Real-time estimation and prediction of the mortality caused due to COVID-19 using particle swarm optimization and finding the most influential parameter

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ABSTRACT

On March 11, 2020, the World Health Organization has declared the outbreak of COVID-19 as Pandemic, which is the massive challenges faced globally. Previous studies have indicated that the meteorological parameters can play a vital role in transmissibility and Mortality. In the present work, the influence of Comorbidity and meteorological parameters are investigated for Mortality caused due to COVID. For this, the most affected city by COVID-19 is considered, i.e., Mumbai, India, as a case study. It was found that Comorbidity is the most influential parameter on the Mortality of COVID-19. The Spearman correlation coefficient for meteorological parameters lies between 0.386 and 0.553, whereas for Comorbidity was found as 0.964. A regression model is developed using particle swarm optimization to predict the mortality cases for Mumbai, India. Further, the developed model is validated for the COVID-19 cases of Delhi, India, to emphasize the utility of the developed model for other cities. The measured and predicted curve shows a good fit with a mean percentage error of 0.00957% and a coefficient of determination of 0.9828. Thus, particle swarm optimization techniques demonstrate very high potential for the prediction of Mortality caused due to COVID-19.

It is insisted that by providing constant health monitoring and adequate care for the comorbidity patients, the Mortality can be suppressed drastically. The present work can serve as an input to the policymakers to overcome the COVID-19 pandemic in India as well as other parts of the world.

1. Introduction

In December 2019, the coronavirus was first discovered in the city of Wuhan, China, and was linked to the seafood market of Wuhan (Chen et al., 2020a). The number of patients was reported with a pneumonia of unknown cause (Zhu et al., 2020). Subsequently, the effect of coronavirus is also seen in other provinces of China. On January 23, 2020, the government sealed all

the boarder of Wuhan (Xie & Zhu, 2020). The Lockdown imposed has alarmed all parts of the world about the severances of the novel coronavirus and the primary threat to public health and economic crises. On March 11, 2020, the world health organization has declared the outbreak of COVID-19 as Pandemic (Cucinotta & Vanelli, 2020). As of May 22, 2020, the world health organization (WHO) has reported 4995996 confirmed cases, whereas 327821 are the Mortality across the globe. A total of 188 countries are affected by Coronavirus, Which has created a serious health issue across the world (Sohrabiet al., 2020). The virus was named as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) by the international committee of Taxonomy, whereas the WHO has officially named the disease as 'COVID-19' (Wang et al., 2020).

The symptoms of the COVID-19 patients are sore throat, dry cough, and fever. Most of the cases are resolved without any complication, but in some instances, severe issues are found, such as; septic shock, severe pneumonia, pulmonary oedema, Acute Respiratory Distress Syndrome, and even organ failure (Chenet al., 2020b). It is observed by (Liu et al., 2020) that the transmissibility and infectivity of COVID-19 are much higher, whereas the mortality rate is low. The transmissibility of COVID-19 is through the respiratory droplet and human to human transmission (Huanget al., 2020). Ge et al. (Geet al., 2013) have reported a coronavirus with an ability to use human ACE2 (Angiotensin Converting Enzyme 2) as a receptor in bat with a high potential to be replicated in human beings.

Further, the Genome analysis carried out by Chen et al. (Chenet al., 2020b) has reported that the recognition rate of SARS-CoV-2 with bat SARS Coronavirus is 96%. Similarly, the recognition rate between the SARS-CoV-2 and the coronavirus from Pangolin is nearly 85.5%–92.4% (Lamet al., 2020). Thus, it is lower as compared to bat coronavirus. Hence Pangolin can be the potential intermediate host. Further, the investigation is needed to identify the role of Bat and Pangolin to be the natural reservoir and intermediate host (Zheng, 2020).

In India, the first case of COVID-19 was reported on January 30, 2020, who was the student of Wuhan University ("https://twitter.com/vija, 1222). In contrast, the first case of COVID-19 in Delhi had a travel history from Vienna, Austria ("https://www.indiatoday.i, 1656). As of May 22, 2020, the total number of cases in India has increased to 118447, whereas 3583 is the Mortality across India ("https://www.mygov.in/cov). A total of 32 state and union territories are affected by COVID-19 in India. The most affected cities in India are Mumbai (27068), Delhi (11088), Ahmedabad (10590), Chennai (11131), Pune (4398), followed by Jaipur (1849). On March 24, 2020, Lockdown was imposed across all Parts of India when the COVID-19 cases were 519, whereas as on May 22, 2020, the cases have increased to 125101. Thus there are widespread COVID-19 across all parts of India (Cucinotta & Vanelli, 2020). Fig. 1 indicates the number of cases before and after a lockdown in India.

Researchers have concluded that the transmissibility and mortality rate of COVID-19 is affected by many factors; the climatic condition (Qiet al., 2020) (Tosepuet al., 2020), older age (Liet al., 2020) (Leung, 2020), sex (Sharma et al., 2020), health conditions (Auler et al., 2020), etc. Ahmadi et al. (Ahmadi et al., 2020) have carried out a correlation test for different provinces of Iran using several input parameters. The correlation test reveals that the most sensitive indicator of the infection of COVID 19 is the high population density and the intra-provincial movement. Further, the provinces of Iran with the wet condition is having a high infection rate, whereas the infection rate in the region of high solar activity is less. The Statistical analysis for five
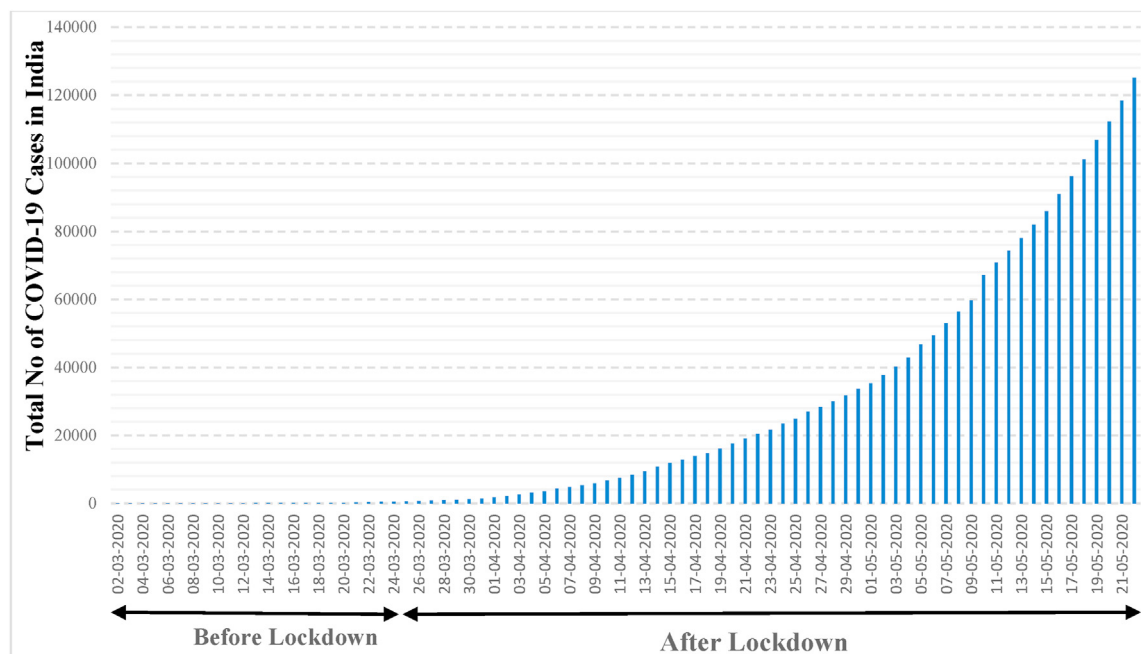

Fig. 1. Number of Covid-19 cases before and after lockdown (Qiet al., 2020).

Brazilian cities is carried out by Auler et al. (Auler et al., 2020) and concluded that the high absolute humidity and mean temperature reduces the infection rate of COVID-19. Bashir et al. (Bashir et al., 2020) have performed the Kendall and Spearmen correlation test for the different climatic indicators in New York, USA. The Kendall and Spearmen correlation coefficient concerning the Mortality rate and air quality is −0.531, which indicates a strong relationship. The negative sign indicates that the mortality rate will decrease by increasing air quality. Also the concentration of nitrogen oxides in the environment is reduce post COVID-19 (Klemeš et al., 2020). Gupta et al. (Gupta et al., 2020) have concluded that the maximum cases in the USA have increased from the region where the absolute humidity and temperature were within the range of 4–6 g/m^3 and 4 °C–11 °C respectively. Jahangiri et al. (Jahangiri et al., 2020) have analyzed the population size and ambient temperature using the ROC (receiver operating characteristic) curve. The study revealed that the population size is having a nonlinear relation, whereas the ambient temperature has a linear relation with the number of infected people.

Char Leung (Leung, 2020) has reported that hypertension, diabetes, cerebrovascular and cardiovascular disease are commonly observed Comorbidity. The casualty due to diabetes and hypertension is 53.2% and 37.8%, respectively. Whereas cerebrovascular and cardiovascular disease is 42.0%. Liu et al. (Liu et al., 2020) have found out that the meteorological parameter and population migration plays a vital role in the transmission of COVID-19. Further, the local condition with low humidity, mild diurnal temperature, and low temperature favors the transmission of COVID-19. Liu et al. (Liu et al., 2020) have worked on the COVID-19 reproduction number. The reproduction number indicates the number of newly infected patients by an infected person in a new population. It was found that the reproduction number is 3.28, which is much higher as compared to the estimation of 1.95 given by WHO. Yueling et al. (Ma et al., 2020) have explored the effect of humidity and temperature on the Mortality of COVID-19 using the generalized additive model. It concluded that the diurnal temperature had a positive association (Spearman's correlation coefficient = 0.44), whereas the relative humidity had a negative association (Spearman's correlation coefficient = −0.32). Further, for one percentage change in diurnal temperature, the mortality rate increases by 2.92%.

Similarly, Ujiie et al. (Mugen et al., 2020) have concluded that low temperature is associated with the increased risk of COVID-19. Prata et al. (Prata et al., 2020) have reported that the temperature and the COVID-19 confirmed cases have a negative linear correlation. Further, it was stated that for a 1 °C rise in temperature, the confirmed cases decrease by −4.8951%.

From the literature, it is evident that different researchers have explored the effect of meteorological parameters, which include Temperature, air quality, relative humidity, etc. Still, the impact of Comorbidity on the mortality rate of COVID-19 cases is not yet explored. Amongst the number of potential confounding factors, we have assessed only the meteorological and Comorbidity factor. The other confounding factor effect is the limitations of the present work due to the lack of available datasets. In the present work, the COVID-19 data is examined for Mumbai, India. The main aim of the current work is;

  I. To find the most influential parameter affect the Mortality of COVID-19
 II. To find the impact of Comorbidity and meteorological parameters on the mortality cases of COVID-19 in Mumbai, India.
III. To develop a regression model using the particle swarm optimization technique, which can predict the Mortality of COVID-19 for Mumbai, India.
IV. The developed regression model for Mortality is validated for the COVID-19 cases for Delhi, India, to emphasize the utility of the developed model for other cities.
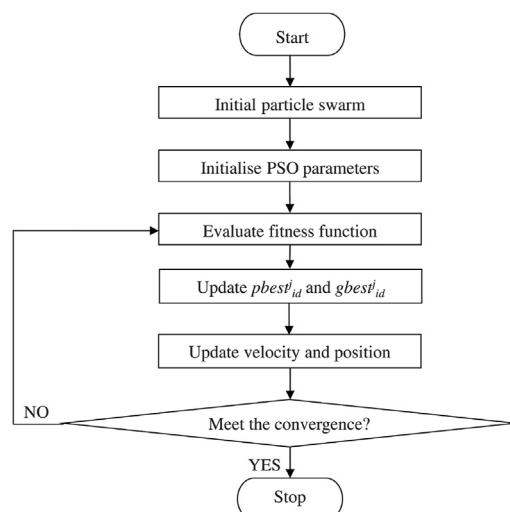

Fig. 2. Indicates the flow chart of the particle swarm optimization technique (Cheng et al., 2013).

2. Meteorological and COVID-19 data

In the present study, the most affected city by COVID-19 is considered, i.e., Mumbai. Mumbai is regarded as the commercial capital of India. The population density in Mumbai is 32303/sq.km. As of May 22, 2020, the total number of positive cases in Mumbai is 27068, and the number of mortalities is 909. The COVID-19 data regarding the number of active cases, Mortality, Comorbidity, and case fatality rate are taken from the Brihan Mumbai Municipal Corporation under the Department of Health ("http://stopcoronavirus.m). The observational period is from March 29, 2020 to May 22, 2020. The meteorological data is taken from the NASA Langley Research Center, Atmospheric Science data Center surface meteorological, and solar energy portal ("https://power.larc.nasa. The following parameters are considered in the present study; Mean, Maximum, Minimum temperature, relative humidity, Wind speed, Solar radiation.

3. Methodology

3.1. Spearman correlation coefficient

In the present work, the spearman correlation coefficient is used to find the strength of the relationship between paired data. Mortality is considered as a dependent function, whereas all other input parameters are considered as an independent variable. The generalized expression for the Spearman correlation coefficient is given as;

$$r_s = 1 - \frac{6\sum D^2}{n^3 - n} \tag{1}$$

Where,

$r_s = Rank\ Correlation$
$D = difference\ in\ paired\ rank$
$n = Number\ of\ Sample$

The strength of the spearman correlation coefficient is given as; 0.0 to 0.3 is negligible, 0.3 to 0.5 is low, 0.5 to 0.7 is moderate, 0.7 to 0.9 is high, and 0.9 to 1 indicates very high correlation (Hinkle et al., 2003). The positive sign indicates the relationship is directly proportional, whereas the negative sign indicates that the correlation is inversely proportional.

3.2. Particle swarm optimization (PSO) technique

Eberhart and Kennedy (Eberhart & Kennedy, 1995) have proposed the particle swarm optimization (PSO) technique. It is one of the metaheuristic techniques which is inspired by the swarming and the flocking behaviour of the birds. The method has gained popularity due to its simplicity in application. Volkan et al. (ÖZSOY & ÖRKÇÜ, 2016) have tested the PSO algorithm on the well-known 28 nonlinear regression tasks of various difficulty levels. The results show that the PSO approach exhibits a rapid convergence to the minimum value of the sum of the squared error function in less iterations, provides accurate estimates. Further, Cheng et al. (Cheng et al., 2013) has concluded that particle swarm optimization can obtain excellent performance on regression analysis problems. Behrang et al. (Behrang et al., 2011) carry out a detailed comparison between the Particle swarm optimization and statistical regression techniques. It is concluded that the average Mean Absolute Percentage Error reduces by 7.56% when the empirical coefficients are obtained by Particle swarm optimization as compared to statistical regression techniques. Thus, the result obtained using Particle swarm optimization has more acceptable performance.

In PSO, several swarms are assigned in a search space with a position and velocity. Each swarm refines its position within the search space for its local best position and the global best position attained by the entire swarm using the fitness function. For an 'n' particle swarm in a "D" dimensional space the particle 'i' has a position of x_i and velocity v_i which is updated for each iteration using the following expression;

Table 1
Summary of descriptive statistics regarding COVID-19 and meteorological parameters for Mumbai, India, during the period of 29–03-2020 to 22-05-2020.

Variable Parameter	Minimum	1st Quartile	Median	3rd Quartile	Maximum	Mean	Standard deviation
Positive Cases	15.000	104.500	218.000	458.000	769.000	305.029	225.334
Death cases	1.000	5.000	10.000	19.000	27.000	12.143	8.292
Co-Morbidities cases	1.000	4.000	7.000	11.500	22.000	8.629	5.885
Case Fatality Rate	0.666	3.361	4.598	5.910	11.392	4.722	2.088
Relative Humidity	55.880	64.695	68.300	69.810	74.590	67.315	3.841
Mean Temperature	28.060	29.310	29.860	30.185	30.920	29.676	0.790
Minimum temperature	24.860	26.075	27.150	27.575	28.350	26.834	0.954
Maximum temperature	31.320	32.900	33.180	33.885	34.530	33.180	0.866
Wind Speed	2.650	3.625	4.080	4.400	5.350	3.997	0.650
Solar Radiation	6.610	6.750	6.820	6.895	7.080	6.821	0.106

$$\overrightarrow{v}_i^{t+1} = \omega^t \overrightarrow{v}_i^t + c_1\tau_{1i}\left(\overrightarrow{pbest}_i^t - x_i^t\right) + c_2\tau_{2i}\left(\overrightarrow{gbest}_i^t - \overrightarrow{x}_i^t\right) \tag{2}$$

Where c_1 and c_2 are the acceleration coefficient. The weight of each particle is denoted by τ_{1i} and τ_{2i} which are generated randomly during each iteration. The fitness function is indicated by equation (2), which shows the minimum coefficient. After each iteration, the position of the particle is updated using equation (3). Fig. 2 indicates the flow chart of the particle swarm optimization technique.

$$Fitness\ function = \sum_i^n (mortality_{actual} - mortality_{Predicted})^2 \tag{3}$$

$$\overrightarrow{x}_i^{t+1} = \overrightarrow{x}_i^t + \overrightarrow{v}_i^{t+1} \tag{4}$$

3.3. Statistical error tests

The following statistical error test is used to estimate the error between the measured and predicted value (Makade et al., 2020);

$$Mean\ Absolute\ Error(MAE) = \frac{1}{n}\sum_{i=1}^n |X_m - X_c| \tag{5}$$

$$Mean\ Percentage\ Error(MPE) = \frac{1}{n}\sum_{i=1}^n \left(\frac{X_m - X_c}{X_m}\right) \times 100 \tag{6}$$

$$Root\ Mean\ Squared\ Error(RMSE) = \sqrt{\frac{1}{n}\sum_{i=1}^n (X_m - X_c)^2} \tag{7}$$

$$Coefficient\ of\ Determination\ \left(R^2\right) = 1 - \frac{\sum_{i=1}^n (X_m - X_c)^2}{\sum_{i=1}^n (X_m - X_{m,avg})^2} \tag{8}$$

Where the ideal value for all the error test is zero accept coefficient of determination whose typical value is one. X_m, X_c indicate the measured and calculated values.

4. Result and discussion

4.1. Descriptive statistics

Table 1 indicates the summary of descriptive statistics regarding COVID-19 and meteorological parameters for Mumbai, India, during the period of 29–03-2020 to 22-05-2020. The total number of COVID-19 positive cases in Mumbai, India, is 27068 during the observation period. The maximum number of positive cases was observed on May 22, 2020, i.e., 1751,

Table 2
The Spearman correlation coefficient, p-value, the coefficient of determination, and a 95% confidence interval.

|	Spearman correlation coefficient	p-values	Coefficients of Determination	Confidence intervals (95%)	
				Lower bound	Upper bound
Comorbidities	0.964	<0.0001	0.928	0.918	0.984
Case Fatality Rate	0.002	0.990	0.000	−0.331	0.335
Relative Humidity	0.455	0.006	0.207	0.127	0.694
Mean Temperature	0.527	0.001	0.278	0.213	0.743
Minimum temperature	0.559	0.001	0.312	0.253	0.763
Maximum temperature	0.386	0.023	0.149	0.048	0.645
Wind Speed	0.426	0.011	0.181	0.093	0.673
Solar Radiation	0.453	0.007	0.206	0.125	0.693
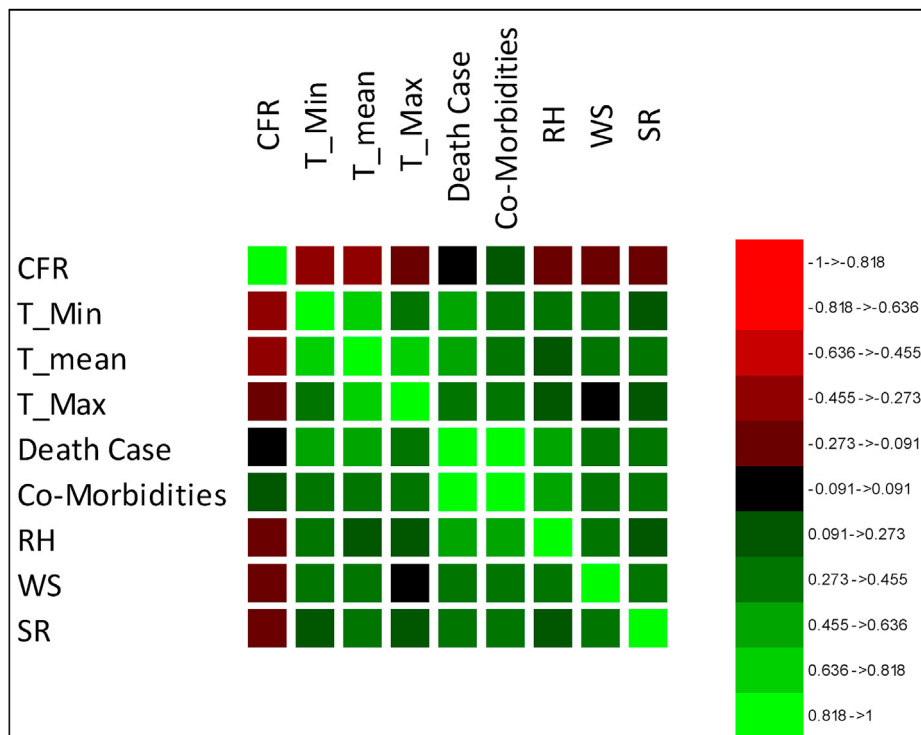
Fig. 3. Correlation matrix amongst all the parameters considered in the present work.

whereas the minimum number of positive cases was found on March 29, 2020, i.e., 15. Similarly, the total mortality cases for the observation period is 909, with the maximum number of deaths occurred on May 19, 2020, whereas the number of minimum death occurred on March 29, 2020.

The term Comorbidity refers to the existence of one or more medical disorders simultaneously. During the observational period, a total of 627 patience with Comorbidity die due to COVID-19. Out of the total death cases during the observational period, 71.1% of cases had comorbidity conditions. For per day average, the death cases are 12.143, out of which 8.629 is due to Comorbidity. Thus, to reduce the mortality rate, the policymaker should implement special health monitoring services for the Comorbidity patient.

The Case fatality rate refers to the ratio and is proportion to the number of deaths due to COVID-19 as compared to the number of positive cases. The case fatality rate for the observed period is 3.981%. The relative humidity for Mumbai lies between 55.88% and 74.59%. The mean, minimum, maximum temperature has a mean value of 29.676 °C, 26.834 °C, 33.180 °C, respectively. Further, the average wind speed and solar radiations are 3.997 m/s and 6.821 (kW-hr/m^2/day), respectively.

4.2. Spearman correlation coefficient

Table 2 indicates the Spearman correlation coefficient between the mortality rate and the considered input parameters in the present study. The strength of the spearman correlation coefficient is given as; 0.0 to 0.3 is negligible, 0.3 to 0.5 is low, 0.5 to 0.7 is moderate, 0.7 to 0.9 is high, and 0.9 to 1 indicates very high correlation (Hinkle et al., 2003). It is observed that the Spearman correlation coefficient for Comorbidity and Mortality is 0.964, which shows a very high correlation. Also, if the Comorbidity cases increase, this will result in an increase in Death cases in Mumbai, India. Amongst the metrological parameter, the minimum temperature has the highest value of the spearman correlation coefficient 0.5559 followed by mean temperature, whose spearman correlation coefficient is 0.527. Thus, the minimum and mean temperature has a moderate correlation with the mortality cases of COVID-19. The observation regarding minimum and mean temperature in the present work is in line with the work of Bashir et al. (Bashir et al., 2020)and Tosepu et al. (Tosepu et al., 2020). The Spearman correlation coefficient for relative humidity, wind speed, solar radiation, and maximum temperature lies between 0.3 and 0.5, thus has a low correlation on the Mortality.

On the contrary, the work carried by Ahmadi et al. (Ahmadi et al., 2020) has a negative value of the Spearman correlation coefficient for relative humidity, wind speed, and solar radiation with the transmissibility of COVID-19. Thus, the transmissibility of COVID-19 will increase with the decreasing value of relative humidity, wind speed, and solar radiation. The coefficient obtained for the Case fatality rate is 0.002, which does not indicate any correlation.
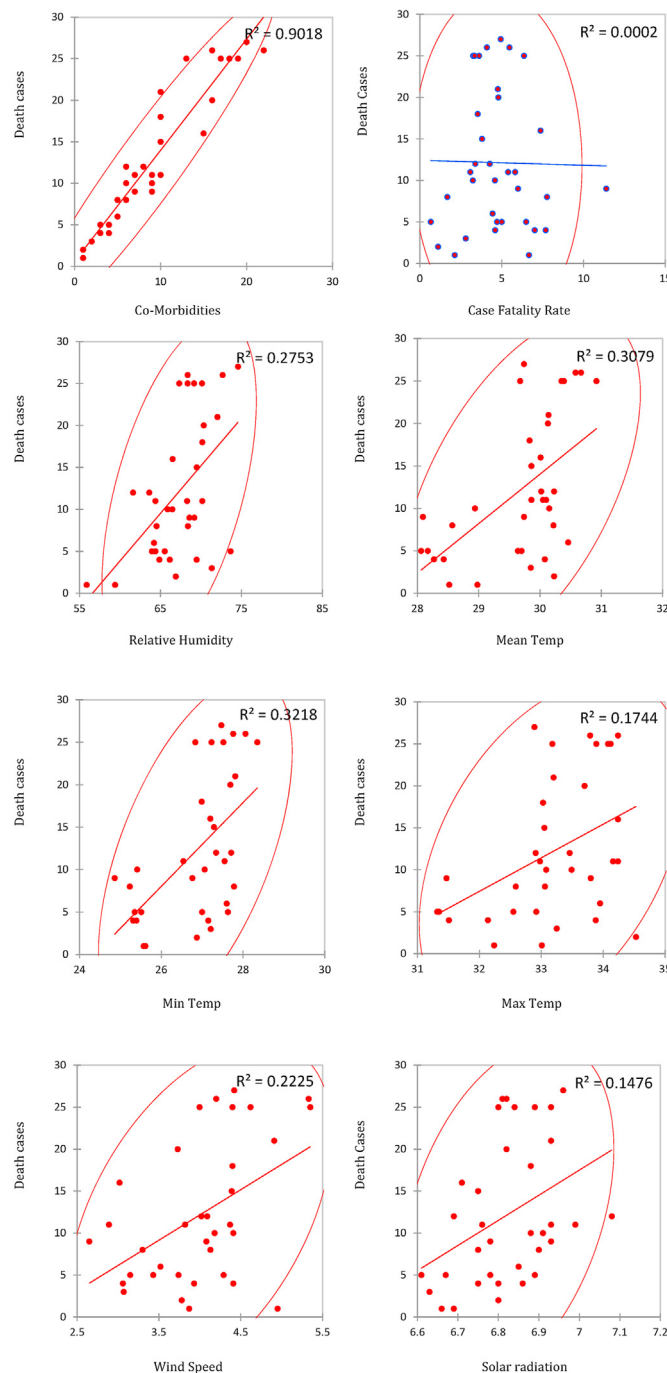
Fig. 4. Scatter plots between the Mortality and the meteorological parameters.

Thus, it can be concluded that the Comorbidity has an extremely strong correlation with the COVID-19 mortality cases in Mumbai as compared to the metrological parameters. The p-value is assumed to be statistically significant for less than 0.05 (5%). From Table 2, it is observed that only the Comorbidity has a p-value of less than 0.0001. Thus, a strong correlation exists between the Comorbidity and Mortality rate. Fig. 3 indicates the correlation matrix to test the multicollinearity amongst all the parameters (Dependent and independent) considered in the present work.

Fig. 4 indicates the scatter plots between the dependent and independent variables. The ideal value for the coefficient of determination is one. Form Fig. 4, it is observed that the coefficient of determination for the linear regression between Co-morbidity and Mortality is 0.9018. The higher value of the coefficient of the determination indicates a smooth linear
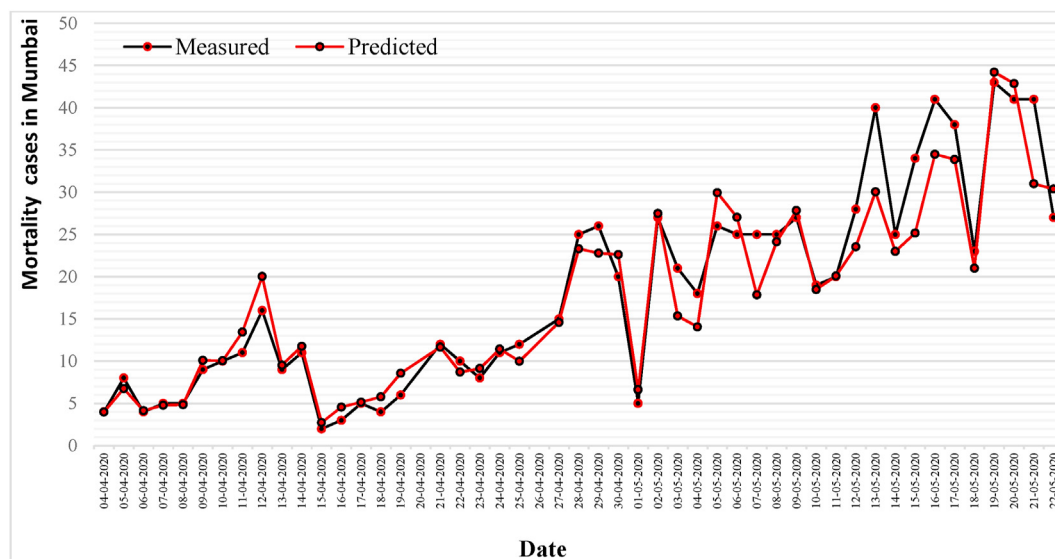
Fig. 5. Variation of the measured and predicted Mortality for Mumbai India.

correlation. Further the coefficient of determination for metrological parameters are; minimum temperature (0.3218), Mean temperature (0.3079), relative humidity (0.2753), wind speed (0.2225), solar radiation (0.1476) and CFR (0.0002).

Thus, it can be concluded that Comorbidity is the most influential factor affecting the mortality cases in Mumbai, India, followed by minimum temperature and average temperature.

4.3. Development of regression model for mortality cases

A linear regression model is developed using the particle swarm optimization (PSO) techniques for the prediction of mortality cases using the COVID-19 and meteorological data for Mumbai, India. In the present work, the data from 04th April to April 22, 2020 is used, which is divided into a training dataset (70%) and validating dataset (30%). For the development of the linear regression model, the independent parameters whose Spearman correlation coefficient is more than 0.5 are considered. The input parameters are Comorbidity, minimum temperature, and mean temperature. The acceleration coefficient used in the present work is (1.5,1.5) (Abdullahet al., 2014).

$$Mortality = -26.8279 + 1.2499 \times Comorbidity - 0.7147 \times T_{Avg} + 1.8417 \times T_{\min} \tag{9}$$

The developed model is tested using a statistical error test; the coefficient of determination for the developed model is 0.8809, and the mean percentage error is −0.0864%. Whereas the Mean absolute and root mean squared error is 2.1326 and 2.7809, respectively, which indicate a good fit between the measures and calculated Mortality for Mumbai, India. Also, Fig. 5 shows the variation between the measured and the predicted Mortality for Mumbai India.

4.4. Validation of the developed regression model for Delhi, India

The developed regression model is validated using the COVID-19, meteorological data of Delhi, India. The COVID -19 data regarding the number of active cases, Mortality, Comorbidity, and the Case Fatality rate for Delhi, India, is taken from the website of Government of Delhi under health and family welfare ("http://health.delhigovt.,2020). The data from 19th April to May 20, 2020 is explored for the validation of the developed model given by equation (09).

Table 3 indicates the variation between the measured and calculated Mortality cases along with the statistical error test for Delhi, India. It is observed that the coefficient of determination is 0.9827, whereas the mean percentage error is 0.00957%. Similarly, the Mean absolute error and the root mean square error is 3.8535, 4.95201, respectively. Fig. 6 indicates a good fit between the measured and predicted mortality cases in Delhi.

5. Conclusions

In the present work, an attempt is made to find the effect of Comorbidity and the meteorological parameter on the mortality cases for Mumbai, India. A linear regression model is developed using particle swarm optimization for the

Table 3
Statistical Error, Measured and calculated Mortality cases for Delhi, India between April 19, 2020 to May 09, 2020.

Date	Measured	Predicted	MAE	MPE	RMSE	R2
19-04-2020	45	40.09220678	3.8535	0.00957	4.95201	0.9828
20-04-2020	47	43.78475112				
21-04-2020	47	40.12409977				
22-04-2020	48	39.74198883				
23-04-2020	50	48.87213793				
24-04-2020	53	48.48447041				
25-04-2020	54	55.02221578				
26-04-2020	54	53.09835434				
27-04-2020	54	48.26626912				
28-04-2020	54	49.69837673				
29-04-2020	56	55.01396083				
30-04-2020	59	60.26688452				
01-05-2020	61	62.13383558				
02-05-2020	64	64.06649842				
03-05-2020	64	65.31173728				
04-05-2020	64	61.38810819				
05-05-2020	64	63.38151497				
06-05-2020	65	66.80733696				
07-05-2020	66	65.13414859				
08-05-2020	68	66.56814997				
09-05-2020	68	68.38206527				
10-05-2020	73	73.44837773				
11-05-2020	73	70.78866206				
12-05-2020	86	89.51832135				
13-05-2020	106	113.5457172				
14-05-2020	115	123.1403323				
15-05-2020	123	131.5505116				
16-05-2020	129	137.3402685				
17-05-2020	148	158.2733354				
18-05-2020	160	168.9149823				
19-05-2020	166	171.6873969				
20-05-2020	176	182.3408651				
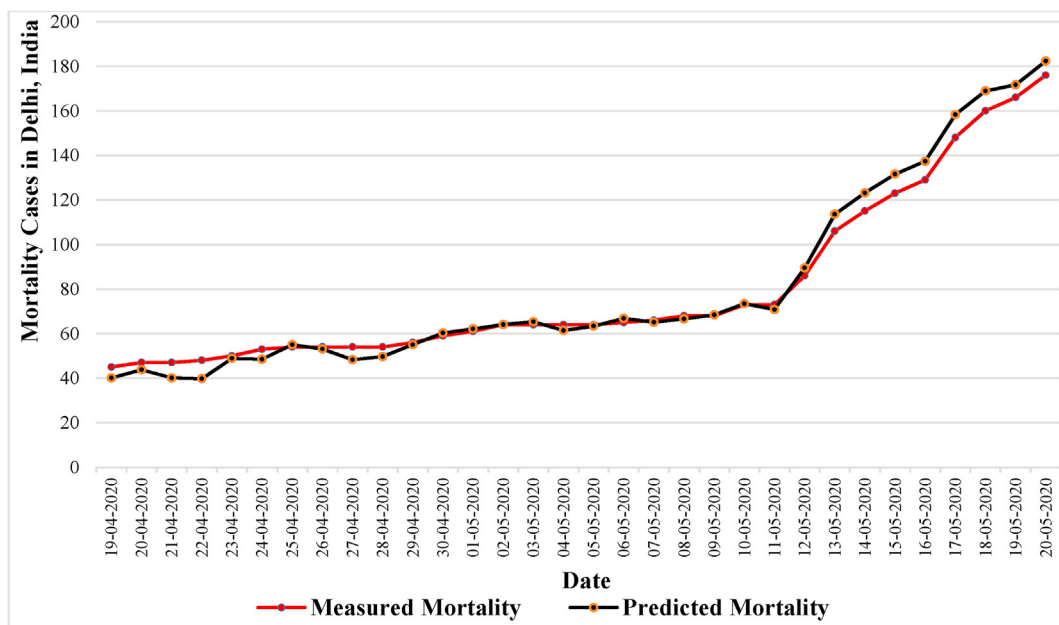
Fig. 6. Comparison between the measured and calculated mortality cases for Delhi, India.

prediction of Mortality cases for Mumbai, India, which is further validated with the data available for Delhi, India, to emphasize its utility for different parts of India. The following are the prominent finding;

1. The most influential parameter for the mortality cases is the Comorbidity factor. The Spearman correlation coefficient is 0.964, which indicates a strong correlation between mortality cases and for Comorbidity cases.
2. Amongst the meteorological parameter, the minimum and the average temperature had a strong, moderate relationship where the Spearman correlation coefficient is more than 0.5.
3. The developed a regression model for mortality cases for Mumbai, India, indicate a coefficient of determination of 0.9217.
4. The validation of the developed regression model for Delhi, India, shows a perfect fit with a mean percentage error of 0.00957% and root mean square error of 4.95201.
5. The particle swarm optimization techniques demonstrate very high potential for the prediction of Mortality of COVID-19.

By constant health monitoring and adequate care for the comorbidity person, the mortality cases can be suppressed to a larger extend. The finding of the present work can serve as an input to the policymakers in suppressing the COVID-19 pandemic in India as well as other parts of the world.

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Declaration of competing interest

None.

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