A Time-Dependent SEIRD Model for Forecasting the COVID-19 Transmission Dynamics

Taarak Rapolu 1, Brahmani Nutakki2, T. Sobha Rani3, S. Durga Bhavani4

1taarak.rapolu@gmail.com
2brahmani3110@gmail.com
3tsrcs@uohyderabad.ernet.in
4sdbcs@uohyderabad.ernet.in

School of Computer and Information Sciences, University of Hyderabad
Hyderabad, India

29 May 2020

Abstract

The spread of a disease caused by a virus can happen through human to human contact or could be from the environment. A mathematical model could be used to capture the dynamics of the disease spread to estimate the infections, recoveries, and deaths that may result from the disease. An estimation is crucial to make policy decisions and for the alerts for the medical emergencies that may arise. Many epidemiological models are being used to make such an estimation. One major factor that is important in the forecasts using the models is the dynamic nature of the disease spread. Unless we can come up with a way of estimating the parameters that guide this dynamic spread, the models may not give accurate forecasts. In this work, using the SEIRD model, attempts are made to forecast Infected, Recovered and Death rates of COVID-19 up to a week using an incremental approach. A method of optimizing the parameters of the model is also discussed thoroughly in this work. The model is evaluated using the data taken from COVID-19 India tracker [2], a crowd-sourced platform for India. The model is tested with the whole country as well as all the states and districts. The results of all the states and districts obtained from our model can be seen in [12]. Forecasts for Infected and Deaths for the whole country and the state of Maharashtra are satisfactory with an average % error rate of 3.47 and 3.60 for infected and 3.88 and 1.61 for deaths respectively. It is supposed to be a reasonable estimate which can help the governments in planning for emergencies such as ICU requirements, PPEs, hospitalizations, and so on as the infection is going to be prevalent for some time to come.
1 Introduction

Novel Coronavirus has become a pandemic within no time from the time of its detection in Wuhan, a province of China. This has been declared as a pandemic by WHO resulting in around 5,719,320 cases worldwide, by 27th of May[3]. Around 1,54,181 were affected in India alone. With 4,373 reported deaths, the cases are rapidly rising, where Maharashtra is leading the tally. Its rapid progress has necessitated the need to come up with models to model the spread of the virus under different conditions like lockdown, hotspots, and migration of people across the places, and so on. The outbreak of novel coronavirus Covid19 and the ensuing utter chaos and the utter uncertainty caused by the pandemic in the entire world is unprecedented. More than ever before, it emphasizes the need for robust mathematical models that can guide policies to control the spread of infection and help in planning the hospital requirements such as PPEs, ventilators, etc [10].

In the literature several epidemiological models such as Susceptible, Infected, Recovered(SIR), Susceptible, Exposed, Infected, Recovered(SEIR) and Susceptible, Exposed, Infected, Recovered and Death (SEIRD), etc have been proposed to model the virus spreads like H1N1, SARS, Ebola, and others. EpiModel is a very useful software package, developed in ‘R’ language, that allows simulation of compartmental models, stochastic individual contact models, and the more recent network models [6].

2 Existing Models

A few existing pandemic models, from which the current model is derived are discussed here. The first model used to model the pandemic virus spread is the SIR model.

2.1 SIR

One of the prediction models available is the SIR or the Susceptible, Infected, Recovered Model. This popular epidemic model considers a closed population. It initially considers a small part of the population as infected. This small percentage is considered to infect $R_0$ others, where $R_0$ is the Basic Reproduction Rate[1]. The SIR model can be described as

$$\frac{dS}{dt} = -\beta \frac{SI}{N}$$

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

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

Here S, I, R stand for Susceptible, Infected and Recovered respectively. $\beta$ is the Transmission rate and $\gamma$ is the Recovery rate.
2.2 SEIR

The SIR model discussed here does not consider the percentage of the population who are exposed to the disease, but do not show any symptoms. When the incubation time i.e, the time elapsed before developing symptoms is significant, the SIR model will not be able to capture it. This leads to the SEIR model- Susceptible, Exposed, Infected, Recovered. The model is similar to SIR except that there is a transition from S to E instead of S to I. And the exposed percentage can also infect the Susceptibles. In a closed population, the SEIR model can be represented as

\[
\begin{align*}
\frac{dS}{dt} &= -\beta \frac{SI}{N} \\
\frac{dE}{dt} &= \beta \frac{SI}{N} - \alpha E \\
\frac{dI}{dt} &= \alpha E - \gamma I \\
\frac{dR}{dt} &= \gamma I
\end{align*}
\]

Here, \(\beta\) is the Transmission rate. \(\alpha\) is the Incubation rate (Transition rate from E to I) while \(\gamma\) is the Recovery rate.
quarantined individuals and hospitalization, etc. Most of the papers in the literature consider the SEIR model with a deterministic approach by fixing the parameters to model the spread of infection.[8][11].

Yang and Wang consider the dynamic nature of the tuning parameters themselves. They consider the time-dependent parameters to model the spread of COVID-19 virus in Wuhan extending the SEIR model [7]. They have concluded that the disease is an endemic process and requires a long term plan to spread of the virus.

The model of B. Tang et al. [4] is one of the few which considers the parameters including the rate of transmission, contact rate, recovery rate as functions of time and simulate the model in order to predict the size of the infected population. They use the Markov Chain Monte Carlo (MCMC) procedure to fit the model to the data.

We observe that one of the main challenges in adopting the compartmental models lies in tuning the number of parameters involved in the model. The work in the literature fixes the parameters based on the indicators given by epidemiological experts in the scenario. The emphasis of the current work is to estimate the parameters in a dynamic manner.

3 Model formulation and Analysis

- **Basic SEIR Model**

  We initially ran our data against a basic SEIR model. It was observed that the results are not as accurate as expected. We were also not able to fit the Recovered rates as expected. So we extended our model to include parameter estimation - an optimized concept to estimate the parameters as per the data rather than assuming them.

- **Models on Parameter Estimation**
  - **Grid Search**
    
    In this model, a Grid Search is used to estimate parameters. A broad range is assigned to each of the parameters. The model then tunes the parameters to get possible values that fit the data.
    
    This model is computationally expensive. It takes about an hour and a half to run it on Google Colab. Once the range of parameters is narrowed down, it forecasts the rates which are more accurate than the previous model.
  
  - **Walk forward with Grid Search**
    
    After working on different models, it is evident that the parameters are non-stationary i.e., they change constantly. This model implements the Walk forward approach. Until the last model, the parameters are estimated for the training set as a whole. In this model, they are estimated incrementally one day at a time. The parameters obtained for the previous day are used to estimate the current day parameters.
    
    Though this model is relatively more accurate than the previous versions, it is extremely expensive in terms of computation. Efforts are made to extend this model using Parallel computation to no avail.
It took about 3-4 hours on Google Colab to run this model with no results.

4 Time-Dependent SEIRD Model

In order to optimize the model, different approaches to the SEIR model are considered. This leads to the implementation of a time-dependent SEIRD model [4].

This approach resulted in accurate forecasts of Infected, Recovered, and Death rates for a week. Run time is exceptionally low, one minute at the most. This model can be represented as follows:

\[ \Delta S = -\frac{\beta(t)S(t)I(t)}{N} \]  
\[ \Delta E = \frac{\beta(t)S(t)I(t)}{N} - \alpha(t)E(t) \]  
\[ \Delta I = \alpha(t)E(t) - \gamma(t)I(t) - \delta(t)I(t) \]  
\[ \Delta R = \gamma(t)I(t) \]  
\[ \Delta D = \delta(t)I(t) \]

From (4), we have

\[ \gamma(t) = \frac{\Delta R}{I(t)} \]  
From (5), we have

\[ \delta(t) = \frac{\Delta D}{I(t)} \]

Using (6) and (7) in (3) yields

\[ \alpha(t) = \frac{\Delta I + \Delta R + \Delta D}{E(t)} \]

Using (8) in (2) yields

\[ \beta(t) = \frac{(\Delta E + \Delta I + \Delta R + \Delta D)N}{S(t)I(t)} \]
4.1 Data requirements and format to run the model

This model takes a .csv file with Cumulative Confirmed, Recovered, and Death values. It forecasts the results based on the parameters of the last five days of the test data. It takes the data file and 'N', the population of the area as input. Shown in Figure [4] is the format of data that is being used.

Figure 4: Data format

| Day | Date     | Confirmed | Recovered | Deaths |
|-----|----------|-----------|-----------|--------|
| 1   | 2020-03-24 | 571       | 40        | 10     |
| 2   | 2020-03-25 | 657       | 43        | 11     |
| 3   | 2020-03-26 | 730       | 50        | 16     |
| 4   | 2020-03-27 | 883       | 75        | 19     |
| 5   | 2020-03-28 | 1019      | 85        | 24     |
| 6   | 2020-03-29 | 1139      | 102       | 27     |

4.2 Model

In our model, the population is classified into 5 categories: the Susceptible, the Exposed, the Infected, the Recovered, and the Deaths. Parameters are estimated on a day to day basis. The data until the previous day and the current day is used to calculate the parameters of the previous day. Then the value for the Exposed population that is calculated is passed on to calculating the parameters for the next day. Unavailability of proper data on Exposed leads to improper results in the long run.

This model is run on the data [2] collected from 24th of March onward for states when the first lockdown is implemented in India. For districts, the data is available from 24th April in [2]. This model requires a minimum training of
18 days. In order to carry out forecasts, parameters for 4\textsuperscript{th} day prior to the last day of training till the last day of the training are used. That is if $T$ is the total number of training days, 1 to $(T - 4)$ days data is used as training and the parameters $\alpha, \beta, \gamma, \delta$ are obtained for $(T - 4)$\textsuperscript{th} day. Then the data of the $(T - 3)$\textsuperscript{rd} day is added to the training and again $\alpha, \beta, \gamma$ and $\delta$ are computed for $(T - 3)$\textsuperscript{rd} day. Like this, all the parameters for $T - 4, T - 3, T - 2, T - 1, T$ days are obtained and used to forecast the values of the infections, deaths, and recoveries. Then out of these 5 forecasts, the median is taken as the final forecast value.

4.3 Algorithm

The code for the model is put up at the link given in [5]. Here, $s[], e[], i[], r[], d[]$ are arrays to store calculated susceptible, exposed, infected, recovered and death values $\alpha[], \beta[], \gamma[], \delta[]$ –arrays to store calculated alpha, beta, gamma and delta values $preds$ are all the predictions stored in an array $pred_values$ are stored in a stack that contains $s, e, i, r, d$ array values in seird function. $start_date$ is starting date of the data taken from data.csv $T$ number of days in the training data taken from data.csv $incub_period$ is the Incubation Period
Algorithm 1 Incremental SEIRD Model

**Input:** N (population), data.csv

**Output:** Forecasts for Infected and Death cases for 5 days from the date

training ends

N ← population

Train ← data.csv

start_date ← Train.date

T ← Train.days

incub_period = 5

for x = 1 to T do

  i[x] = Train.c[x] − Train.r[x] − Train.d[x]

  r[x] = Train.r[x]

  d[x] = Train.d[x]

end for

for t = 1 to T do

  parameter_estimation(t)

end for

prediction()

end

parameter_estimation(k)

if k = 1 then

  alpha[k] = 1/incub_period

  gamma[k] = (r[k + 1] − r[k])/i[k]

  gamma[k + 1] = (r[k + 2] − r[k + 1])/i[k + 1]

  delta[k] = (d[k + 1] − d[k])/i[k]

  delta[k + 1] = (d[k + 2] − d[k + 1])/i[k + 1]

  e[k] = (i[k + 1] − ((1 − gamma[k] − delta[k]) * i[k]))/alpha[k]

  e[k + 1] = (i[k + 2] − ((1 − gamma[k + 1] − delta[k + 1]) * i[k + 1]))/alpha[k]

  s[k] = N − e[k] − i[k] − r[k] − d[k]

else

  alpha[k] = ((i[k + 1] − i[k]) + (r[k + 1] − r[k]) + (d[k + 1] − d[k]))/e[k]

end if

beta[k] = (((e[k + 1] − e[k]) + (i[k + 1] − i[k]) + (r[k + 1] − r[k]) + (d[k + 1] − d[k])) * N)/(s[k] * i[k])

gamma[k] = ((r[k + 1] − r[k])/i[k])

delta[k] = ((d[k + 1] − d[k])/i[k])

seird(alpha[k], beta[k], gamma[k], delta[k], k, k+1)

end

seird(alpha, beta, gamma, delta, k, t)

s[t] = s[k] − beta * s[k] * i[k]/N

e[t] = e[k] − beta * s[k] * i[k]/N − alpha * e[k]

e[t + 1] = e[k + 1] − beta * s[k + 1] * i[k + 1]/N − alpha * e[k + 1]

i[t] = i[k] + alpha * e[k] − gamma * i[k] − delta * i[k]

r[t] = r[k] + gamma * i[k]

d[t] = d[k] + delta * i[k]

pred_values = (s[t], e[t], i[t], r[t], d[t])

RETURN pred_values

end
5 Results and Analysis

Forecasted infected and death values and plots for India, few states and districts are shown here. For these experiments, training data from 24th of March to 19th of May for states and 21st of April to 19th of May for districts is considered. Test data from 20th of May to 26th of May is used. Results are shown for the the states of Maharashtra, Gujarat, and the districts Mumbai, Thane and Pune in Maharashtra and Ahmedabad, Surat and Vadodara in Gujarat. The calculated error % for Maharashtra for Infected and Death cases over the week is 3.6 and 1.6 respectively.

| Date      | Actual | Forecast |
|-----------|--------|----------|
| 2020-05-20| 27590  | 27691    |
| 2020-05-21| 28463  | 29529    |
| 2020-05-22| 30483  | 31197    |
| 2020-05-23| 32210  | 32969    |
| 2020-05-24| 33997  | 34850    |
| 2020-05-25| 35187  | 36847    |
| 2020-05-26| 36013  | 38965    |

| Date      | Actual | Forecast |
|-----------|--------|----------|
| 2020-05-20| 1389   | 1353     |
| 2020-05-21| 1453   | 1420     |
| 2020-05-22| 1516   | 1491     |
| 2020-05-23| 1576   | 1566     |
| 2020-05-24| 1634   | 1645     |
| 2020-05-25| 1694   | 1729     |
| 2020-05-26| 1791   | 1817     |

Figure 5: Forecasted Infected and Death Cases for Maharashtra on test data
| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 6571   | 6523     |
| 2020-05-21 | 6649   | 6682     |
| 2020-05-22 | 6591   | 6854     |
| 2020-05-23 | 6671   | 7039     |
| 2020-05-24 | 6793   | 7237     |
| 2020-05-25 | 6944   | 7448     |
| 2020-05-26 | 6775   | 7673     |

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 749    | 744      |
| 2020-05-21 | 773    | 770      |
| 2020-05-22 | 802    | 797      |
| 2020-05-23 | 829    | 824      |
| 2020-05-24 | 858    | 852      |
| 2020-05-25 | 888    | 881      |
| 2020-05-26 | 915    | 911      |

Figure 6: Forecasted Infected and Death Cases for Gujarat on test data

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 18925  | 18502    |
| 2020-05-21 | 19916  | 19599    |
| 2020-05-22 | 20573  | 20774    |
| 2020-05-23 | 21772  | 22030    |
| 2020-05-24 | 22471  | 23371    |
| 2020-05-25 | 23863  | 24800    |
| 2020-05-26 | 23896  | 26323    |

Figure 7: Forecasted Infected and Death Cases for Mumbai on test data

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 3755   | 3977     |
| 2020-05-21 | 4084   | 4266     |
| 2020-05-22 | 4461   | 4580     |
| 2020-05-23 | 4816   | 4921     |
| 2020-05-24 | 4946   | 5292     |
| 2020-05-25 | 5373   | 5695     |
| 2020-05-26 | 5052   | 6131     |

Figure 8: Forecasted Infected and Death Cases for Thane on test data

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 226    | 221      |
| 2020-05-21 | 2557   | 2493     |
| 2020-05-22 | 2810   | 2617     |
| 2020-05-23 | 2916   | 2753     |
| 2020-05-24 | 2960   | 2900     |
| 2020-05-25 | 3063   | 3059     |
| 2020-05-26 | 3223   | 3230     |

Figure 9: Forecasted Infected and Death Cases for Pune on test data
Figure 10: Forecasted Infected and Death Cases for **Ahmedabad** on test data

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 5484   | 5442     |
| 2020-05-21 | 5500   | 5544     |
| 2020-05-22 | 5421   | 5663     |
| 2020-05-23 | 5468   | 5796     |
| 2020-05-24 | 5332   | 5945     |
| 2020-05-25 | 5681   | 6109     |
| 2020-05-26 | 5473   | 6287     |

Figure 11: Forecasted Infected and Death Cases for **Surat** on test data

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 354    | 323      |
| 2020-05-21 | 347    | 322      |
| 2020-05-22 | 349    | 321      |
| 2020-05-23 | 347    | 322      |
| 2020-05-24 | 362    | 323      |
| 2020-05-25 | 358    | 324      |
| 2020-05-26 | 368    | 326      |

Figure 12: Forecasted Infected and Death Cases for **Vadodara** on test data

| Date    | Actual | Forecast |
|---------|--------|----------|
| 2020-05-20 | 231    | 248      |
| 2020-05-21 | 245    | 255      |
| 2020-05-22 | 261    | 262      |
| 2020-05-23 | 281    | 270      |
| 2020-05-24 | 304    | 277      |
| 2020-05-25 | 309    | 285      |
| 2020-05-26 | 331    | 293      |

Table 1: Forecasts of **India** for the upcoming week
5.1 Analysis

The Actual vs Forecasted plots for Infected and Death cases of Maharashtra, Gujarat, Mumbai, Pune, Thane, Ahmedabad, Surat and Vadodara from 13\textsuperscript{th} May to 26\textsuperscript{th} May are shown below:

Figure 13: Plots for Actual vs Forecasted Infected Cases for Maharashtra; MAPE 3.60%

Figure 14: Plots for Actual vs Forecasted Death Cases for Maharashtra; MAPE 1.61%
Figure 15: Plots for Actual vs Forecasted Infected Cases for **Gujarat**; MAPE 5.39%

Figure 16: Plots for Actual vs Forecasted Death Cases for **Gujarat**; MAPE 0.6%

Figure 17: Plots for Actual vs Forecasted Infected Cases for **Mumbai**; MAPE 3.43%
Figure 18: Plots for Actual vs Forecasted Death Cases for **Mumbai**; MAPE 5.92%

Figure 19: Plots for Actual vs Forecasted Infected Cases for **Thane** on Test Data; MAPE 7.36%

Figure 20: Plots for Actual vs Forecasted Death Cases for **Thane**; MAPE 25.55%
Figure 21: Plots for Actual vs Forecasted Infected Cases for Pune; MAPE 2.85%

Figure 22: Plots for Actual vs Forecasted Death Cases for Pune on Test Data; MAPE 1.49%

Figure 23: Plots for Actual vs Forecasted Infected Cases for Ahmedabad; MAPE 5.98%
Figure 24: Plots for Actual vs Forecasted Death Cases for Ahmedabad; MAPE 6.76%

Figure 25: Plots for Actual vs Forecasted Infected Cases for Vadodara; MAPE 6.25%

Figure 26: Plots for Actual vs Forecasted Death Cases for Vadodara; MAPE 7.34%
From the results obtained for the above mentioned states and districts, it can be summarized that the model can capture the current-trend properly. Its forecasts are based on the growth rate of the actual curve. If there is a sudden increase or decrease in the growth rate, the forecasts will be a bit inaccurate until the model stabilizes.

The average Infected and Death MAPE of 28 districts from various states in India from 20\textsuperscript{th} of May to 26\textsuperscript{th} of May is 6.69\% and 1.76\% respectively. Individual MAPE values can be seen in\textsuperscript{2}.

6 Limitations

- This model considers a closed population. Birth, Mortality rates, and others are not considered.
- This model is limited to short term forecasts as the parameters are dynamic and they can not be approximated to long term.
- The transmission rate for the exposed is not considered due to the uncertainty in calculating the exposed.
7 Future Scope

- Considering population density instead of a homogeneous population to forecast accurate results.
- Transmission rate for exposed has to be tuned properly.
- Quarantine factor and others can be included to get a more detailed analysis of the situation.

8 Conclusions

Several papers are published which use SEIR to predict the results. The initial parameters are assumed to be constant in these papers. The parameters were assumed based on input from hospitals and other sources. In this model, we try to calculate these parameters from the data instead of assuming them to be constant. The goal was to forecast these results so that we can estimate and plan for Hospital equipment and Personal Protective Equipment in advance.

9 Acknowledgements

We would like to thank Dr. Bharat Sharma, Dakshas for initiating us into this study and Raakhil Rapolu, Bennett University for his inputs and useful discussions on this project.

References

[1] Sourish Das, Prediction of Covid-19 Disease Progression in India, arXiv:2004.03147 [q-bio.PE], 2020.

[2] Covid19India https://api.covid19india.org/

[3] Worldometer, https://www.worldometers.info/coronavirus/

[4] Yi-Cheng Chen, Ping-En Lu, Cheng-Shang Chang, Tzu-Husan Liu, A Time-dependent SIR Model for COVID-19 with Undetected Infected Persons, http://gibbs1.ee.nthu.edu.tw/A_TIME_DEPENDENT_SIR_MODEL_FOR_COVID_19.PDF, 2020.

[5] Github Link https://github.com/Taarak9/COVID-19_Predictive_Model_SEIRD/

[6] Samuel M. Jenness, Steven M. Goodreau, Martina Morris EpiModel: An R Package for Mathematical Modeling of Infectious Disease over Networks, J Stat Softw. doi:10.18637/jss.v084.i08, (2018).

[7] Chayu Yang and Jin Wang , A mathematical model for the novel coronavirus epidemic in Wuhan, China, Mathematical Biosciences and Engineering, Volume 17, Issue 3, 2708–2724, (2020).
[8] Zifeng Yang, Zhiqi Zeng, Ke Wang et al. Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions, J Thorac Dis, 12(3):165-174, (2020).

[9] Biao Tang, Nicola Luigi Bragazzi, Qian Li et al. An updated estimation of the risk of transmission of the novel coronavirus (2019-nCov), Infectious Disease Modelling 5, 248-255, (2020).

[10] Meher K. Prakash, Shaurya Kaushal, Soumyadeep Bhattacharya, Akshay Chandran, Alok Kumar and Santosh Ansumali, A minimal and adaptive prediction strategy for critical resource planning in a pandemic, medRxiv preprint doi: https://doi.org/10.1101/2020.04.08.20057414, April, (2020).

[11] Gaurav Pandey, Poonam Chaudhary, Rajan Gupta, Saibal Pal, SEIR and Regression Model based COVID-19 outbreak predictions in India, arXiv:2004.00958 [q-bio.PE], (2020).

[12] http://c19.dakshas.org:5000/

A Infected and Death MAPE values

This section contains the Infected and Death MAPE values of 28 districts of various states from 20th of May to 26th of May.
| State                | District           | Infected MAPE (%) | Death MAPE (%) |
|----------------------|-------------------|-------------------|---------------|
| Andhra Pradesh       | Krishna           | 5.99              | 5.25          |
| Andhra Pradesh       | Visakhapatnam     | 5.28              | 0.00          |
| Andhra Pradesh       | Godavari          | 3.94              | 0.00          |
| Bihar                | Munger            | 8.53              | 0.00          |
| Bihar                | Supaul            | 9.14              | 0.00          |
| Gujarat              | Ahmedabad         | 5.98              | 6.77          |
| Gujarat              | Dahod             | 9.41              | 0.00          |
| Gujarat              | Surat             | 8.98              | 4.23          |
| Gujarat              | Vadodara          | 6.26              | 7.34          |
| Haryana              | Sirsa             | 7.14              | 0.00          |
| Karnataka            | Belagavi          | 9.74              | 0.00          |
| Karnataka            | Dakshina Kannada | 9.39              | 7.14          |
| Madhya Pradesh       | Jabalpur          | 9.72              | 0.00          |
| Maharashtra          | Mumbai            | 3.44              | 5.92          |
| Maharashtra          | Pune              | 3.72              | 1.49          |
| Rajasthan            | Dausa             | 9.27              | 0.00          |
| Rajasthan            | Dholpur           | 9.36              | 0.00          |
| Rajasthan            | Karauli           | 2.85              | 0.00          |
| Telangana            | Medchal-Malkajgiri| 8.16              | 0.00          |
| Telangana            | Nalgonda          | 4.76              | 0.00          |
| Telangana            | Suryapet          | 0.47              | 0.00          |
| Telangana            | Vikarabad         | 1.29              | 0.00          |
| Uttar Pradesh        | Auraiya           | 4.08              | 0.00          |
| Uttar Pradesh        | Ghaziabad         | 7.84              | 0.00          |
| West Bengal          | Howrah            | 6.11              | 11.29         |
| West Bengal          | Nadia             | 9.72              | 0.00          |
| Jammu and Kashmir    | Ramban            | 9.68              | 0.00          |
| Ladakh               | Leh               | 7.14              | 0.00          |

Table 2: MAPE values for 28 districts