Modeling of Ozone Interactions with Various Air Pollutants and Meteorological Factors Using Jaya and Teaching-Learning Based Optimization (TLBO) Algorithms

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ABSTRACT
Ozone (O$_3$), nitrogen oxides (NOx) and carbon monoxide (CO) concentrations and some meteorological parameters measured hourly have been analyzed to examine the interaction patterns between O$_3$ and NOx, CO, air temperature, wind speed, relative humidity, and air pressure by taking into account the diurnal variations of them at urban site (Akçaabat) in Trabzon. Variations of O$_3$ levels have been modeled via Jaya and Teaching-Learning Based Optimization (TLBO) algorithms considering the effects of certain parameters (NOx and CO concentration, air temperature, wind speed, relative humidity, and air pressure) called as the independent variables. The accuracy of Jaya and TLBO methods has been determined and these methods have been carried out with four different functions: quadratic, exponential, linear and power. Some statistical indices have been applied to evaluate the performance of these models. In conclusion, it is shown that Jaya and TLBO algorithms can be used in the optimization of the regression function coefficients in modelling some air pollutants interactions and the best-fit equation for each parameter is obtained from the quadratic function.

Keywords: Air pollution, Ozone concentration, Modeling

Jaya ve Öğretme-Öğrenme Tabanlı Optimizasyon Algoritmalarını Kullanarak Meteorolojik Faktörler ve Çeşitli Hava Kirleticileri ile Ozon Etkileşimlerinin Modellenmesi

ÖZET
Ozon (O$_3$), azot oksitler (NO$_x$) ve karbon monoksit (CO) konsantrasyonları ve saatlik olarak ölçülen bazı meteorolojik parametreler, O$_3$ ile NO$_x$, CO, hava sıcaklığı, rüzgar hızı, bağılı nem ve hava basınçını arasındaki etkileşim eğilimini incelemek için, onların Trabzon'daki kentsel alanda (Akçaabat) günlük değişimlerini dikkate alarak analiz edildi. Bağımsız değişkenler olarak adlandırılan belirli parametrelerin (NO$_x$ ve CO konsantrasyonu, hava sıcaklığı, rüzgâr hızı, bağılı nem ve hava basınçını) etkilerini dikkate alarak O$_3$ seviyelerinin değişimleri Jaya ve Öğretme-Öğrenme Tabanlı Optimizasyon (TLBO) algoritmaları ile modellenmiştir. Jaya ve TLBO yöntemlerinin doğruluğunu belirlemiş ve bu yöntemler ikinci dereceden, üstel, doğrusal ve güç olmak üzere dört farklı fonksiyona uygulanmıştır. Bu modellerin başarısını test etmek için bazı istatistiksel belirteçler (ortalama karesel hata, ortalama karesel hatanın karekökü, ortalama mutlak hata, ortalama mutlak yüzde hata ve belirleme katsayısı) kullanılmıştır. Sonuç olarak, Jaya ve TLBO algoritmalarının, bazı hava kirleticileri etkileşimlerinin modellenmesinde regresyon fonksiyonu kataylıkların optimizasyonunda kullanılabileceğini ve her parametre için en uygun denklemin ikinci derece fonksiyonundan elde edildiği görülmüştür.

Keywords: Hava Kirliliği, Ozon konsantrasyonu, Modelleme
I. INTRODUCTION

Photochemical air pollution is formed through the interactions between ozone (O\textsubscript{3}) and its main precursors of nitrogen oxides (NO\textsubscript{x}) and volatile organic compounds (VOC\textsubscript{y}) under intense sunlight. It is known that O\textsubscript{3} has an important function in upper layers of atmosphere as it conserves living organisms from sun radiation, but it is accepted as harmful gas in layers nearer to earth's surface. According to Turkey and European Union countries Air Quality Assessment and Management Regulation, the average O\textsubscript{3} amount of 8 hours must be 120 µg/m\textsuperscript{3} [1]. Potential impacts of O\textsubscript{3} to health are irritation to eyes, nose and throat, as well as its effects on vegetation and materials. Surface O\textsubscript{3} is a major component of photochemical smog characterized by high O\textsubscript{3} owing to complex and non-linear chemistry and meteorology. The concentration of ozone in the atmosphere changes with the formation and transport of ozone, photochemical reactions and meteorological factors. O\textsubscript{3} is produced by the reaction of an oxygen molecule (O\textsubscript{2}) with an oxygen atom occurring from the photolysis of nitrogen dioxide (NO\textsubscript{2}) by solar radiation. However, O\textsubscript{3} is destroyed by reacting with NO to form NO\textsubscript{2} and O\textsubscript{2}. In addition, hydrocarbons and VOC\textsubscript{y} in the atmosphere are oxidized to CO, CO\textsubscript{2} and water vapour. The oxidation processes include a number of cyclic stages driven by the hydroxyl radical (OH) leading to reactions with the present NO and therefore, leading to the accumulation of O\textsubscript{3}. As these complex reactions happen in the atmosphere, measuring O\textsubscript{3} levels alone cannot help in evaluating photochemical conditions [2-7].

Meta-heuristic optimization algorithms solve optimization problems by imitating animal behavior, biological or physical events. Today, a range of meta-heuristic optimization algorithms such as Jaya[8], Teaching-Learning-Based Optimization (TLBO) [9], Artificial Bee Colony (ABC) [10], Coyote Optimization (COA) [11], Cuckoo Search (CS) [12], Crow Search (CSA) [13], Differential Search (DS) [14], Grey Wolf Optimizer (GWO) [15], Harris Hawks Optimization (HHO) [16], Neural Network (NNA) [17], Symbiosis Organisms Search (SOS) [18], Teaching-Learning Based Artificial Bee Colony (TLABC) [19], Weighted Differential Evolution (WDE) [20] are widely used in solving problems.

In this study, O\textsubscript{3} concentration and its correlation with NO\textsubscript{x}, CO and some meteorological parameters in Trabzon (Akçaabat) for 2016 and 2017 datasets obtained from Ministry of Environment and Urban Planning-air quality monitoring stations [21] are modelled using Jaya and TLBO algorithms. There are several studies on estimation algorithms in the literature [22-26].

Jaya algorithm, meaning “victory” in Indian language, was developed by Rao in 2016. This algorithm can maximize the size of a target function by trying to get closer to the best and to get away from the worst among the candidate solutions that are created and refreshed in each iteration [8].

TLBO algorithm simulates the relationship between students and the teacher in the class. The algorithm is consisting of teacher and student stages. The teacher phase represents the education of the students by the teacher. Also, the student phase represents the learning which is the result of the interaction among the students themselves. Further information about the algorithm can be obtained from related reference[9].

The objective of this study is to generate equations being quadratic, exponential, linear and power functions for modeling of O\textsubscript{3} levels via Jaya and TLBO algorithms.

II. METHODOLOGY

Trabzon is a city located at the geographic coordinates of 40°N and 39°E with a population over 779000 with an area of about 4664 km\textsuperscript{2}. Although there are six different stations measured various pollutants in Trabzon, in this study, Akçaabat station has been chosen because of regional characteristic, providing
different emissions, particularly O₃. Relationships between O₃ emission levels and some meteorological parameters - the other emission (NOₓ, CO) levels have been modelled via Jaya and TLBO methods.

In the present work, the objective function of the models is minimization of mean square error (MSE) calculated as follows:

$$\min f(x) = \frac{1}{N} \sum_{i=1}^{N} (P_i - E_i)^2$$  \hspace{1cm} (1)

where N is the number of data sets, Eᵢ is the iᵗʰ measured O₃ amount, and Pᵢ is the iᵗʰ estimated O₃ amount for the regression functions. Root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination (R²) for data sets have been selected to measure the performance of models of Jaya and TLBO.

$$\text{RMSE} = \left[ \frac{1}{N} \sum_{i=1}^{N} (P_i - E_i)^2 \right]^{\frac{1}{2}}$$ \hspace{1cm} (2)

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |P_i - E_i|$$ \hspace{1cm} (3)

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|P_i - E_i|}{E_i}$$ \hspace{1cm} (4)

$$R^2 = 1 - \left( \frac{\sum_{i=1}^{N} (P_i - E_i)^2}{\sum_{i=1}^{N} (P_i - \bar{P})^2} \right)$$ \hspace{1cm} (5)

Jaya and TLBO algorithms have been applied to reach optimum coefficient of the regression functions (quadratic, exponential, linear and power) formed with eight delayed data sets. For example, these regression functions have been created depending on time for two independent variables and two delayed data sets as follows:

$$Y(t) = w_1 + w_2 \cdot X_1(t-2) + w_3 \cdot X_1(t-1) + w_4 \cdot X_1(t) + w_5 \cdot X_2(t-2) + w_6 \cdot X_2(t-1) + w_7 \cdot X_2(t) + w_8 \cdot Y(t-2) + w_9 \cdot Y(t-1)$$ \hspace{1cm} (6)

$$Y(t) = w_1 + \exp(w_2 + w_3 \cdot X_1(t-2) + w_4 \cdot X_1(t-1) + w_5 \cdot X_1(t) + w_6 \cdot X_2(t-2) + w_7 \cdot X_2(t-1) + w_8 \cdot X_2(t) + w_9 \cdot Y(t-2) + w_{10} \cdot Y(t-1))$$ \hspace{1cm} (7)

$$Y(t) = w_1 \cdot X_1(t-2)^{w_2} \cdot X_1(t-1)^{w_3} \cdot X_1(t)^{w_4} \cdot X_2(t-2)^{w_5} \cdot X_2(t-1)^{w_6} \cdot X_2(t)^{w_7} \cdot Y(t-2)^{w_8} \cdot Y(t-1)^{w_9}$$ \hspace{1cm} (8)

$$Y(t) = w_1 + w_2 \cdot X_1(t-2) + w_3 \cdot X_1(t-1) + w_4 \cdot X_1(t) + w_5 \cdot X_1(t-2) \cdot X_1(t-1) + w_6 \cdot X_1(t-2) \cdot X_1(t) + w_7 \cdot X_1(t-1) + w_8 \cdot X_1(t) + w_9 \cdot X_1(t-2) \cdot X_1(t-1) + w_{10} \cdot X_1(t) + w_{11} \cdot X_2(t-2) \cdot X_2(t-1) + w_{12} \cdot X_2(t-2) \cdot X_2(t) + w_{13} \cdot X_2(t-1) + w_{14} \cdot X_2(t) + w_{15} \cdot X_2(t-2) \cdot X_2(t-1) + w_{16} \cdot X_2(t-2) \cdot X_2(t) + w_{17} \cdot X_2(t-1) \cdot X_2(t) + w_{18} \cdot X_2(t-2) + w_{19} \cdot X_2(t-1) + w_{20} \cdot X_2(t) + w_{21} + w_{22} \cdot Y(t-2) + w_{23} \cdot Y(t-1) + w_{24} \cdot Y(t-2) + w_{25} \cdot Y(t-1) + w_{26} \cdot Y(t-1)^2$$ \hspace{1cm} (9)
Population size and maximum number of cycles of the algorithms have been taken 20 and 8000, respectively. The algorithms have been programmed in MATLAB (2014).

III. RESULT AND DISCUSSION

The main statistics of the data sets are given in Table 1. There is a negative correlation between $O_3$ concentration and NO$_x$, CO and relative humidity, while air temperature, wind speed and air pressure have a positive correlation.

Table 1. The main statistics of the data sets

| Data sets         | Unit     | Min   | Mean   | Max   | Standard Deviation | Coefficient of variation | Correlation |
|-------------------|----------|-------|--------|-------|--------------------|--------------------------|-------------|
| NO$_x$            | µg/m$^3$ | 11    | 35.056 | 197   | 21.733             | 61.995                   | -0.245      |
| CO                | µg/m$^3$ | 111   | 1618.634 | 4151 | 924.303             | 57.104                   | -0.223      |
| Air temperature  | °C       | 0     | 15.973 | 29    | 7.216              | 45.175                   | 0.051       |
| Wind speed        | m/s      | 1     | 1.603  | 3     | 0.509              | 31.755                   | 0.196       |
| Relative humidity | %        | 31    | 73.896 | 96    | 11.12              | 15.049                   | -0.194      |
| Air pressure      | mbar     | 998   | 1013.131 | 1035 | 6.262              | 0.618                    | 0.11        |

When the findings obtained from models developed with TLBO and Jaya algorithms are examined, it is seen that the best relationship between dependent variable and independent variables is between NO$_x$-relative humidity and $O_3$ and the worst relationship is between air pressure and $O_3$. Considering the functions used in modeling these relationships, it is understood that the function giving the smallest error is quadratic, and the function giving the largest error is the exponential function (Table 2 and 3).

Table 2. Results of TLBO algorithm model

| Independent Variable | Dependent Variable | Function   | MSE    | RMSE   | MAE    | MAPE   | R$^2$  |
|----------------------|--------------------|------------|--------|--------|--------|--------|--------|
| Relative Humidity    | $O_3$              | Linear     | 24.9541| 4.9954 | 3.8567 | 0.0826 | 0.7225 |
|                      | $O_3$              | Power      | 24.9017| 4.9902 | 3.8801 | 0.0833 | 0.7231 |
|                      | $O_3$              | Exponential| 25.8241| 5.0817 | 3.9591 | 0.0852 | 0.7128 |
|                      | $O_3$              | Quadratic  | 22.8448| 4.7796 | 3.7002 | 0.0792 | 0.7459 |
| Air Pressure         | $O_3$              | Linear     | 26.1388| 5.1126 | 3.9375 | 0.0846 | 0.7093 |
|                      | $O_3$              | Power      | 26.2456| 5.1231 | 3.9597 | 0.0853 | 0.7081 |
|                      | $O_3$              | Exponential| 27.6076| 5.2543 | 4.0609 | 0.0876 | 0.6930 |
|                      | $O_3$              | Quadratic  | 24.1535| 4.9146 | 3.8693 | 0.0829 | 0.7314 |
| CO                   | $O_3$              | Linear     | 26.4889| 5.1467 | 3.9919 | 0.0852 | 0.7054 |
|                      | $O_3$              | Power      | 26.6624| 5.1636 | 4.036  | 0.0863 | 0.7035 |
|                      | $O_3$              | Exponential| 27.8172| 5.2742 | 4.0894 | 0.0878 | 0.6906 |
|                      | $O_3$              | Quadratic  | 24.11  | 4.9102 | 3.7942 | 0.0803 | 0.7319 |
Table 2 (continuation). Results of TLBO algorithm model

| Independent Variable | Dependent Variable | Function   | MSE   | RMSE  | MAE   | MAPE  | R²   |
|----------------------|--------------------|------------|-------|-------|-------|-------|------|
| NO₂                  | O₃                 | Linear     | 25.088| 5.0088| 3.9106| 0.0832| 0.7210|
|                      |                    | Power      | 25.0103| 5.001 | 3.9343| 0.084 | 0.7218|
|                      |                    | Exponential| 25.9412| 5.0933| 3.9984| 0.0853| 0.7115|
|                      |                    | Quadratic  | 23.3103| 4.8281| 3.7382| 0.0792| 0.7408|
| NO₂-Relative Humidity| O₃                 | Linear     | 20.5103| 4.5288| 3.485 | 0.0742| 0.7719|
|                      |                    | Power      | 20.6423| 4.5434| 3.5139| 0.0754| 0.7704|
|                      |                    | Exponential| 21.5837| 4.6458| 3.6256| 0.0777| 0.7600|
|                      |                    | Quadratic  | 19.5954| 4.4267| 3.4084| 0.0723| 0.7821|
| NO₂-CO               | O₃                 | Linear     | 24.1502| 4.9143| 3.7867| 0.0804| 0.7314|
|                      |                    | Power      | 24.2741| 4.9269| 3.85  | 0.0821| 0.7300|
|                      |                    | Exponential| 25.4763| 5.0474| 3.9186| 0.0834| 0.7167|
|                      |                    | Quadratic  | 22.8192| 4.7769| 3.7425| 0.0789| 0.7462|
| NO₂-Air Temperature  | O₃                 | Linear     | 24.0054| 4.8995| 3.7834| 0.0806| 0.7330|
|                      |                    | Power      | 24.1707| 4.9164| 3.8135| 0.0815| 0.7312|
|                      |                    | Exponential| 25.1732| 5.0173| 3.9114| 0.0838| 0.7200|
|                      |                    | Quadratic  | 22.2127| 4.713 | 3.6721| 0.0776| 0.7530|
| NO₂-Relative Humidity-Wind Speed | O₃       | Linear     | 20.8774| 4.5692| 3.5222| 0.0752| 0.7678|
|                      |                    | Power      | 21.1807| 4.6023| 3.5513| 0.0762| 0.7644|
|                      |                    | Exponential| 21.6881| 4.657 | 3.6596| 0.0785| 0.7588|
|                      |                    | Quadratic  | 19.8181| 4.4518| 3.4388| 0.0734| 0.7796|
| NO₂-Air Temperature-Wind Speed | O₃       | Linear     | 22.6849| 4.7629| 3.6651| 0.078 | 0.7477|
|                      |                    | Power      | 23.0582| 4.8019| 3.7316| 0.0795| 0.7436|
|                      |                    | Exponential| 23.9079| 4.8896| 3.7838| 0.0812| 0.7341|
|                      |                    | Quadratic  | 21.8516| 4.6746| 3.6214| 0.0769| 0.7570|

Table 3. Results of Jaya algorithm model

| Independent Variable | Dependent Variable | Function | MSE   | RMSE  | MAE   | MAPE  | R²   |
|----------------------|--------------------|----------|-------|-------|-------|-------|------|
| Relative Humidity     | O₃                 | Linear   | 25.0469| 5.0047| 3.8678| 0.0829| 0.7214|
|                      |                    | Power    | 24.9278| 4.9928| 3.8823| 0.0833| 0.7228|
|                      |                    | Exponential| 28.4483| 5.3337| 4.1710| 0.0886| 0.6836|
|                      |                    | Quadratic| 23.0213| 4.4041| 3.3021| 0.0796| 0.7320|
| Air Pressure          | O₃                 | Linear   | 26.3712| 5.1353| 3.9638| 0.0854| 0.7067|
|                      |                    | Power    | 26.3020| 5.1286| 3.9693| 0.0855| 0.7075|
|                      |                    | Exponential| 28.4661| 5.3354| 4.1563| 0.0900| 0.6834|
|                      |                    | Quadratic| 25.8934| 5.0643| 3.8432| 0.0842| 0.7120|
### Table 3 (continuation). Results of Jaya algorithm model

| Independent Variable | Dependent Variable | Function         | MSE   | RMSE   | MAE   | MAPE  | $R^2$  |
|----------------------|--------------------|------------------|-------|--------|-------|-------|--------|
| **CO**               |                    |                  |       |        |       |       |        |
| O$_3$                | Linear             | 27.5249          | 5.2464| 4.0798 | 0.0871| 0.6937|
| O$_3$                | Power              | 27.7776          | 5.2704| 4.1210 | 0.0883| 0.6909|
| O$_3$                | Exponential        | 29.9449          | 5.4722| 4.2226 | 0.0906| 0.6668|
| O$_3$                | Quadratic          | 26.7520          | 5.1732| 3.9877 | 0.0834| 0.7182|
| **NO$_x$**           |                    |                  |       |        |       |       |        |
| O$_3$                | Linear             | 26.0840          | 5.1073| 3.9975 | 0.0853| 0.7097|
| O$_3$                | Power              | 25.8172          | 5.0811| 4.0216 | 0.0859| 0.7127|
| O$_3$                | Exponential        | 27.6407          | 5.2574| 4.1382 | 0.0883| 0.6924|
| O$_3$                | Quadratic          | 24.9367          | 5.0122| 3.9562 | 0.0809| 0.7238|
| **NO$_x$-Relative Humidity** |            |                  |       |        |       |       |        |
| O$_3$                | Linear             | 22.6981          | 4.7642| 3.6572 | 0.0778| 0.7474|
| O$_3$                | Power              | 22.1524          | 4.7066| 3.6758 | 0.0794| 0.7535|
| O$_3$                | Exponential        | 27.3535          | 5.2301| 4.0873 | 0.0878| 0.6956|
| O$_3$                | Quadratic          | **20.2672**      | **4.4910**| **3.0435**| 0.0786| 0.7052|
| **NO$_x$-CO**        |                    |                  |       |        |       |       |        |
| O$_3$                | Linear             | 26.7909          | 5.1760| 4.0365 | 0.0863| 0.7019|
| O$_3$                | Power              | 29.5671          | 5.4376| 4.2719 | 0.0886| 0.6710|
| O$_3$                | Exponential        | 30.2055          | 5.4960| 4.2862 | 0.0946| 0.6639|
| O$_3$                | Quadratic          | 26.1360          | 5.0645| 3.9031 | 0.0823| 0.7080|
| **NO$_x$-Air Temperature** |                |                  |       |        |       |       |        |
| O$_3$                | Linear             | 25.6974          | 5.0693| 3.9716 | 0.0845| 0.7140|
| O$_3$                | Power              | 26.3697          | 5.1351| 4.0540 | 0.0870| 0.7066|
| O$_3$                | Exponential        | 27.7133          | 5.2643| 4.1176 | 0.0886| 0.6916|
| O$_3$                | Quadratic          | 24.3560          | 5.0192| 3.7396 | 0.0810| 0.7235|
| **NO$_x$-Relative Humidity-Wind Speed** |           |                  |       |        |       |       |        |
| O$_3$                | Linear             | 23.8372          | 4.8823| 3.6551 | 0.0786| 0.7347|
| O$_3$                | Power              | 21.9946          | 4.6898| 3.6256 | 0.0776| 0.7552|
| O$_3$                | Exponential        | 24.8762          | 4.9876| 3.8821 | 0.0844| 0.7232|
| O$_3$                | Quadratic          | 21.5493          | 4.5239| 3.5927 | 0.0740| 0.0765|
| **NO$_x$-Air Temperature-Wind Speed** |             |                  |       |        |       |       |        |
| O$_3$                | Linear             | 25.4261          | 5.0424| 3.9448 | 0.0845| 0.7171|
| O$_3$                | Power              | 27.6849          | 5.2616| 4.1076 | 0.0864| 0.6919|
| O$_3$                | Exponential        | 31.3367          | 5.5979| 4.3522 | 0.0941| 0.6513|
| O$_3$                | Quadratic          | 24.3786          | 5.0213| 3.3826 | 0.0823| 0.7195|

Optimum coefficients ($w_i$) of the independent variables ($x_i$) from these regression functions by both algorithms have been obtained. Obtained optimum coefficients from Jaya analysis of linear function explaining relationship between NO$_x$ emission levels - relative humidity and O$_3$ emission levels are shown as an example in Table 4.
Table 4. The coefficient obtained from Jaya analysis

| Coefficients | W_1 | W_2 | W_3 | W_4 | W_5 | W_6 | W_7 | W_8 | W_9 | W_10 |
|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
|              | 0.027 | 0.094 | -0.072 | 0.049 | -0.010 | 0.165 | 0.047 | -0.036 | 0.372 | -0.614 |

| Coefficients | W_{11} | W_{12} | W_{13} | W_{14} | W_{15} | W_{16} | W_{17} | W_{18} | W_{19} | W_{20} |
|--------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
|              | 0.035 | 0.007 | -0.017 | 0.119 | 0.033 | 0.098 | 0.030 | 0.038 | -0.332 | 0.070 |

| Coefficients | W_{21} | W_{22} | W_{23} | W_{24} | W_{25} | W_{26} | W_{27} |
|--------------|--------|--------|--------|--------|--------|--------|--------|
|              | 0.032 | -0.002 | 0.078 | 0.056 | 0.034 | 0.121 | 0.545 |

Figure 1 illustrates a comparison of the measured O_3 with the predicted ones from the determined quadratic function by depending on NO\_X and relative humidity. Figure 2 also supplies a different presentation of the performance for the obtained best fitting model via Jaya analysis. If the points gather around the diagonal, smaller error and greater R^2 values are obtained.

![Figure 1](image-url)
IV. CONCLUSION

In order to model which chemicals and meteorological factors are more effective in the formation of O\(_3\), which is a component of photochemical air pollution, the data set was first analyzed, and then the relationship between O\(_3\) concentration and some parameters was modeled with Jaya and TLBO algorithms. When the main statistics of the data sets were analyzed, it was observed that the O\(_3\) concentration was negative correlation between NO\(_X\), CO and relative humidity, while it was positively correlated with other parameters. According to the data obtained from both algorithms, the best fit equation between ozone and NO\(_X\) - relative humidity is obtained from the quadratic function. Also, the results of the study show that the quadratic function provide the best fit equation for each parameter. Higher correlations of ozone with NO\(_X\)-relative humidity than of ozone with the other independent variables are found pointing that NO\(_X\) and relative humidity are highly effective on modelling of ozone. However, the Jaya model shows the relationship between ozone with NO\(_X\) and relative humidity by a slightly higher correlation than the TLBO model. On the other hand, lower correlations pointed that the ozone formation in this region depends on many meteorological and chemical factors. Results of both models suggest that formation of surface ozone pollution is much more closely related to the amount of NO\(_X\) and relative humidity rather than other parameters.

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