigned the same weights, the weighted moving average is more accurate than the basic moving average for determining trade direction.

HOW TO CALCULATE THE WEIGHTED MOVING AVERAGE:

When computing the weighted moving average, current data points are weighted more heavily than previous data points. It is employed when the figures in a data collection have varied weights relative to one another. The total of the weights should equal one or 100%.

It differs from the simple moving average, in which all values are given equal weighting. The final weighted moving average value represents the significance of each data point, making it more descriptive of the frequency than the standard moving average.

FORMULA FOR WEIGHTED MOVING AVERAGE:

$$\text{WMA} = \frac{Price_1 \times n + Price_2 \times (n-1) + \cdots Price_n}{[n \times (n+1)]/2}$$

Where: N is the time period

Example:

Covid-19 data on (Jan-Jun 2021) with weighted moving average:

Month	New Cases	Deaths	Recoveries	WMA
Jan 2021	--	400,000	--	--
Fed 2021	20,630,023	370,000	19,500,000	--
Mar 2021	11,199,463	300,000	10,500,000	15,121,820
Apr 2021	14,782,474	5,00,000	13,500,000	15,698,569
May 2021	22,413,765	550,000	20,500,000	16,61,069
Jun 2021	19,459,191	400,000	18,000,000	18,174,468

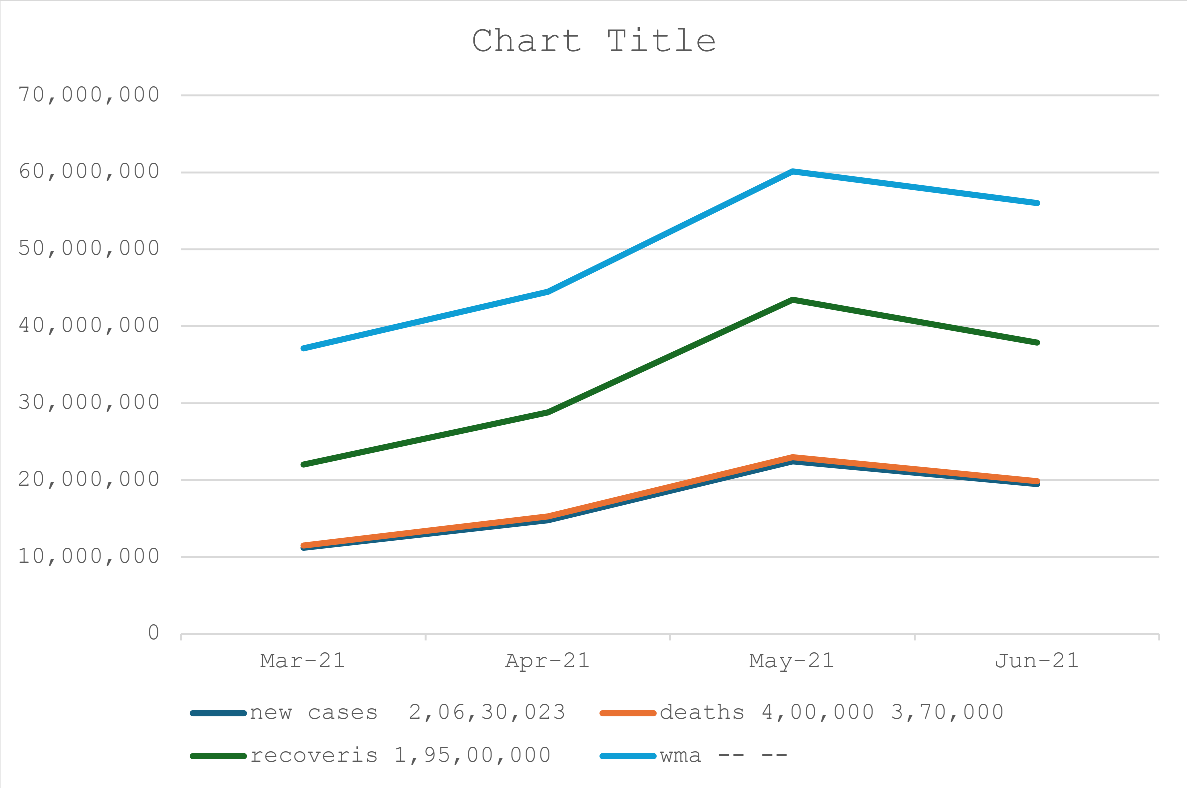
$$WMA = \frac{(M_1 \times 3) + (M_2 \times 2) + (M_3 \times 1)}{6}$$

WMA Calculation for march 2021:

$$\text{WMA} = \frac{(11{,}199{,}463\times)+(20{,}630{,}023\times 2)}{6} = \frac{33{,}598{,}389+41{,}260{,}046}{6}$$

$$= \frac{74{,}858{,}435}{6}$$

$$=12{,}476{,}406$$



REAL-LIFE APPLICATION ON WMA:

1. **Finance & Trading:**

Stock & trend analysis: Trading use linearly weighted moving average (e.g.,50-or 200- day) to detect trending momentum. Assigning heavier weight to recent price helps react faster to market shifts

Exponential MA: A Special weighted variant commonly used to generate trading signals—e.g., when short-term EMAs cross long-term ones

Volume- weighted average price: integrated prices and trading volumes to benchmark intraday performance; large traders buy below VWAP and sell above

2. **Demand forecasting & inventory management:**

Companies assign recent sales data higher weights to forecast within six months demand and optimize stock levels. Examples span warehouse, retail chain, and spare parts suppliers

A Case: assigning recent months higher weights helped a retailer pivot product line fast, reducing waste and boosting profits 18% within six months

3. **Weather & Environmental Analysis:**

Meteorologists apply WMAs to temperature, precipitation, and other climate variables to smooth data and detect trends

4. **Healthcare & Environmental:**

In clinics, WMAs smooth glucose-level readings to monitor diabetes trends Environmental scientists apply WNAs to sensor data (e.g., temperature shifts), aiding in trend identification

5. **Sports Analytics:**
   Coaches and analyst's smooth player performance data –like batting averages or running speed—by weighting recent games more heavily

6. **Policy impact Assessment:**
   By applying WMA before and after intervention (like lockdown or vaccination drives), government can measure more clearly.

7. **Short-term Forecasting:**
   WMA allows better forecasting of short-term case trends, helping hospitals and government prepare for expected surges in cases