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Machine Learning for Markov Modeling of COVID-19 Dynamics Concerning Air Quality Index, PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3

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ABSTRACT

In this research Python machine learning module sklearn has been utilized to solve the Markov model. Markov modelling of the COVID-19 dynamics with air quality index (AQI), PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively. Data of the Chhattisgarh state of India has been analyzed in two phases. In phase-1 the time duration is from March 15, 2020, to May 01, 2020, and for phase-2 it is from Jun 01, 2020, to Jul 15, 2020. It has been noticed that initially change in AQI from 103 to 84.83 changed disease dynamics, and the first cases of COVID-19 reported. In the next two fortnights March 15, 2020, and April 01, 2020, the dynamics are the same, later the AQI change from 84.83 to 63.83, but no change reported disease dynamics from April 15, 2020, to Jul 15, 2020. In phase 1, a cyclic trend has been observed for changes concerning PM-$_{2.5}$. The trends for PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively are same, but for O_3 it is different. COVID-19 reports a negative correlation with AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$. Moreover, a positive correlation with O_3. This proves that the lockdown and ban on transport activities improved AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, but not O_3.

1. INTRODUCTION

Novel corona virus initially originated from Wuhan City, Hubei Province, of China. The first case reported by the World Health Organization was on 31 December 2019. The corona virus pandemic has reported a huge number of losses in terms of life and economic sabotage. All the nations of the World have fulfilled their corporate social responsibility by implementing strict safety measures to reduce its effects. Scientists around the world are striving untiringly to investigate the true nature and the remedy of the COVID-19 virus. The most dangerous effect of corona virus infection is its presence without symptoms at the initial stages and thereafter requiring a long duration of isolation [1] and now Cytokine's storm caused by the virus is the most serious challenge before the scientific world which is the main reason for organs dysfunctions and mortality.

Machine learning is a field of study concerning the development of statistical based learning algorithms. Machine learning models learn from data and then generalize the unseen data so that no explicit instructions are required. Different techniques of machine learning have been adopted to model the disease spreads, disease diagnostics and suggesting medications for various diseases. Uncertainty in system modeling is an important aspect to address. Many authors in the World tried to model uncertainty in the modeling process. Khan et al. [2-4] incorporated uncertainty in system modeling. Khan and Rafique [5] used fuzzy uncertain information to model the aviation network of US airline. Khan and Karam [6] used DEA models to address the performance of the US Airlines. In the research [7], adoptive techniques were adopted to solve linear programming models. Machine leaning approach was adopted in the study [8] to address the adsorption removal in textile wastewater. In the study [9], machine learning approach was adopted to delay problem in aviation network. Thus, it is clear that the machine learning techniques have positively used in the literature for system modeling.

A positive correlation between the air pollution index and COVID-19 cases has been reported from different parts of the world [10]. It is believed that the air pollution is one of the major contributors for unnatural death across the world and about 8% of total death, especially in Asia, Africa, and Europe occurs due to air pollution, and nearly 91% population of the world are living in a polluted environment (WHO, 2016). Air pollution-induced cardiovascular failure, respiratory failure, and finally death has been reported [11, 12]. The primary target of COVID-19 is the lungs which cause potential alveolar damage which leads to asphyxia and finally death [13].

In this study changes in air quality due to lockdown using machine learning in Buenos Aires, Argentina is reported. Lovrić et al. [14] used machine learning techniques to compare the concentrations recorded in the normal situations and lockdown for PM_1, $PM_{2.5}$, and PM_{10}, in Zargeb, Croatia. Mehmood et al. [15] presented the advantages of using machine learning techniques for predicting air quality. Kazi et al. [16] studied the relationship among $PM_2.5$, PM_{10}, SO_2, NO_2, NO and CO using linear regression model in R language. Méndez et al. [17] proposed a survey of the machine learning approaches for predicting air quality. Islam et al. [18] used machine learning approaches for predicting $PM_{2.5}$ in Dhaka, Bangladesh. Zukaib et al. [19] studied the impact of air quality on the cases of COVID-19.

It has been also reported that the serious damage of cardiac tissue at both histological and physiological levels is being caused by the COVID-19 virus up to a fatal level. Thus, there is sufficient evidence that air pollutants accelerate present pandemic and lethality. There is no doubt that human is the main contributor in air pollution and with the suspension of human activities during lockdown period the air quality improvement was expected and reported, but the impact of improved air quality and dynamics of COVID-19 pathogenicity has not been studied properly.

Now it is a serious challenge before us to plan a methodology to stop the transmission of virus because still we do not have any effective tool to protect the population. In this condition, the mathematical modeling may be helpful to understand the transmission dynamics of SARS-CoV-2 and will be helpful for future planning. As per the report of WHO, 2002, around 26% of worldwide mortality in 2001 was caused by infectious disease. In recent past sudden increase in infectious disease viz. SARS-CoV in 2003, Mers-CoV in 2012, Ebola in 2014, and SARS-CoV-2 in 2019 have posed a serious threat before human civilization and thus prediction and understanding about the dynamics of the epidemic is nowadays an urgent need of the hour. A proper understanding of disease dynamics may be helpful for its effective control and elimination. The SIR (Susceptibility, infected, and recovered) model may be extremely helpful for the protection of human life. In India, four major epidemiology models are being practiced. The first model is developed by the Indian Council of Medical Research (ICMR); the second model by the University of Michigan; the third by John Hopkins University and the fourth one is the model proposed by Cambridge University. Some objections have been raised about the above models with the arguments that the above models have not considered larger population size and population driving factors.

A review of the literature depicts that Markov model of the COVID-19 dynamics have never been addressed with the help of machine learning approach. In this study machine learning technique is adopted for Markov modelling of the COVID-19 dynamics with variations in AQI, $PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$, and O_3, respectively. The long-run dynamics of the novel corona virus infection dynamics are investigated related to changes in AQI, $PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$, and O_3, respectively, in the Chhattisgarh state of India. The present study is an attempt to addresses the following objectives.

(1) To formulate the Markov model of the long-run dynamics of the novel corona virus infections concerning changes in the AQI ($PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$, and O_3) the Chhattisgarh state of India.

(2) To solve the formulate model in step 1 using Machine learning techniques.

(3) To address the initial dynamics of the novel corona virus infections related to changes in $PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$, and O_3 levels in the Chhattisgarh state of India based on the initial transition matrix.

The study is supposed to answer the following hypothesis.

(1) There is a direct relation between AQI and the cases of COVID-19 cases.

(2) $PM\text{-}_{2.5}$ level and the cases of COVID-19 cases are positively related.

(3) There is positive relation between NO_2 level and COVID-19 cases.

(4) $PM\text{-}_{10}$ level and COVID-19 cases have a direct relation.

(5) O_3 level and COVID-19 cases are directly related.

In the present study, the Markov process is elaborated in Section 2. In Section 3, the Markov process is implemented for addressing the long-run disease dynamics concerning changes in AQI levels. In Section 4, the proposed machine learning for Markov model of the long-run disease dynamics concerning changes in $PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$, and O_3 levels, respectively is presented. In Section 5, the results obtained for addressing the long-run disease dynamics concerning changes in AQI levels analyzed and discussed. In Section 6, the results obtained for the disease dynamics concerning changes in $PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$, and O_3 levels, respectively are analyzed. Correlation of COVID-19 Infections concerning $PM\text{-}_{2.5}$, NO_2, $PM\text{-}_{10}$ and O_3 is presented in Section 7. Finally, the findings have been concluded in Section 8.

2. MARKOV PROCESS AND EIGEN SPACE DECOMPOSITION

Markov chain is a process where the future state of a system can be predicted based on its current state. A transition matrix is an $n*n$ two dimensions array of elements having n rows and n columns and it is denoted as $T = [t_{ij}]$, $1 \le i \le n$, $1 \le j \le n$. The column matrix "u" given in (1) is called the long-run vector.

$$u = \begin{bmatrix} u_1 \\ u_2 \\ . \\ . \\ . \\ u_n \end{bmatrix}, 1 \le i \le n \tag{1}$$

One of the characteristic properties of the transition matrix is to determine the system states at future times by knowing the current state. Assume if $x^{(k)}$ denote the state vector at any time "k", where $x^{(0)}$ is the initial state, denoted as (2).

$$x^{(k)} = \begin{bmatrix} p_1^{(k)} \\ p_2^{(k)} \\ . \\ . \\ . \\ p_n^{(k)} \end{bmatrix}, 0 \le k \tag{2}$$

Theorem (1) helps to identify the future state of Markov's Process.

Theorem 1: If "T" is the transition matrix of a Markov process, the future state $x^{(k+1)}$ can be found from the knowing of the state $x^{(k)}$ as in (3).

$$x^{(k+1)} = Tx^{(k)} \tag{3}$$

Proof:
From Eq. (3), we can find (4).

$$x^{(1)} = Tx^{(0)} \tag{4}$$

$$x^{(2)} = Tx^{(1)} \tag{5}$$

Put Eq. (4) in Eq. (5).

$$x^{(2)} = Tx^{(1)} = TT(x)^0 = T^2(x)^0 \tag{6}$$

$$x^{(3)} = Tx^{(2)} = TT^2(x)^0 = T^3(x)^0 \tag{7}$$

Continuing in this way, we finally get Eq. (8).

$$x^{(n)} = T^n x^{(0)} \tag{8}$$

This completes the proof.

Definition 1: Given a transition matrix "T", as $n \to \infty$, T^n approaches (9) [20].

$$A = \begin{bmatrix} u_1 & u_1 & \cdot & \cdot & \cdot & u_1 \\ u_2 & u_2 & \cdot & \cdot & \cdot & u_2 \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ u_n & u_n & & & & u_n \end{bmatrix} \tag{9}$$

Theorem 2: Given "T" is the transition matrix and "A" and "u" satisfy Definition 1, then (a) and (b) holds.

(a) For a transition matrix "x", $T^n x \to u$ as $n \to \infty$, "u" is called the steady-state vector.

(b) The steady-state vector "u" is uniquely satisfying $Tu = u$.

Proof:

(a) Let consider the matrix (10).

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{bmatrix} \tag{10}$$

We know from Definition 1, that as $n \to \infty$, $T^n \to A$, giving $T^n x \to Ax$. Using (9) and (10) we can construct (11).

$$Ax = \begin{bmatrix} u_1 & u_1 & \cdot & \cdot & \cdot & u_1 \\ u_2 & u_2 & \cdot & \cdot & \cdot & u_2 \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ u_n & u_n & & & & u_n \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{bmatrix} \tag{11}$$

$$Ax = \begin{bmatrix} u_1x_1 + u_1x_2 + & \cdot & \cdot & \cdot & +u_1x_n \\ u_2x_1 + u_2x_2 + & \cdot & \cdot & \cdot & +u_2x_n \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ \cdot & & & & \cdot \\ u_nx_1 + u_nx_2 + & \cdot & \cdot & \cdot & +u_nx_n \end{bmatrix} \tag{12}$$

Also, $(x_1 + x_2 + \ . \ . \ . \ + x_n) = 1$ thus (12) can be written as (13).

$$Ax = \begin{bmatrix} u_1(x_1 + x_2 + \cdot \cdot \cdot + x_n) \\ u_2(x_1 + x_2 + \cdot \cdot \cdot + x_n) \\ \cdot \\ \cdot \\ \cdot \\ u_n(x_1 + x_2 + \cdot \cdot \cdot + x_n) \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \\ \cdot \\ \cdot \\ u_n \end{bmatrix} \tag{13}$$

Eq. (13) proves $T^n x \to u$.

(b) We have $T^n \to A$ as $n \to \infty$, which means $T^{n+1} \to A$. Knowing $T^{n+1} = T^n \cdot T$. Thus $T^{n+1} \to A$, so $TA = A$. Thus we can write $Tu = u$.

Moreover, it is required that "u" is unique. Suppose "v" is another matrix such that $Tv = v$. From part (a) we know, $T^n v \to u$. Moreover, $Tv = v$ implying $T^n v = u, \forall n$, so u=v.

If the transition matrix $T = [t_{ij}]$, $1 \le i \le n$, $1 \le j \le n$, of a Markov process, then for variables "x", when $n \to \infty$, $T^n x \to u$, where, u denotes steady-state vector. Note that the steady-state vector satisfies (14).

$$Tu = u \tag{14}$$

$$Tu = I_n u \tag{15}$$

$$I_n u - Tu = 0 \tag{16}$$

$$(I_n - T)u = 0 \tag{17}$$

The modeled Eq. (17) is referred to as the eigen space of the transition matrix "T". Solving (17), we can determine the eigen space decomposition of the matrix "T". Python machine learning module sklearn is adopted to solve the Markov model (17).

3. PROPOSED MACHINE LEARNING FOR MARKOV MODEL OF COVID-19 CASES WITH AIR QUALITY INDEX (AQI)

This section is dedicated to studying the effects of the air quality index on the COVID-19 dynamics in the Chhattisgarh state of India. The fortnightly data of the AQI level and disease confirmed cases are shown in Table 1.

From the data given in Table 1 the transition matrix of the corona virus infection (Tex translation failed) concerning the air quality index (AQI) can be formulated as in Eq. (18).

The transition matrix T_{AQI} in show the matrix of average change in the cases of COVID-19 with average change in the AQI level spanned over different fortnights. It is worth noting that matrix (18) is not the probabilities, it the matrix showing the change in the COVID-19 with respect to change in AQI. Eq. (19) models the eigen space decomposition of the COVID-19 concerning the air quality index in the Chhattisgarh state of India.

Solving Eq. (21) with help of Python machine learning module sklearn we get the eigen values as shown in the program run file given below. The gradient decent optimizer of the Python machine learning module sklearn is utilized to report the following solution for the Markov's model developed in (21).

Table 1. Average air quality index of the Chhattisgarh state and cases of corona virus infections

Month	**Average Air Quality Index of the Chhattisgarh State (μg/m^3)**	**Cases of Corona Virus Infections**
Mar-01	103	0
Mar-15	84.83	1
Apr-01	63.83	8
Apr-15	64.61	33
May-01	101.05	40
May-15	67.16	60
Jun-01	56.16	498
Jun-15	35.83	1715
Jul-01	43.66	2660
Jul-15	29.33	4379
Jul-20		5407

$$T_{AQI}=\begin{bmatrix} \text{State} & 103 & 84.83 & 63.83 & 64.61 & 101.05 & 67.16 & 56.16 & 35.83 & 43.66 & 29.33 \\ 103 & 1 & -0.055 & -0.025 & -0.0260 & -0.5128 & -0.0278 & -0.0213 & -0.01488 & -0.0168 & -0.2135 \\ 84.83 & 0.3852 & 1 & -0.3333 & -0.3461 & 0.4315 & -0.3961 & -0.2441 & -0.1428 & -0.1700 & -0.1261 \\ 63.83 & 0.6382 & 1.189 & 1 & 32.05 & 0.6716 & 7.50 & -3.25 & -0.8928 & -1.23 & -0.7246 \\ 64.61 & 0.1823 & 0.3461 & -8.97 & 1 & 0.1920 & 2.745 & -0.8284 & -0.2432 & -0.3341 & -0.1984 \\ 101.05 & 10.25 & -1.233 & -0.5373 & -0.5488 & 1 & -0.590 & -0.4455 & -0.3066 & -0.3484 & -0.2788 \\ 67.16 & 12.22 & 24.787 & -131.53 & -171.76 & 12.92 & 1 & -39.81 & -13.98 & -18.63 & -11.57 \\ 56.16 & 25.98 & 42.44 & 158.67 & 144.02 & 27.11 & 110.3 & 1 & -59.86 & -97.36 & -45.35 \\ 35.83 & 14.06 & 19.28 & 33.75 & 32.83 & 14.48 & 30.16 & 46.48 & 1 & 120.68 & -145.38 \\ 43.66 & 28.98 & 41.75 & 85.22 & 82.05 & 29.95 & 73.14 & 137.52 & -219.54 & 1 & -119.95 \\ 29.33 & 13.95 & 18.52 & 29.79 & 29.13 & 14.33 & 27.17 & 38.31 & 158.15 & 71.73 & 1 \end{bmatrix} \quad (18)$$

$$\left(\lambda I_n - T_{AQI}\right)u = 0 \quad (19)$$

$$\left(\lambda\begin{bmatrix} 1&0&0&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0&0&0 \\ 0&0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0&0 \\ 0&0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&0&1 \end{bmatrix} - \begin{bmatrix} 1 & -0.055 & -0.025 & -0.0260 & -0.5128 & -0.0278 & -0.0213 & -0.01488 & -0.0168 & -0.2135 \\ 0.3852 & 1 & -0.3333 & -0.3461 & 0.4315 & -0.3961 & -0.2441 & -0.1428 & -0.1700 & -0.1261 \\ 0.6382 & 1.189 & 1 & 32.05 & 0.6716 & 7.50 & -3.25 & -0.8928 & -1.23 & -0.7246 \\ 0.1823 & 0.3461 & -8.97 & 1 & 0.1920 & 2.745 & -0.8284 & -0.2432 & -0.3341 & -0.1984 \\ 10.25 & -1.233 & -0.5373 & -0.5488 & 1 & -0.590 & -0.4455 & -0.3066 & -0.3484 & -0.2788 \\ 12.22 & 24.787 & -131.53 & -171.76 & 12.92 & 1 & -39.81 & -13.98 & -18.63 & -11.57 \\ 25.98 & 42.44 & 158.67 & 144.02 & 27.11 & 110.3 & 1 & -59.86 & -97.36 & -45.35 \\ 14.06 & 19.28 & 33.75 & 32.83 & 14.48 & 30.16 & 46.48 & 1 & 120.68 & -145.38 \\ 28.98 & 41.75 & 85.22 & 82.05 & 29.95 & 73.14 & 137.52 & -219.54 & 1 & -119.95 \\ 13.95 & 18.52 & 29.79 & 29.13 & 14.33 & 27.17 & 38.31 & 158.15 & 71.73 & 1 \end{bmatrix}\right) \cdot \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \\ u_7 \\ u_8 \\ u_9 \\ u_{10} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (20)$$

$$\left(\begin{bmatrix} \lambda-1 & 0.055 & 0.025 & 0.0260 & 0.5128 & 0.0278 & 0.0213 & 0.01488 & 0.0168 & 0.2135 \\ -0.3852 & \lambda-1 & 0.3333 & 0.3461 & -0.4315 & 0.3961 & 0.2441 & 0.1428 & 0.1700 & 0.1261 \\ -0.6382 & -1.189 & \lambda-1 & -32.05 & -0.6716 & -7.50 & 3.25 & 0.8928 & 1.23 & 0.7246 \\ -0.1823 & -0.3461 & 8.97 & \lambda-1 & -0.1920 & -2.745 & 0.8284 & 0.2432 & 0.3341 & 0.1984 \\ -10.25 & 1.233 & 0.5373 & 0.5488 & \lambda-1 & 0.590 & 0.4455 & 0.3066 & 0.3484 & 0.2788 \\ -12.22 & -24.787 & 131.53 & 171.76 & -12.92 & \lambda-1 & 39.81 & 13.98 & 18.63 & 11.57 \\ -25.98 & -42.44 & -158.67 & -144.02 & -27.11 & -110.3 & \lambda-1 & 59.86 & 97.36 & 45.35 \\ -14.06 & -19.28 & -33.75 & -32.83 & -14.48 & -30.16 & -46.48 & \lambda-1 & -120.68 & 145.38 \\ -28.98 & -41.75 & -85.22 & -82.05 & -29.95 & -73.14 & -137.52 & 219.54 & \lambda-1 & 119.95 \\ -13.95 & -18.52 & -29.79 & -29.13 & -14.33 & -27.17 & -38.31 & -158.15 & -71.73 & \lambda-1 \end{bmatrix}\right) \cdot \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \\ u_7 \\ u_8 \\ u_9 \\ u_{10} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (21)$$

runfile('C:/Users/Ehsan/.spyder-py3/temp.py', wdir='C:/Users/Toshiba/.spyder-py3')

[0.25137211+269.603379j 0.25137211-269.603379j 1.20795455+104.37879212j 1.20795455-104.37879212j 1.41174851+32.71252034j 1.41174851-32.71252034j 1.62399294+3.23631201j 1.62399294-3.23631201j 0.50493189+1.20088642j 0.50493189-1.20088642j]

The corresponding eigen space is give below in python program runfile.

runfile('C:/Users/Ehsan/.spyder-py3/temp.py', wdir='C:/Users/Toshiba/.spyder-py3')

[0.25137211+269.603379j 0.25137211-269.603379j

[9.32594206e-05-4.33783496e-05j 9.32594206e-05+4.33783496e-05j
5.15105486e-04-6.16206590e-04j 5.15105486e-04+6.16206590e-04j
-2.95210718e-03+4.97001251e-03j -2.95210718e-03-4.97001251e-03j
-5.46487389e-02+6.53587008e-02j -5.46487389e-02-6.53587008e-02j
8.48866277e-02+1.60693406e-03j 8.48866277e-02-1.60693406e-03j]
[4.77093239e-05+6.23698503e-04j 4.77093239e-05-6.23698503e-04j
8.25279752e-04-2.02434977e-03j 8.25279752e-04+2.02434977e-03j
-3.61688735e-03+6.28184619e-03j -3.61688735e-03-6.28184619e-03j
6.05143864e-02+5.96991228e-02j 6.05143864e-02-5.96991228e-02j
5.11313568e-02+2.44398974e-01j 5.11313568e-02-2.44398974e-01j]
[1.75794669e-03+5.66361516e-03j 1.75794669e-03-5.66361516e-03j
-2.91305369e-02-1.83967222e-02j -2.91305369e-02+1.83967222e-02j
-8.93964292e-03-1.45665309e-01j -8.93964292e-03+1.45665309e-01j
1.47439956e-01-8.00542150e-03j 1.47439956e-01+8.00542150e-03j
1.39866167e-01-2.77316566e-04j 1.39866167e-01+2.77316566e-04j]
[5.02757782e-04+1.58039634e-03j 5.02757782e-04-1.58039634e-03j
-7.88965875e-03-7.71389291e-03j -7.88965875e-03+7.71389291e-03j
5.23782798e-02-3.51401601e-02j 5.23782798e-02+3.51401601e-02j
-9.66502337e-02+4.24311422e-02j -9.66502337e-02-4.24311422e-02j
-1.14377611e-01+1.69986941e-02j -1.14377611e-01-1.69986941e-02j]
[2.63939859e-04+1.23137334e-03j 2.63939859e-04-1.23137334e-03j
9.14892894e-04-3.78954396e-03j 9.14892894e-04+3.78954396e-03j
-5.86746773e-03+1.05177189e-02j -5.86746773e-03-1.05177189e-02j
1.50977618e-01+3.45604122e-01j 1.50977618e-01-3.45604122e-01j
-2.82296530e-01-1.87691619e-01j -2.82296530e-01+1.87691619e-01j]
[-3.00539422e-03+7.96984546e-02j -3.00539422e-03-7.96984546e-02j
-1.60952084e-02-3.24995953e-01j -1.60952084e-02+3.24995953e-01j
3.82300573e-01+2.36400816e-01j 3.82300573e-01-2.36400816e-01j
3.76387989e-01-1.71265407e-01j 3.76387989e-01+1.71265407e-01j
4.66110948e-01-7.05657507e-02j 4.66110948e-01+7.05657507e-02j]
[1.97441548e-01+2.58104409e-01j 1.97441548e-01-2.58104409e-01j
-6.55321573e-01+0.00000000e+00j -6.55321573e-01-0.00000000e+00j
-3.00486585e-01+2.72072492e-01j -3.00486585e-01-2.72072492e-01j
-3.08052737e-01-1.85951023e-02j -3.08052737e-01+1.85951023e-02j
-2.73133553e-01+2.76245203e-03j -2.73133553e-01-2.76245203e-03j]
[2.40476322e-01-4.55764974e-01j 2.40476322e-01+4.55764974e-01j
-8.07288211e-02-3.29823300e-01j -8.07288211e-02+3.29823300e-01j
-2.79939180e-01+1.90652195e-02j -2.79939180e-01-1.90652195e-02j
-2.53791134e-01-7.19302442e-03j -2.53791134e-01+7.19302442e-03j
-2.36739698e-01-2.09770937e-04j -2.36739698e-01+2.09770937e-04j]
[6.72441831e-01+0.00000000e+00j 6.72441831e-01-0.00000000e+00j
1.35297091e-01+3.60492639e-01j 1.35297091e-01-3.60492639e-01j
5.47825474e-01+0.00000000e+00j 5.47825474e-01-0.00000000e+00j
5.27347068e-01+0.00000000e+00j 5.27347068e-01-0.00000000e+00j
5.03337385e-01+0.00000000e+00j 5.03337385e-01-0.00000000e+00j]
[-2.22706975e-01-3.47377578e-01j -2.22706975e-01+3.47377578e-01j
-3.45526665e-01+2.83537188e-01j -3.45526665e-01-2.83537188e-01j
4.51477148e-01+1.59574064e-01j 4.51477148e-01-1.59574064e-01j
4.48455654e-01+2.05894360e-02j 4.48455654e-01-2.05894360e-02j
4.19900200e-01+5.84583950e-03j 4.19900200e-01-5.84583950e-03j]]

These results are further discussed and analyzed in section 5.

4. PROPOSED MACHINE LEARNING FOR MARKOV MODEL OF COVID-19 CASES CONCERNING PM-$_{2.5}$, NO_2, PM-$_{10}$, AND O_3

This study was conducted in two phases. In phase-1, the disease dynamics concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively were studied from March 15, 2020, to May 01, 2020, in the state of Chhattisgarh. In phase-2, Corona dynamics concerning PM-$_{2.5}$, NO2, PM-$_{10}$, and O_3, respectively were studied from June 1, 2020, to July 15, 2020, in the state of Chhattisgarh. The levels of PM-$_{2.5}$, NO_2, PM-$_{10}$ and O_3, in phase-1 are in Table 2.

Table 2. Average level of PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 for Chhattisgarh state and cases of corona virus infections

Time	Average Level of PM-$_{2.5}$	Average Level of NO_2	Average Level of PM-$_{10}$	Average Level of O_3	Cases of Corona Virus Infections
Mar-15	102	47	95	4	1
Apr-01	61	58	47	4.5	8
Apr-15	58	59	49	5	33
May-01	119	64	117	5.5	40
May-15	69	57	58	6	60
Jun-01	42	42	36	12	498
Jun-15	23	34	16	20	1715
Jun-30	29	39	22	7	2660
Jul-15	18	30	14	3	4379

Table 3. Transition matrix for average number of corona virus cases concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 in phase-1 for Chhattisgarh state

Time	Change in Average COVID Cases w. r. t Change in Average Level of $PM_{2.5}$	Change in Average COVID Cases w. r. t Change in Average Level of NO_2	Change in Average COVID Cases w. r. t Change in Average Level of PM_{10}	Change in Average COVID Cases w. r. t Change in Average Level of O_3
Mar-15	-0.5	-0.1428	-0.5	-1
Apr-01	-0.1707	0.6363	-0.1458	14
Apr-15	-8.333	25	12.5	50
May-01	0.1147	1.4	0.1029	14

Table 4. Transition matrix for average number of corona virus cases concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 in phase-2 for Chhattisgarh state

Time	Change in Average COVID Cases w. r. t Change in Average Level of $PM_{2.5}$	Change in Average COVID Cases w. r. t Change in Average Level of NO_2	Change in Average COVID Cases w. r. t Change in Average Level of PM_{10}	Change in Average COVID Cases w. r. t Change in Average Level of O_3
Jun-01	-16.22	-29.2	-19.9	73
Jun-15	-64.05	-152.12	-60.85	152.12
Jun-30	157.5	189	157.5	-72
Jul-15	-156.27	-191	-214.87	-429.75

The information is given in Table 2 is used to formulate the transition matrix for phase-1 as shown in Table 3 and Eq. (22).

$$T_1 = \begin{bmatrix} -0.5 & -0.1428 & -0.8 & -1 \\ -0.1707 & 0.6363 & -0.1458 & 14 \\ -8.333 & 25 & 12.5 & 50 \\ 0.1147 & 1.4 & 0.1029 & 14 \end{bmatrix} \tag{22}$$

The transition matrix in (22) show the matrix of average change in the cases of COVID-19 with average change in the PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 spanned over different fortnights. It is worth noting that matrix (22) does not denote the probabilities, it the matrix showing the change in the COVID-19 with respect to change in AQI. The situation is also shown in Table 3. The eigen space for (22) is given as (23).

$$\left(\lambda I_n - T_1\right)u = 0 \tag{23}$$

$$\left(\lambda \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} -0.5 & -0.148 & -0.8 & -1 \\ -0.1707 & 0.636 & -0.158 & 14 \\ -8333 & 25 & 125 & 50 \\ 0.1147 & 1.4 & 0.1029 & 14 \end{bmatrix}\right)\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{24}$$

Eq. (24) reduces to (25).

$$\left(\begin{bmatrix} \lambda + 055 & 0.1428 & 0.8 & 1 \\ 0.1707 & \lambda - 0.636 & 0.1458 & -14 \\ 8.333 & -25 & \lambda - 125 & -50 \\ -0.1147 & -1.4 & -0.1029 & \lambda - 14 \end{bmatrix}\right)\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{25}$$

Python machine learning module sklearn solves the model (25) and the results are presented below. The gradient decent optimizer of the Python software is utilized to report the following solution for the Markov's model developed in (25).

runfile('C:/Users/Ehsan/untitled0.py', wdir='C:/Users/Toshiba')
[-0.59830406+0.4925565j -0.59830406-0.4925565j 11.1152819 +0.j
16.71762621+0.j]

Furthermore, the eigen space is given in the program run file below.

runfile('C:/Users/Ehsan/untitled0.py', wdir='C:/Users/Toshiba')
[[0.10057133+0.59609944j 0.10057133-0.59609944j-0.04110036+0.j-0.03265455+0.j]
[-0.36931397+0.27075848j-0.36931397-0.27075848j-0.03556054+0.j 0.04164904+0.j]
[0.65039065+0.j 0.65039065-0.j 0.998382+0.j 0.99692292+0.j]

[0.03104194-0.02960238j 0.03104194+0.02960238j-0.01672071+0.j 0.05782493+0.j]]

This completes the results of phase-1. These results are analyzed and discussed later in section 6.

Based on Table 2, we construct the transition matrix of change in corona virus infections concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively, given in Table 4 and Eq. (26).

$$T_2 = \begin{bmatrix} -16.22 & -29.2 & -19.9 & 73 \\ -64.05 & -152.12 & -60.85 & 152.12 \\ 157.5 & 18.9 & 157.5 & -72 \\ -156.27 & -191 & -214.87 & -429.75 \end{bmatrix} \quad (26)$$

The transition matrix in (26) show the matrix of average change in the cases of COVID-19 with average change in the PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 spanned over different fortnights. It is worth noting that matrix (26) does not denote the probabilities, it the matrix showing the change in the COVID-19 with respect to change in AQI. The situation is also shown in Table 4. The eigen space for (26) is given as (27).

$$(\lambda I_n - T_2)u = 0 \quad (27)$$

$$\left(\lambda \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -1622 & -292 & -199 & 13 \\ -6105 & -122 & -60.8 & 122 \\ 157.5 & 189 & 1575 & -12 \\ -16627 & -191 & -21487 & -29.5 \end{bmatrix}\right) \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (28)$$

Eq. (28) further reduces to (29).

$$\left(\begin{bmatrix} \lambda + 16.22 & 29.2 & 19.9 & -73 \\ 64.05 & \lambda + 152.12 & 60.85 & -15212 \\ -157.5 & -189 & \lambda - 157.5 & 72 \\ 156.27 & 191 & 214.87 & \lambda + 429.75 \end{bmatrix}\right) \cdot \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad (29)$$

Solution of (29) by the sklearn module of the Python is presented in the following run file.

The gradient decent optimizer of the Python module sklearn is utilized to report the following solution for the Markov's model developed in (29).

runfile('C:/Users/Ehsan/untitled0.py', wdir='C:/Users/Toshiba')

[-414.13840934 115.09774881-6.60203666-134.94730281]

Moreover the eigen space is give in the following run file.

runfile('C:/Users/Ehsan/untitled0.py', wdir='C:/Users/Toshiba')

[[-0.139249-0.0838735 0.69179567-0.02729547]
[0.4223546 0.36495388 0.07238706-0.81164678]
[-0.21091667-0.89334181-0.7145629 0.56998975]
[-0.87048289 0.24842366 0.07469088 0.12488454]]

These results are discussed and analyzed in section 6.

5. DISCUSSION AND ANALYSIS ON THE DYNAMICS OF COVID-19 INFECTIONS WITH AIR QUALITY INDEX (AQI)

This section is dedicated to discuss and analyze the long-run disease dynamics of the COVID-19 concerning changes in the air quality index. The results obtained in section 3 have been presented through graphical analysis to analyze the disease dynamics in association with the air quality index. The first evidence which is the characteristic property of the eigen space decomposition is the stable and long-run behavior of the disease, this means that the behavior of the disease has not changed. The first case was reported on March 01, 2020, and the long-run behavior of the disease initially is shown in Figure 1. The figure has been drowned and calculated for the period of March 01, 2020, to March 15, 2020, when the AQI has been changed from 103 to 84.83 and the first case has appeared. The graph shows initially a stable behavior, then an increase and then decrease in the Corona infections in the long run for the state of Chhattisgarh. In the next two fortnights March 15, 2020, and April 01, 2020, disease dynamics were found the same as shown in Figure 2 and Figure 3. During this period, the AQI has been changed from 84.83 to 63.83, but without any effect on the disease dynamics in long run. This period has been characterized by a stable, then a decreasing, increasing, and finally a decreasing behavior. In the rest of all fortnights from April 15, 2020, to Jul 15, 2020, the dynamics, in the long run, were found the same as shown in Figures 4-10 which explains that the AQI change does not affect the disease dynamics. The disease dynamics are cyclic with the increasing and decreasing patterns with finally decreasing behavior. The analysis deduces that in long run the disease dynamics change occurs at an AQI 103 to 84.83 and then at 64.61. Changes that occurred in AQI between April 15, 2020, to Jul 15, 2020, did not affect the disease dynamics in long run and in all the cases the long-term dynamics of COVID-19 were finally found moving downward.

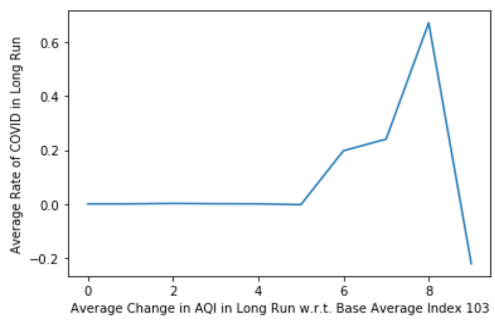

Figure 1. Average rate of change corona virus infections with average change in AQI concerning base index 103

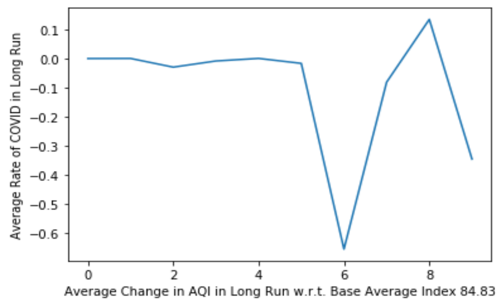

Figure 2. Average rate of change corona virus infections with average change in AQI concerning base index 84.83

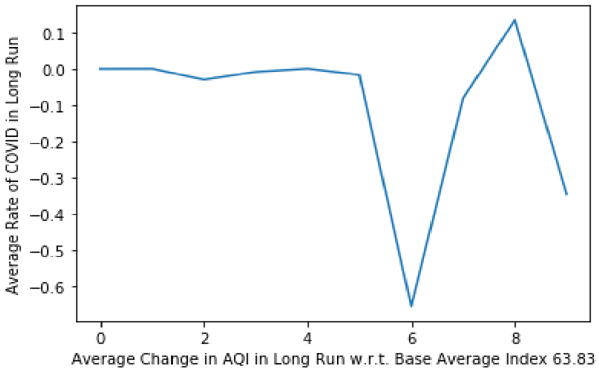

Figure 3. Average rate of change corona virus infections with average change in AQI concerning base index 63.83

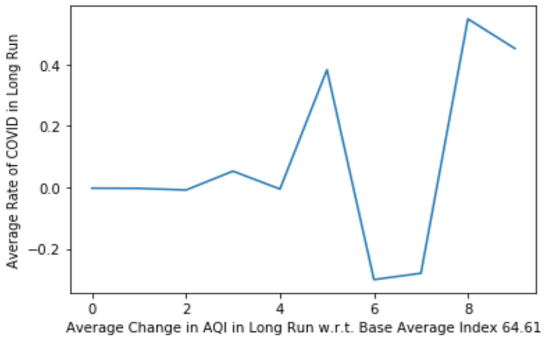

Figure 4. Average rate of change corona virus infections with average change in AQI concerning base index 64.61

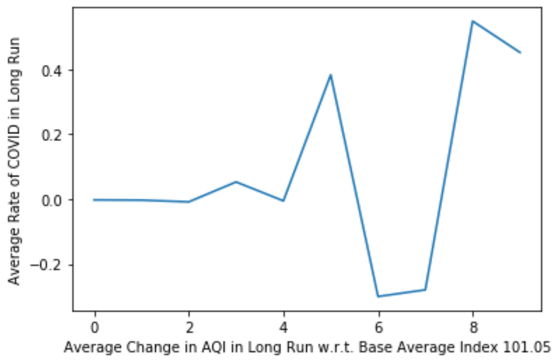

Figure 5. Average rate of change corona virus infections with average change in AQI concerning base index 101.05

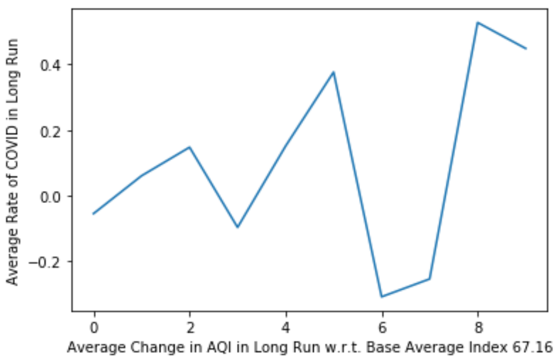

Figure 6. Average rate of change corona virus infections with average change in AQI concerning base index 67.16

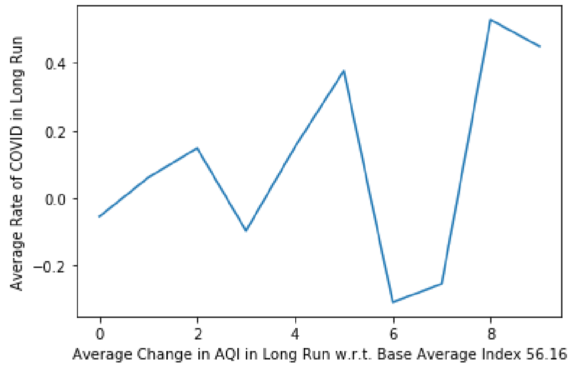

Figure 7. Average rate of change corona virus infections with average change in AQI concerning base index 56.16

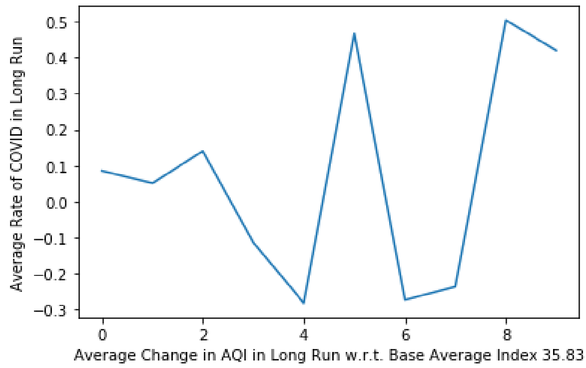

Figure 8. Average rate of change corona virus infections with average change in AQI concerning base index 35.83

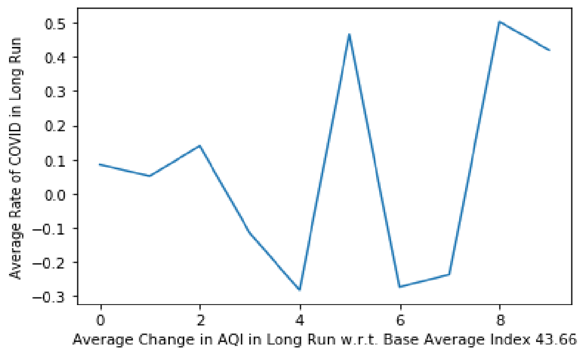

Figure 9. Average rate of change corona virus infections with average change in AQI concerning base index 43.63

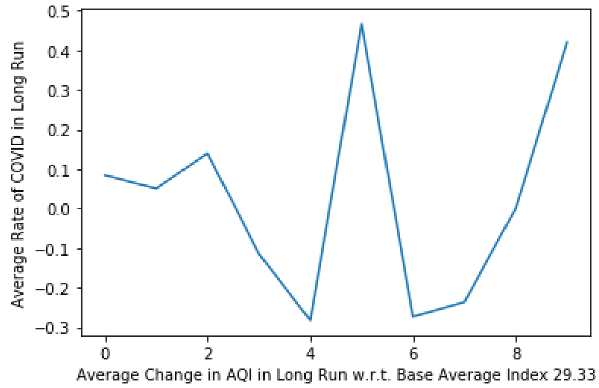

Figure 10. Average rate of change corona virus infections with average change in AQI concerning base index 29.33

6. DISCUSSION AND ANALYSIS ON THE DYNAMICS OF COVID-19 INFECTIONS CONCERNING PM-$_{2.5}$, NO_2, PM-$_{10}$ and O_3

In this section long-run dynamics of COVID-19 Infections concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively, have been studied. The study is concluded in two phases. In phase-1 the duration was from March 15, 2020, to May 01, 2020, and in phase-2 the duration was from Jun 01, 2020, to Jul 15, 2020. In phase-1 the solution obtained in section 4 and Figure 11 shows a cyclic trend with initially decreasing, then increasing, and again a decreasing trend. The long-run behavior of NO_2 was initially found stable, then become increasing and finally decreasing as shown in Figure 12. The behavior of both PM-$_{10}$ and O_3 was similar with a slight difference from that of NO_2, and both are shown in Figures 13 and 14, where initially they do not affect the disease dynamics. This is followed by an increase and finally decreasing behavior of the COVID-19 virus infections which has been depicted.

The disease dynamics in phase-2 have been calculated in section 4 and shown in Figures 15-18. Analyzing the figures, we can easily deduce that PM-$_{2.5}$ and NO_2 have a slightly similar effect in long run on the COVID-19 virus infections in the Chhattisgarh State of India as shown in Figures 15 and 16. This trend exhibits from a decreasing to an increasing one. Moreover, in the long run, PM-$_{10}$ and O_3 have similar effects on the COVID-19 virus as shown in Figures 17 and 18. Both of these trends are promising, and they show a behavior from an increasing to a decreasing trend.

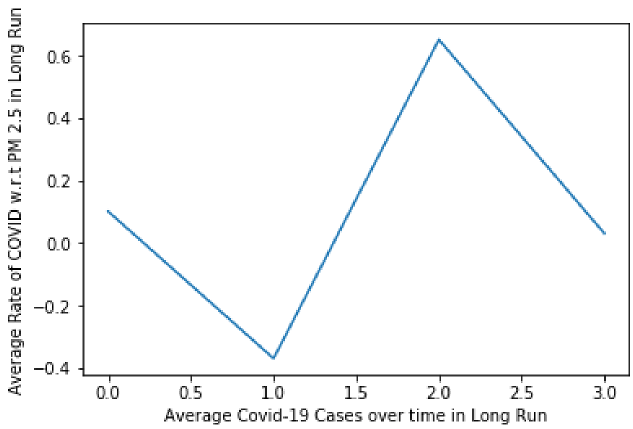

Figure 11. Average Rate of change corona virus infections with average change in $PM_{2.5}$ in phase 1

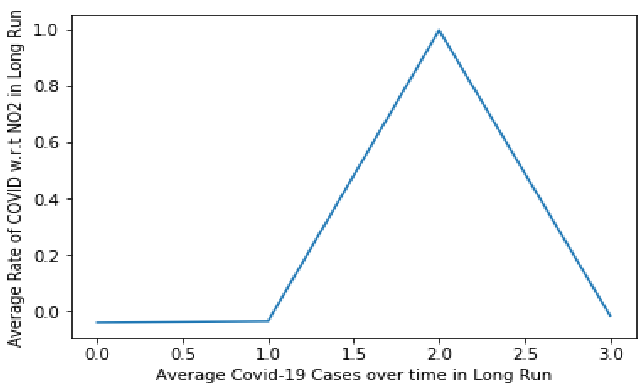

Figure 12. Average rate of change corona virus infections with average change in NO_2 in phase 1

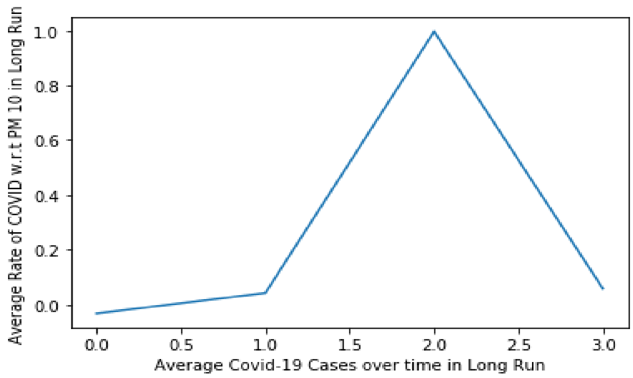

Figure 13. Average rate of change corona virus infections with average change in PM-$_{10}$ in phase 1

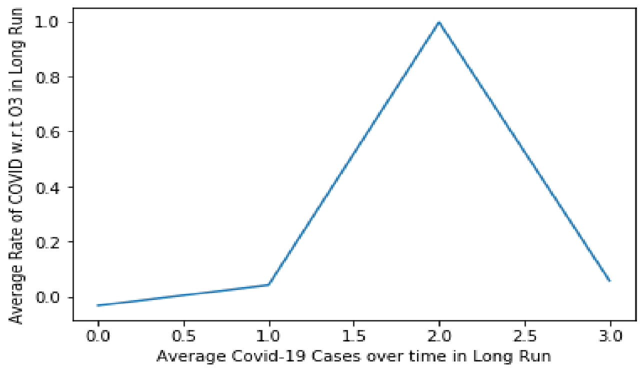

Figure 14. Average rate of change corona virus infections with average change in O_3 in phase 1

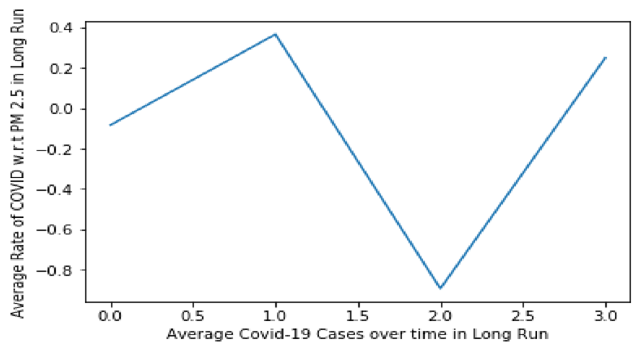

Figure 15. Average rate of change corona virus infections with average change in PM-$_{2.5}$ in phase 2

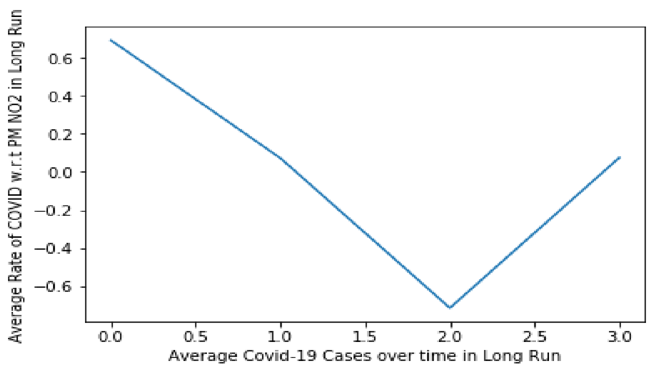

Figure 16. Average rate of change corona virus infections with average change in NO_2 in phase 2

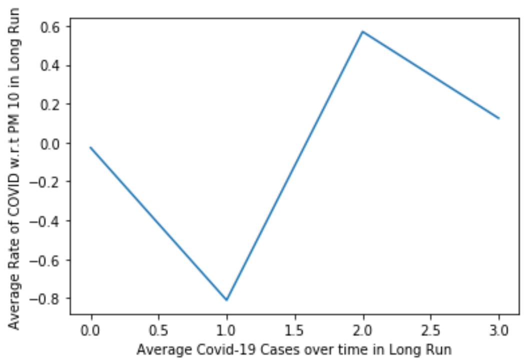

Figure 17. Average rate of change corona virus infections with average change in PM-$_{10}$ in phase 2

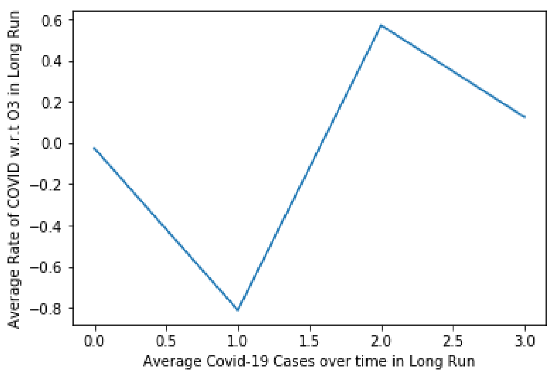

Figure 18. Average rate of change corona virus infections with average change in O_3 in phase 2

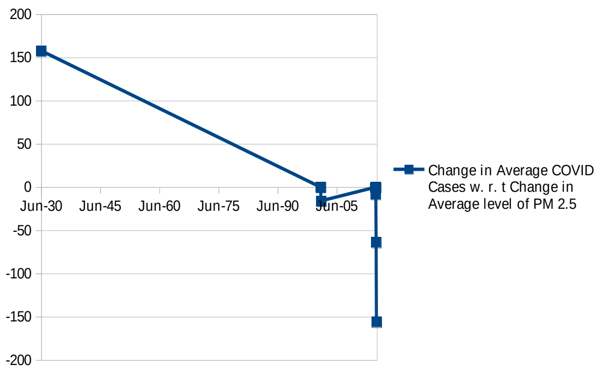

Figure 19. Average rate of change corona virus infections with average change in PM-$_{2.5}$ based on initial transition

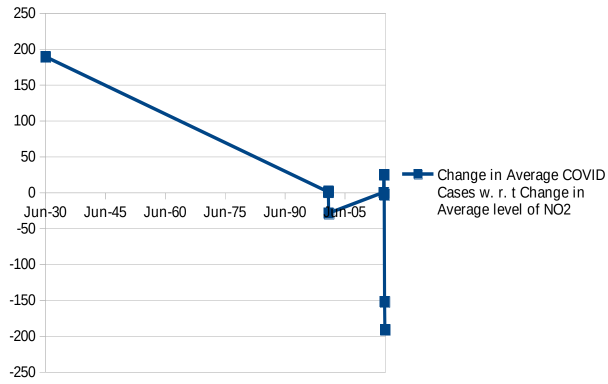

Figure 20. Average rate of change corona virus infections with average change in NO_2 based on initial transition

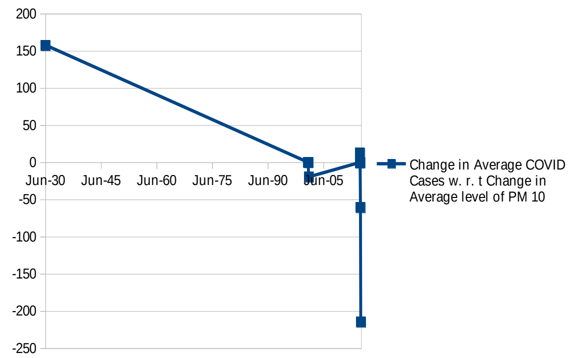

Figure 21. Average rate of change corona virus infections with average change in PM-$_{10}$ based on initial transition

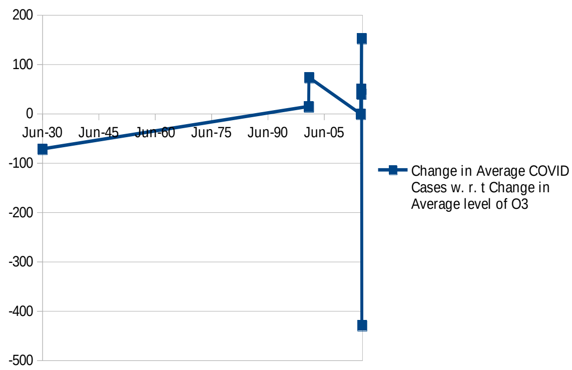

Figure 22. Average rate of change corona virus infections with average change in O_3 based on initial transition

Table 5. Initial transition matrix for average number of corona virus cases concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 for Chhattisgarh state

Time	Change in Average COVID Cases w. r. t Change in Average Level of $PM_{2.5}$	Change in Average COVID Cases w. r. t Change in Average Level of NO_2	Change in Average COVID Cases w. r. t Change in Average Level of PM_{10}	Change in Average COVID Cases w. r. t Change in Average Level of O_3
Mar-15	-0.5	-0.1428	-0.5	-1
Apr-01	-0.1707	0.6363	-0.1458	14
Apr-15	-8.333	25	12.5	50
May-01	0.1147	1.4	0.1029	14
May-15	-0.4	-2.85	-0.338	40
Jun-01	-16.22	-29.2	-19.9	73
Jun-15	-64.05	-152.12	-60.85	152.12
Jun-30	157.5	189	157.5	-72
Jul-15	-156.27	-191	-214.87	-429.75

Finally, the disease dynamics concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively, have been visualized in Figures 19-22 and Table 5. They show that initially, the disease dynamics follow the same trend for PM-$_{2.5}$, NO_2, and PM-$_{10}$ with only slight changes in the values. In these cases, the rate of disease spread was found decreasing as shown in Figures 19-21. Moreover, for O_3 the disease dynamics were found different than the other three parameters, whereby the disease infection rate increases and then decreases as shown in Figure 22. Again, in all the cases, the disease trend was found decreasing.

Several authors have presented some models to combat the problem. The studies [21, 22] have developed model for calculating transmittablility of virus among bats-host-reservoir-people transmission. Lipsitch et al. [23] have established characteristics of epidemiological time distribution. Zhou et al. [10] have proposed statistical model for COVID-19 dynamics for Wuhan. In the present study, the disease dynamics have been modeled as Markov process and solved with the help of machine learning techniques. It has been established that the eigen space decomposition method is suitable for the understanding the long run disease dynamics under influence of the air quality index which is inevitable in near future. In a country like India, it is very difficult to quickly vaccinate the population up to such extend to attain herd immunity when the quantum of the population is 1.35 billion and vaccine production is in the juvenile stage. It is also notable that the half-life of antibody produced after vaccination is not very much stable and is speculated that after one year the next booster dose will be required which may be a herculean task for the system of the country. Thus under such circumstances, the finding of the present study may contribute significantly to the management of dynamics of epidemics along with inevitable seasonal alterations in air quality index and planning of control measures.

7. CORRELATION OF COVID-19 INFECTIONS CONCERNING PM-$_{2.5}$, NO_2, PM-$_{10}$ AND O_3

This section is dedicated to know the important environmental factors contributing to the virus transmission. Tables 6 and 7 show the correlation between the COVID-19 concerning AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$ and O_3, respectively. It is clear that COVID-19 has negative relation concerning AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$. Moreover, it has positive relation with ozone O_3. This is due to the fact that due to lockdown and ban on transport the air index have improved in all regions of the world as well as in Chhattisgarh state. Although cases of COVID were increasing, the negative effects of -0.77, -0.75, -0.87 and -0.75 were recorded for AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, respectively due to lockdown. This showed that due to lockdown AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, respectively were improved but the ozone O_3 level was not improved in the Chhattisgarh state. This finding agrees with the Sarmadi et al. [24], where they asserted a negative correlation for PM-$_{2.5}$, NO_2, PM-$_{10}$, respectively. They furthered that the O_3 level was not improved in almost all major cities of the world due to COVID-19 lockdown.

Table 6. Correlation of corona virus cases concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3 for Chhattisgarh state

RowID	PM-$_{2.5}$	NO_2	PM-$_{10}$	O_3	AQI	COVID Cases
PM-$_{2.5}$	1.0	0.84	0.96	-0.54	0.96	-0.75
NO_2	0.84	1.0	0.84	-0.45	0.83	-0.87
PM-$_{10}$	0.96	0.84	1.0	-0.51	0.99	-0.75
O_3	-0.54	-0.45	-0.51	1.0	-0.50	0.13
AQI	0.96	0.83	0.99	-0.50	1.0	-0.77
COVID Cases	-0.75	-0.87	-0.75	0.13	-0.77	1.0

Table 7. Correlation of corona virus cases concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, O_3

First Column Name	Second Column Name	Correlation Value	P Value	Degrees of Freedom
PM-$_{2.5}$	NO_2	0.84	0.004308801358964498	7
PM-$_{2.5}$	PM-$_{10}$	0.96	3.46412906206961E-5	7
PM-$_{2.5}$	O_3	-0.54	0.13026512479868854	7
PM-$_{2.5}$	AQI	0.96	1.8616157591022642E-5	7
PM-$_{2.5}$	COVID Cases	-0.75	0.019512835447252165	7
NO_2	PM-$_{10}$	0.84	0.004189401707549889	7
NO_2	O_3	-0.45	0.21688487313146854	7
NO_2	AQI	0.83	0.00489527245350696	7
NO_2	COVID Cases	-0.87	0.0021296542434908793	7
PM-$_{10}$	O_3	-0.51	0.15260095715429275	7
PM-$_{10}$	AQI	0.99	8.794618144847277E-9	7
PM-$_{10}$	COVID Cases	-0.75	0.01876983678434396	7
O_3	AQI	-0.50	0.16838793274749242	7
O_3	COVID Cases	0.13	0.7231742104993175	7
AQI	COVID Cases	-0.77	0.015127837246095331	7

Based Tables 6 and 7, we answer the hypothesis as under.

1. There is a direct relation between AQI and the cases of COVID-19 cases.

Reject the null hypothesis as there is negative relation between AQI and the cases of COVID-19.

2. PM-$_{2.5}$ level and the cases of COVID-19 cases are positively related.

Reject the null hypothesis as there is negative relation between PM-$_{2.5}$ level and the cases of COVID-19.

3. There is positive relation between NO_2 level and COVID-19 cases.

Reject the null hypothesis as there is negative relation between NO_2 level and the cases of COVID-19.

4. PM-$_{10}$ level and COVID-19 cases have a direct relation.

Reject the null hypothesis as there is negative relation between PM-$_{10}$ level and the cases of COVID-19.

5. O_3 level and COVID-19 cases are directly related.

Accept the null hypothesis as there is positive relation between O_3 level and the cases of COVID-19. The O_3 level was not improved due to COVID-19 lockdown in the Chhattisgarh state as shown in the previous studies.

Finally, we compare our findings with some studies. The main findings of this study are that AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$ decreased during the lockdown in the Chhattisgarh state. Whereas the level of O_3 increased in the Chhattisgarh state during the lockdown. The decrease in NO_2 is due to ban on transportation resulting an increase in O_3. In normal situations, the concentration of NO_3 increases during night. Due to lockdown decrease in NO was reported. This decrease in NO slowed down the degradation of O_3 by NO forming NO_2. Thus, an access of O_3 was present in the atmosphere and at the same time the formation of NO_2 was decreased in the lockdown. Diaz Resquin et al. [13] reported more than 87% increase in concentration of O_3 attributed to the decline in NOx emissions. Kazi et al. [16] reported the degradation of O_3 using NO forming NO_2. Wong et al. [12] asserted that the concentrations of NO_2 and O_3 reduced to 14.9% and 5.8% after the lockdown in COVID-19 in Taiwan. This support the idea that NO_2 and O_3 whose degradation was stopped during lockdown reacted after the lockdown and their concentrations were reduced. Lovrić et al. [14] reported no difference between the concentrations recorded in the normal situations and lockdown for PM_1, $PM_{2.5}$, and PM_{10}, in Zargeb, Croatia. Zukaib et al. [19] reported 42% reduction in PM2.5, 72% reduction in PM_{10}, 29% reduction in NO_2, and increase of 20% in O_3 concentration.

Moreover, it is deducted from our study that COVID-19 transmission has negative correlation with AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, and, positive correlation with $O_{3.}$ Research studies [24, 25] reported a negative correlation for PM-$_{2.5}$, NO_2, PM-$_{10}$, respectively. They furthered that the O_3 level was not improved in almost all major cities of the world due to COVID-19 lockdown. Ali and Islam [26] pointed that in Germany, particulate matters depicted a weak negative correlation. Nigam et al. [27] concluded that a rapid reduction in the pollutant concentrations (PM_{10}, $PM_{2.5}$, CO, SO_2) was recorded, with an increment in ozone concentration due to major reduction in NO_2. Khan et al. [28] studied the effect of lockdown on air quality in Pakistan and observed reduced level of $PM_{2.5}$. They furthered that the O_3 level increased. Zoran et al. [29] found positive correlation between ozone with confirmed total COVID-19 infections and total death cases in Milan. Mahato et al. [30] observed 53% decrease in NO_2 in initial lockdown in the city of Delhi. This decrease in NO_2 is due to ban on transportation resulting an increase in O_3. Moreover, the concentration of NO_3 increased during night. The decrease in NO is another cause of increase O_3. This is due to reaction of NO and O_3 forming NO_2 is decreased because of low level of NO in air Bray et al. [31]. $PM_{2.5}$ decreased by 43% in Delhi Sharma et al. [32], in lockdown and in the major cities of the world Chauhan and Singh [33]. From these comparisons it can be easily deducted that the cases of COVID-19 have negative correlations with AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, and, positive correlation with O_3 in the Chhattisgarh state of India. Moreover, the study provides important guidelines for environmental scientists and health officials to take due care of factors significantly increasing the cases of COVID-19 and controlling its adverse effects.

This study implies that the transportation ban has resulted in decrease the hazardous substances in the air. The improvement in the air quality could have a better effect on the health of the citizens. Thus, we conclude that it would be a better choice to reduce the concentrations of the hazardous particles in the air by regulating partial bans.

8. CONCLUSIONS

The gradient decent optimizer of the Machine learning technique has been adopted to solve the Markov model of the COVID-19 transmission with respect to changing dynamics of the AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively. The machine learning capability of the renowned Python module sklearn is used to solve the Markov model. Long-run disease dynamics of the COVID-19 are studied concerning the AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively, for the Chhattisgarh state of India. First of all, the long run COVID-19 disease dynamics has been studied concerning changes in AQI values. Secondly, the long-run disease dynamics of the Corona Virus infections concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively have been analyzed. Results show that initially when AQI change from 103 to 84.83, the first cases of COVID-19 are reported. For the next two fortnights March 15, 2020, and April 01, 2020, no change in the disease dynamics are observed. For all the rest of the fortnights from April 15, 2020, to Jul 15, 2020, no change in the disease dynamics in long run is observed. In long run, the change is found at points with AQI 103 to 84.83 and then at 64.61. Changes that occurred in AQI from April 15, 2020, to Jul 15, 2020, have no effect on the disease dynamics in long run. Further, in all the cases the long-term dynamics of COVID-19 are finally found to decrease. Secondly, the long-run COVID-19 infections concerning PM-$_{2.5}$, NO_2, PM-$_{10}$, and O_3, respectively, are studied in two phases. The trend for NO_2 is found initially stable, then increasing and finally decreasing. The trend of PM-$_{10}$ and O_3 are similar. Moreover, PM-$_{10}$ and O_3 have similar effects on the COVID-19. The dynamics are same for PM-$_{2.5}$, NO_2, PM-$_{10}$, respectively, whereas different spread spectrum for O_3. COVID-19 exhibits negative correlation with AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$. Moreover a positive correlation with $O_{3.}$ This proved that lockdown and ban on transport activities improved AQI, PM-$_{2.5}$, NO_2, PM-$_{10}$, but not $O_{3.}$ The findings of the present study establish that machine learning base Markov model better present the disease dynamics and can be used for planning and controlling spread of virus.

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