



A correlation study between meteorological parameters and COVID-19 pandemic in Mumbai, India

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ARTICLE INFO

Article history:

Received 12 August 2020

Received in revised form

30 August 2020

Accepted 1 September 2020

Keywords:

India

COVID-19

Meteorology

Correlation

Artificial neural network

ABSTRACT

Background and aims: Meteorological parameters play a major role in the transmission of infectious diseases such as COVID-19. In this study, we aim to analyze the correlation between meteorological parameters and COVID-19 pandemic in the financial capital of India, Mumbai.

Methods: In this research, we collected data from April 27 till July 25, 2020 (90 days). A Spearman rank correlation test along with two-tailed p test and an Artificial Neural Network (ANN) technique have been used to predict the associations of COVID-19 with meteorological parameters.

Results: A significant correlation of COVID-19 was found with temperature (T_{\min}), dew point (DP_{\max}), relative humidity (RH_{\max} , RH_{avg} , RH_{\min}) and surface pressure (P_{\max} , P_{avg} , P_{\min}). The parameters which showed significant correlation were then taken for the modeling and prediction of COVID-19 infections using Artificial Neural Network technique.

Conclusions: It was found that the relative humidity and pressure parameters had the most influencing effect out of all other significant parameters (obtained from Spearman's method) on the active number of COVID-19 cases. The finding in this study might be useful for the public, local authorities, and the Ministry of Health, Govt. of India to combat COVID-19.

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1. Introduction

The first outbreak of a novel coronavirus (COVID-19) was initially recognized in Wuhan, Hubei Province, in late December 2019 [1]. The World Health Organization (WHO) recognized COVID-19 as an infectious disease and declared it as an international public health emergency after it spread globally, outside of China. The WHO officially named this coronavirus disease as coronavirus disease 2019 (COVID-19) and the causative agent as SARS-CoV-2 [2]. COVID-19 is spreading continuously at a faster rate and has led to one of the biggest panics of the 21st century with a lockdown of more than 6 billion people on the planet.

The common symptoms experienced by COVID-19 patients are mild to moderate respiratory illness such as coughing, fever and shortness of breath. The most frequent symptom is fever, followed by a cough. The approximate incubation period for COVID-19 ranges from 1 to 14 days, but most commonly around five days [3]. In more severe cases, an infection can lead to pneumonia,

severe acute respiratory syndrome, kidney failure and can cause death [4].

Menebo et al. investigated the correlation between meteorological parameters and COVID-19 pandemic in Oslo, the capital city of Norway. The basic weather parameters included maximum temperature, average temperature, minimum temperature, normal temperature, wind speed and precipitation level. Spearman's correlation test was used for data analysis. Precipitation was negatively associated, whereas normal temperature and maximum temperature were positively associated [3]. Ma et al. analyzed the associations between COVID-19 death, meteorological parameters and air pollutants in Wuhan, China. A general additive model (GAM) was applied to explore the effect of humidity, temperature and diurnal temperature range (DTR) on death counts of COVID-19. The study showed that the daily mortality rate of COVID-19 is negatively associated with absolute humidity and positively associated with diurnal temperature range [5]. Tosepu et al. investigated the associations between the meteorological parameters and COVID-19 pandemic in Jakarta, Indonesia. The meteorological parameters included maximum temperature, average temperature, minimum temperature, humidity and precipitation. The data was analyzed using Spearman correlation test. It was found that only average

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temperature is significantly correlated with COVID-19 pandemic [6]. Şahin et al. examined the correlation between coronavirus disease 2019 (COVID-19) and weather conditions in nine cities of Turkey. The weather parameters included for research were temperature, humidity, dew point and wind speed. The effects of each parameter were examined within 1, 3, 7 and 14 days. The data analysis was conducted based on Spearman-rank correlation coefficients. It was concluded that temperature on a day and the maximum wind speed in 14 days, had the highest correlation with COVID-19 cases [1]. Pani et al. investigated the impact of Singapore's weather in COVID-19 transmission, by studying the correlation between COVID-19 pandemic cases and meteorological parameters in Singapore. The COVID-19 data was collected from the Ministry of Health (MOH), Singapore and the data were analyzed using the Kendall and Spearman rank correlation test to examine the correlation between COVID-19 pandemic cases and meteorological parameters. The weather parameters included temperature, dew point, relative humidity, absolute humidity, water vapour, wind speed and surface pressure. It was found that temperature and dew point had a significant positive association with daily as well as cumulative COVID-19 cases. Relative humidity favoured the transmission of SARS-CoV-2 virus, whereas absolute humidity and wind speed associations were more effective than relative humidity [7]. Goswami et al. investigated the occurrence pattern of COVID-19 cases with different meteorological parameters in Indian states namely Maharashtra, Gujarat Tamil Nadu, Delhi, Rajasthan, Madhya Pradesh, Uttar Pradesh, Andhra Pradesh, West Bengal, Punjab and Telangana. The COVID-19 daily cases were collected from the Ministry of Health and Family Welfare of India. The trend of COVID-19 cases and weather parameters were analyzed using the Sens Slope and Man-Kendall test. Also, a Generalized Additive Model (GAM) and Verhulst (Logistic) Population Model was used to predict the trend. The weather parameters used for analysis were average temperature, average relative humidity, maximum temperature and minimum temperature. A significant interaction between average relative humidity and average temperature was found with COVID-19 cases [8]. Kumar studied the effects of meteorological parameters such as temperature, relative humidity, absolute humidity as well as aerosols (AOD) and other pollution (NO_2) in the transmission of SARS-CoV-2 virus in India. The daily average weather data for the last three years (2017–2019) for March, April and May with the same for the year 2020 were analyzed. It was concluded that positive associations exist between COVID-19 cases and temperature and a diverse association with absolute and relative humidity [9].

The first COVID-19 case in India was reported on January 30, in Thrissur district of Kerala (Ministry of Health and Family Welfare, Govt. Of India). Now, the pandemic COVID-19 has posed a major threat to India. Several countries, including India, have gone into a lockdown situation to curb down the spreading of COVID-19. India had gone through four lockdowns. The first phase of nationwide lockdown was between March 25 – April 14, 2020, and the final phase of lockdown ended on May 31, 2020. Presently, India is going through the unlock phase. But throughout the lockdown, the COVID-19 cases have been gradually growing. The Ministry of Health and Family Welfare has confirmed 13, 870, 87 cases with 32,108 deaths in India till July 25, 2020 (<https://www.mohfw.gov.in/>).

According to World Bank data (<https://www.worldbank.org/>), India is the second-most populous nation in the world after China. Due to this, an uncontrolled pandemic in India can affect about 1/6th of the world's total population [8]. Study of pandemic and its correlation with the basic meteorological parameters helps the government to take the required steps to curb the effects of this global pandemic. In this paper, using the data obtained from

reported COVID-19 cases of India, the relationship between frequent occurrences of COVID-19 cases and meteorological causes were examined to give statistical evidence on the potential evolution of COVID-19 under varying climatic conditions [10].

2. Data and methodology

2.1. Study area

Mumbai is known as the capital of the Indian state of Maharashtra. Mumbai is the commercial, financial and entertainment capital of India and lies on the Konkan coast on the west coast of India. The total area covered by Mumbai is approximately 603.4 km² (<http://dm.mcgm.gov.in/>), with a population density of 20,482 persons per square kilometer (<https://censusindia.gov.in/>). Due to its geographical location, it has a tropical climate, specifically a tropical wet and dry climate. The total COVID-19 cases in Mumbai, for the period from April 27 to July 25, 2020, were 1,02,653 (<https://www.covid19india.org/>) (Fig. 1).

2.2. Data collection

For the study, the daily number of COVID-19 confirmed cases, were taken from public sources like COVID-19 Tracker/India (<https://www.covid19india.org/>) and MyGov (<https://www.mygov.in/covid-19>) for the period from April 27 to July 25, 2020. The basic meteorological parameters, including maximum temperature (T_{max}), average temperature (T_{avg}), minimum temperature (T_{min}), maximum dew point (DP_{max}), average dew point (DP_{avg}), minimum dew point (DP_{min}), maximum relative humidity (RH_{max}), average relative humidity (RH_{avg}), minimum relative humidity (RH_{min}), maximum wind speed (WS_{max}), average wind speed (WS_{avg}), minimum wind speed (WS_{min}), maximum surface pressure (P_{max}), average surface pressure (P_{avg}), minimum surface pressure (P_{min}), were collected from online database archives of Weather Underground (<https://www.wunderground.com/>). Weather Underground is a commercial weather service which provides real-time weather information over the Internet. It is a reputable and reliable online platform, and the data from this source has been used for various atmospheric research applications worldwide [7,11–13].

2.3. Calculation of absolute humidity (AH)

Absolute Humidity (in gm⁻³) is defined as the weight of water vapour per unit volume of air. The estimated absolute humidity using Clausius-Clapeyron equation is as follows [14,15]:

$$AH = 2.1674 \times RH \times \frac{6.112 \times \exp\left(\frac{17.67 \times T}{243.5 + T}\right)}{(273.15 + T)} \quad (1)$$

where, T represents temperature in degree Celsius.

2.4. Statistical approaches

In the current study, Spearman rank correlation coefficient was used to find the associations between COVID-19 and the basic meteorological parameters. The Spearman rank correlation is a non-parametric test and the Spearman rank correlation coefficient i.e. Spearman's Rho (r_s) measures the strength and direction of association between two ranked variables. The estimation of Spearman's Rho (r_s) is given as:

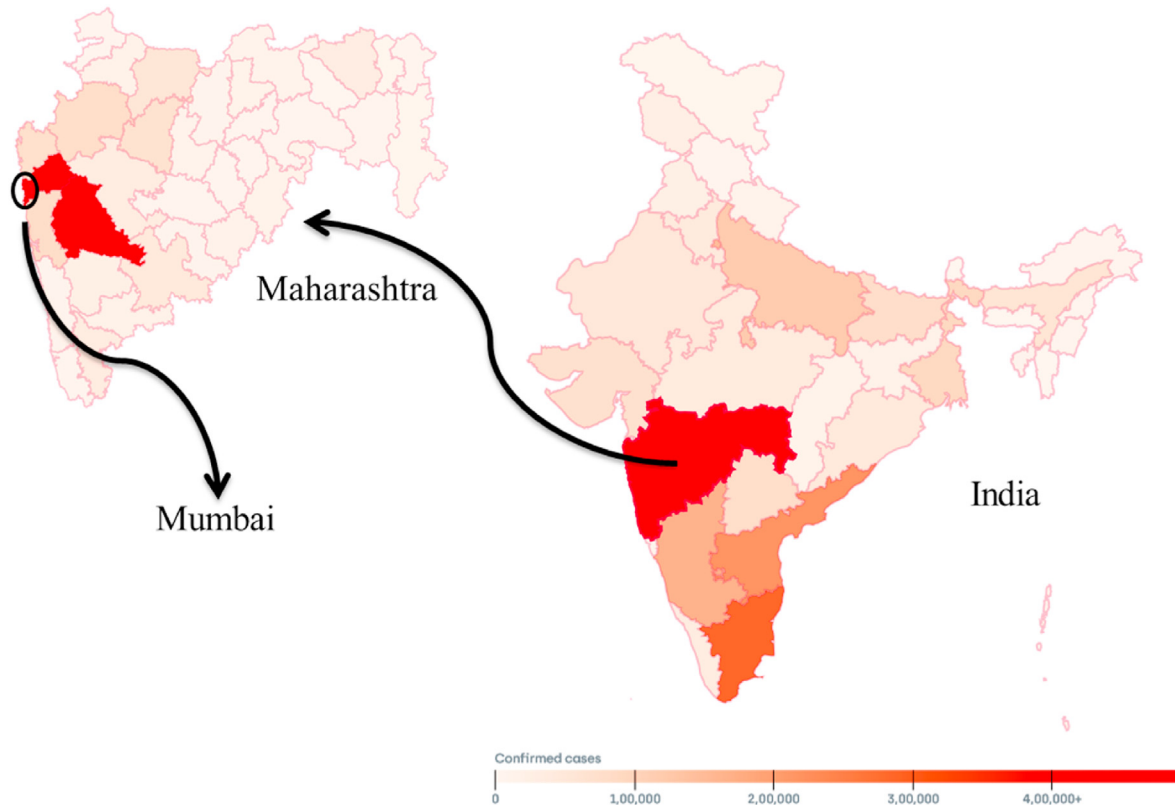


Fig. 1. Geographical location of Mumbai, and total confirmed cases as on July 25, 2020 (This map is adopted from <https://www.covid19india.org/>).

$$r_s = 1 - 6 \times \frac{\sum d_i^2}{n(n^2 - 1)} \quad (2)$$

where d_i represents difference between two variables (parameters) and n represents number of cases. Spearman's Rho (r_s) returns a value from -1 to 1 , where $r_s = +1$ and $r_s = -1$ represents a perfect positive correlation between ranks and a perfect negative correlation between ranks respectively.

2.5. Artificial neural network (ANN)

Artificial Neural Network is a concept based on the working of a biological neural network of the human brain and trying to reproduce the behavior of the biological neuron. To do so, ANN has the basic building block which is known as an artificial neuron which is a mathematical model containing different functions. The information is passed into the artificial neuron as an input and then it is processed by the functions available to generate the output. Setting up an ANN structure needs to define three basic elements involved in the process. The three elements are ANN architecture, training algorithm, and the mathematical functions. The architecture or topology of the ANN depicts how the neurons are organized and the flow of information in the network. Based on this if neurons are organized in more than one layer then it is called multilayer ANN otherwise single layer ANN. The training phase of the ANN can be considered as the function minimization problem, where the optimum value of weights and bias are determined by minimizing an error function. Depending on the training algorithms used, various types of ANNs exist. At last, the mathematical functions also known as activation functions are used to generate the output. There are several performance measurement methods used in ANN

such as MSE, RMSE, MAPE, r , and R^2 [16]. In this study, the correlation coefficient (r) is used which estimates the correlation between the observations and ANN model (see Fig. 4).

3. Results and discussion

3.1. Daily variations in COVID-19 cases and meteorological parameters

As of July 25, 2020, the total number of COVID-19 active cases reported in Mumbai is 1,08,060. Daily counts of COVID-19 new infection from April 27 to July 25, 2020 (90 days) are shown in Fig. 2(a). Despite the complete lockdown in the city to minimize the number of daily incoming cases of COVID-19, data shows an increase in the numbers (Fig. 2(a)). Daily variations in the meteorological parameters in Mumbai city during those dates are shown in Figs. 2 and 3. Highest temperature recorded during this period was 35°C and the lowest was 22.8°C . Relative humidity (RH) is mainly a function of pressure and temperature of the environment. It is the ratio of the actual water vapour pressure to saturated water vapour pressure at the prevailing temperature. Highest RH recorded during this period was 86% and the lowest was 67%. Dew Point (DP) is the temperature at which air must be cooled to become saturated without varying the pressure and is an important factor that determines human comfort. Over Mumbai, DP ranged between $28.9^\circ\text{C} - 18.9^\circ\text{C}$ and thus indicates the human uncomfortable levels

3.2. Correlation between COVID-19 and meteorological parameters

Due to data discrepancy, the clear count of the total active cases of COVID-19 cases was available from April 27, 2020, onwards.

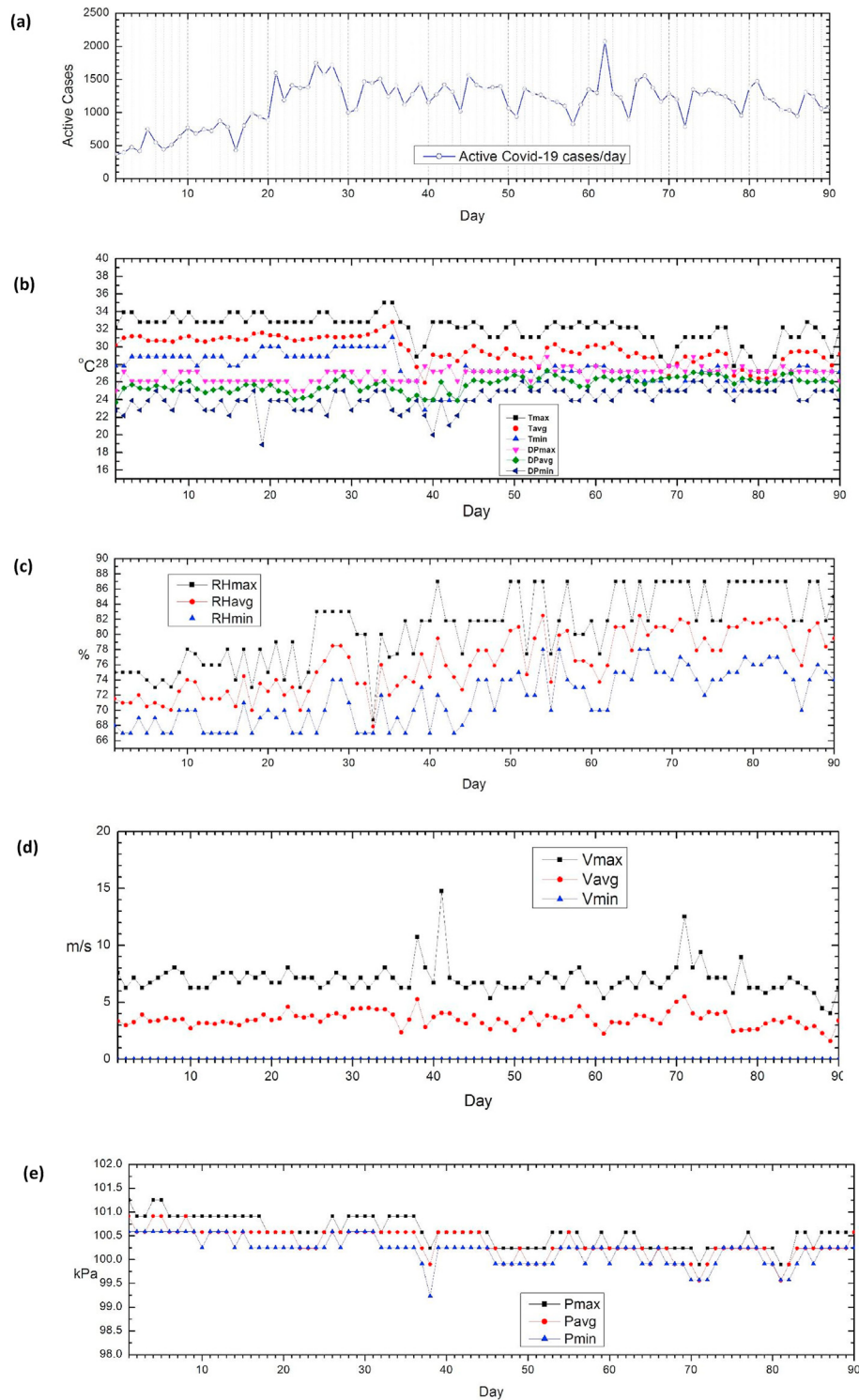


Fig. 2. (a) Cases of COVID-19 in Mumbai, Daily variations in (b) Temperature and Dew point (°C), (c) Relative humidity (%), (d) Wind speed (ms^{-1}), (e) Surface pressure (KPa), from April 27 to July 25, 2020.

Hence data from April 27 to July 25, 2020, were used for correlation test. Table 1 summarizes the result obtained from the Spearman correlation test. The most fundamental factor associated with the human living environment is the Temperature (T) and can have an impact in public-health concerning epidemic development, control and its prevention [17]. From Table 1, T_{\min} , DP_{\max} shows significant negative and positive correlations with new COVID-19 cases over

Mumbai. However, T_{\max} , T_{avg} and DP_{avg} are insignificant parameters. Similarly, RH_{\min} , RH_{avg} and RH_{\max} values show significant positive associations with the daily COVID-19 cases. Absolute Humidity (AH), relates to both relative humidity and temperature. The relation of daily confirmed cases with Absolute Humidity was also estimated and AH_{\max} , AH_{\min} , AH_{avg} has no effect on COVID-19 cases. P_{\max} , P_{avg} and P_{\min} depicts an inverse relationship with daily

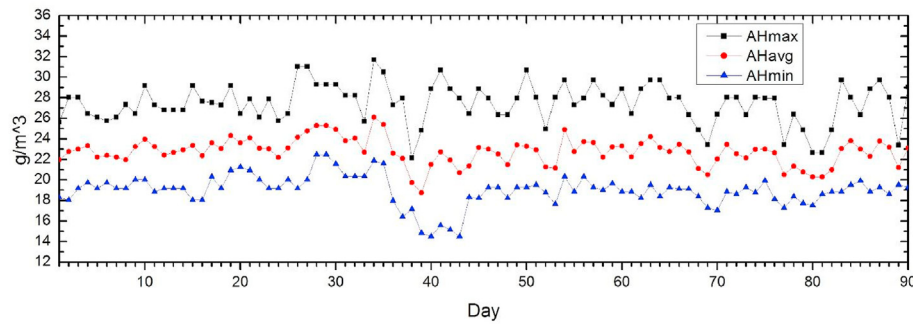


Fig. 3. Daily variations in Absolute humidity (gm^{-3}), from April 27 to July 25, 2020.

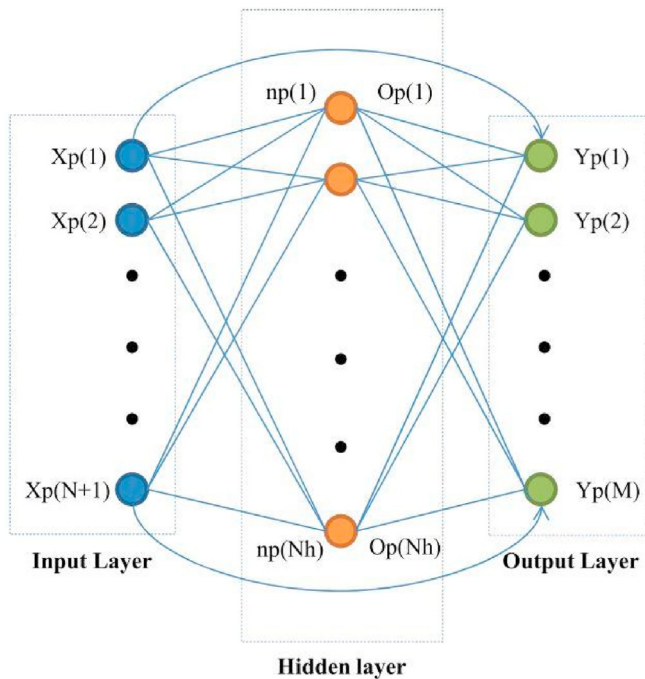


Fig. 4. A feed-forward multilayer perceptron artificial neural network structure with single hidden layer.

COVID-19 cases over Mumbai. The study shows some similarities to the other studies done earlier on COVID-19 cases in Europe, Turkey, China, USA, but overall, it was found that absolute humidity (AH) does not contribute to the COVID-19 cases and is an insignificant meteorological parameter [9].

This research study presents a novel insight into the association of meteorological parameters with COVID-19 pandemic in Mumbai. The results gained from this study might help to exhibit a meteorology-based forecasting model for SARS-CoV-2 activity [18–21]. This study also has some shortcomings. Firstly, the COVID-19 over the period was through the lockdown phase in Mumbai, which might have curbed the actual confirmed cases daily. Secondly, the meteorological parameters were gathered from a single website which might have affected the statistics and the correlation factor. Thirdly, the spread of SARS-CoV-2 highly depends on personal hygiene such as the use of sanitizer and frequent hand washing which needs to be investigated. Lastly, the virus transmission is also influenced by population genetics, age group, health infrastructure, individual immunity and endurance, self-isolation and self-evaluation. So, several factors need to be considered for

Table 1

Summary of the Spearman's rank correlation between COVID-19 and meteorological parameters for a period from April 27 to July 25, 2020 in Mumbai.

Parameters	Spearman rank correlation New cases	
	r_s	p^a
T_{\max}^b	−0.16	0.13
T_{avg}^b	−0.16	0.98
T_{\min}^e	−0.18	0.09
DP_{\max}^c	0.28	<0.01
DP_{avg}^b	0.16	0.14
DP_{\min}^b	0.16	0.98
WS_{\max}^b	−0.04	0.70
WS_{avg}^b	0.15	0.17
RH_{\max}^c	0.36	<0.01
RH_{avg}^c	0.34	<0.01
RH_{\min}^c	0.26	0.01
P_{\max}^c	−0.29	<0.01
P_{avg}^d	−0.20	0.05
P_{\min}^d	−0.23	0.03
AH_{\max}^b	0.10	0.37
AH_{avg}^b	0.11	0.30
AH_{\min}^b	−0.03	0.78

^a Significance level of the two-tailed test.

^b Statistics are insignificant.

^c Statistics are significant at 99% significance level.

^d Statistics are significant at 95% significance level.

^e Statistics are significant at 90% significance level.

Table 2

Value of correlation coefficient (r) obtained using artificial neural network for different structures.

Significant Parameters	ANN Structures		
	1-1-1	1-2-1	1-3-1
T_{\min}	0.1990	0.2917	0.1276
P_{avg}	0.3133	0.4572	0.43338
P_{\min}	0.5032	0.4479	0.4970
DP_{\max}	−0.0391	0.0228	0.2660
RH_{\max}	0.2721	0.3565	0.4511
RH_{avg}	0.5668	0.6496	0.5698
RH_{\min}	0.2564	0.2075	0.2539
P_{\max}	−0.0875	0.5295	0.5291

an extensive evaluation.

3.3. Implementation of ANN in establishing statistical model

As an alternative method to the above mentioned method, ANN is used as a general correlating tool which belongs to artificial intelligence methods, and used in different fields [22–26]. A new

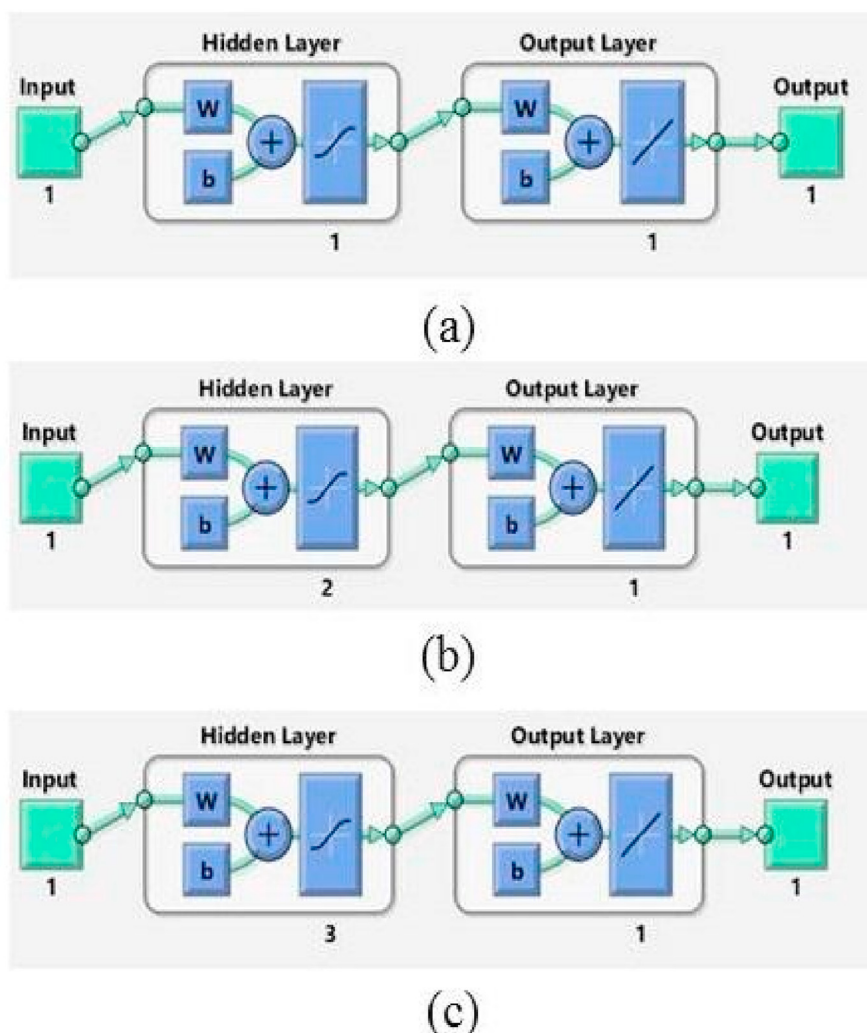


Fig. 5. Three different artificial neural network structures are (a) 1-1-1, (b) 1-2-1, and (c) 1-3-1.

Table 3

Fitting equation for all the significant parameter and highest r values.

Parameters	Fitting Equation
T_{\min}	$y = 0.075 * x + 1e + 03$
P_{avg}	$y = 0.14 * x + 1e + 03$
P_{\min}	$y = 0.21 * x + 9.3e + 02$
DP_{\max}	$y = 0.071 * x + 1.1e + 03$
RH_{\max}	$y = 0.18 * x + 9.6e + 02$
RH_{avg}	$y = 0.34 * x + 7.7e + 02$
RH_{\min}	$y = 0.062 * x + 1.1e + 03$
P_{\max}	$y = 0.29 * x + 7.9e + 02$

ANN is proposed here with an aim to establish the correlation between the significant parameters obtained from Spearman's method to find a regression fit to the data and defining the correlation coefficient (r). The significant parameters deduced from Spearman's method were T_{\min} (90% significance level), P_{avg} , P_{\min} (95% significance level), DP_{\max} , RH_{\max} , RH_{avg} , RH_{\min} , and P_{\max} (99% significance level). The ANN model consisting of a single hidden layer is used for the study. Three different network structures (1-i-1, where $i = 1, 2$, and 3) were taken. The results obtained from the ANN modeling are presented in Table 2.

The three structures taken for the modeling are shown in Fig. 5. The input for the ANN model was taken as significant parameters one by one and the output was taken as the active number of COVID-19 cases. The parameter selected to train the ANN models are training function-TRAINLM, learning function-LEARNGDM, performance function-MSE, transfer function-TANSIG (for the hidden layer) and PURELIN (for output layer), epochs-1000, min_grad-1e-7, mu-0.001 and max_fail-6. From Table 2, it can be observed that even the significant parameters calculated by the Spearman's method have a level of influence on the output parameter which is clearly depicted by ANN modeling. Out of the three r values, the maximum of them (highlighted with bold in Table 2) is considered and the fitting equation is reported for that particular r value in Table 3.

It can be observed from Table 2 that surface pressure and relative humidity parameters influence the active number of COVID-19 cases during the study period (90 days). As the surface pressure variation is negligible so it can be dropped and thus the final influencing parameters can be related to humidity itself. The influence of humidity on the active number of COVID-19 cases has also been found in various studies done in different locations around the world [5,7,8,10,18,21,27–32].

4. Conclusions

The present study mainly aims to contribute to the research community by investigating the relation between COVID-19 active cases and meteorological parameters over Mumbai, India. The results revealed that out of the several meteorological parameters considered, T_{\min} (90% significance level), P_{avg} , P_{\min} (95% significance level), DP_{\max} , RH_{\max} , RH_{avg} , RH_{\min} , and P_{\max} (99% significance level) have an association with the COVID-19 active number of cases, which was found out using Spearman's method. However, the other parameters such as T_{\max} , T_{avg} , DP_{avg} , DP_{\min} , WS and AH showed anti-correlation with COVID-19. Furthermore, an artificial intelligence tool such as an artificial neural network is implemented to predict the most influencing parameter out of the significant parameters found by Spearman's method. It was found that RH and P were having relatively strong influence on the COVID-19 active cases. Since the surface pressure parameter was having negligible variation during the study period therefore it can be dropped off and finally, RH can be regarded as the major parameter. The present study provides requisite information for the general public as well as the government to assess the influence of meteorological parameters on the active number of COVID-19 cases in Mumbai region. However, further assessments of such kind should be required by including huge observational datasets of the meteorological parameters as well as the active number of COVID-19 cases. It is well to mention limitations such as; (1) this study is confined to the currently available facts and data and does not claim any prospective pattern for COVID-19 transmission, (2) inconsistency of results obtained from studies of various states of India which requires further study of the meteorological variables on a large demographic as well as geographic area. In addition, various studies from all across different cities and provinces (states) of the world could help to generalize this result. Active measures such as wearing masks, maintaining hygiene and social distancing should be followed all around the world to break the chain of transmission.

Credit authorship contribution statement

Gaurav Kumar: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Rituraj Kumar:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are thankful to the Ministry of Health and Family Welfare (MoHFW), India and COVID-19 Tracker/India for managing the updated reports of COVID-19 cases. The contributions from Worldmeter, Weather Underground are evenly acknowledged. No funding was received for this study.

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