Machine Learning for Markov Modeling of COVID-19 Dynamics Concerning Air Quality Index, PM-2.5, NO2, PM-10, and O3

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Abstract

In this research machine learning technique is adopted for Markov modelling of the COVID-19 dynamics with variations in Air Quality Index AQI, PM\textsubscript{-2.5}, NO\textsubscript{2}, PM\textsubscript{-10}, and O\textsubscript{3}, respectively. Thus the long-run disease dynamics of the COVID-19 are studied concerning the Air Quality Index (AQI), PM\textsubscript{-2.5}, NO\textsubscript{2}, PM\textsubscript{-10}, and O\textsubscript{3}, respectively, by using eigen space decomposition. Data of the Chhattisgarh state of India is taken into consideration and the study analyzed in two phases. In Phase-1 the time duration is from March 15, 2020, to May 01, 2020, and for Phase-2 the time duration was from Jun 01, 2020, to Jul 15, 2020. Change in COVID-19 related to AQI showed that initially when the AQI changed from 103 to 84.83 the disease dynamics also changed, and the first cases of COVID-19 were reported. In the next two fortnights from March 15, 2020, and April 01, 2020, the dynamics were the same, latter the AQI changed from 84.83 to 63.83, but this change does not affect the disease dynamics in long run from April 15, 2020, to Jul 15, 2020. In phase 1 the solution obtained shows a cyclic trend with initially decreasing, then increasing, and again a decreasing trend for changes concerning PM\textsubscript{-2.5}. The disease dynamics concerning PM\textsubscript{-2.5}, NO\textsubscript{2}, PM\textsubscript{-10}, and O\textsubscript{3}, respectively, based on initial transition showed the same trend for PM\textsubscript{-2.5}, NO\textsubscript{2}, and PM\textsubscript{-10}. Moreover, for O\textsubscript{3} the disease dynamics were found different than the other three parameters. COVID-19 showed a negative correlation with AQI, PM\textsubscript{-2.5}, NO\textsubscript{2}, PM\textsubscript{-10}. Moreover a positive correlation with O\textsubscript{3}. This proved that the lockdown and ban on transport activities improved AQI, PM\textsubscript{-2.5}, NO\textsubscript{2}, PM\textsubscript{-10}, but not O\textsubscript{3}. The research exploits the learning capability of renowned Python machine learning module sklearn to solve the Markov model. The findings prove that Markov modeling is promising method for planning control measures for disease with compatibility to air quality alterations.

**Keyword:** Novel Corona Virus, AQI, PM\textsubscript{-2.5}, NO\textsubscript{2}, PM\textsubscript{-10}, O\textsubscript{3}, Eigen Space Decomposition, COVID-19

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 Wang et al., (2020) 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.
A positive correlation between the air pollution index and COVID-19 cases has been reported from different parts of the world Zhu et al., (2020). 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 by several authors (Peng et al., 2009; Wong et al., 1999; Katanoda et al., 2011; Nakao et al., 2018 and Spix et al., 1998). The primary target of COVID-19 is the lungs which cause potential alveolar damage which leads to asphyxia and finally death (Puntmann et al., 2020; Liu, C. et al., 2020, Franks et al., 2003; Nicholls et al., 2003).

Resquin et al., (2021) studied changes in air quality due to lockdown using machine learning in Buenos Aires, Argentina. Lovrić et al., (2022) used machine learning techniques to compare the concentrations recorded in the normal situations and lockdown for PM1, PM2.5, and PM10, in Zargeb, Croatia. Mehmood et al., (2022) presented the advantages of using machine learning techniques for predicting air quality. Kazi et al., (2023) studied the relationship among PM2.5, PM10, SO2, NO2, NO and CO using linear regression model in R language. Wong et al., (2023) used AI based techniques to quantify the impact of NO2 and O3 on COVID-19 in Taiwan. Menez et al., (2023) proposed a survey of the machine learning approaches for predicting air quality. Islam et al., (2023) used machine learning approaches for predicting PM2.5 in Dhaka, Bangladesh. Zukaib et al., (2023) 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 (Puntmann et al., 2020). 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 Air Quality Index (AQI), PM-2.5, NO2, PM-10, and O3, respectively. The long-run dynamics of the Novel Corona virus infection dynamics are investigated related to changes in Air Quality Index, PM-2.5, NO2, PM-10, and O3, 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 Air Quality Index (PM-2.5, NO2, PM-10, and O3) 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-2.5, NO2, PM-10, and O3 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-2.5 level and the cases of COVID-19 cases are positively related.

3. There is positive relation between NO2 level and COVID-19 cases.

4. PM-10 level and COVID-19 cases have a direct relation.

5. O3 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-2.5, NO2, PM-10, and O3 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-2.5, NO2, PM-10, and O3 levels, respectively are analyzed. Correlation of COVID-19 Infections concerning PM-2.5, NO2, PM-10 and O3 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 $n \times n$ two dimensions array of elements
having \( n \) rows and \( n \) columns and it is denoted as \( T = [t_{ij}] \), \( 1 \leq i \leq n \), \( 1 \leq j \leq n \). The column matrix “\( u \)” given in (1) is called the long-run vector.

\[
\[ u = \begin{bmatrix}
u_1 \\
u_2 \\
\vdots \\
u_n \\
\end{bmatrix}, \quad 1 \leq i \leq n
\]

(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).

\[
x^{(k)} = \begin{bmatrix}
p_1^{(k)} \\
p_2^{(k)} \\
\vdots \\
p_n^{(k)} \\
\end{bmatrix}, \quad 0 \leq k
\]

(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).

\[
x^{(k+1)} = Tx^{(k)}
\]

(3)

**Proof:**

From equation (3), we can find (4).

\[
x^{(1)} = Tx^{(0)} \quad (4)
\]

\[
x^{(2)} = Tx^{(1)} \quad (5)
\]

Put equation (4) in equation (5).

\[
x^{(2)} = Tx^{(1)} = TT(x)^0 = T^2(x)^0 \quad (6)
\]

\[
x^{(3)} = Tx^{(2)} = TT^2(x)^0 = T^3(x)^0 \quad (7)
\]

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

\[
x^{(n)} = T^n x^{(0)} \quad (8)
\]

This completes the proof.

**Definition 1:** Given a transition matrix “\( T \)”, as \( n \to \infty \), \( T^n \) approaches (9), (Kolman and Hill, 2004).
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”, $T^n x \rightarrow u$ as $n \rightarrow \infty$, “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).

$$\begin{bmatrix} u_1 & u_1 & \cdot & \cdot & \cdot & u_1 \\ u_2 & u_2 & \cdot & \cdot & \cdot & u_2 \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ u_n & u_n & \cdot & \cdot & \cdot & u_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{bmatrix}$$

(9)

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

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

(11)

Also, $(x_1 + x_2 + \cdot \cdot \cdot + x_n) = 1$ thus (12) can be written as (13).
Equation (13) proves $T^nx \rightarrow u$.

b) We have $T^n \rightarrow A$ as $n \rightarrow \infty$. It means $T^{n+1} \rightarrow A$. Knowing $T^{n+1} = T^n A$. Thus $T^{n+1} \rightarrow A$, 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, $T^nv \rightarrow u$. Moreover, $Tv = v$ implying $T^nv = u$, $\forall n$. so $u = v$.

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

$$Tu = u$$  \hspace{1cm} (14)
$$Tu = I_nu$$  \hspace{1cm} (15)
$$I_nu - Tu = 0$$  \hspace{1cm} (16)
$$(I_n - T)u = 0$$  \hspace{1cm} (17)

The modeled equation (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) in the Chhattisgarh State

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).

<table>
<thead>
<tr>
<th>Month</th>
<th>Average Air Quality Index of the Chhattisgarh State (µg/m³)</th>
<th>Cases of Corona Virus Infections</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar-01</td>
<td>103</td>
<td>0</td>
</tr>
<tr>
<td>Mar-15</td>
<td>84.83</td>
<td>1</td>
</tr>
</tbody>
</table>
From the data given in Table (1) the transition matrix of the Corona Virus infection concerning the air quality index AQI can be formulated as in equation (18).

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

Equation (19) models the eigen space decomposition of the COVID-19 concerning the air quality index in the Chhattisgarh state of India.

\[
(\lambda I_n - T_{AQI})u = 0
\]
\[
\begin{bmatrix}
\lambda -1 & 0.055 & 0.025 & 0.0260 & 0.5128 & 0.0278 & 0.0213 & 0.01488 & 0.0168 & 0.2153 \\
-0.3852 & \lambda -1 & 0.3333 & 0.3461 & -0.4315 & 0.3961 & 0.2441 & 0.1428 & 0.1700 & 0.1261 \\
-0.6382 & -1.189 & \lambda -1 & -32.05 & -0.6716 & -7.30 & 3.25 & 0.8928 & 1.23 & 0.7246 \\
-0.1823 & -0.3461 & 8.97 & \lambda -1 & -0.1920 & -2.745 & 0.8284 & 0.2432 & 0.3341 & 0.1984 \\
-10.25 & 1.233 & 0.5373 & 0.5488 & \lambda -1 & 0.590 & 0.4455 & 0.3066 & 0.3484 & 0.2788 \\
-25.98 & -42.44 & -158.67 & -144.02 & -27.11 & -110.3 & \lambda -1 & 59.86 & 97.36 & 45.35 \\
-14.06 & -19.28 & -33.75 & -32.83 & -14.48 & -30.16 & -46.48 & \lambda -1 & -120.68 & 145.38 \\
-28.98 & -41.75 & -85.22 & -82.05 & -29.95 & -73.14 & -137.52 & 219.54 & \lambda -1 & 119.95 \\
-13.95 & -18.52 & -29.79 & -29.13 & -14.33 & -27. & -38.31 & -158.15 & -71.73 & \lambda -1 \\
\end{bmatrix} \begin{bmatrix}
u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \\ u_6 \\ u_7 \\ u_8 \\ u_9 \\ u_{10}
\end{bmatrix} = 0
\]

Solving (21) with help of Python machine learning module sklearn we get the eigen values as shown in the program run file given below.

runfile(C:/Users/Ehsan/spyder-3/temp.py', wdir=C:/Users/Toshiba/spyder-3/py3)

runfile(C:/Users/Ehsan/spyder-3/temp.py', wdir=C:/Users/Toshiba/spyder-3/py3)

\[ \text{The corresponding eigen space is give below in python program run file.} \]
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, NO₂, PM-10, and O₃

This study was conducted in two phases. In Phase-1, the disease dynamics concerning PM-2.5, NO₂, PM-10, and O₃, 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 O₃, respectively were studied from June 1, 2020, to July 15, 2020, in the state of Chhattisgarh. The levels of PM-2.5, NO₂, PM-10, and O₃, in Phase-1 are in Table (2).

Table 2. Average Level of PM-2.5, NO₂, PM-10, O₃ for Chhattisgarh State and Cases of Corona Virus Infections.

<table>
<thead>
<tr>
<th>Time</th>
<th>Average Level of PM-2.5</th>
<th>Average Level of NO₂</th>
<th>Average Level of PM-10</th>
<th>Average Level of O₃</th>
<th>Cases of Corona Virus Infections</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar-15</td>
<td>102</td>
<td>47</td>
<td>95</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Apr-01</td>
<td>61</td>
<td>58</td>
<td>47</td>
<td>4.5</td>
<td>8</td>
</tr>
<tr>
<td>Apr-15</td>
<td>58</td>
<td>59</td>
<td>49</td>
<td>5</td>
<td>33</td>
</tr>
<tr>
<td>May-01</td>
<td>119</td>
<td>64</td>
<td>117</td>
<td>5.5</td>
<td>40</td>
</tr>
<tr>
<td>May-15</td>
<td>69</td>
<td>57</td>
<td>58</td>
<td>6</td>
<td>60</td>
</tr>
<tr>
<td>Jun-01</td>
<td>42</td>
<td>42</td>
<td>36</td>
<td>12</td>
<td>498</td>
</tr>
<tr>
<td>Jun-15</td>
<td>23</td>
<td>34</td>
<td>16</td>
<td>20</td>
<td>1715</td>
</tr>
<tr>
<td>Jun-30</td>
<td>29</td>
<td>39</td>
<td>22</td>
<td>7</td>
<td>2660</td>
</tr>
<tr>
<td>Jul-15</td>
<td>18</td>
<td>30</td>
<td>14</td>
<td>3</td>
<td>4379</td>
</tr>
</tbody>
</table>

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

\[ T_i = \begin{bmatrix} -0.5 & -0.1428 & -0.8 & -1 \\ -0.1707 & 0.6363 & -0.1458 & 14 \\ -8.333 & 25 & 12.5 & 50 \\ 0.1147 & 1.4 & 0.1029 & 14 \end{bmatrix} \]

(22)

The eigen space for (22) is given as (23).

\[ (\lambda I_i - T_i)u = 0 \]  

(23)

Table 3. Transition Matrix for Average Number of Corona Virus Cases concerning PM-2.5, NO₂, PM-10, O₃ in Phase-1 for Chhattisgarh State.
### COVID Cases w. r. t Change in Average level of PM\(_{2.5}\) and NO\(_{2}\), Change in Average level of PM\(_{10}\) and O\(_{3}\)

<table>
<thead>
<tr>
<th>Time</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of PM(_{2.5})</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of NO(_{2})</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of PM(_{10})</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of O(_{3})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar-15</td>
<td>-0.5</td>
<td>-0.1428</td>
<td>-0.5</td>
<td>-1</td>
</tr>
<tr>
<td>Apr-01</td>
<td>-0.1707</td>
<td>0.6363</td>
<td>-0.1458</td>
<td>14</td>
</tr>
<tr>
<td>Apr-15</td>
<td>-8.333</td>
<td>25</td>
<td>12.5</td>
<td>50</td>
</tr>
<tr>
<td>May-01</td>
<td>0.1147</td>
<td>1.4</td>
<td>0.1029</td>
<td>14</td>
</tr>
</tbody>
</table>

Let 

\[
\lambda = \begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{pmatrix}
\]

\[
\begin{pmatrix}
-0.5 & -0.1428 & -0.8 & -1 \\
-0.1707 & 0.6363 & -0.1458 & 14 \\
-8.333 & 25 & 12.5 & 50 \\
0.1147 & 1.4 & 0.1029 & 14 \\
\end{pmatrix}
\begin{pmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
\end{pmatrix} = \begin{pmatrix} 0 \\
0 \\
0 \\
0 \\
\end{pmatrix}
\]

Equation (24) reduces to (25).

\[
\begin{pmatrix}
\lambda + 0.5 & 0.1428 & 0.8 & 1 \\
0.1707 & \lambda - 0.6363 & -0.1458 & -0.14 -14 \\
8.333 & -25 & \lambda - 12.5 & -50 \\
-0.1147 & -1.4 & -0.1029 & \lambda - 14 \\
\end{pmatrix}
\begin{pmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
\end{pmatrix} = \begin{pmatrix} 0 \\
0 \\
0 \\
0 \\
\end{pmatrix}
\]

Equation (25) further reduces to:

\[
\begin{pmatrix}
\lambda + 0.5 & 0.1428 & 0.8 & 1 \\
0.1707 & \lambda - 0.6363 & -0.1458 & -0.14 -14 \\
8.333 & -25 & \lambda - 12.5 & -50 \\
-0.1147 & -1.4 & -0.1029 & \lambda - 14 \\
\end{pmatrix}
\begin{pmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
\end{pmatrix} = \begin{pmatrix} 0 \\
0 \\
0 \\
0 \\
\end{pmatrix}
\]

Python machine learning module sklearn solves the model (25) and the results are presented below.

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

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

### Phase -2

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 equation (26).

#### 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.

<table>
<thead>
<tr>
<th>Time</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of PM(_{2.5})</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of NO(_{2})</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of PM(_{10})</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of O(_{3})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jun-01</td>
<td>-16.22</td>
<td>-29.2</td>
<td>-19.9</td>
<td>73</td>
</tr>
</tbody>
</table>
### Table

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Jun-15</td>
<td>-64.05</td>
<td>-152.12</td>
<td>-60.85</td>
<td>152.12</td>
</tr>
<tr>
<td>Jun-30</td>
<td>157.5</td>
<td>189</td>
<td>157.5</td>
<td>-72</td>
</tr>
<tr>
<td>Jul-15</td>
<td>-156.27</td>
<td>-191</td>
<td>-214.87</td>
<td>-429.75</td>
</tr>
</tbody>
</table>

\[
T_2 = \begin{bmatrix}
-16.22 & -29.2 & -19.9 & 73 \\
-64.05 & -152.12 & -60.85 & 152.12 \\
157.5 & 18.9 & 157.5 & -72 \\
-156.27 & -191 & -214.87 & -429.75 \\
\end{bmatrix}
\]

The eigen space for (26) is given as (27).

\[
(\lambda I_n - T_2)u = 0
\]

\[
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
\lambda & -16.22 & -29.2 & -19.9 & 73 \\
\lambda & -64.05 & -152.12 & -60.85 & 152.12 \\
\lambda & 157.5 & 18.9 & 157.5 & -72 \\
\lambda & -156.27 & -191 & -214.87 & -429.75 \\
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
\end{bmatrix}
= \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
\end{bmatrix}
\]

Equation (28) further reduces to (29).

\[
\begin{bmatrix}
\lambda + 16.22 & 29.2 & 19.9 & -73 \\
64.05 & \lambda + 152.12 & 60.85 & -152.12 \\
-157.5 & -18.9 & \lambda - 157.5 & 72 \\
156.27 & 191 & 214.87 & \lambda + 429.75 \\
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2 \\
u_3 \\
u_4 \\
\end{bmatrix}
= \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
\end{bmatrix}
\]

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

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

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

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

These results are further 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 to Figure 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](image1.png)

**Figure 1.** Average Rate of Change Corona Virus Infections with Average Change in AQI concerning Base Index 103.

![Figure 2](image2.png)

**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.
6 Discussion and Analysis on the Dynamics of COVID-19 Infections concerning PM-2.5, NO₂, PM-10 and O₃
In this section long-run dynamics of COVID-19 Infections concerning PM-2.5, NO2, PM-10, and O3, 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 NO2 was initially found stable, then become increasing and finally decreasing as shown in Figure 12. The behavior of both PM-10 and O3 was similar with a slight difference from that of NO2, and both are shown in Figure 13 and Figure 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.

![Figure 11. Average Rate of Change Corona Virus Infections with Average Change in PM 2.5 in Phase 1.](image1)

![Figure 12. Average Rate of Change Corona Virus Infections with Average Change in NO2 in Phase 1.](image2)

![Figure 13. Average Rate of Change Corona Virus Infections with Average Change in PM-10 in Phase 1.](image3)
The disease dynamics in Phase-2 have been calculated in section 4 and shown in Figure 15 to Figure 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 Figure 15 and Figure 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 Figure 17 and Figure 18. Both of these trends are promising, and they show a behavior from an increasing to a decreasing trend.
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, 20, 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. Zhang et al., (2015) proposed about cure effect on the virus model considering cell to cell or cell to virus transmission; Rhian et al., (1982) have proposed interaction dynamics model among human cell and virus. Chen et al., (2020) have developed model for calculating transmissibility of virus among bats-host-reservoir-people transmission. Li et al., (2020) have established characteristics of epidemiological time distribution. Riou and Althaus (2020) have predicted about human to human transmission of novel Corona Virus. Zuo et al., (2020) have proposed statistical model for COVID-19 dynamics for Asian countries. Car et al, (2020) have developed a data set for training a multilayer perception artificial neural network and have proposed susceptible -exposed- infections-removed (SEIR) model. Zeb et al., (2020) have investigated SEIR model for isolated population. Lin et al., (2020) have developed model considering individual reaction, governmental action and immigration. He et al., (2013) have developed a model capable to capture general propagation of COVID-19. 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.

Table 5. Initial Transition Matrix for Average Number of Corona Virus Cases concerning PM-2.5, NO2, PM-10, O₃ for Chhattisgarh State.

<table>
<thead>
<tr>
<th>Time</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of PM₂.₅</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of NO₂</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of PM₁₀</th>
<th>Change in Average COVID Cases w. r. t Change in Average level of O₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mar-15</td>
<td>-0.5</td>
<td>-0.1428</td>
<td>-0.5</td>
<td>-1</td>
</tr>
<tr>
<td>Apr-01</td>
<td>-0.1707</td>
<td>0.6363</td>
<td>-0.1458</td>
<td>14</td>
</tr>
<tr>
<td>Apr-15</td>
<td>-8.333</td>
<td>25</td>
<td>12.5</td>
<td>50</td>
</tr>
<tr>
<td>May-01</td>
<td>0.1147</td>
<td>1.4</td>
<td>0.1029</td>
<td>14</td>
</tr>
<tr>
<td>May-15</td>
<td>-0.4</td>
<td>-2.85</td>
<td>-0.338</td>
<td>40</td>
</tr>
<tr>
<td>Jun-01</td>
<td>-16.22</td>
<td>-29.2</td>
<td>-19.9</td>
<td>73</td>
</tr>
<tr>
<td>Jun-15</td>
<td>-64.05</td>
<td>-152.12</td>
<td>-60.85</td>
<td>152.12</td>
</tr>
<tr>
<td>Jun-30</td>
<td>157.5</td>
<td>189</td>
<td>157.5</td>
<td>-72</td>
</tr>
<tr>
<td>Jul-15</td>
<td>-156.27</td>
<td>-191</td>
<td>-214.87</td>
<td>-429.75</td>
</tr>
</tbody>
</table>

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 NO₂ 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 O₃ Based on Initial Transition.

7 Correlation of COVID-19 Infections concerning PM-2.5, NO₂, PM-10 and O₃
This section is dedicated to know the important environmental factors contributing to the virus transmission. Table 6-7 and Figure 23 show the correlation between the COVID-19 concerning AQI, PM-2.5, NO₂, PM-10 and O₃, respectively. It is clear that COVID-19 has negative relation concerning AQI, PM-2.5, NO₂, PM-10. Moreover, it has positive relation with ozone O₃. 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, NO₂, PM-10, respectively due to lockdown. This showed that due to lockdown AQI, PM-2.5, NO₂, PM-10, respectively were improved but the ozone O₃ level was not improved in the Chhattisgarh state. This finding agrees
with the Sarmadi et al., (2021), where they asserted a negative correlation for PM-2.5, NO₂, PM-10, respectively. They furthered that the O₃ level was not improved in almost all major cities of the world due to COVID-19 lockdown.

Figure 23. Correlation of Corona Virus Cases concerning PM-2.5, NO₂, PM-10, O₃.

Table 6. Correlation of Corona Virus Cases concerning PM-2.5, NO₂, PM-10, O₃ for Chhattisgarh State.

<table>
<thead>
<tr>
<th>RowID</th>
<th>PM-2.5</th>
<th>NO₂</th>
<th>PM-10</th>
<th>O₃</th>
<th>AQI</th>
<th>COVID Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM-2.5</td>
<td>1.0</td>
<td>0.84</td>
<td>0.96</td>
<td>-0.54</td>
<td>0.96</td>
<td>-0.75</td>
</tr>
<tr>
<td>NO₂</td>
<td>0.84</td>
<td>1.0</td>
<td>0.84</td>
<td>-0.45</td>
<td>0.83</td>
<td>-0.87</td>
</tr>
<tr>
<td>PM-10</td>
<td>0.96</td>
<td>0.84</td>
<td>1.0</td>
<td>-0.51</td>
<td>0.99</td>
<td>-0.75</td>
</tr>
<tr>
<td>O₃</td>
<td>-0.54</td>
<td>-0.45</td>
<td>-0.51</td>
<td>1.0</td>
<td>-0.50</td>
<td>0.13</td>
</tr>
<tr>
<td>AQI</td>
<td>0.96</td>
<td>0.83</td>
<td>0.99</td>
<td>-0.50</td>
<td>1.0</td>
<td>-0.77</td>
</tr>
<tr>
<td>COVID Cases</td>
<td>-0.75</td>
<td>-0.87</td>
<td>-0.75</td>
<td>0.13</td>
<td>-0.77</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Table 7. Correlation of Corona Virus Cases concerning PM-2.5, NO₂, PM-10, O₃.

<table>
<thead>
<tr>
<th>First column name</th>
<th>Second column name</th>
<th>Correlation value</th>
<th>p value</th>
<th>Degrees of freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM-2.5</td>
<td>NO₂</td>
<td>0.84</td>
<td>0.004308801358964498</td>
<td>7</td>
</tr>
<tr>
<td>PM-2.5</td>
<td>PM-10</td>
<td>0.96</td>
<td>3.46412906206961E-5</td>
<td>7</td>
</tr>
<tr>
<td>PM-2.5</td>
<td>O₃</td>
<td>-0.54</td>
<td>0.13026512479868854</td>
<td>7</td>
</tr>
</tbody>
</table>
Based on figure 23 and Tables 6-7, 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 Bray et al. (2021). This decrease in NO slowed down the degradation of
O₃ by NO forming NO₂. Thus an access of O₃ was present in the atmosphere and at the same time the formation of NO₂ was decreased in the lockdown. Resquin et al., (2021) reported more than 87% increase in concentration of O₃ attributed to the decline in NOx emissions. Kazi et al., (2023) reported the degradation of O₃ using NO forming NO₂. Wong et al., (2023) asserted that the concentrations of NO₂ and O₃ reduced to 14.9% and 5.8% after the lockdown in COVID-19 in Taiwan. This support the idea that NO₂ and O₃ whose degradation was stopped during lockdown reacted after the lockdown and their concentrations were reduced. Lovrić et al., (2022) reported no difference between the concentrations recorded in the normal situations and lockdown for PM1, PM2.5, and PM10, in Zargeb, Croatia. Zukaib et al., (2023) reported 42% reduction in PM2.5, 72% reduction in PM10, 29% reduction in NO₂, and increase of 20% in O₃ concentration. Moreover, it is deducted from our study that COVID-19 transmission has negative correlation with AQI, PM-2.5, NO₂, PM-10, and, positive correlation with O₃. Research studies (Gope et al., 2021; Sarmadi et al., 2021) reported a negative correlation for PM-2.5, NO₂, PM-10, respectively. They furthered that the O₃ level was not improved in almost all major cities of the world due to COVID-19 lockdown. Ali and Islam (2020) pointed that in Germany, particulate matters depicted a weak negative correlation. The results of Nigam et al., (2021) concluded that a rapid reduction in the pollutant concentrations (PM10, PM2.5, CO, SO2) was recorded, with an increment in ozone concentration due to major reduction in NO₂. Khan et al., (2021) studied the effect of lockdown on air quality in Pakistan and observed reduced level of PM2.5. They furthered that the O₃ level increased. Zoran et al. (2020) found positive correlation between ozone with confirmed total COVID-19 infections and total death cases in Milan. Mahato et al. (2020) observed 53% decrease in NO₂ in initial lockdown in the city of Delhi. This decrease in NO₂ is due to ban on transportation resulting an increase in O₃. Moreover, the concentration of NO₃ increased during night. The decrease in NO is another cause of increase O₃. This is due to reaction of NO and O₃ forming NO₂ is decreased because of low level of NO in air Bray et al. (2021). PM2.5 decreased by 43% in Delhi Sharma et al., (2020), in lockdown and in the major cities of the world Chauhan and Singh (2020). From these comparisons it can be easily deducted that the cases of COVID-19 have negative correlations with AQI, PM-2.5, NO₂, PM-10, and, positive correlation with O₃ 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.

8 Conclusions

Machine learning technique was adopted to solve the Markov model of the COVID-19 transmission with respect to changing dynamics of the Air Quality Index, PM-2.5, NO₂, PM-10, and O₃, respectively. The machine learning capability of the renowned Python machine learning module sklearn was used to solve the Markov model. Long-run disease
dynamics of the COVID-19 were studied concerning the Air Quality Index, PM-2.5, NO2, PM-10, and O3, respectively, for the Chhattisgarh state of India. First of all, the long run COVID-19 disease dynamics were studied concerning changes in AQI values. Secondly, the long-run disease dynamics of the Corona Virus infections concerning PM-2.5, NO2, PM-10, and O3, respectively. Results show that changing AQI from 103 to 84.83, disease dynamics changed, and the first cases of COVID-19 were reported. For the next two fortnights March 15, 2020, and April 01, 2020, no change in the disease dynamics were observed. In this period the AQI changes were reported from 84.83 to 63.83, but this change reported no effect on the disease dynamics in long run. For all the rest of the fortnights from April 15, 2020, to Jul 15, 2020, no change in the disease dynamics in long run was observed. In long run, the change was 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 were finally found to decrease. Secondly, the long-run COVID-19 infections concerning PM-2.5, NO2, PM-10, and O3, respectively, were studied in two phases. The trend for NO2 was found initially stable, then increasing and finally decreasing. The COVID-19 trend for both PM-10 and O3 was similar. Moreover, PM-10 and O3 have similar effects on the Covid-19 virus where the trend was from an increasing to a decreasing one. Corona virus dynamics concerning PM-2.5, NO2, PM-10, and O3, respectively, based on initial transition showed the same trend for PM-2.5, NO2, and PM-10, whereas a different spread spectrum for O3. COVID-19 showed a negative correlation with AQI, PM-2.5, NO2, PM-10. Moreover a positive correlation with O3. This proved that due to lockdown and ban on transport activities improved AQI, PM-2.5, NO2, PM-10, but not O3. 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.

Compliance with Ethical Standards
 Disclosure of potential conflicts of interest
The authors disclose that there is no conflict of interest.
Research involving human participants and/or animals
The study contains no experiments performed on human participants and/or animals.
Informed consent
The study contains no experiments performed on human participants and/or animals to be communicated for informed consent.

Acknowledgments
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