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# Comparative analysis of dynamical and statistical models for COVID-19: A comprehensive review

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## Abstract

This paper is a review on dynamical and statistical modelling of infectious disease corona virus (COVID-19). Owing to the high population density in India, the rate social contact from human to human is high. Therefore, controlling the pandemic in early stage is quite challenging in India. For this the mathematical models are formulated to study the behaviour of the disease and identifying the parameters to reduce disease outbreak. In dynamical it is observed that most of the mathematical modelling is done based on the classical models such as SIR model, fractal SIR model, SEIR model etc., which evolves as set of differential equations and is used to estimate the rate of transmission of the COVID-19 disease. Also, statistical analysis of infectious disease and modelling as a time series models are applied to estimate the short term and long-term transmission of COVID-19 disease. From the driven data, the number of basic reproductions is calculated and studied effectiveness of the disease reported. Some precautionary measures and their effect are discussed, and predicted the future trends of rate of virus transmission with some control measures and summarized. The aim of this work is to conduct a comparative study of dynamical and statistical analysis of COVID-19.

**Keywords:** COVID-19; Dynamical and Statistical model; SIR Model; Plasma Therapy.

## 1. Introduction

This family of viruses causes illnesses ranging from mild symptoms like fever, cold, and cough to more severe diseases such as acute respiratory syndrome or Middle East respiratory syndrome. The world is currently facing an unprecedented crisis due to a novel virus. This novel coronavirus, a previously unidentified strain, causes the infectious disease known as severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2). This review discusses the dynamical modeling of infectious diseases and their time series analysis, leading to statistical modeling and forecasting using various methods. Dynamical models result in differential equations, which are complex to solve and involve large-scale computations. In contrast, statistical models rely on data analysis to visualize patterns and identify trends [1].

The compartmental dynamical transmission model for COVID-19 is formulated to mimic real-world phenomena using a set of mathematical equations. These equations vary over time and by location, and they are adjusted to reflect changes in the transmission dynamics of SARS-CoV-2. Infectious disease models are based on the transmission rates from susceptible to infected individuals, from infected to recovered, and from recovered back to susceptible. These mathematical models play a crucial role in informing disease control strategies and gradually reducing risks. Several models exist, starting from the simple susceptible-infectious-recovered (SIR) model to more complex ones. For COVID-19, transmission models have been used to simulate disease growth by calculating the basic reproduction number for all districts in India using available data. The transmission rate's impact is also studied, with higher transmission rates

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correlating to faster detection times. Various models have been used to understand the epidemic's behavior, with the SIR model helping predict the disease's spread and development [2].

In statistical analysis, COVID-19 transmission rates and control measures are estimated through data analysis and pattern recognition, aiding in prediction and prevention efforts. Time series models, based on parameter estimation and validation, make statistical analysis more efficient compared to dynamical models. These data-driven models are validated using various statistical methods based on the original data. As the virus has spread globally, governments have taken proactive measures based on forecasting results [3].

The author studied the spread of COVID-19 by collecting time series data, analyzing it, and building models to accurately predict short-term trends. However, the growth rate of COVID-19 varies by country due to factors like healthcare infrastructure, lifestyle, environmental changes, and other conditions. Consequently, the disease's transmission depends on the number of COVID-19 cases in contact with the broader population, along with regional differences in medical facilities [4].

The researcher proposed forecasting long-term COVID-19 trends using a dynamic model, which assists health authorities in managing virus transmission. They introduced the Dynamic-Susceptible-Exposed-Infective-Quarantine (D-SEIQ) model, a modified version of the Susceptible-Exposed-Infectious-Recovered (SEIR) model, to predict long-term and cumulative COVID-19 cases. The effectiveness of plasma therapy and immunotherapy for patient recovery was also examined. As lockdown restrictions were eased, the second wave of COVID-19, more infectious and severe than the first, swept through the country. In the meantime, various vaccines were developed and approved, but the large-scale production and distribution of these vaccines presented significant challenges. To control the spread of COVID-19 during vaccination efforts, specific precautionary measures were recommended. Eventually, state governments implemented second lockdowns in several regions of India. The third wave of COVID-19 has since begun, with predictions based on data from the second wave, both with and without lockdown measures [5].

## 2. Mathematical Models

### 2.1. Dynamical Models

This section covers the discussion of dynamical models such as the SIR model and the fractal SIR model used to model the spread of infectious diseases. These models rely on differential equations to describe how a disease transmits through different stages in a population: susceptible, infectious, and recovered. The classical SIR model assumes a well-mixed population, where individuals move through these compartments based on predefined rates. The fractal SIR model extends the classical model by incorporating fractal geometry, capturing more complex, real-world patterns of disease spread across different scales and environments [6].

*2.1.1. SIR model:*

The rapid spread of SARS-CoV-2 has caused widespread disruption worldwide, affecting millions of people across various countries. To understand the structure of this infectious disease and its transmission dynamics, the SIR model, a basic mathematical framework, has been developed. The SIR model is a compartmental model that divides the population into three distinct groups: **Susceptible, Infected, and Recovered**.

- **Susceptible**: Individuals who are at risk of contracting the virus.
- **Infected**: Those who have already contracted the virus and are capable of spreading it to others.
- **Recovered**: Individuals who have either recovered from the infection after receiving treatment and care or have developed immunity.

The SIR model is formulated using a system of ordinary differential equations (ODEs) that describe the interaction between these three compartments. These equations quantify how individuals move from being susceptible to becoming infected and, eventually, recovered. The model helps in predicting the progression of the virus and is crucial for assessing the impact of control measures on disease spread [7].

$$\frac{ds}{dt} = -\beta IS$$

$$\frac{dI}{dt} = \beta IS - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

In the SIR model, β represents the disease transmission rate, which determines the likelihood of the disease spreading from an infected individual to a susceptible one. γ represents the recovery rate, which is the rate at which infected individuals recover within a given period. The relationship between these two parameters is crucial in understanding the dynamics of the disease.

To assess the infectious potential of the disease, the basic reproduction number R0 is calculated using the formula R0= =γ/β. This value indicates the average number of secondary infections generated by one infected individual in a fully susceptible population. A higher transmission probability (β) results in a higher R0R_0R0, meaning the disease is more likely to spread rapidly.

When R0 is multiplied by the proportion of susceptible individuals, and the result equals 1, it indicates a balanced state, where the disease's spread neither increases nor decreases. Additionally, if we assume a proportion p of the population has immunity, the state is expressed as R0(1−p), leading to p=1−1/R0. This means that increasing the immunity of the population (through vaccination or natural immunity) can help halt the spread of the disease.

*2.1.2. Fractional SIR model*

The COVID-19 outbreak remains ongoing, and the mortality rate in 2021 surpassed that of 2020. The increase in viral transmission and death rates led to the enforcement of control measures like sanitizing infected areas, implementing lockdowns, and expanding medical facilities. In densely populated areas, the infection rate was particularly high. To study this, an SIR model was developed to analyze COVID-19 transmission across different regions in India[8]. The author proposed classical compartmental models to examine transmission rates, using parameters such as contact rate and population density. It was observed that, to fully understand the spread in large areas, the disease needed to be examined at smaller regional levels, such as districts [9].

Preventive measures and knowledge of how the disease disperses highlighted the importance of mathematical modeling in combatting COVID-19. Developing epidemic models for this purpose is a challenging task, as uncertainties in transmission must be accounted for by assigning them to different sources in related parameters. Gupta et al. used long-term climate records, including data on rainfall, wind speed, solar radiation, air temperature, and population density, to determine infection density. To forecast COVID-19 spread over 30 days in the 10 most affected Indian states, Rafiq et al. developed a prognostic model [10].

The relationship between population density and the basic reproduction number (R0R_0R0) of COVID-19 was explored by using fixed slopes and linear mixed models [11], with affirming that higher population density results in higher transmission rates. Mahajan et al. constructed the Susceptible-Exposed-Symptomatic-Purely Asymptomatic-Hospitalized-Recovered-Deceased (SIPHERD) model to assess the impact of lockdowns and the number of COVID-19 tests conducted daily, ultimately predicting total deaths, confirmed cases, and active cases. Shaik et al. used fractional-order derivatives and compartmental models to estimate the effectiveness of preventive measures [12].

The author argued that more complex models may not necessarily improve predictions compared to simpler models, supporting the use of the SIR model for COVID-19 analysis in India. Using contact rates and population density, the SIR model predicted transmission rates before and after lockdowns, with basic reproduction numbers being calculated through spatial distribution. A graphical analysis of the SIR model was performed to compare transmission with and without lockdown measures in different Indian districts [13].

## 2.2. Statistical Models

In this section, we examine statistical models that forecast both the short-term and long-term progression of COVID-19 using time series analysis. These models leverage historical data to detect trends, seasonal patterns, and fluctuations in the spread of the virus over time. By utilizing parameter estimation and validation techniques, these models can predict future infection rates, helping authorities in decision-making and planning effective interventions. Time series models, such as ARIMA (Autoregressive Integrated Moving Average), have been widely applied in this context to generate reliable short-term forecasts, while more advanced models are used for long-term projections [14].

### *2.2.1. Forecasting of COVID-19 based on time series analysis*

The Auto-Regressive Integrated Moving Average with Explanatory Variables (ARIMAX) model and exponential smoothing methods, as applied are key time series analysis tools used in forecasting COVID-19 trends. These methods identify patterns in the data to predict the number of confirmed cases and cumulative deaths. While exponential smoothing helps smooth out the data, ARIMAX is more robust for modeling, accounting for time dependencies and external factors. This makes ARIMAX particularly useful for predicting confirmed, recovery, and death rates [15].

To ensure the model's accuracy, a separate validation set of data was used. The model's performance was then tested on this data, comparing the forecasted values against actual outcomes for the same period. A suitable test was conducted during the validation period to evaluate the model's efficiency and reliability in forecasting future trends. Despite the average estimates provided by these models, the variability in outcomes remains a question, highlighting the limitations of statistical modelling in capturing all possible fluctuations [16].

### *2.2.2. Short term forecasting of COVID-19*

COVID-19 cases in India have been rising steadily. Numerous studies have shown that the virus's spread is influenced by various factors, including population density, health infrastructure, and mobility patterns. In response, the Indian government implemented several precautions and control measures to curb transmission. To make informed decisions and allocate resources effectively, different mathematical models have been employed to predict the spread of COVID-19 both within India and globally [17].

The author utilized several models, including the Gompertz growth model, logistic growth model, exponential growth model, and the ARIMAX model, to forecast the progression of the pandemic in India post-lockdown. By applying these models, they estimated the root mean square error and percentage error to assess the goodness of fit. The study forecasted the number of confirmed cumulative cases and deaths in India and its most affected states for 15 days into the future based on available data. Among the various models used, the ARIMA model was found to provide the best fit for predicting the spread of the virus in India and its highly impacted regions [18].

### *2.2.3. Long term forecasting of COVID-19*

Long-term forecasting of the COVID-19 pandemic is critical for understanding the transmission characteristics of the virus and for implementing control measures. Machine learning models developed to predict infectious disease trends often face challenges such as underfitting or overfitting due to the nature of the data. In this paper, a new model, the Dynamic-Susceptible-Exposed-Infective-Quarantined (D-SEIQ) model, is proposed. This model is a modification of the SEIR model, incorporating aspects of machine learning techniques like logistic regression to better handle long-term predictions of COVID-19[19].

The SEIR model, which relies on parameters such as the basic reproduction number R0R_0R0, incubation rate, and infectious period, is often difficult to apply accurately in real-world scenarios due to the challenge of estimating these parameters. With data inconsistencies and limitations, machine learning models can struggle with overfitting, which affects the accuracy of short-term trends. However, the D-SEIQ model addresses this by improving the forecast for extended periods of COVID-19 transmission [20].

The key distinction between the SEIR and D-SEIQ models lies in replacing the "Recovered" compartment (R) with "Quarantined" individuals (Q). Moreover, the D-SEIQ model introduces a dynamic reproduction number that varies over time, providing a more accurate reflection of the disease's spread. As COVID-19 patients are typically quarantined to prevent further transmission, this adaptation of the model improves predictive capability.

The equations formed by the D-SEIQ model reflect these updates, and the dynamic nature of the reproduction number enables more precise predictions. This makes the D-SEIQ model an effective tool for understanding long-term COVID-19 trends and aiding in the development of prevention strategies.

$$\frac{ds(t)}{dt} = -\frac{s(t)I(t)}{N}$$

$$\frac{dE(t)}{dt} = \frac{s(t)I(t)}{N} - \mathrm{E(t)}$$

$$\frac{dI(t)}{dt} = \mathrm{E(t)} - \mathrm{I(t)} - \varepsilon\mathrm{I(t)} - \mu\mathrm{I(t)}$$

$$\frac{dQ(t)}{dt} = I(t)$$

Here N= total population, i.e, N= S(t) + E(t) + I(t) + Q(t) + Ru(t) + Du(t).

$$\beta = R_t / TE$$

In this context, β represents the rate of infections, which determines how quickly the virus spreads through a population. The effective reproduction number, denoted by Rt, measures the average number of secondary infections at any given time, adjusting dynamically based on factors like intervention measures and population behavior. The average incubation period, TE, reflects the time from exposure to symptom onset, with the parameter $\sigma=1/TE$ representing the incubation rate. Similarly, $\gamma=1/TI$ indicates the quarantine rate, where TI is the infectious period. Parameters μ and ε denote the death rate and the proportion of undetected recoveries, respectively. In this study, the dynamic reproduction number Rt is generalized from the basic reproduction number R0, which applies to the early, uncontrolled phase of the pandemic. Introducing time-dependence to Rt allows for more accurate simulation and prediction of disease transmission, particularly as conditions evolve with interventions and changes in behavior.

*2.2.4. Effect of Immuno-therapy and Plasma therapy for recovery of corona-virus infected individuals*

Plasma therapy and immunotherapy have been utilized for decades in the treatment of viral infections like H1N1, SARS, and MERS. The author developed a mathematical model to analyze the transmission of COVID-19 and its recovery dynamics, focusing on key parameters like the basic reproduction number R0R_0R0. Using ordinary differential equations, the model incorporates five control measures: plasma therapy, immunotherapy, quarantine, herd immunity, and self-isolation. These interventions collectively aid in the recovery of COVID-19 patients, although some individuals still require hospitalization [21].

Bifurcation analyses and numerical simulations have been performed to understand the current pandemic. The author highlighted the transmission of COVID-19 through respiratory droplets, underscoring the importance of precautions such as hand sanitization, quarantine, and social distancing.

Several drugs have shown potential in combating COVID-19. For example, the author [22] discussed the efficacy of antibiotics like azithromycin and the antimalarial drug chloroquine. Similarly, Remdesivir has shown promising results, as observed by authors [23].

The control measures were applied together in a 50-day strategy to fight the virus. The effectiveness of self-isolation ranged from 10–32%, immunotherapy around 33%, quarantine at 21%, and plasma therapy at 10%, with the optimal time for plasma therapy being approximately 15 days post-infection. Therefore, both plasma therapy and immunotherapy have proven effective as therapeutic agents against viral infections like COVID-19.

## 2.3. Characteristics of the Second wave of COVID-19 in India

The second wave of COVID-19 hit many countries hard, including India, as lockdown measures began to ease and social activities resumed. During this period, various vaccines, such as Pfizer-BioNTech (Comirnaty), Bharat Biotech (Covaxin), Oxford-AstraZeneca (Covishield/Vaxzevria), the authors, were developed and received approval in many countries. However, the large-scale production and distribution of these vaccines posed significant challenges.

To control the spread of the virus during the vaccination drive, several measures, such as partial lockdowns, mask mandates, and social distancing, were implemented. In India, the second wave began around February 11, 2021, and presented a serious situation across the country. Evidence from past research suggests that the second wave was more contagious and spread more effectively than the first wave, even though the daily death rate initially appeared lower. However, with the rapid increase in cases, the number of daily deaths also rose [24].

According to the author effective reproduction number (Rt) for India and its states was higher during the second wave, indicating that the virus was spreading more quickly. Unlike the first wave, which mainly affected urban areas, the second wave spread throughout all states, including rural regions, necessitating lockdowns to break the chain of transmission until enough vaccines were available [25].

To assess the initial growth rates of COVID-19 infections during the first and second waves, an exponential regression model was used, analyzing data based on 7-day averaged, smoothed data. The comparison of COVID-19 infection spread across 16 states of India, using total cumulative cases, showed that the epidemic was causing unknown disruptions among the population. Therefore, a well-organized vaccination drive, administrative intervention, and public participation were crucial to flatten the curve and manage the epidemic situation effectively.

### 2.4. Third wave of COVID-19 in India

Early execution of control measures for COVID-19 effectively reduced the virus's spread during its initial stages. However, as social activities resumed with the easing of restrictions, the number of cases in India surged rapidly during the second wave. According to a World Health Organization (WHO) report, India saw 390,000 new cases in the first week of July 2021, with numbers continuing to rise daily. The peak of the second wave occurred in the second week of May 2021, with a gradual decline starting in July 2021[26].

Given the discussions and predictions regarding the second wave, there was also concern about a potential third wave in India. To predict this third wave, data from the second wave was used as the baseline. The results indicated that the third wave could start in the first week of August 2021 and potentially end by October 2021. Research by author suggested that the third wave might peak in September 2021, while a fractal model showed a possible peak in October 2021[27].

The spread of the infection in the third wave could potentially be controlled through various strategies. If these strategies were effectively implemented, they could reduce the peak and perhaps even prevent the wave from occurring at all. However, the proposed mathematical models used for these predictions were based on the available data and did not account for restrictions such as lockdowns or the impact of vaccination campaigns.

## 3. Discussion

The review highlights two main types of mathematical analyses used to study the infectious disease COVID-19. In India, and its most affected regions, simple mathematical models have been employed to understand the transmission features of COVID-19. It has been observed that existing mathematical models are often adapted and customized to examine the relative advantages of different non-pharmaceutical interventions, such as lockdowns, partial lockdowns, weekend lockdowns, quarantine, and testing, to control the spread of the disease.

Most studies focus on compartmental models like SIR (Susceptible, Infected, Recovered) and SEIR (Susceptible, Exposed, Infected, Recovered) to estimate the transmission dynamics and predict the future growth of COVID-19. To enhance the accuracy of these models, additional factors such as age classification, state healthcare preparedness, real-time transport data, and testing rates are incorporated to predict the spread of infection with greater precision.

Once a mathematical model is built using nonlinear differential equations, it must be thoroughly assessed and verified against the available data. For more accurate long-term and short-term forecasts, the model should be tested repeatedly to estimate trends. However, long-term forecasts can sometimes lead to public uncertainty and confusion among policymakers.

The review also examines different studies related to social distancing, focusing on its determinants, effectiveness in mitigating the spread of COVID-19, and compliance. Future research could include a comparative study on dynamical and statistical analysis to understand the transmission fitness of any novel virus better.

## 4. Conclusion

The aim of this work is to compare and conduct further research on the infectious disease COVID-19 by examining various mathematical models and methods. In the comparative study of the literature, the following models and methods are discussed:

- A dynamical compartmental model based on the SIR model is used to estimate the spread of the coronavirus (COVID-19), and to determine the number of infected individuals as well as those who have recovered or died.
- In contrast, statistical modeling of COVID-19 through time series analysis relies on the latest collected data, whereas a dynamic model's time series analysis is based on the inherent patterns within the data itself. Therefore, accurate and sufficient data is essential to detect the disease in its early stages for short-term forecasts. This model uses data collected at specific times to determine the basic reproduction number, recovery rate, and infection rate of the coronavirus, revealing significant changes in virus spread among the population. Among the four models considered, the ARIMA model is found to be the best fit for forecasting the available data.

- The D-SEIQ model is applied under conditions such as adequate medical capacity, timely detection and reporting, and consistent containment measures. Thus, a new methodology for estimating the long-term trend of COVID-19 is proposed, with parameters from this model proving valuable for analyzing and combating new epidemic diseases.
- A significant level of the COVID-19 outbreak can be controlled within three weeks by implementing all control measures simultaneously. This approach increases recovery rates and reduces hospitalization. While immunotherapy is effective for hospitalized individuals, the long-term benefits of plasma therapy are still being observed. Vaccines are now widely available across India, and getting vaccinated is crucial because it is safe, effective, and reduces the risk of severe illness, helping to fight against COVID-19.

## Compliance with ethical standards

### *Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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