A Novel Approach to Estimate the Air Temperature Through the Air Pollution and Meteorological Conditions in Biskra Under the Parameters Astronomical, and Atmospheric

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Research

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A novel approach to estimate the air temperature through the air pollution and meteorological conditions in Biskra under the parameters astronomical, and atmospheric

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Abstract

Propose of the experimental study a found a sufficient model to predict the ambient temperature over the area of Biskra, Algeria, taking into account new air pollution factors such as CO, CO_2, O_3, and NO_2. We found that the effect of air pollution, astronomical and meteorological elements have obvious in the ambient temperature, and be behavior, according to regional characteristics. Using the fitting of the experimental data for establishing a set of prediction data sets of pollutants, astronomical, and meteorological elements at the University of Biskra, Algeria. We recorded the highest NO_2 value in March at an estimated value of $1.6.10^{15}$ (mole/cm), where the ambient temperature rate is low. The mathematical model obtained gives a satisfactory results, because they were substantially identical and without almost any error with the experimental data. Finally, the latter can be used by engineers and especially those who work in the environmental field which is very sensitive to temperature variation and it can influence the health of the human being.

Keywords: pollution, prediction, temperature, CO, CO_2, O_3 and NO_2, atmosphere, meteorological

1. Introduction

Air pollution is the presence of some pollutant materials in the air in different concentrations that are harmful to human health, animals, plants, soil and in general the environment. There are two main types of air pollution: external air pollution and internal air pollution

Increasing the level of carbon dioxide, methane and nitrous oxide in the air, would lead to a rise in the global temperature, and thus an increase in continental dryness and may lead to a weakening of the surface solar radiation, so these variables could have an impact on the prediction of solar radiation. There are several air pollutants, such as PM2.5, PM10, SO_2, NO_2, CO, and O_3, and each one of them has its own effect (Junliang et al. (2018); Kalisa et al. 2018; Whanhee et al. 2019).

Among the methods of forecasting and studying the impact of pollution on temperature, and winds the mathematical models, which are used to assess the current situation and predict scenarios that will occur, and to facilitate planning and analysis of studies, they must be properly and accurately designed and evaluated.

On this basis, a study was conducted in Iran, which a combination of fog systems, and neural networks (Ebrahimi and Qaderi 2021). Researcher (Sheen et al. 2019; Samakosh and Mirzaie 2019) developed a model for predicting air pollution using artificial neural networks (ANN).

In the article (Teerachai et al. 2019), a weather research and prediction chemistry model (WRF-CHEM) was used which simulates precipitation and temperature. For more accuracy effective approaches must be entered into the mathematical model, and this is what the authors of the article (Ebrahimi and Qaderi 2021) concluded, where ambiguous qualitative neural inference systems were used taking into account the influencing parameters such as pressure, temperature, wind speed, humidity, and gas oil.

It is known that pollution affects fish production, this is why Anupam Khatua and others have proposed a new mathematical model using ambiguous inferences to find out the effects of global warming and water pollution and their impact on the production of Helsa fish. A tidal method was applied to infer the model based on fuzzy rules. The model was implemented using Fuzzy Logic.

In the article (Anupam et al. 2020), it is confirmed that the traditional time-series prediction models assume a linear relationship between variables, while it is a non-linear relationship. And for that researcher (Victoria et al. 2017) used a new modelling approach using neuro-fuzzy in studying the effect of NH3 contamination and comparing the health effects and predictions estimated from NFIS with those obtained from real emission dispersion, and the results were very satisfactory. To improve the accuracy of daily pollutant prediction by analyzing time-series data (Masoomeh et al. 2020) are used in the research Neuro-Fuzzy Adaptive.

As we said earlier, the effect of pollutants weakens the surface solar radiation, and this necessitates that we find an appropriate and accurate model of solar radiation, and this is what researchers are seeking. In a study presented by (Ashour et al. 2017), fourteen solar radiation models were used for evaluation, monthly, and the most appropriate model for prediction was chosen for the proposed model. The experiment was in southern Algeria, and gets very stimulated results.

In the same context, the researcher (Bakirci 2015) the experiment was in Turkey, using fifteen solar radiation models during a long period of sunshine.

Abdelaziz and others used a new combination with linear regression (LR) to predict daily global solar irradiance (DGSR). The performance of the studied models was validated using a real data set measured in the Applied Research Unit for Renewable Energies

(URAER) located in southern Algeria (Rabehi et al. 2020). In a study presented by Junliang Fan and others (Junliang et al. 2018) the six air pollutants mentioned above in addition to the Air Quality Index (AQI) were selected to analyze their individual and complementary effects on the prediction of global and diffuse daily solar radiation (Rsand Rd). The results showed the importance of appropriate selection of the air pollution inputs. To improve forecast accuracy. (Belmahdi et al. 2020) have presented a method for forecasting over several months (one month, two months, and three months) of the daily, monthly average of global solar irradiance and predicting solar radiation data on a large scale. ARMA and ARIMA models are used to predict the incoming value of the global time series of solar radiation. Accurate and reliable prediction of solar radiation can bring significant benefits to electricity generation and modern smart grid distribution. (Bixuan et al 2020) suggest a new CEEMDAN-CNN-LSTM model for hourly radiation prediction. (Fen et al. 2020) have proposed two new models for estimating hourly diffusion. Using the radiation data for a model year from Beijing meteorological as training samples. Model 1 was a combination of four classic models, including (Liu and Jordan 1960, Orgill and Hollands 1977, Erbs et al. 1982 and Reindl et al. 1990) in which the parameter was determined by weather types derived from the Clarity Index. In Model 2, the weather type classification was revised by Total cloud cover, and Principal Component Analysis (PCA) was further applied to identify key meteorological variables for each weather type as input to the model.

(Chabane 2020) proposed a predicting solar radiation model, where he introduced several air pollutants such as CO_2. CO and CH_4. This mathematical model concerns the city of Tamanrasset (Algeria) according to two components, direct radiation, and diffuse radiation.

The objective of our work is to find a temperature model according to the parameters that pollute the environment and to see the impact of the pollution elements on the ambient

temperature in the region of Biskra, Algeria. The important parameters that have been added in our model include the pollution factor CO_2, O_3, CO, and NO_2.

2. Materials and methods

2.1. Study area

Biskra is located in the southeast of Algeria, at an altitude of 112 meters from the Mediterranean Sea, which makes it among the lowest cities in Algeria. The state of Biskra occupies a total area of 21.671.20 square kilometers. The total population of the state is estimated at 775797 people (statistics 2010) with an average population density of 36 inhabitants / km^2 Fertile.

The state of Biskra is known for its desert climate dry in summer and mild in winter. The average precipitation ranges between 120 and 150 milliliters per year and an average temperature of 20.9 degrees throughout the year.

2.2. Database details

The U.S. National Aeronautics and Space Administration (NASA) provide a petabyte worth of global earth science data collected from satellites. Some of these data can be used to analyze the climate, atmosphere, and types of pollutants present in atmospheric layers; NASA's satellite data can thereby be used to monitor the environment and the earth. The program My NASA Data allows data analysis by researchers around the world. It is an online tool that allows researchers to easily locate areas that they wish to analyze and enables the examination of relevant scientific data. paired with coordinates

2.3. Methodology

In the literature, there are several mathematical models. Ours is non-linear in the form of a sine function, it is made up of several pollution parameters which influence the temperature of the region of Biskra. Algeria. Regarding the form proposed with the constant

placed and distributed according to this established model, the change in temperature showed a remarkably perfect convergence, and it is for this reason that we benefited from the equivalent constants for use in the final mathematical model. We used polluting factors which are changeable according to each month of the year.

3. Mathematical modeling of temperature curves

This flowchart shows the process of building a mathematical model that predicts ambient temperature based on meteorological, astronomical, and atmospheric parameters.

In the first step, we enter all the experimental data, such as the astronomical data like the angle of the sun h, the hourly angle ω, longitude, and altitude of the site control point, declination of the earth, and atmospheric parameter such as pollutant data correspond to the studied site and last parameter which estimates meteorological parameters such as ambient temperature.

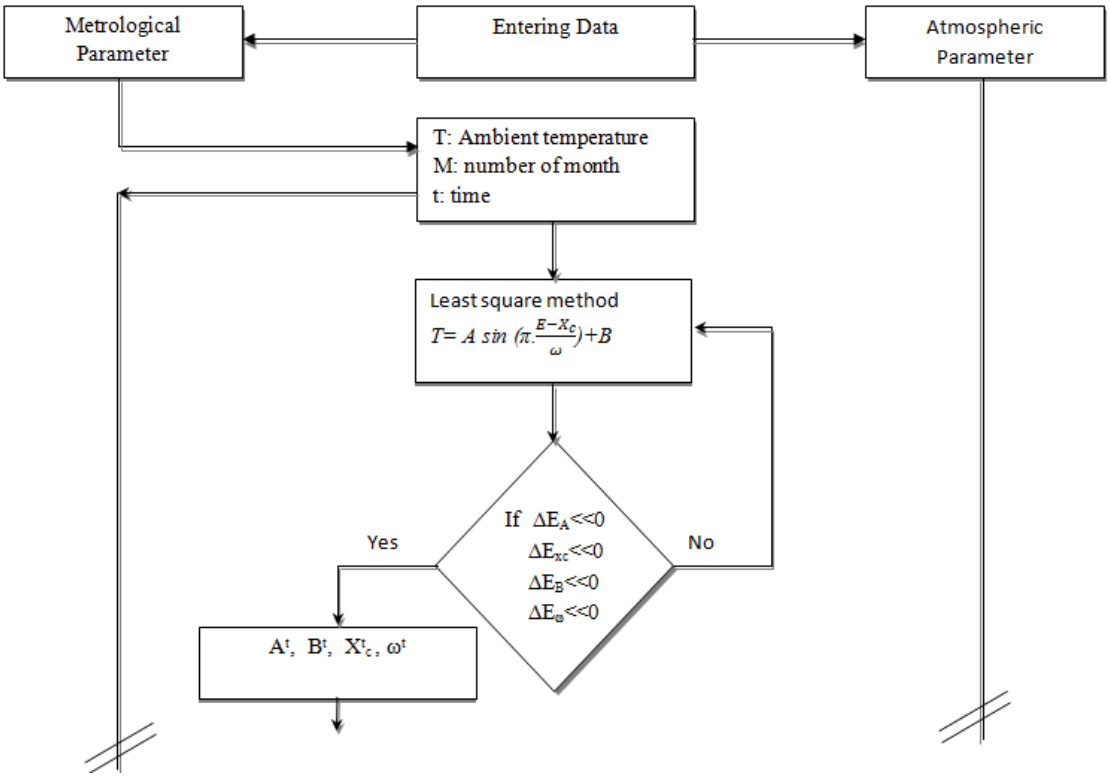


Figure 1. organizational program process part 1

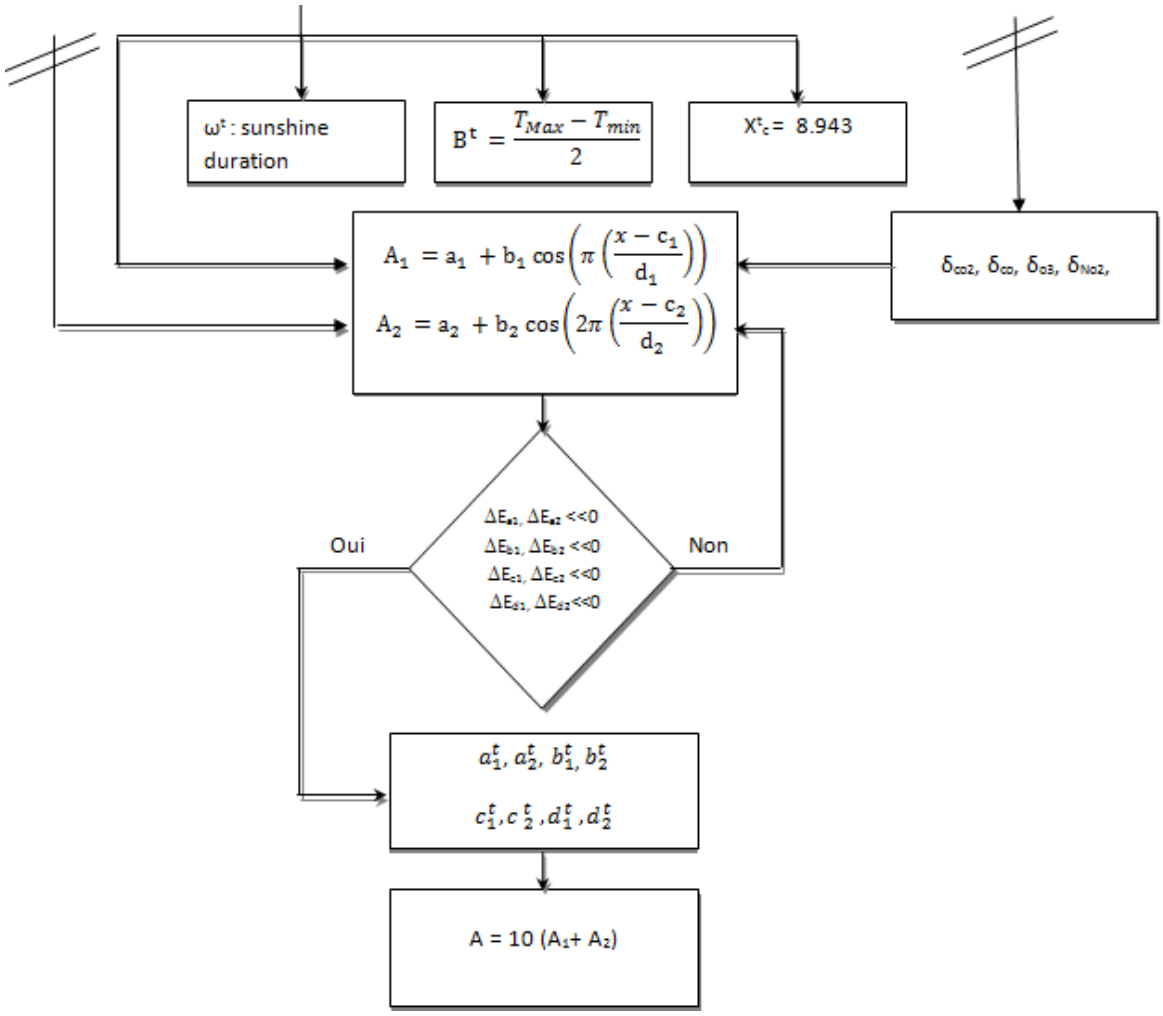


Figure 2. organizational program process part 2

The program chooses to update the ambient temperature with the number of months, and after that we give the form of a mathematical model when predicts our study in sinusoidal form, using the method of least squares to obtain the constants of the correlation such as A, B, Xc and ω and then, we have to check the program errors, such as the constants to get a low error.

The second step of the program calls the meteorological and astronomical parameters to predict the constants found A in form $10.(A_1 + A_2)$. Then we obtain two mathematical models of the same sinusoidal shape according to the new variables χ which links to other new atmospheric variables δ_{co2}, δ_{co}, δ_{o3}, δ_{No2}, and the number of months ses Fig.1 and Fig.2. We

checked the errors of the program such as the constants a_1, b_1, c_1, and d_1 to get a low error. It has been explored that the constant B estimates the deviation of the max and min ambient temperature divided by two, Xc is a constant value of 8.943.

Finally, the program gives us good results, and takes into account meteorological, astronomical, and atmospheric parameters.

Table 1.The constants of the correlation, according to months

Month	1	2	3	4	5	6	7	8	9	10	11	12
y0	285.22	283.68	286.433	294.03	293.42	307.67448	301.83	302.86	304.29	295.74	290.12	284.16
xc	8.83	9.16	8.640	9.292	8.560	8.767	9.32	9.81	8.668	8.945	8.421	8.90
w	11.15	8.74	11.28	10.236	12.26	11.349	10.19	11.018	10.548	11.30	9.112	9.26
A	5.32	4.07	7.414	6.7241	7.403	8.51	6.203	5.77	5.625	6.568	4.628	3.37
χ^2	1.21	0.86	2.66	0.9784	1.1069	1.23	0.340	0.926	0.719	1.812	0.673	0.354
R^2	0.925	0.907	0.916	0.96	0.962	0.968	0.9836	0.948	0.959	0.926	0.944	0.94
CO	99.35	102.06	102.54	103.05	95.518	81.212	73.563	73.99	74.80	74.78	83.153	89.01
NO2	1.30	1.230	1.58	1.159	1.303	0.917	1.165	1.055	1.249	0.952	1.089	1.122
CO2	400.72	408.13	402.21	403.11	403.78	405.91	399.76	403.02	400.68	399.27	401.02	403.10
O3	367.71	383.73	422.39	398.68	408.14	387.34	374.41	374.06	362.13	338.35	355.82	367.29

Table (1) shows the different correlation constants, for several forms of established model and atmospheric parameters such as CO, CO_2, NO_2, and O_3, we notice that the constants take fixed values just for a well-defined month and these constants are changed according to the change of month and day.

From our perspective, we can see that there are constants in the table which are almost values closer to the length of the year. Therefore, it is better to replace it with the average value, this example estimates the constant Xc.

From the table, the square residuals: R^2 and χ^2 take on acceptable values. For a mathematical model that predicts the variation in ambient temperature are linked with several astronomical and atmospheric variables.

$$A = 10 \times (A_1 + A_2) \; R^2 = 0.794 \tag{1}$$

$$A_1 = \left[-14.78 - 15.56 \times \cos\left(\pi \left(\frac{\chi - 94.02}{-87.74} \right) \right) \right] \tag{2}$$

$$A_2 = \left[0.124 \times \sin\left(2\pi \left(\frac{\chi - 0.983}{0.95} \right) \right) \right] \tag{3}$$

$$\chi = \delta_{O3} + \delta_{CO2} + \delta_{NO2} + \delta_{CO} + M \tag{4}$$

$$\delta_{O3} = \left[\frac{O3 - MIN(O3)}{MAX(O3)} \right] \tag{5}$$

$$\delta_{CO2} = \left[\frac{CO2 - MIN(CO2)}{MAX(CO2)} \right] \tag{6}$$

$$\delta_{NO2} = \left[\frac{NO2 - MIN(NO2)}{MAX(NO2)} \right] \tag{7}$$

$$\delta_{CO} = \left[\frac{CO - MIN(CO)}{MAX(CO)} \right] \tag{8}$$

$$T = \frac{T_{\max} - T_{\min}}{2} + 10 \times (A_1 + A_2) \times \sin\left(\pi \left(\frac{t - 8.943}{\kappa} \right) \right) \tag{9}$$

Finally, the final correlation of ambient temperature is obtained according to the atmospheric and astronomical variables. As long as the temperature value which estimates the meteorological parameter, see eq. (9).

$$T_{am} = y_0 + A \times \sin\left(\pi \left(\frac{t - \mathrm{X}_c}{\omega} \right) \right) \tag{10}$$

The main mathematical equation or the first case is, written according to equation (10), from the results obtained in table (1) above, we can say that the constant y_0 of the established

model estimates the difference between the two maximum and minimum ambient temperatures which is divided by two.

$$y_0 = \frac{T_{\max} - T_{\min}}{2} \tag{11}$$

On the other hand, with respect to the correlation constant A, we try to create other models (see equations 2 and 3). The values of A in the table are not stable for the whole year, so the new model established from A has been a perfect approach.

The main remark, it is that the established model is related to the new atmospheric variables which are called out by equations (4) and (8). With respect to the constant ω, we can select the variable K as a duration of sunshine.

4. Results and discussion

Figure 3, shows the variation in ambient temperatures as a function of daily weather, according to the first six months which correspond to the experimental measurements. We notice the evolution of the ambient temperature changes according to each month, we target that the ambient temperature variation takes the maximum value in June, it reaches the estimated value of 317 K and decreases successively until January and February with a value of 287 K and 291 K.

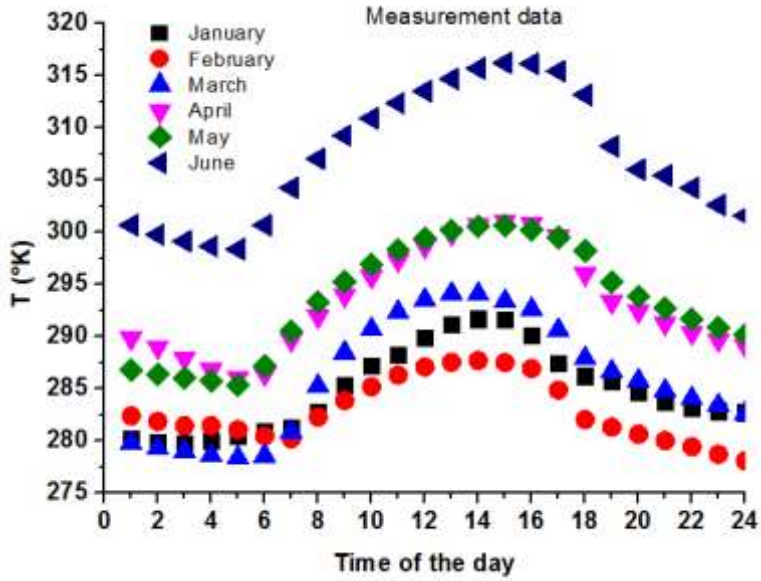


Figure 3**.** Ambient temperatures as a function of daily weather, according to the first six months (experimental measurement)

Figure 4, shows the change in ambient temperature correlated as a function of daily time, it corresponds to the first six months of the year. We observe the remarkable resemblance between figure (3) and figure (4) which gives a perfect approach.

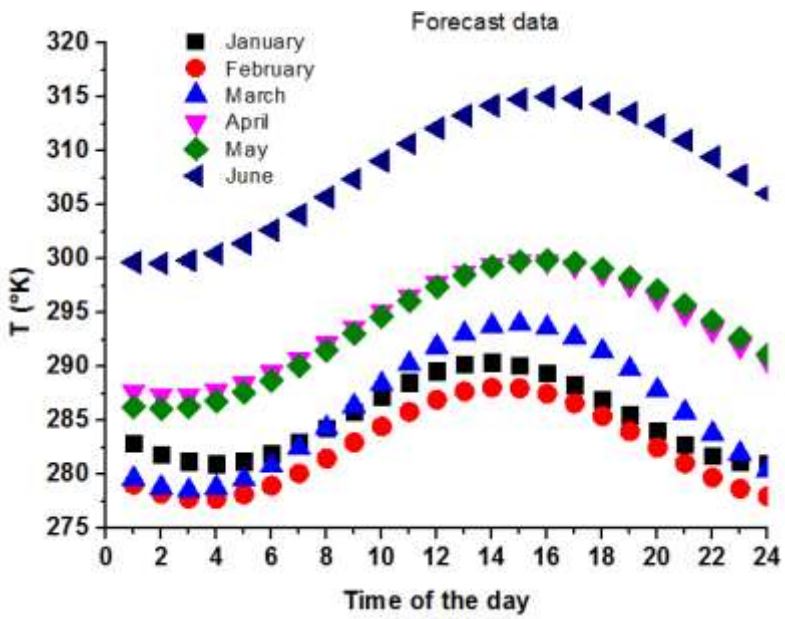


Figure 4**.** Ambient temperatures as a function of daily weather, according to the first six months (prediction data)

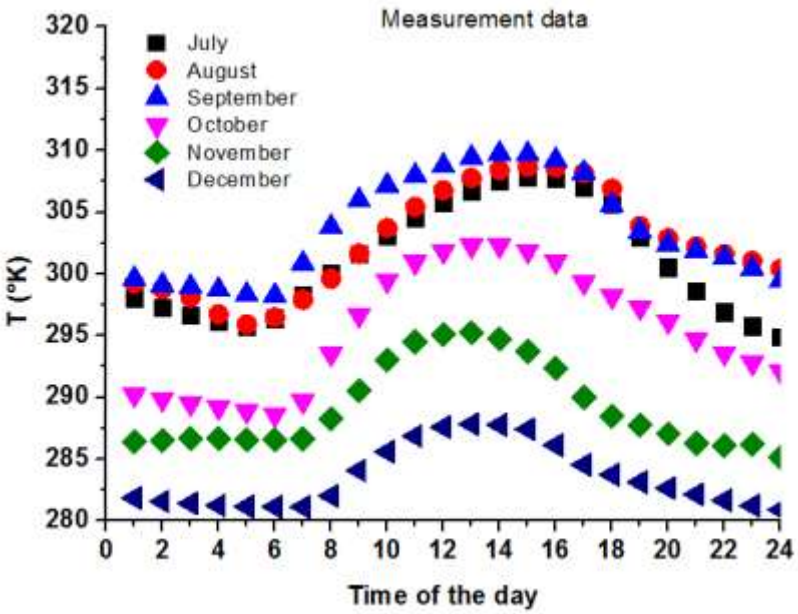


Figure 5. Ambient temperatures as a function of daily weather, according to the second six months (experimental measurement)

The figures (5) and (6) represent the variation of ambient temperature, according to the daily time by each month one must compare between the figure (5) and the figure (6) which estimates the experimental and numerical values. It has been found that the change in ambient temperature between the two gives the best prediction with the measured data.

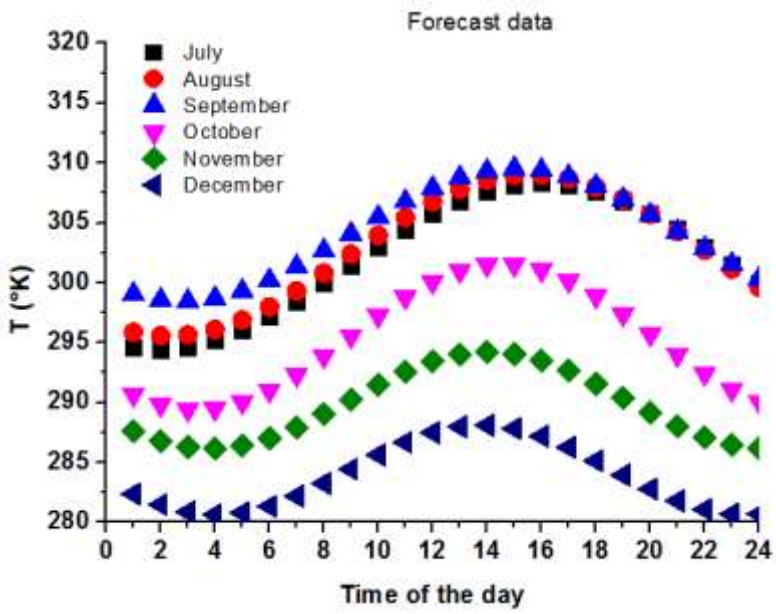


Figure 6. Ambient temperatures as a function of daily weather, according to the second six months (prediction data)

Changes in climate, and atmospheric parameters have influenced the evolution of ambient temperature. We do not forget the astronomical influence that it is presented by the duration of the sunshine which has a relation between the movement of the earth and the sun (see figure 13).

This addition of polluting parameters gave rise to very sensitive parameters, perfect, and real, and this translates to a resemblance between the experimental and the digital.

The latter results in an increase in the ambient temperature in September compared to other months, which is observable that can be explained by the effect of increasing pollutant values which are estimated by CO (75 ppbv). NO2 (1.25 mol/cm^3 .10^{15}) and CO_2 (400.5 ppmv). (See figures 7, 8, and 9).

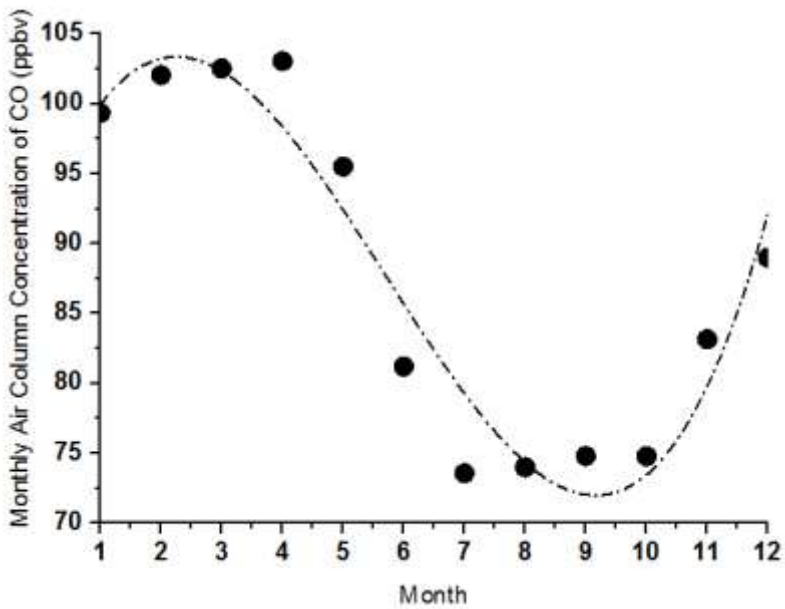


Figure 7. Monthly air column concentration of CO, according to the months

Figure 7, explains the variation in the monthly carbon monoxide concentration as a function of the months of the year. We find that the shape of the curve is sinusoidal. It starts with max values for the 4 months and gradually decreases until July. It stabilizes until October and increases successively until the last month of the year.

The max values reached the value 102 ppbv, for the month of April and a reliable carbon dioxide value selected in June which reaches 73 ppbv. All this translates into the equation (8).

Figure 8, illustrates the variation of NO_2 as a function of the months of the year. We can distinguish who there is an observable disturbance. This last max value is amortized at the end of a minimum value, the cause of penetration of NO_2 in the two equations (2 and 3) results on the influence of ambient temperature on everything in the month of September which gives us the action of the polluting parameters.

This change is explained in figure (8), or the measured point of NO_2 in the month of September reaches a value 102.5 (10^{15}mol /cm^2) which represents the maximum value for the months of July and August. All of this translates into the equation (7) which represents a new creative parameter that links the max and min values of NO_2. The new parameter δ_{NO2} is injected into equations (2, 3, and 4).

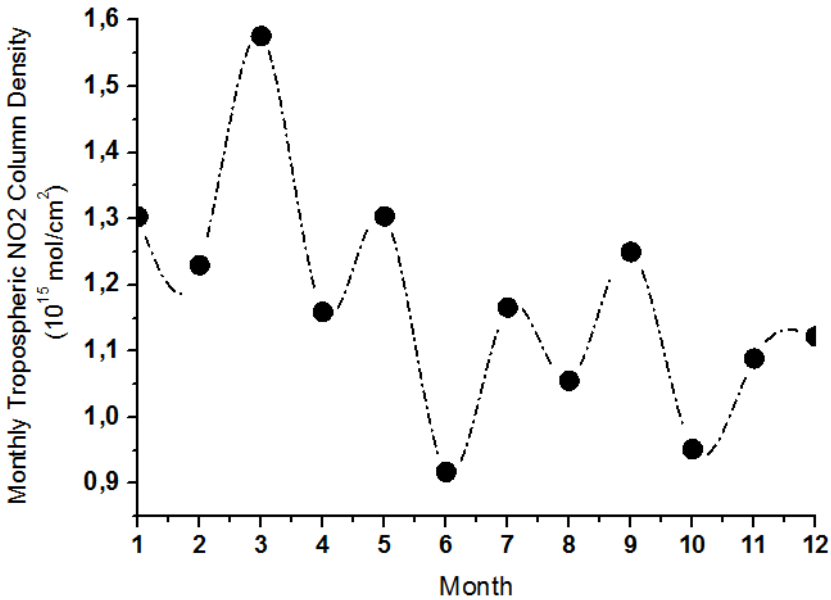


Figure 8. Monthly tropospheric NO_2 column density, according to the months

Figure (9) shows the variation of carbon dioxide as a function of the months of the year. Note the evolution of the curve of CO_2 takes the same as the variation of NO_2 (Figure 8).

In that case, we can say that the influence of NO_2 and CO_2 participated in the evolution of the greenhouse effect which is presented in figures (3 and 5) we can always explain that the month of September when the value of CO_2 reaches the value 400.5 ppmv, the latter is higher than the month of July, which means the influence in the ambient temperature on everything in that selected month (see figure 3). This translates into the equation (6) which is injected into the equation (4). The latter is added in equations 2 and 3. Finally, all these parameters participate in the final correlation which is represented by equation (9).

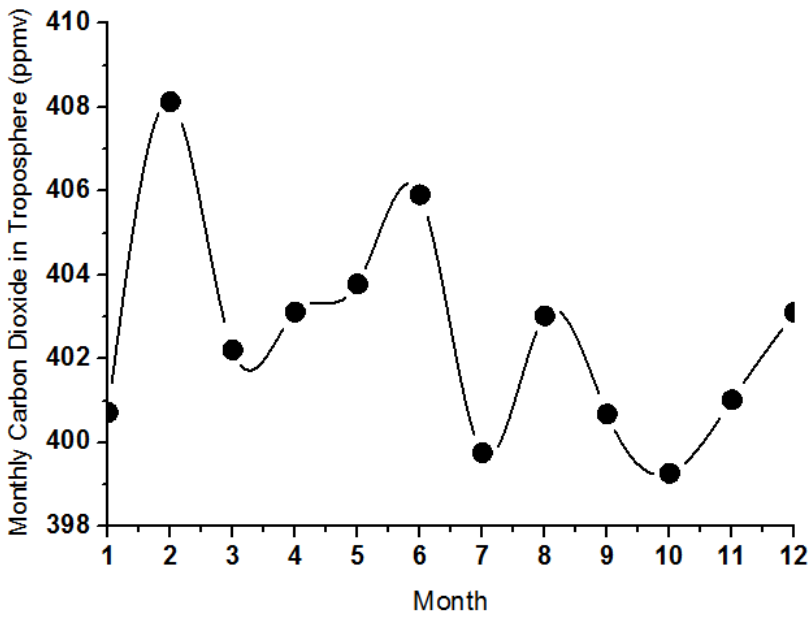


Figure 9. Monthly carbon dioxide in troposphere, according to the months

Figure 10, shows the monthly change in ozone as a function of the month of the year. It is targeted that this evolution can take the same shape as the variation of carbon monoxide, CO, this is explained by the two polluting parameters. These have the same influence depending on the greenhouse effect, it is affected in the correlation that predict the ambient temperature. We find the point of the month of September which estimates the point of view, therefore the ozone value is low compared to July and August.

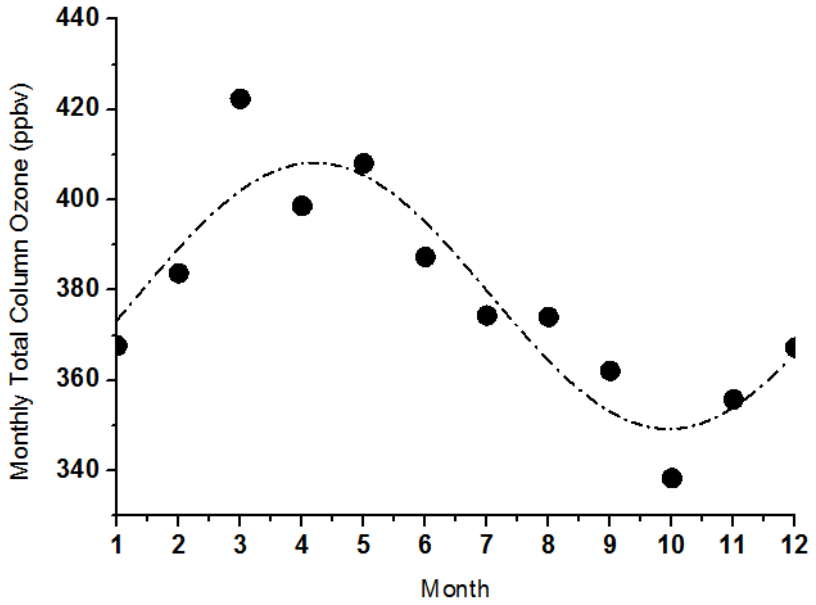


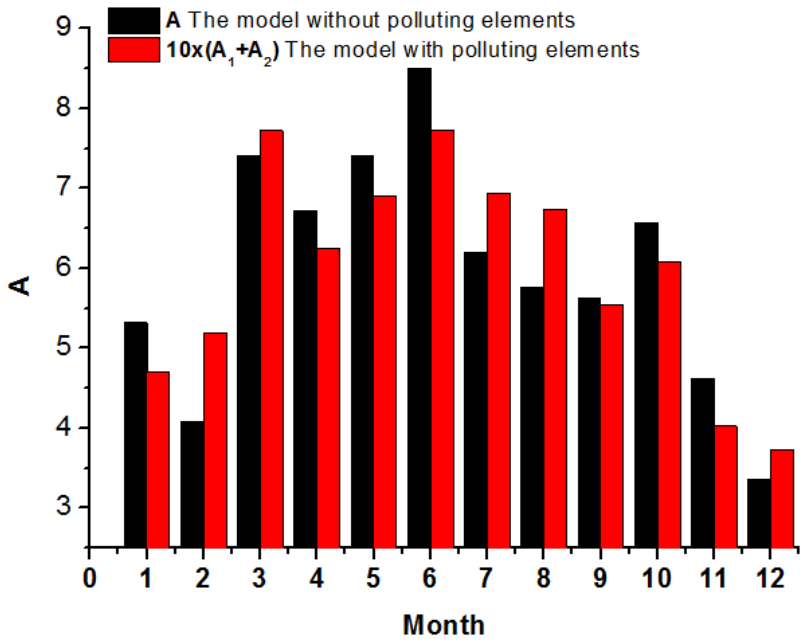
Figure 10. Monthly total column Ozone, according to the months

The maximum change in ozone in March which reaches the value (422 ppbv), and minimum in October which gives the value of (340 ppbv).

This variation is integrated, according to the new variable, which is linked by the maximum and minimum values of the zone. See (eq.5), the latter is injected into equations (2, 3, and 4).

Figure 11, shows the change in the main correlation constant A with the modification in change by variable $10x(A_1+A_2)$ which depend on the final correlation value (see equation 10), we observe that the values are simulated between them.

The constant variable **A** the under the polluting parameters, in that case, we will try to shout new parameters $10.(A_1+A_2)$, according to the polluting parameters. The results are satisfactory, with a good approach between the old parameter A without the polluting elements and the new models with the polluting parameters (see equation 1).



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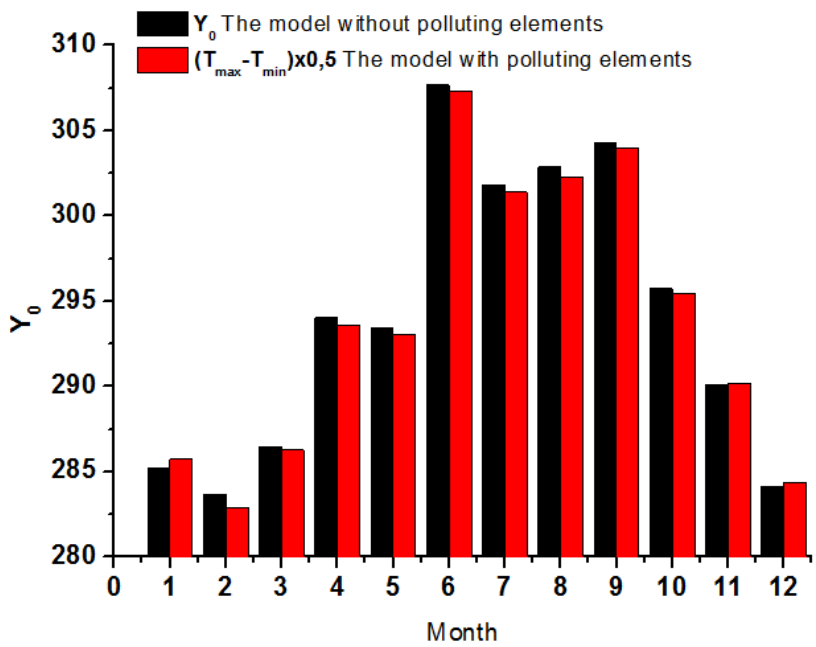

Figure 12. Constant of the Y_0, and $(T_{max}-T_{min})/2$, according to the months

Figure 12, shows the variation of the main correlation constant y_0 as a function of the months of the year with the new model which predicts the variable y_0. We have found that the model y_0 represents the difference temperature of the maximum, and the minimum divided by two (see equation 9), we notice that the error is zero and these two approaches are superimposed (see figure 12).

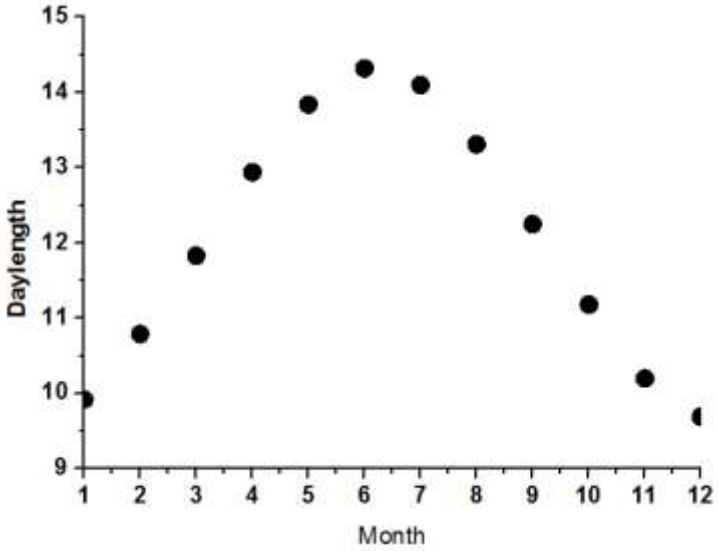

Figure 13. Daylength, according to the months

Figure 13, shows the variation in sunshine duration as a function of month. We can see that the duration of sunshine takes a minimum value in the first month and at the end of the month of the year.

The increase successively starts from the first month up to the maximum value following the month of June which is the center of the year, and this variation in the duration of sunshine decreases until December.

5. Conclusion

Concluding that aims study is how to define the ambient temperature by different parameters, such as the condition Astronomic, atmospherics, and meteorological, which helps us a lot to understand all the influence of the environment on the temperature of the atmosphere. Due to the difference in places in terms of industrial areas, agricultural areas and densely populated areas, the ambient temperature takes a different value, whether it increases or decreases.

Without forgetting that the solar radiation factor plays an active role in the temperature of the environment, and due to the nature of the atmosphere in terms of clearness, cloudy or partial, it significantly affects the temperature.

Given the impact of global warming on the Earth, especially the global warming, these causes are air pollutants caused by the most industrialized areas of fuels and chemicals. For this reason, we tried to link the temperature with all the impact of polluting variables, for example, carbon dioxide in the troposphere, total column Ozone, tropospheric NO_2 column density, and air column concentration of CO. Solar radiation is trapped in the atmosphere, due to the greenhouse effect. The latter comes from pollution. It has a very important role in increasing the temperature. In this work, we showed the effect of parameters that pollute the environment on the ambient temperature in the region of Biskra in Algeria.

The correlation under pollution gave values very close to the experimental for each month of the year. The mathematical model found is very important in the calculation and prediction.

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Not applicabl

Ethical Approval

Not applicable, because this article does not contain any studies with human or animal subjects

Conflict of interest

The authors declare they have no conflict of interest.

Consent to Participate

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We indicate the specific contributions made by each author. All names which participate Previously of each author indicated appear at least once in each of the three categories below.

Foued Chabane: Conception, writing,and design of study and acquisition of data and analysis with an interpretation of data.

Ali Arif: Drafting the manuscript and revising the manuscript critically for important intellectual content

Abderrazak Guettaf : Their contribution to the experimental study was to dry up with taking all data on the days studied

References

Achour L, Bouharkat M, Assas O, Behar O (2017) Hybrid model for estimating monthly global solar radiation for the Southern of Algeria: (Case study: Tamanrasset, Algeria). Energy 135: 526-539, https://doi.org/10.1016/j.energy.2017.06.155

Anupam K, Soovoojeet J, Tapan KK (2020) A fuzzy rule-based model to assess the effects of global warming, pollution and harvesting on the production of Hilsa fishes. Ecological Informatics 57, 101070, https://doi.org/10.1016/j.ecoinf.2020.101070

Bakirci K (2015) Models for the estimation of diffuse solar radiation for typical cities in Turkey. Energy 82 :827-838, https://doi.org/10.1016/j.energy.2015.01.093

Belmahdi B, Louzazni M, El Bouardi A (2020) One month-ahead forecasting of mean daily global solar radiation using time series models. Optik - International Journal for Light and Electron Optics 219: 165-207, https://doi.org/10.1016/j.ijleo.2020.165207

Bixuan G, Xiaoqiao H, Junsheng S, Yonghang T, Jun Z (2020) Hourly forecasting of solar irradiance based on CEEMDAN and multi-strategy CNNLSTM neural networks. Renewable Energy 162:1665-1683, https://doi,org/10,1016/j,renene,2020,09,141,

Chabane F (2020) Estimation of direct and diffuse solar radiation on the horizontal plane considering air quality index and turbidity factor in Assekrem, Tamanrasset, Algeria. Air Quality, Atmosphere & Health 13:1505–1516 https://doi,org/10,1007/s11869-020-00904-9,

Ebrahimi M, Qaderi F (2021) Determination of the most effective control methods of SO2 Pollution in Tehran based on adaptive neuro-fuzzy inference system. Chemosphere 263, 128002, https://doi.org/10.1016/j.chemosphere.2020.128002

Erbs DG, Klein SA and Duffie JA (1982) Estimation of the Diffuse Radiation Fraction for Hourly, Daily and Monthly-Average Global Radiation. Solar Energy 28 (4): 293-302

Fen L, Yilun L, Jianping G, Yue W, Ling M, Yang C, Yongqing B (2020) Novel models to estimate hourly diffuse radiation fraction for global radiation based on weather type classification. Renewable Energy 157:1222-1232, https://doi.org/10.1016/j.renene.2020.05.080

Junliang F., Lifeng W, Fucang Z, Huanjie C, Xiukang W, Xianghui L, Youzhen, X (2018) Evaluating the effect of air pollution on global and diffuse solar radiation prediction using support vector machine modeling based on sunshine duration and air temperature. Renewable and Sustainable Energy Reviews 94: 732–747, https://doi.org/10.1016/j.rser.2018.06.029

Kalisa E, Fadlallah S, Amani M, Nahayo L, Habiyaremye G (2018) Temperature and air pollution relationship during heatwaves in Birmingham, UK", *Sustainable Cities and Society*, https://doi,org/10,1016/j,scs,2018,08,033,

Liu BYH and Jordan RC (1960) The Interrelationship and Characteristic Distribution of Direct, Diffuse, and Total Solar Radiation. Solar Energy 4: 1-19

Masoomeh Z, Abdoulmohammad GC, Feybi AG, Jirí JK (2020) Air pollution prediction using semi-experimental regression model and Adaptive Neuro-Fuzzy Inference System" Journal of Cleaner Production 261, 121218, https://doi.org/10.1016/j.jclepro.2020.121218

Orgill JF and Hollands KGT (1977) Correlation Equation for Hourly Diffuse Radiation on Horizontal Surface. Solar Energy 19 4: 357-359

Rabehi A, Guermoui M, Lalmi D (2020) Hybrid Models for Global Solar Radiation Predection: case of study. International Journal of Ambient Energy, 41: 31-40, https://doi,org/10,1080/01430750,2018,1443498,

Reindl DT, Beckman WA and Duffie JA (1990) Diffuse Fraction Correlation. Solar Energy 45(1) : 1-7

Samakosh JD, Mirzaie M (2019) Flash-over voltage prediction of silicone rubber insulators under longitudinal and fan-shaped non-uniform pollution condition. Computers and Electrical Engineering 78:50–62, https://doi.org/10.1016/j.compeleceng.2019.07.004

Sheen MC, John KC, Ben RH (2019) A review of artificial neural network models for ambient air pollution prediction. Environmental Modelling and Software 119:285–304, https://doi.org/10.1016/j.envsoft.2019.06.014

Teerachai A, Ronald CM, Suratsawadee K (2019) Modeling the effect of VOCs from biomass burning emissions on ozone pollution in upper Southeast Asia. Heliyon 5, e02661, https://doi.org/10.1016/j.heliyon.2019.e02661

Victoria BV, Manuella LC, Esmaeil SN (2017) A novel approach for exposure assessment in air pollution epidemiological studies using neuro-fuzzy inference systems: Comparison of exposure estimates and exposure-health associations. Environmental Research 154: 196–203, https://doi.org/10.1016/j.envres.2016.12.028

Whanhee L, Hayon MC, Dahye K, Yasushi H, Yue-Liang LG, Ho K (2019) Synergic effect between high temperature and air pollution on mortality in Northeast Asia. Environmental Research 178, 108735, https://doi.org/10.1016/j.envres.2019.108735