ORIGINAL ARTICLE

Modeling Ground Level Ozone (O_3) of Air Pollution Using Regression Technique

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ABSTRACT

Introduction: Ground-level ozone (O_3) was a secondary pollutant involving several types of reactions arising from complicated atmospheric chemistry. This research utilized statistical equations to discern the complex influence of meteorological parameters and precursor contaminants influencing O_3 chemistry and concentrations. The goal of this study was to predict ozone (O_3) concentrations in Nilai, Negeri Sembilan. **Methods:** Data were collected from 1 January 2016 until 31 December 2018 that including ozone (O_3), nitrogen oxide (NO_x), nitric oxide (NO), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), temperature, and relative humidity (RH). The data were analyzed by using Multiple Linear Regression (MLR) in predicting the next hours of O_3 concentration. **Results:** O_3 concentration reached its peak during 15:00 hours and lower at night time (20:00 hours) due to the absence of sunlight and redox reactions. There exists strong significant correlation between O_3 and temperature ($r= 0.729$, $p<0.01$), relative humidity ($r= -0.732$, $p<0.01$), NO_x ($r= -0.654$, $p<0.01$), NO ($r= -0.630$, $p<0.01$) and NO_2 ($r= -0.535$, $p<0.01$). Meanwhile, MLR models executed high accuracy for $O_{3,t+1}$ ($R^2= 0.5565$), $O_{3,t+2}$ ($R^2= 0.5326$) and $O_{3,t+3}$ ($R^2= 0.5197$). **Conclusion:** In conclusion, the MLR model is suitable for the next hours O_3 concentration prediction.
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Keywords: Ozone, Regression, Correlation, Ozone Precursor, Prediction

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INTRODUCTION

In a total of air volume, a trace gas known as ozone (O_3) comprises of less than 0.001 percent which critically needed for the survival of life on the earth. Two ozone layers are imposed known as stratospheric and tropospheric. The protection from harmful ultraviolet solar rays was protected by stratospheric layer and the latter known as bad ozone formed in the tropospheric layer (1). Regardless of location, high ozone concentrations might occur especially in the urban area as a result of horizontal transport. Moreover, vertical transport played an important role for the increment of ozone concentrations as investigated in Portugal (2, 3). The detrimental impact of surface ozone on people was determined and documented (4-6). Ozone is created during the photochemical process among the ozone precursors of nitrogen oxides (NO_x) and volatile organic compound (VOC). In specific, precursors were emitted from anthropogenic sources, and certain VOC has emitted from plant-based biogenic materials. The rise in O_3 was responsible for morbidity and death in humans. In addition, it facilitates short-term effects of ventilation and cardiovascular system issues and breathing death, and asthmatic problems. Furthermore, high ozone concentration harmed the ecosystem in our environment which including the crop stunting, ecology problem and species threatened. In addition, it also explains why the global atmosphere is adapting to our environment (7).

Machine learning models were developed in a short period of time to improve the accuracy of general environmental prediction models. The ozone concentrations prediction models generally adopted the statistical modeling approach which uses the empirical data. The models combined weather parameters such as wind speed, relative humidity, ambient temperature, and solar radiation, as well as gaseous factors such as methane, carbon monoxide, and nitrogen oxide precursor gases (8). These large number of parameters are suitable to feed into the Multiple Linear Regression (MLR), which very popular statistical model used for the empirical data. MLR was simple and easy to compute, leading to better and commonly used mathematical modelling to explain the underlying influencing factors of O_3 variation (9). Training of models for the prediction of ozone concentrations largely depending on the multivariate statistical performances of the MLR (10). The performance itself depends on the variability of the inserted input. The predictive performance of the developed models are assessed using the performance indicators. The performance indicators comprises of error and accuracy measure such as Mean Square Error (MSE) and Coefficient of Determination (R^2). A smaller MSE has indicated higher model goodness of fit. A closer R^2 value to 1.0 indicated higher model goodness of fit.

MATERIALS AND METHODS

Study area and data acquisition

Data were collected at one of Air Quality Monitoring Stations (AQMS) at Nilai, Negeri Sembilan. The sources at the study area are mainly came from the domestic fuel burning and motor vehicles which have significant impact to the atmosphere came from human activities. Meteorology and human activity combined to raise pollution levels in the study area. Period of study inclusively taken for three years from 2016 to 2018. The data set was acquired from Malaysian Department of Environment (DOE). The data were available every 1-hour average. Parameters included ozone concentration, nitrogen oxides, nitric oxide (NO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), temperature (T), and relative humidity (RH) were plotted by using a line graph to compare the trend with New Ambient Air Quality Standard (NAAQS.) The value in the dataset may be missing for a variety of reasons. All the missing records were omitted from this study in order to reduce the risk of bias. The dataset was used to develop models 70% and the remaining 30% for validation.

Data analysis

The data are used for the development of statistical model utilizing the MLR. The data collected were used to calculate the descriptive statistics for mean, median, mode, sample variance, standard deviation, maximum, minimum, skewness, and kurtosis value to determine the trend of ozone by using a line graph to compare with NAAQS. MLR research leads to a deeper and commonly used interpretation of the underlying driving factors of O_3 heterogeneity by statistical simulation through quick and fast computation. Future concentrations of O_3 were important for prediction, since effective steps may be suggested by the local authority for any suitable preventive measures and increase the quality of the air (9). The model of with multiple parameters MLR is shown in Equation (1).

$$y = \beta_0 + \sum_i \beta_i x_i + \varepsilon_i \qquad (1)$$

Where,

x_i = the explanatory variable of i (or independent variable)
y = the dependent variable
β_i= the regression coefficient
ε_i = the residual

The decision on selection of best-fitted MLR models were used the concept of error and accuracy. Error measures used are Root Mean Square Error (RMSE) and Normalized Absolute Error (NAE), while the accuracy measures used are R^2 and Prediction Accuracy (PA). The error values near to zero were considered as the best model, and for the accuracy must near to one. The specification of performance metrics used in this analysis was illustrated in Equations (2) – Equation (5) (11).

(a) Root Mean Square Error

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} [P_i - O_i]^2 \right)^{1/2} \qquad (2)$$

(b) Normalized Absolute Error

$$NAE = \frac{\sum_{i=1}^{n} |P_i - O_i|}{\sum_{i=1}^{n} O_i} \qquad (3)$$

(c) Prediction of Accuracy

$$PA = \sum_{i=1}^{n} \frac{[P_i - \bar{P}]}{(n-1)\, S_{pred}\, S_{Obs}} \qquad (4)$$

(d) Coefficient of Determination

$$R^2 = \left(\frac{\sum_{i}^{n} (P_i - \bar{P})(O_i - \bar{O})}{n.S_{pred}\, S_{Obs}} \right)^2 \qquad (5)$$

Where,

n = total number of data
P_i = predicted values
O_i = observed values
P = mean of predicted
$\bar{O}$ = mean of observed values
S_{pred} = standard deviation of predicted values
S_{obs} = standard deviation of observed values

RESULT

Descriptive statistics is used for describing the trend of selected parameters which including the gaseous pollutants and meteorological factors such as O_3 concentration, NO_x, NO, SO_2, NO_2, CO, T and RH as tabulated in Table I. The mean for O_3 concentration is 0.0170 ppm, NO_x (0.0248 ppm), NO (0.0098 ppm), SO_2 (0.0025), NO_2 (0.0151 ppm), CO (0.5908 ppm), T (28.1 °C) and RH (73.5%). The minimum value for O3 concentration, NO_x, SO_2, NO_2, and CO is 0 while the minimum value for NO is 0.0007 ppm, T (20.7 °C), and RH (39.0%). The maximum value for O_3 concentration is 0.1350 ppm, NOx (0.1510 ppm), NO (0.1290 ppm), SO_2 (0.0170 ppm), NO_2 (0.0530 ppm), CO (2.4560 ppm), T (36.1 °C) and RH (98.0%). The median for O_3 concentration is 0.0113 ppm, NO_x (0.0196 ppm), NO (0.0050ppm), SO_2 (0.0014 ppm), NO_2 (0.0140 ppm), CO (0.5400 ppm), T (27.6 °C) and RH (27.6%). The mode for O_3 concentration is 0.0030 ppm, NO_x (0.0100 ppm), NO (0.0010 ppm), SO_2 (0.0020 ppm), NO_2 (0.0070 ppm), CO (0.4500 ppm), T (26.1 °C) and RH (85.0%). The sample variance for O_3 concentration and NO_x is 0.0003 ppm, NO (0.0002 ppm), SO_2 (0 ppm), NO_2 (0.0001 ppm), CO (0.0549 ppm), T (8.0 °C) and RH (183.5%). The standard deviation for O_3 concentration is 0.0170 ppm, NO_x (0.0179 ppm), NO (0.0131 ppm), SO_2 (0.0024 ppm), NO_2 (0.0080 ppm), CO (0.2343), T (2.8 °C) and RH (13.5 %). Fig. 1(a) shows the average ground level O_3 concentration.

Table I Descriptive statistics for gaseous pollutants and meteorological factors

Parameter	Ozone (O_3) (ppm)	Temperature (°C)	Relative Humidity (%)	Nitrogen Oxide (NO_x) (ppm)	Nitric Oxide (NO) (ppm)	Sulfur Dioxide (SO_2) (ppm)	Nitrogen Dioxide (NO_2) (ppm)	Carbon Monoxide (CO) (ppm)
Mean	0.0170	28.1	73.5	0.0248	0.0098	0.0025	0.0151	0.5908
Median	0.0113	27.6	74.0	0.0196	0.0050	0.0014	0.0140	0.5400
Mode	0.0030	26.1	85.0	0.0100	0.0010	0.0020	0.0070	0.4500
Variance	0.0003	8.0	183.5	0.0003	0.0002	0	0.0001	0.0549
Standard Deviation	0.0170	2.8	13.5	0.0179	0.0131	0.0024	0.0080	0.2343
Minimum	0	20.7	39.0	0	0.0007	0	0	0
Maximum	0.1350	36.1	98.0	0.1510	0.1290	0.0170	0.0530	2.4560
Skewness	1.6577	0.4	-0.2	1.6041	2.8036	1.7846	0.7309	0.8677
Kurtosis	3.2773	-0.8	-0.9	3.6368	10.6577	3.3914	0.4606	1.5817

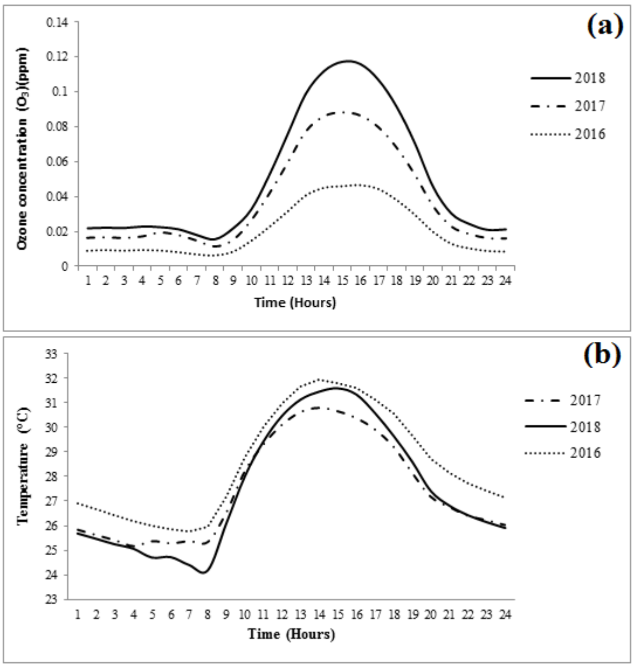

Fig 1: Average ground-level ozone (O_3) concentration and temperature (°C). Ozone reached highest concentration in the middle of the day due to presence of solar radiation (a). The incoming solar radiation comprising high temperature is in line with the high concentration of ozone due to the photochemical reactions (b).

Correlation analysis was introduced to correlate the two variables among the interested parameters utilizing the Statistical Packages for Social Sciences (SPSS®) as shown in Table II. Two variables were correlated using Spearman's correlation coefficient. Analyses of correlations between O_3 and selected pollutants are carried out in this study in order to determine if there is a correlation between O_3 and other pollutants. Emissions, the height of the planetary boundary layer, and long-distance transport all have an effect on pollutant concentrations, including O_3 (12). More than 0.50 is considered strong, 0.40-0.49 is considered moderate, and less than 0.30 is regarded as weak (13). O_3 and T ($r= 0.729$, $p<0.01$), RH ($r= -0.732$, $p<0.01$), NO_x ($r= -0.654$, $p<0.01$), NO ($r= -0.630$, $p<0.01$), and NO2 ($r= -0.535$, $p<0.01$) have a strong significant correlation. RH a significant impact on the O_3 variability, and the lower O_3 associated with increasing relative humidity was a surprise (14). When it comes to T and RH, there is an extremely strong negative correlation ($r=-0.894$, $p<0.01$). Because the study area is temperature-sensitive, these findings indicate the photochemical reaction of O_3 formation is a major contributor to this phenomenon (9). A strong correlation between NO_x and NO ($r= 0.834$, $p<0.01$) and NO_2 ($r= 0.863$, $p<0.01$) was found. NO and NO_2 were found to have a strong correlation ($r=0.521$, $p<0.01$). The correlation between O_3 and CO ($r= -0.423$, $p<0.01$) is moderately significant. T is expected to influence O_3 variability, but CO emissions associated with biomass on the O_3 surface have been shown to be of significant importance (14). T has a moderately significant correlation with NO_x ($r= -0.442$, $p<0.01$), NO ($r= -0.427$, $p<0.01$), and NO_2 ($r= -0.346$, $p<0.01$). There is a correlation between the presence of sunlight and high temperatures and nitrogen's value decreasing (9). Another significant correlation was found between NO_x ($r= 0.484$; $p<0.01$) and NO ($r= 0.362$; $p<0.01$) as well as NO_2 ($r= 0.454$; $p<0.01$) and CO with RH ($r= 0.365$; $p<0.01$). This study found that there was a moderately significant correlation between NO_x ($r=0.472$), NO ($r=0.343$), and CO ($r=0.494$). T ($r= 0.143$; $p<0.01$), RH ($r= -0.299$; $p<0.01$), NO_x ($r= 0.084$; $p<0.01$) and NO_2 ($r= -0.023$; $p<0.05$) were all found to have weak significant correlations with SO_2 and O_3 ($r= 0.140$; $p<0.01$).

Table II Summary of spearman correlation analysis (r-value) between O_3 concentration, meteorological factors, and gaseous pollutants

Parameter	O_3	T	RH	NO_x	NO	SO_2	NO_2	CO
O_3	1							
T	0.729**	1						
RH	-0.732**	-0.894**	1					
NO_x	-0.654**	-0.442**	0.484**	1				
NO	-0.630**	-0.427**	0.362**	0.834**	1			
SO_2	0.140**	0.143**	-0.299**	0.084**	0.206**	1		
NO_2	-0.535**	-0.346**	0.454**	0.863**	0.521**	-0.023**	1	
CO	-0.423**	-0.280**	0.365**	0.472**	0.343**	-0.066**	0.494**	1

**Correlation is significant at the 0.01 level (2-tailed)

All data (n=5451) from the MLR models were analysed and summarised in Table III. Durbin Watson statistics show that the models can handle autocorrelation, as the value was in the range of (0.413-1.333). MLR is used to determine which variables are most important in predicting the concentration of O_3. The predicted R2 for $O_{3',t+1}$ ($R^2= 0.5565$), $O_{3,t+2}$ ($R^2= 0.5326$) and $O_{3,t+3}$ (R2= 0.5197). The significant predictors were $O_{3,t+1}$ (O_3, T, NO_2, CO, NO, NO_x, and SO_2), $O_{3,t+2}$ (O_3, T, NO_2, CO, NO, NO_x, SO_2, and RH), and $O_{3,t+3}$ (T, O_3, NO_2, NO, CO, NO_x, SO_2 and RH).

Table III Summary of the Multiple Linear Regression (MLR) models for O_3 forecasting at the study area

Model	R^2	D-W Statistics
$O_{3,t+1}$= 0.751 (O_3)+0.139 (T)+0.155 (NO_2)+0.077 (CO)+0.593 (NO)-0.631 (NO_x)-0.014 (SO_2)-0.036	0.5565	1.333
$O_{3,t+2}$= 0.475 (O_3)+0.197 (T)+0.144 (NO_2)+0.129 (CO)+0.746 (NO)-0.735 (NO_x)-0.031 (SO_2)-0.030 (RH)-0.009	0.5326	0.636
$O_{3,t+3}$= 0.043+0.185 (T)+0.250 (O_3)+0.134 (NO_2)+0.871 (NO)+0.148 (CO)-0.803 (NO_x)-0.038 (SO_2)-0.054 (RH)	0.5197	0.413

D-W: Durbin-Watson; R^2: Correlation Coefficient

DISCUSSION

The O_3 concentration in the study area rises from 08:00 hours to 15:00 hours due to the emissions of NO_x, mainly from automobiles, which could cause the O_3 concentration to rise (9). The diurnal pattern shows that the O_3 concentration was increasing towards noon. It is due to the increasing of solar radiation, emission from vehicles, and high population growth notified through human activities such as construction activities, open burning, and mobile resources (7). In meeting the economic expansion, industrial activities as well as traffic have become the culprit for the increases of ozone sources (15). Starting from 09:00 to 13:00-15:00 hours, an increase of O_3 concentration and temperature shows that the O_3 concentration is highly correlated with temperature (16). A high level of O_3 concentration during the afternoon around 13:00 hours to 15:00 hours is due to the maximum temperature and the high intensity of solar radiation occurred during this time (17). Based on Fig. 1(a) and Fig. 1(b), the average ground level O_3 concentration and the average temperature have the same form of the line graph. The sensitivity of ozone concentration decreases along with temperature as a results of the declination of NO_x and VOCs (18). According to (16), maximum ozone concentration can be found in the mid of the day which is around 14:00 hours until 15:00 hours while there was starting slower O_3 concentration during night time around 20:00 hours due to the photochemical reaction of O_3 precursors, such as VOC with ambient air from the natural resources and the long-distance transport of NO_x react to sunlight. The higher solar radiation intensity during day time may lead to favorable conditions for powering photochemical reactions (13). NO_x accumulated during nigh time as a result of reaction of NO and NO_2 during the daytime, which clarified as the main reason on the existence of ozone concentration during night time with the help of inversion layer (9). The O_3 concentration was decreasing slowly towards evening starting at 16:00 hours and night time around 21:00 hours in line with the disappearing of sun and redox process (19). It was supported by (20) which stated that during the nighttime, the O_3 concentration was far lower than the day-time concentration due to the absence of photochemical reactions. The ozone concentrations continues to its lower value in the morning until the solar radiation present (7). The O_3 concentration decreases progressively until evening starting at 16:00 hours and then keep on decreasing more gradually during the night-time (21:00 hours) until morning (07:00 hours) because of lack of solar radiation (13). The O_3 concentration was generally low and in a stable condition because of the absence of photochemical reactions (13). High intensity of solar radiation helps in the ozone concentration formation during the day time (9).

The higher the temperature, the greater the concentration of O_3. When the temperature rises above a certain threshold in Malaysia (a tropical country), ozone is diluted because of the increased production of ozone-forming organic compounds (O_3) in the atmosphere (9). It's important to consider the residual (error) when determining the size of the factual model. Errors that show a pattern are interpreted as a sign that the model does not handle all of the methodological data (Fig. 2(a)-(c) and Fig. 3(a)-(c)). O_3 model residual histograms are shown in Fig. 2(a)-(c). Analyses of the residuals show them to be symmetrical in shape, with zero mean and zero variance. According to the O_3 model, there is no correlation between the fitted values and residuals because the residuals are in a horizontal band, which indicates that the variance is constant. As can be seen in Fig. 4(a)-(c), the predicted O_3 concentration at Nilai is plotted against the actual O_3 concentration (ppm). As a result of using the MLR method, the models' equations are listed in Table III. For example, each precursor has a coefficient, but it doesn't correspond to how much of a factor it has in determining how much ozone is present in the atmosphere (21). Coefficients are analogous to one another when they are transformed into standardised regression, so the largest coefficient may indicate the independent variables that have the greatest influence on O_3 (22).

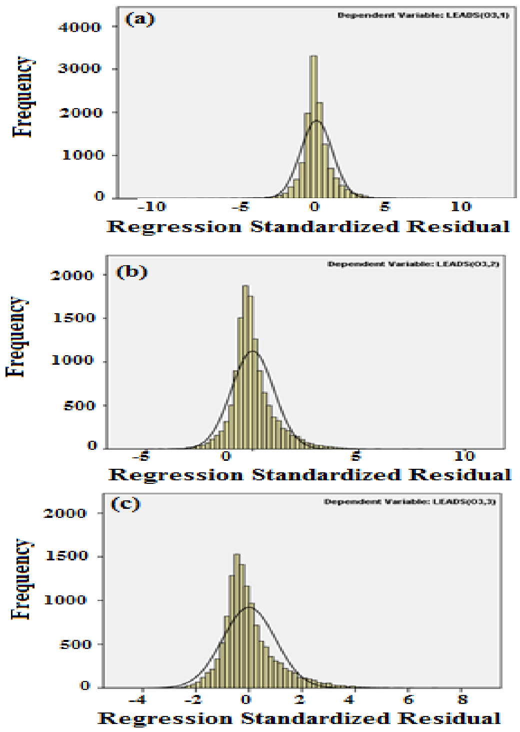

Fig 2: Residual of Multiple Linear Regression (MLR). The residual analysis shows that the residuals were normally distributed with zero mean and constant variance for next-hour (a). The residual analysis shows that the residuals were normally distributed with zero mean and constant variance for next two-hour (b). The residual analysis shows that the residuals were normally distributed with zero mean and constant variance for next three-hour (c).

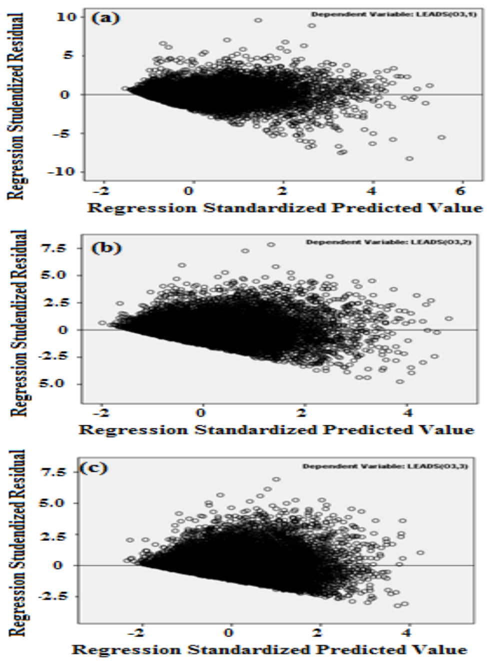

Fig 3: Testing assumption of variance and uncorrelated with mean equal to zero for Multiple Linear Regression (MLR). The residuals are uncorrelated because the residuals are contained in a horizontal band and hence obviously that variance is constant for next-hour (a). The residuals are uncorrelated because the residuals are contained in a horizontal band and hence obviously that variance is constant for next two-hour (b). The residuals are uncorrelated because the residuals are contained in a horizontal band and hence obviously that variance is constant for next three-hour (c).

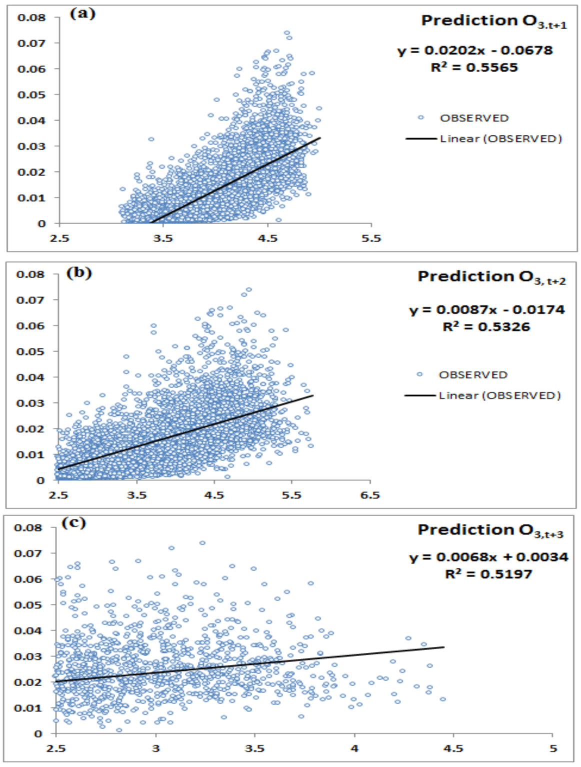

Fig 4: Scatter plot of forecasted O_3 concentration (ppm) against observed O_3 concentration (ppm) at Nilai. The models showing the prediction of O_3 concentration for the next-hour (a). The models showing the prediction of O_3 concentration for the next two-hour (b). The models showing the prediction of O_3 concentration for the next three-hour (c).

CONCLUSION

In conclusion, the ozone concentrations are fluctuating during the day and night time as a result of solar radiation and temperature inversion, respectively. The ozone concentrations are significantly correlated with the meteorological factors and air pollutants which these parameters influence the ozone formation at the study area. It indicates because of nitrogen start to decrease in value when the presence of sunlight with high temperature produces. The predicted coefficients for the three next one, two, and three hours are R^2=0.5565, R^2= 0.5326, and R^2= 0.5197, respectively. The developed MLR models are the most suitable model for forecasting the prediction of O_3 concentration to the next hours.

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REFERENCES

1. Jindal P, Shukla MV, Sharma SK, Thapliyal PK. Retrieval of ozone profiles from geostationary infrared sounder observations using principal component analysis. Quarterly Journal of the Royal Meteorological Society. 2016; 142: 3015-3025. https://doi.org/10.1002/qj.2884
2. Yusoff MF, Latif MT, Juneng L, Khan MF, Ahamad F, Chung JX et al. Spatio-temporal assessment of nocturnal surface ozone in Malaysia. Atmospheric Environment. 2019; 207: 105-116. https://doi.org/ 10.1016/j.atmosenv.2019.03.023
3 Kulkarni PS, Bortoli D, Silva AM, Reeves CE. Enhancements in nocturnal surface ozone at urban sites in the UK. Environmental Science and Pollution Research. 2015; 22: 20295-20305. https://doi.org/ 10.1007/s11356-015-5259-z
4. Zhang J, Wei Y, fang Z. Ozone Pollution: A Major Health Hazard Worldwide. Frontiers in Immunology. 2019; 10: 2518. https://doi.org/ 10.3389/fimmu.2019.02518
5. Li A, Zhou Q, Xu Q. Prospects for ozone pollution control in China: An epidemiological perspective. Environmental Pollution. 2021; 285: 117670. https://doi.org/ 10.1016/j.envpol.2021.117670
6. Gorai AK, Tchnounwou PB, Tuluri F. Association between Ambient Air Pollution and Asthma Prevalence in Different Population Groups Residing in Eastern Texas, USA. International Journal of Environmental Research and Public Health. 2016; 13(4): 378. https://doi.org/ 10.3390/ ijerph13040378
7. Napi NNLM, Abdullah S, Ahmed AN, Mansor AA, Ismail M. Annual and Diurnal Trend of Surface Ozone (O3) in Industrial Area. IOP Conference Series: Earth and Environmental Science. 2020; 498: 012062. https://doi.org/10.1088/1755-1315/498/1/012062
8. Hamid NZA, Noorani MSM, Adenan NH. Chaotic analysis and short-term prediction of ozone pollution in Malaysian urban area. Journal of Physics: Conference Series. 2017; 890: 012157. https://doi.org/10.1088/1742-6596/890/1/012157
9. Abdullah S, Nasir NHA, Ismail M, Ahmed AN, Jarkoni MNK. Development of Ozone Prediction Model in Urban Area. International Journal of Innovative Technology and Exploring Engineering. 2019; 8(10): 2278-3075. https://doi.org/10.35940/ ijitee.J1127.0881019
10. Liao K, Huang X, Dang H, Ren Y, Zuo S, Duan C. Statistical Approaches for Forecasting Primary Air Pollutants: A Review. Atmosphere. 2021; 12: 686. https://doi.org/10.3390/atmos12060686
11. Abdullah S, Napi NNLM, Ahmed AN, Mansor WNW, Mansor AA, Ismail M et al. Development of Multiple Linear Regression for Particulate Matter (PM10) Forecasting during Episodic Transboundary Haze Event in Malaysia. Atmosphere. 2020; 11(3): 289. https://doi.org/10.3390/atmos11030289
12. Ahamad F, Griffiths PT, Latif MT, Juneng L, Xiang CJ. Ozone Trends from Two Decades of Ground Level Observation in Malaysia. Atmosphere. 2020; 11(7):

755. https://doi.org/10.3390/atmos11070755
13. Awang NR, Ramli NA, Yahaya AS, Elbayoumi M. High Nighttime Ground-Level Ozone Concentrations in Kemaman: NO and NO2 Concentrations Attributions. Aerosol and Air Quality Research. 2015; 15(4): 1357-1366. https://doi.org/10.4209/aaqr.2015.01.0031
14. Laban TL, van Zyl PG, Beukes JP, Vakkari V, Jaars K, Borduas-Dedekind N et al. Seasonal influences on surface ozone variability in continental South Africa and implications for air quality. Atmospheric Chemistry and Physics. 2018; 18(20): 1-42. https://doi.org/10.5194/acp-2017-1115
15. Suryati I, Khair H, Gusrianti D. Distribution analysis of nitrogen dioxide (NO2) and ozone (O3) in Medan city with Geographic Information System (GIS). MATEC Web of Conferences. 2019; 276: 06013. https://doi.org/10.1051/matecconf/201927606013
16. Ismail M, Abdullah S, Yuen FS, Ghazali NA. A Ten-Year Investigation on Ozone and It Precursors at Kemaman, Terengganu, Malaysia. EnvironmentAsia. 2016; 9(1): 1-8. https://doi.org/10.14456/ea.1473.1
17. Zainordin NS, Ramli NA, Elbayoumi M. Distribution and Temporal Behaviour of O3 and NO2 Near Selected Schools in Seberang Perai, Pulau Pinang and Parit Buntar, Perak, Malaysia. Sains Malaysiana. 2017; 46(2): 197-207. http://dx.doi.org/10.17576/jsm-2017-4602-03
18. Otero N, Rust HW, Butler T. Temperature dependence of tropospheric ozone under NOx reductions over Germany. Atmospheric Environment. 2021; 253: 118334. https://doi.org/10.1016/j.atmosenv.2021.118334
19. Warminski K, Bes A. Atmospheric Factors Affecting a Decrease in the Night-Time Concentrations of Tropospheric Ozone in a Low-Polluted Urban Area. Water, Air & Soil Pollution. 2018; 229: 350. https://doi.org/10.1007/s11270-018-4012-x
20. Hashim NIM, Noor NM, Yusof SY. Temporal Characterizations of Ground-level Ozone Concentration in Klang Valley. E3S Web of Conferences. 2018; 34: 02047. https://doi.org/10.1051/e3sconf/20183402047
21. Verma N, Satsangi A, Lakhani A, Kumari KM. Prediction of Ground level Ozone concentration in Ambient Air using Multiple Regression Analysis. Journal of Chemical, Biological and Physical Sciences. 2015; 5(4): 3685-3696.
22. Allu SK, Srinivasan S, Maddala RK, Reddy A, Anupoju GR. Seasonal ground level ozone prediction using multiple linear regression (MLR) model. Modeling Earth Systems and Environment. 2020; 6: 1981-1989. https://doi.org/10.1007/s40808-020-00810-0