Journal of Engineering and Science Research 6 (3): 12-16, 2022
e-ISSN: 2289-7127

DOI: 10.26666/rmp.jesr.2022.3.2

Fitting Statistical Distribution Functions of Ground Level Ozone in Different Urban Locations in Malaysia

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Abstract: Ground level ozone is an unstable substance in the atmosphere which reacts with nitrogen dioxide (NOx) in the presence of sunlight normally found near ground level. Ground level ozone is known as one of the major air quality issues worldwide. The presence of the NOx volatile organic compounds (VOCs) can influence the concentration levels of ground level ozone. This pollutant can affect crops and human health. The main aim of this research is to find the best fit distribution for urban monitoring stations in Kuala Terengganu, Kota Bharu and Alor Setar. Secondary data from 2011 to 2015 used in this study was obtained from the Department of Environment (DoE). This research used the central fitting probability distribution which is between gamma, Nakagami, lognormal and log logistic distributions. Meanwhile, the method of moments was used to estimate the parameters. The best distribution represented the monitoring station and predicted the return period of the concentration. The results show that the Nakagami distribution represented the Kuala Terengganu station from 2011 to 2015. In Kota Bharu however, the gamma distribution fit better compared to other distributions in 2013. The gamma distribution seems to fit the data from 2011 to 2014 whereas in 2015, the Nakagami distribution fit better than other distributions for the Alor Setar station. In addition, no return period was predicted for concentrations above 0.10 ppm found at the Kuala Terengganu monitoring station.

Keywords: *Long-term prediction, lognormal distribution, Nakagami distribution.*

Introduction

The main issues in environmental pollution nowadays have shifted to air pollution due to the increasing trend of polluted ambient air worldwide. Ambient air pollution affects developed countries in America and Europe more due to urbanization and industrialization compared to developing countries in Asia and Africa (World Health Organisation, 2016). Moreover, air pollution has been shown to affect human health, agriculture, material and the environment significantly. Air pollution has been found to cause numerous human diseases and even death in some cases (Goudarzi et al., 2015).

The O_3 pollutant is formed by inducing the emission of nitrogen dioxide (NO_2) and volatile organic compounds (VOCs) in the presence of solar radiation (sunlight) (Ghazali et al., 2010). According to Kim et al.(2015), the air pollutant which is most dangerous to human health is particulate matter followed by O_3. Particulate matter and O_3 have resulted in deaths of 2.1 million and 0.47 million people, respectively. In the past decade, PM_{10} was reported as a significant pollutant in air quality studies. For example, studies on PM_{10} profiles associated with human health were conducted in Iran (Maleki et al., 2016). The forecasting of PM_{10} concentrations was also done in Malaysia using several statistical methods in order to predict future PM_{10} concentrations (Ul-Saufie et al.,2012; Sansuddin et al., 2011). Compared to PM_{10}, O_3 receives substantial concern worldwide due to significant deleterious effects to human health.

The modelling of air pollution is an important tool for providing early information related to ambient air quality status in future. This study used the statistical distribution method in order to predict future O_3 concentrations. In previous studies, the PM_{10} pollutant was investigated by numerous researchers to predict the exceedance level using statistical distribution. The prediction of exceedances and return period at four different locations in Malaysia, namely Kuantan, Kota Kinabalu, Nilai and Johor Bharu was done using gamma distribution (Sansuddin et al., 2011). Similar studies comparing generalized extreme value distribution (GEV) and

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generalized Pareto distribution (GPD) to develop a model for extreme PM_{10} data in Johor Bharu to estimate the return period were conducted (Amin et al., 2015). These studies mostly focused on PM_{10} concentrations. This indicated that there are limited statistical distribution studies on O_3 concentrations. For instance, gamma and lognormal distributions were applied in Pasir Gudang to examine the return period of O_3 (Hamid et al., 2018). The studies on statistical distributions to predict the exceedance probablity and return period of O_3 focused more on common, widely used statistical distributions.

The objective of this research is to fit models using two types of statistical distribution in order to predict the exceedances and return period of O_3 concentrations in three different urban areas in Malaysia. New knowledge is expected to be contributed by this research in terms of statistical distribution modelling of air quality data as statistical distribution methods such as the Nakagami distribution and gamma distribution applied to O_3 data have never been applied in previous studies.

Monitoring Stations

Three urban monitoring locations were selected in this study. The first monitoring station is located in Kota Bharu which is the capital city of Kelantan with total estimated area is 115.6 km^2 . The second monitorins station involved in this study is Kuala Terengganu which is the capital city of Terengganu with a total area of 605 km^2. The third monitoring station is located in the capital city of Kedah, Alor Setar. The total area of Alor Star is 666 km^2. All three monitoring stations are situated in the city center where the O_3 concentration is influenced by the number of motor vehicles as the main source of its precursor (Department of Environment Malaysia, 2016). The total number of motor vehicles in these three states is 626,603, 894,265 and 1,345,100 for Terangganu, Kelantan and Kedah, respectively. Additionally, these three monitoring stations are located near the coastal area with an estimated distance of 8km for Kuala Terengganu and Alor Setar while Kota Bahru has an estimated distance of 7km from the coastal area. The areas situated near the coastal area are probably influenced by sea breeze which transports sea salt aerosol which contains the O_3 precursor, NO_x (Wallace and Hobbs, 2006). Thus, this area may have similar O_3 characteristics due to the location and number of motor vehicles which influence the dispersion of O_3 concentrations. Hence, the selection of these areas are due to the conditions mentioned above.

Air Quality Data

The hourly average of O_3 concentration data from 2011 to 2015 was used and analyzed in this study. This data from the monitoring stations in Kuala Terengganu, Kota Bharu dan Alor Setar was provided by the air division, Department of Environment, Malaysia.

Research Methodology

This research used two statistical distributions to fit the O_3 concentration data, thus predicting the return period of the pollutant concentration. Probability density function (PDF) and cumulative distribution function (CDF) were used to estimate exceedance probability of O_3 concentration. In this research, two-parameter gamma and Nakagami, distributions were used to analyze O_3 concentration. According to Hamid et al. (2014) , method of moments (MoM) can be used as an estimator for all parameter distributions in this research.

Gamma distribution

Forbes *et al*. (2011) (Evans et al., 2011) defined gamma distribution as follows:

$$f\left(x\right)=\left[\frac{1}{\mu\Gamma\left(x\right)}\right]\left(\frac{x}{\mu}\right)^{\lambda-1}\exp\left(-\frac{x}{\mu}\right) \quad (1)$$

$$x>0,\mu>0,\lambda>0$$

where λ and μ is the shape parameter and scale parameter respectively. Method of Moment is used to estimate the parameter is given by Forbes *et al*. (2011) as below:

$$\mu=\frac{s^2}{\bar{x}} \qquad (2)$$

$$\lambda=\left[\frac{\bar{x}}{s}\right]^2 \qquad (3)$$

Nakagami distribution

The Nakagami distribution defined by Binoti *et al.* (2012) is shown below:

$$f\left(x\right)=\frac{2\lambda^{\lambda}}{\Gamma\left(\lambda\right)\mu^{\lambda}}x^{2\lambda-1}\exp\left(-\frac{\lambda}{\mu}x^2\right) \quad (4)$$

$$x>0,\mu>0,\lambda>0$$

where λ and μ is the shape parameter and scale parameter respectively. The parameter can be estimated by the method of moments which is defined by (Noga and Studanski 2016).

$$\lambda = \frac{\bar{x}}{\left(s^2 - \bar{x}^2\right)} \quad (5)$$

$$\mu = \bar{x} \quad (6)$$

Performance Indicator

Five performance indicators will be used to describe how well and fit the set of observation to the distribution as shown in Table 1.

Table 1. Performance indicator

No	Performance Indicator	Equation
1	Root mean square error (RMSE)	$\sqrt{\left(\frac{1}{N-1}\right)\sum_{i=1}^{1}\left(P_i - O_i\right)^2}$ Smallest value of RMSE indicate the best estimator.
2	Normalized absolute error (NAE)	$\frac{\sum_{i=1}^{n} ABS\left(P_i - O_i\right)}{\sum_{i=1}^{n} O_i}$ Smallest value of NAE indicate the best estimator.
3	Coefficient of determination (R^2)	$\left[\frac{\sum_{i=1}^{N}\left(P_i - \bar{P}\right)\left(O_i - \bar{O}\right)}{N.S_{pred}.S_{obs}}\right]^2$ Value of R^2 near to 1 indicate best estimator.
4	Index of agreement (IA)	$1 - \left[\frac{\sum_{i=1}^{N}\left(P - O_i\right)^2}{\sum_{i=1}^{N} O_i}\right]$ Value IA near to 1 indicate best estimator.
5	Prediction accuracy (PA)	$\frac{\sum_{i=1}^{N}\left(P_i - \bar{O}\right)^2}{\sum_{i=1}^{N}\left(O_i - \bar{O}\right)^2}$ Value of PA near to 1 indicates is appropriate to simulate the experimental data.

Selection of the best fit distribution for O_3 concentration

The best statistical distribution was determined by using performance indicators which represent the ground level ozone concentration for the urban monitoring stations. The results of these stations are tabulated in Table 3 according to the year and the monitoring station, respectively. Based on the estimated value of scale and shape parameters, the probability density function (PDF) and cumulative density functions (CDF) can be plotted as shown in Figure 1, Figure 2 and Figure 3 (PDF) and Figure 4, Figure 5 and Figure 6 (CDF) below, respectively.

Table 3. Parameter estimation for urban monitoring stations

Year	Distribution	Scale parameter	Shape parameter
Kuala Terengganu			
2011	Nakagami	0.00040	1.4960
2012	Nakagami	0.00037	1.2402
2013	Nakagami	0.00046	1.3945
2014	Nakagami	0.00070	1.7159
2015	Nakagami	0.00060	1.4350
Kota Bharu			
2011	Nakagami	0.00039	2.0081
2012	Nakagami	0.00022	6.4892
2013	Gamma	0.00036	5.9959
2014	Nakagami	0.00012	2.2301
2015	Nakagami	0.00049	2.0992
Alor Setar			
2011	Gamma	0.00120	1.6318
2012	Gamma	0.00088	0.0169
2013	Gamma	0.00052	3.5403
2014	Gamma	0.00088	2.2397
2015	Nakagami	0.00025	7.8223

Probability of exceedances

The probability density function plots are shown in Figure 1, Figure 2 and Figure 3 whereas the cumulative distribution function plots are shown in Figure 4, Figure 5 and Figure 6 respectively. The result show that the predicted hourly average for ground level ozone will not exceed the limits set by the Malaysian Ambient Air Quality Guidelines (MAAQG) which is 0.10 ppm. According to the results based on the performance indicator, the Nakagami distribution has a better fit compared to other distributions from 2011 to 2015. The probability of the ground level ozone equal to or less than 0.10 ppm is 1.0 and the probability greater than 0.10 ppm is 0. In addition, this indicated that for five conservative years, the ground level ozone stays below 0.10 ppm and that there is no return period predicted for concentrations above 0.10 ppm. For the Kota Bharu station, the results show that the Nakagami distribution fits better in 2011, 2012, 2014 and 2015 but in 2013, the gamma distribution fit better than other distributions. In 2013, the probability of ground level ozone equal to or less than

0.10 ppm is 0. and the probability greater than 0.10 ppm is 0 . In addition, there is no return period for other years from 2011 to 2015.

The results obtained by the Alor Setar station show that the gamma distribution has the best fit even though the Nakagami distribution showed a better fit in 2015. In 2011, the probability of the ground level ozone equal to or less than 0.10 ppm is 0.99912. Moreover, there is no return period from 2012 to 2015. The probability of exceedances and the return period derived from the CDF plot are shown in Table 4 for all urban monitoring stations.

Table 4. Probability of exceedances for ground level ozone in urban areas

Year	Probability	Actual return period (days)	Predicted return period (days)
Kuala Terengganu			
2011	1.0	0	0
2012	1.0	0	0
2013	1.0	0	0
2014	1.0	0	0
2015	1.0	0	0
Kota Bharu			
2011	1.0	0	0
2012	1.0	0	0
2013	0.99986	8902	0
2014	1.0	0	0
2015	1.0	0	0
Alor Setar			
2011	0.99912	1250	0
2012	1.0	0	0
2013	1.0	0	0
2014	1.0	0	0
2015	1.0	0	0

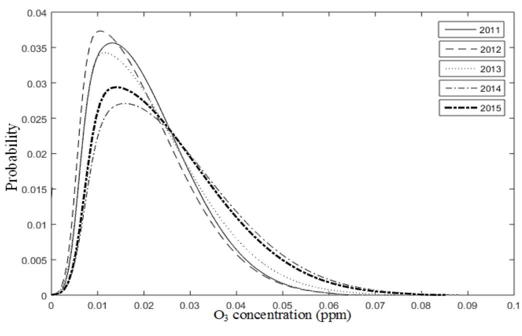

Figure 1. Probability density function (PDF) plot of ground level ozone for Kuala Terengganu

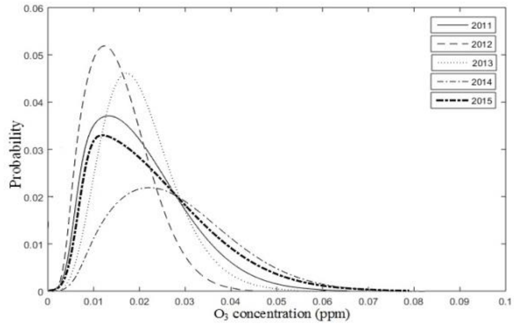

Figure 2. Probability density function (PDF) plot of ground level ozone for Kota Bharu

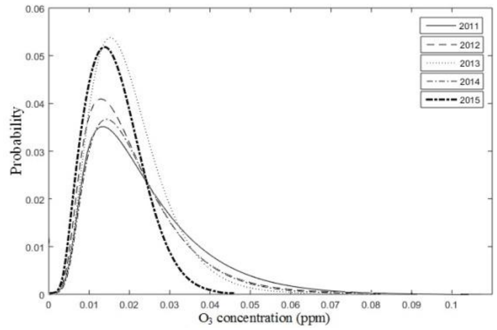

Figure 3. Probability density function (PDF) plot of ground level ozone for Alor Setar

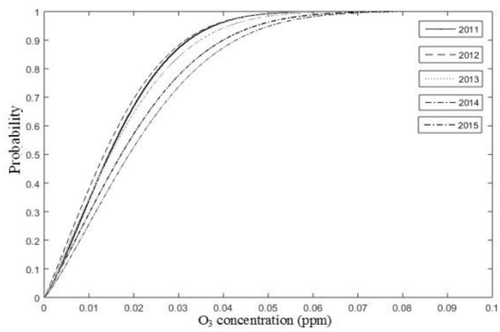

Figure 4. Cumulative distribution function (CDF) of ground level ozone for Kuala Terengganu

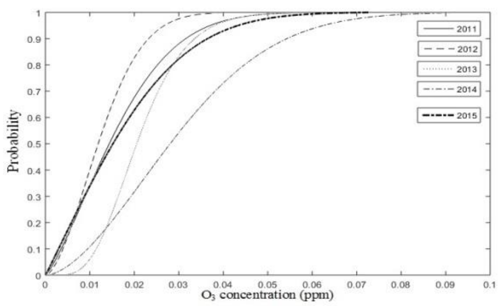

Figure 5. Cumulative distribution function (CDF) of ground level ozone for Kota Bharu

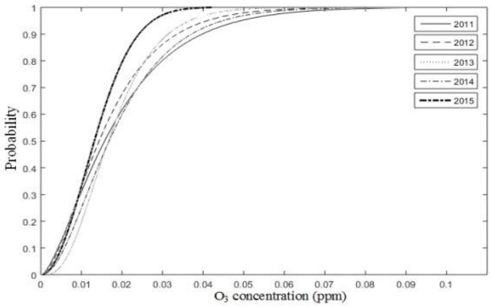

Figure 6. Cumulative distribution function (CDF) of ground level ozone for Alor Setar

Conclusion

Based on the results obtained from the analysis at urban monitoring stations for ground level ozone from 2011 to 2015, the concentrations recorded by the urban monitoring stations have a lower annual average of 0.10 ppm. The probability exceedances did not show that O_3 concentrations will exceed the limit for future predictions. The comparison between gamma and Nakagami distributions show that the Nakagami distribution is a much more appropriate fit for the actual monitoring data recorded by the Kuala Terengganu station from 2011 to 2015 as well as the monitoring data recorded by the Kota Bharu station in 2011, 2012, 2014 and 2015. However, the gamma distribution was found to be a better fit for the monitoring data recorded by the Alor Setar station except in 2015 where the Nakagami distribution was found to be more appropriate.

Acknowledgements

Special thanks to Universiti Sains Malaysia for provide the funding for this research under the short term grant 304/PJJAUH/6315089.

The authors also wishes to thanks Universiti Tun Hussein Onn Malaysia (UTHM) for Post Graduate Research Grant Vot. U700.

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