International Journal of Engineering & Technology, 7 (3.7) (2018) 590-593

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Environmental Modelling through Chaotic Approach: A Case Study on Ozone and Temperature Time Series

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Abstract

The main objective of this study is to develop a suitable model for analysing and predicting environmental variable. Since O_3 pollution is harmful and the changes in temperature can have serious consequences to health, therefore, both variables are chosen. Tanjong Malim, a semi-urban educational area located in Perak Malaysia is selected since it is well known that educational area is frequently visited by peoples. Thus, the environmental modelling is necessary. Analysis by the phase space plot and Cao method shown that the chaotic nature presents in both observed time series. Hence, both time series are predicted through the chaotic approach. Results from the local mean approximation method shown that both time series are predicted well with correlation coefficient near to one. Therefore, chaotic approach is suitable to be applied in environmental modelling. These findings are expected to help stakeholders such as Ministry of Education, Meteorological Department and Department of Environment in having a better environment management.

Keywords: *Modelling, Chaotic Approach, Ozone, Temperature, Prediction*

1. Introduction

A clean environment is essential for maintaining health. Thus, environmental modelling is necessary. Breathe and inhale the ozone (O_3) in the air can cause dangerous reactions in the respiratory system. Recent studies in leading cities and countries such China [1], Canada [2] and India [3] reported that O_3 pollution increased mortality because it leads to a variety of respiratory and cardiovascular disease. Therefore, the development of prediction models of O_3 pollution is important.
The temperature is always uncertain and the changes in temperature can have serious consequences, especially to health. Therefore, to get an early warning about the increase and decrease in temperature, the development of prediction models of temperature time series is very essential.
Recently, chaotic approach is widely applied in environmental modelling. Some examples are modelling of river flow [4], modelling of sea level [5], modelling of particulate matter [6] and modelling of O_3 [7]. In Malaysia, chaotic approach has been successfully applied to the time series of river flow by [8], O_3 by [9]–[11] and particulate matter by [12]. Application of this approach is still new in Malaysia. Thus, this study will contribute to the enhancement on application of chaotic approach for environmental modelling in Malaysia.
Researches by [13] and [14] found that O_3 time series is chaotic in nature through the method of correlation dimension, Lyapunov exponent and correlation integral while research by [7] found that temperature time series is chaotic in nature through the calculation of Lyapunov exponent. Phase space plot and Cao method [15] are also able to classify the nature of the time series. However, both methods are rarely use. Therefore, in this study, both methods will be used. If the chaotic nature is present, then, the prediction model will be built using chaotic approach. In this study, the observed time series will be predicted through one of the basic method from chaotic approach namely the local mean approximation method.
In this paper, modelling through chaotic approach is divided into two parts: i) the reconstruction of phase space and ii) the development of prediction model. The first part contributes to determine the present of chaotic nature of the O_3 and temperature time series and the second part contributes to predict the future time series of both variables.

2. Time Series Data

The O3 and temperature time series used in this study were observed at one of the semi-urban area located in the state of Perak, Malaysia namely Tanjong Malim. The total area of Tanjong Malim is about 950 km². Tanjong Malim is known as educational area since one of the leading university namely Sultan Idris Education University is located there. Tanjong Malim is frequently visited by peoples. Hence, the prediction of air pollution such as O3 and environmental variables such as temperature in this area is very necessary to maintain public health. This present study used hourly O3 and temperature data observed for three months, from 1st June until 31st August. However, the data are from different year because the latest data for O3 is from year 2014 while for temperature, the most recent data is from year 2016.

3. Reconstruction of Phase Space

The observed time series is recorded in the form of:

$$X = \left(x_1, x_2, x_3, ..., x_{N-1}, x_N\right) \tag{1}$$

where x_t is the time series at t -th hour and N is the total hours of observation. X was divided into two parts; X_{train} and X_{test} . X_{train} was used as a training data to find the unknown parameters, while X_{test} was used to test the performance of the prediction model.
This present study chose hourly data observed for two months, from 1st June until 31st July as X_{train} and the rest one month was used as X_{test} . The time series in (1) will be reconstructed into the m -dimensional phase space of:

$$\mathbf{Y}_j^m = \left(x_j, x_{j+\tau}, x_{j+2\tau}, \quad ..., x_{j+(m-1)\tau}\right) \tag{2}$$

From Equation 2, the value of delay time, τ and embedding dimension, m must be determined. Since the time series data are observed hourly (every one hour), therefore, this study decided to use $\tau = 1$. In computing parameter m , it has been proved by Cao [15] that Cao method:

does not contain any subjective parameters and
does not depend on the number of data.

Thus, Cao method is applied to compute m . Cao method involved equation of:

$$E1(m) = \frac{E(m+1)}{E(m)} \tag{3}$$

With

$$E(m) = \frac{1}{N - m\tau} \sum_{j=1}^{N-m\tau} \frac{\left\|\mathbf{Y}_j^{m+1} - \mathbf{Y}_n^{m+1}\right\|}{\left\|\mathbf{Y}_j^m - \mathbf{Y}_n^m\right\|} \tag{4}$$

Symbol $\|\bullet\|$ is for the maximum norm and $\mathbf{Y}_n^m$ is the nearest neighbour to $\mathbf{Y}_j^m$. The value of minimum embedding dimension m is selected at the value when $E1(m)$ begins to saturate. For a random time series data, $E1(m)$ will not reach saturation with increasing m . For a chaotic time series data, $E1(m)$ will reach saturation with increasing m . Therefore, if there exist saturation of $E1(m)$, then the behaviour of the time series is chaotic. Next, Cao introduced the parameter of $E2(m)$:

$$E2(m) = \frac{E*(m+1)}{E*(m)} \tag{5}$$

where

$$E*(m) = (1/U - m\tau) \sum_{j=1}^{U-m\tau} \left|x_{j+m\tau}^m - x_{w+m\tau}^m\right| \tag{6}$$

According to Cao, if all the values of $E2(m)$ are equal to one, then the behaviour of the observed time series is random. On the other hand, if there is at least one value of $E2(m)$ is not equal to one, then the observed time series is chaotic.

4. Development of Prediction Model

Prediction of $\mathbf{Y}_{j+1}^m$ is done based on the nearest neighbors of $\mathbf{Y}_j^m$ with:

$$\mathbf{Y}_{j+1}^m = f\left(\mathbf{Y}_j^m\right) \tag{7}$$

k nearest neighbors $\mathbf{Y}_{j'}^m$ are selected based on the minimum value of $\left\|\mathbf{Y}_{j'}^m - \mathbf{Y}_j^m\right\|$, where $j' < j$ and $\|*\|$ is the Euclidean distance. According to [16], the predicted $\mathbf{Y}_{j+1}^m$ is taken as the average of the $\mathbf{Y}_{j'+1}^m$ values where:

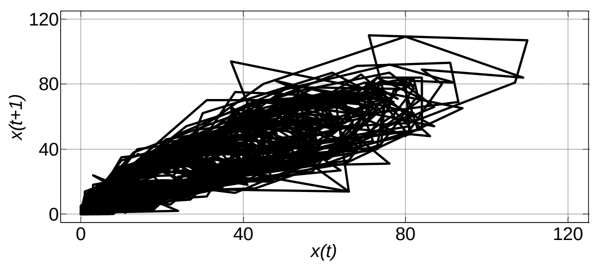
$$\mathbf{Y}_{j+1}^m = \frac{1}{k} \sum_{q=1}^{k} Y_{j'_q+1}^m \tag{8}$$

The correlation coefficient r [17] was used to measure the method's performance. The closer r to -1 or +1 explains that the observed and predicted data series are close to each other. All of the computational part is carried out using the Matlab software.

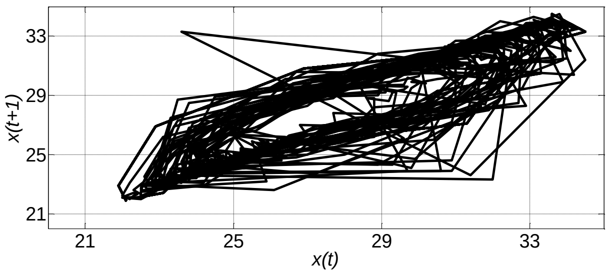
5. Results and Discussion

In this paper, phase space plot and Cao method are used to detect whether chaotic nature present in the observed times series. The phase space for both time series is reconstructed in the $\{x_t, x_{t+\tau}\}$ plane. Using $\tau = 1$, the phase space of O3 time series (Figure 1a) and temperature time series (Figure 1b) are plotted.
Over both phase spaces, it can be clearly seen that most of the points are converging to the middle of the phase space. These are also known as an attractor [18]. The existence of attractor in both phase spaces suggest that chaotic nature is present in both O3 and temperature time series. However, there are some points which are away from the attractor. These are called outliers, which may result from some noise disturbance.
Figure 2 is the results from Cao method. From Figure 2, $m = 5$ and $m = 4$ for O3 and temperature time series respectively. Beside calculating m , Cao method is applied to detect the presence of chaotic nature. From Figure 2, $E1(m)$ start to saturate at $m = 5$ and $m = 4$ for O3 and temperature time series respectively. For random time series, $E1(m)$ will not reach saturation value with increasing m . Thus, the saturations of $E1(m)$ show that the chaotic nature is present in both time series.

In addition, there exist $E2(m) \neq 1$. The existence of $E2(m) \neq 1$ also indicates that chaotic nature is present in both time series. Thus, the results from Cao method and phase space plot are consistent. Therefore, the chaotic nature is present in both O3 and temperature time series.



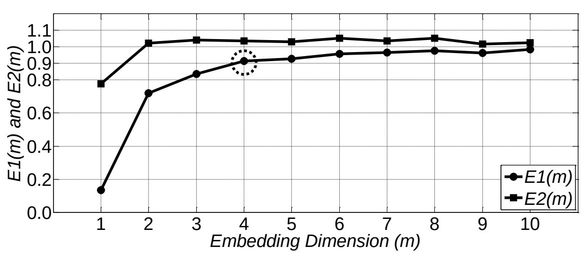
(a)



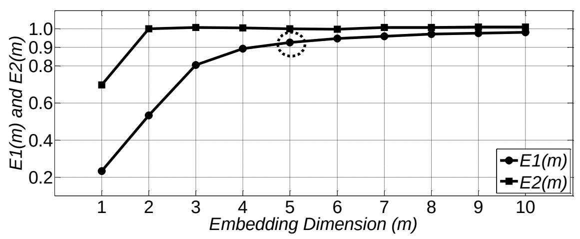
(b)

Figure 1: Phase space plot for (a) O_3 time series and (b) temperature time series

Prediction is done for accounting periods from 1st to 31st August. Figure 3 shows a comparison of predicted and observed values. It can be seen that the data trend (up and down) can be predicted well. The correlation coefficient between the observed and predicted data for both O3 and temperature time series are 0.9255 and 0.9613 respectively. These values are near to one and indicate that there is a high correlation between predicted and observed values. Thus, the results demonstrate that the local mean approximation method is good in predicting both O3 and temperature time series. It can be seen that the too high time series of O3 concentrations are not predicted at its best. In future, local mean approximation method needs to be improved to overcome this problem.

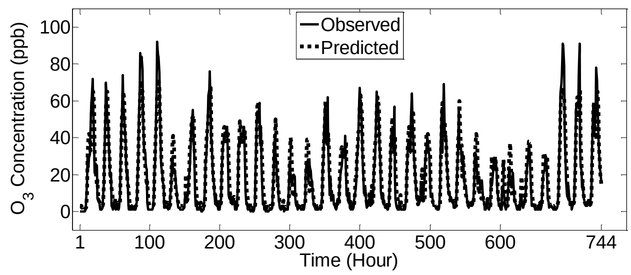


(a)

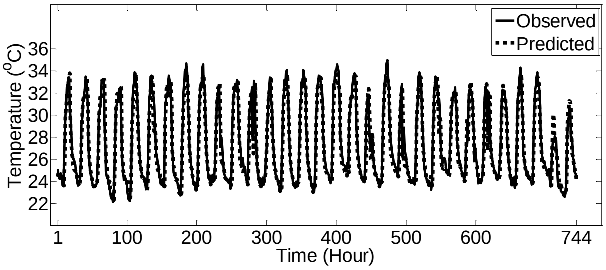


(b)

Figure 2: Results of Cao method for (a) O_3 time series and (b) temperature time series



(a)



(b)

Figure 3: Observed and predicted (a) O_3 time series and (b) temperature time series

6. Conclusion

In this study, the chaotic nature of O3 and temperature time series at Tanjong Malim educational area is detected through the phase space plot and Cao method. Results shown that both time series are predicted well through the local mean approximation method with correlation coefficient near to one. Therefore, it is hoped that these findings can help stakeholders such as Ministry of Education Malaysia, Malaysian Meteorological Department and Department of Environment Malaysia to have a better environment management. In future, the approach is suggested to be applied towards other environmental variables such as wind speed and humidity and air pollution such as haze and carbon monoxide.

Acknowledgement

A special thanks to the Department of Environment, Malaysia and Malaysian Meteorological Department for providing the O3 and temperature time series. This study is under the sponsorship of the research grants with the code 2015-0174-102-72 (RAGS/1/2015/SG0/UPSI/02/1) and 2016-0188-102-01 (Research University Grant).

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