International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)
Web Site: www.ijettcs.org Email: editor@ijettcs.org
Volume 6, Issue 4, July- August 2017 ISSN 2278-6856

Modelling Long-Term Pattern Pollutants Using Recurrence Quantification Tools. Case-study: PM10 at Mexico City

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Abstract

Various techniques have been used to model the long-term trends for particulate matter (PM) in the environment. However, the non-linear behavior of airborne pollution (PM10, in this case) and the variety of compounds present in the environment make long-term pattern modelling a challenging task.

In this contribution, Recurrence plots and its extension RQA (Recurrence Quantification Analysis) explore the long-term trends on PM10 in Mexico City. To determine the feasibility of this technique over a long period of time, data was obtained for various monitoring stations from different stations over 12 years. The trends resulted were then compared with statistical analyses from other authors. The results confirm that this technique could be used to model long-term patterns of particulate matter given that the right RQA tools are used. Furthermore, the importance of this work relies on the fact that this type of analysis with such an amount of data using RPs has not been carried out before, which makes this tool to find PM10 trends buried in large databases, useful for this case analysis. Also, different approaches have been performed and preliminary conclusions are drawn from these experiments.

Keywords: Recurrence Plots; Recurrence Quantification Analysis; PM10; Particulate Matter

1. Introduction

Modeling the behavior of of the changes in complex systems is not a trivial task. For these systems, a linear approach is often not sufficient to analyze their data. In the past years, many non-linear techniques have emerged to help analyze data from complex systems.

One of the techniques emerged to deal with non-stationary data series is called recurrence plots (RP), which has been introduced by Eckmann [1] and has acquired importance due to its visual interpretation.

However, since RP is a tool of qualitative and visual interpretation, its results are often not conclusive when dealing with dynamic and complex systems, which may be considered as a drawback. To overcome this drawback an extension of this method is used in this study, called Recurrence Quantification Analysis developed by Zbilut [2] to detect transition in complex systems. Arguably, modelling of PMx may be more challenging since their behavior depends upon the particulate size, regardless their chemical composition, hence the importance of having reliable tools to model long-term particle concentration.

In this contribution, such linear behavior of particulate matter, specially PM10 is investigated. Long-term patterns are analyzed and quantified at various sites at Mexico City for over 12 years. Lastly, the main goal of this investigation is whether is feasible the long-term modelling using Recurrence Plots and Recurrence Quantification Analysis.

2. BACKGROUND

2.1. Urban Air Pollution

Air pollution is one of the most important environmental problems that urban areas face nowadays due mainly to the presence of high concentrations of primary pollutants emitted during industrial and transport activities, and secondary pollutants generated in the atmosphere through in situ chemical reactions [3].

The health effects of air pollution have been subject to intense study in recent years and have been widely documented [4][5][6]. Exposure to pollutants such as airborne particulate matter and ozone has been associated with increases in mortality and hospital admissions due to respiratory and cardiovascular diseases [7][8][9].

2.2. PM10

Several authors indicate in their studies that PM10 is responsible for several health issues like Lung function [10], Central nervous system of children [11], cardiovascular diseases [12][13] even if the exposure to pollution is short or limited, Also, Peng [14] and Huang [15] state that particulate matter may contribute to air quality in terms of visibility degradation and acid rain.

In general terms, Mexico City is no different than most megalopolis in terms of health effects due to pollution. There have been many studies carried out in Mexico that link pollution with health effects. For instance, Gold [16] and Moffet [17] have associated pollution from fine PM with the decrease of respiratory function, specially for vulnerable sector such as children and the elderly. Although, environmental national authorities recognize the importance of this health issue and criticality of tackling the problem of reducing the amount of emissions and attain worldwide air quality standards [18].

Furthermore, some authors [19] have linked that in the case of Mexico City, there have been an increase of 20 µg/m3 of PM10, which was associated with an 8% increase in respiratory illness in asthmatic children, whilst Rojas [20] associated PM10 increase in Mexico with lung dysfunction in children.

2.3. Monitoring Sites used in the Study

The monitoring Sites used for this study were chosen accordingly to their geographical location and data availability. Also, the sites were chosen to demonstrate that using recurrence quantification is feasible for many types of locations, this is, a commercial area, a residential or industrial region. Thus, the geographical regions chosen for this study were as follows: In the Northeast, 2 cities were chosen namely: La Villa (LVI) and Xalostoc (XAL), which is an industrial area; in the northwest Tlalnepantla (TLA) and FES Acatlán (FAC); in the City Center Merced (MER), which is a commercial area; in the Southeast Cerro de la Estrella (CES) and Tlahuac (TAH); and in the Southwest Pedregal (PED), which is a residential area.

The map of the monitoring sites chosen is be illustrated on Figure 1. Notice that the monitoring network of Mexico City and its metropolitan area is far greater that those sites. Nevertheless, as it was stated, these sites were chosen due to its geographical location and data availability for large periods of time.

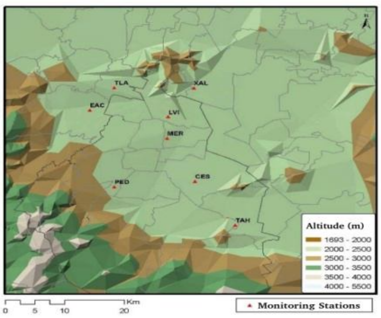


Figure 1 Map for the monitoring sites at Mexico City.

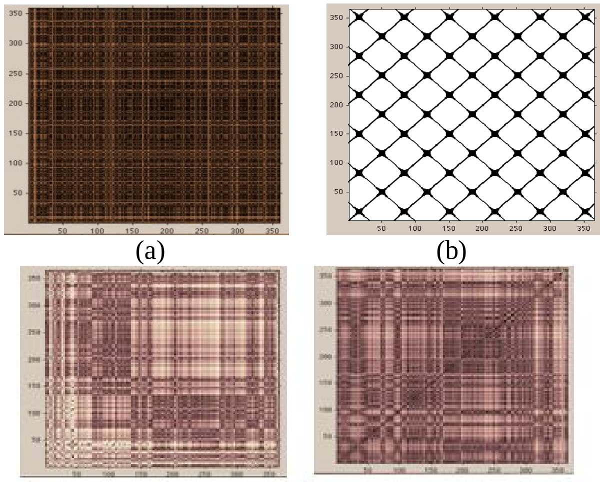
3. RECURRENCE PLOTS

Recurrence Plots have gained importance and have been used for a number of applications over the past few years. For example, Karakasidis [21] has measured temperature changes on turbulent jets. Another industrial application has been showed by Litak [22] where the author has described oscillations and vibrations using RPs for milling and cutting and also during steel turning [23]. Furthermore, in biomedical applications RPs and RQA have been used extensively. For instance, Goshvarpour [24] has shown that the dynamics of heart rate signals when breathing could be discriminated. Also, Mazaheri [25] used RQA to detect musculoskeletal disorder in patients. There are other works applied to biomedical applications that used RPs or their extension RQA such as [26][27][28], among others. In terms of PM10 modeling or airborne pollution the only contribution found using RP has been the previous work carried out by these authors [29].

Based on RPs, the dynamics, transitions, or synchronization of complex systems can be studied [30]. In particular, such transitions can be uncovered from a changing recurrence structure. The different features of recurrences can be deduced by measures of complexity, also known as recurrence quantification analysis (RQA)[31]. Given a trajectory of a dynamical system consisting of different values $\mathbf{x}_i$, where i indicates the time of observation, the corresponding RP is defined as

$$R^{m,\varepsilon^i}_{i,j} = \Theta(\varepsilon_i - \|\vec{X_i} - \vec{X_j}\|), \vec{X_i} \in \Re^m, \quad i,j = 1..N, \qquad (1)$$

where, N is the number of considered states xi; $\|\mathbf{x}_i - \mathbf{x}_j\| \equiv d_{i,j}$ is a threshold distance, ε predefined threshold for the proximity of two states in phase space and Θ (.) the Heaviside function[32]. The Heaviside function may be interpreted as a recurrence of a state that fall into an m-dimensional neighborhood. By using the time-series of an observable variable, which is concentration of airborne particulate matter (PM10), in this case, it is possible to reconstruct a phase space trajectory. Determining the embedding parameters, such as time delay, embedding dimension, among other parameters must be the first step when analyzing non-linear systems [31][33]. The aim of time-delay embedding is to unfold the phase space trajectory in a sufficiently large state space. The state space of a non-linear system is often high-dimensional and noise incline to increase the dimension. Figure 2 shows the recurrence plots of a random signal, a sine wave and two RPs chosen randomly as examples for airborne particle concentration.



(a) (b)

(c) (d)

Figure 2 Recurrence Plots using (a) a random signal, (b) a sine wave, (c) particle concentration of PM10 over 2009 at Mexico NorthWest (TLA) and (d) particle concentration of PM10 over 2007 at Mexico DownTown (MER) (daily mean) showing the Line of Identity (diagonal line).

Recurrence quantification analysis is a way to parametrize the RP. Isolated recurrence points occur if states are rare, if they do not persist for any time or if they fluctuate heavily[28]. Diagonal lines occur when a segment of the trajectory runs in parallel with another segment, i.e. when the trajectory visits the same region of the phase space at different times. Vertical (horizontal) lines mark a time length in which a state does not change or changes very slowly.

The main idea of this project is to determine to which extend this technique is reliable in quantify the dynamics in the phase space and to reconstruct the unknown dynamics in the phase space buried in large datasets of PM10.

In general terms, the features measured in a RP are: recurrence rate, determinism, ratio, entropy and trend. In this contribution, an extension of these characteristics was also considered such as Laminarity and Trapping time.

3.1. Recurrence Rate

The recurrence rate is a measure of recurrences, or density of recurrence points in the RP. This rate gives the mean

probability of recurrences in the system [34]. The recurrence rate is given by:

$$\mathrm{RR} = \frac{1}{N^2}\sum_{i,j}^{N}\mathbf{R}_{i,j} = \frac{1}{N^2}\sum_{l=1}^{N} lP(l), \qquad (2)$$

3.2. Determinism

Deterministic systems are often characterized by repeated similar state evolution. This corresponds to a local predictability [31].

The Determinism of a system is calculated as:

$$DET = \frac{\sum_{l\geq l_{\min}} lP(l)}{\sum_{i,j} R_{i,j}} \qquad (3)$$

Where P(l) denotes the probability of finding a diagonal line of length l in the RP. This measure quantifies the predictability of a system [32]. The measure of determinism(DET) ranges from 0 to 1. Numbers near zero indicate randomness while those approaching one indicate the presence of a strong signal component [28].

3.3. Ratio

The Ratio variable is defined as the quotient of determinism (DET) divided by the recurrence (REC). It is useful to detect transitions between states: this ratio increases during transitions but settles down when a new quasi-steady state is achieved [33].

3.4. Entropy

This measure refers to the Shannon entropy of the frequency distribution of the diagonal line lengths [31]. According to several authors, the basic idea is that information (Shannon) entropy of the random processes is abundantly supplied with the qualitative and quantitative data on the object under research [2][21][23][25][27].

The entropy of a system is given by:

$$ENT = \sum_{l=l_{min}}^{N} p(l)\log p(l) \; with \quad p(l) = \frac{p^{\varepsilon}(l)}{\sum_{l=l_{min}}^{N} P^{\varepsilon}(l)} \qquad (4)$$

3.4. Trend

The trend is a linear regression coefficient over the recurrence point density of the diagonals parallel to the Line Of Identity (LOI). The trend measurement is given by:

$$TREND = \frac{\sum_{i=1}^{N}\left(i - \frac{N}{2}\right)(RR_i = \{RR_i\})}{\sum_{i-1}^{N}\left(i = \frac{N}{2}\right)^2} \qquad (5)$$

3.5. Laminarity

Laminarity may be defined as the amount of recurrence points which form vertical lines[33]. Thus, laminarity (LAM) can be quantified as expressed on equation 6.

$$LAM = \frac{\sum_{v=v_{min}}^{N} v.P(v)}{\sum_{v=1}^{N} v.P(v)} \qquad (6)$$

Where P(v) is the frequency distribution of the lengths v of the vertical lines, which have at least a length of vmin. It is noteworthy that Laminarity is evidence of chaotic transitions and is related with the amount of laminar phases in the system (intermittency) [33].

3.6. Trapping Time

Trapping Time shows the average length of the vertical lines and is given by equation 7:

$$TT = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=v_{min}}^{N} P(v)} \qquad (7)$$

Where v is the length of the vertical lines, v_{min} is the shortest length that is considered a line segment and P(v) is the distribution of the corresponding lengths. TT shows the time that the system has been trapped in the same state [21].

4 Experimental Results

As mentioned previously, one of the main goal of this study was to determine the feasibility of long-term trends of PM10 using RQA as a main tool. Therefore, it seems reasonable that in order to make a reliable comparison, work from other authors who already published their work must be compared with the finding in this work. For this reason, the work from Stephens [35] was compared. This author showed weekly patterns over a number of years (1986-2007). Although the dates vary from this work with the work from Stephens, in general terms, the patterns may be similar in order to lay the foundations that the comparison may be reliable in terms of results´ similarity.

In this contribution, RQA analysis was performed from the year 1999 to 2010 for only a few sites, due to the reasons already explained on section 2.3.

This analysis has been carried out for recurrence rate (REC), determinism (DET), Ratio, Trapping Time (TT), Laminarity (LAM) and Trend. As shown on section 3, choosing the right parameters is key to a successful extraction of the embedded information in the signal. In this contribution, the best dimension value is calculated for each recurrence plot using the algorithm of false nearest neighbors (FNN) as shown on [32], being this dimension m = 11 on average.

Also, when calculating an RP a norm must be chosen [21]. The most widely used norms are the L1, L2 (Euclidean norm) and L∞(Zbilut, 2002). In this work, the Euclidean norm was used. Also, delay $\tau = 1$ was used for all RPs.

Due to the amount of data and the results from other authors, the results from this contribution for long-term particle concentration has been separated as follows:

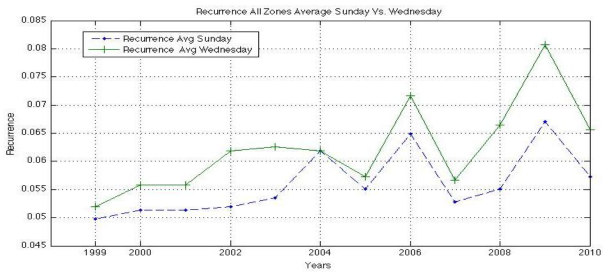
- Analysis of RQA Wednesday Vs. Sunday for PM10
- Analysis of RQA for Day of the Week (all Sites)

4.1. RQA Results between Wednesday and Sunday data

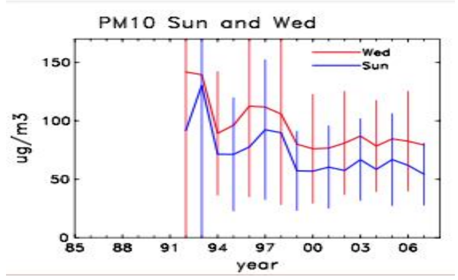
This approach shows whether the overall trend of PM10 corresponds to its RQA analysis. This analysis does not take into account the monitoring zone. For this reason, the mean of each monitoring site was taken to calculate the values of the RQA altogether. Figure 3 shows a comparison using RQA and statistical analysis from other authors [35].

Figure 3 shows that overall as the particle concentration for PM10 increases (figure 3b), the recurrence rate decreases. Nevertheless, the trend shows tat Wednesday has a higher particle concentration and the recurrence rate is higher than the average Sunday value (figure 3a).

This analysis shows that although the differences in particle concentration are not linearly related to the recurrence rate, the overall trend for a long-term analysis is maintained. This differences in particle concentration may be due to a number of factors. Firstly, the years compared are not the same; also, it must be taken into account the highly non-linearity of PM10 data itself, which was one of the challenges to tackle on this paper in the first place.



(a)

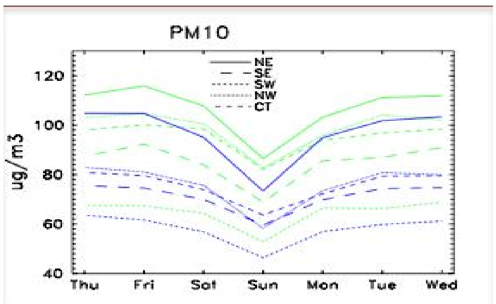


(b)

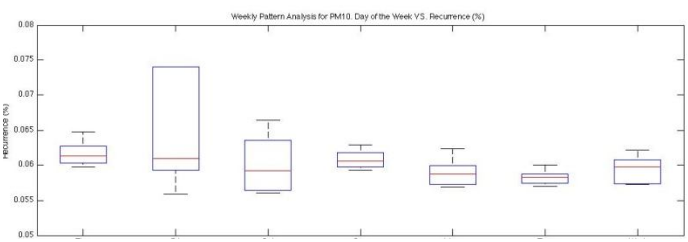
Figure 3. Comparison between PM10 results between RQA - Recurrence rate (%) and Statistical analysis Wednesday and Sunday. a) Recurrence rate for PM10 Wednesday and Sunday for years 1999-2010. b) Long term trends for PM10 for Wednesdays and Sundays years 1992-2007 ([35] Fig. 2d)

4.2. Results for Long-term Weekly Patterns

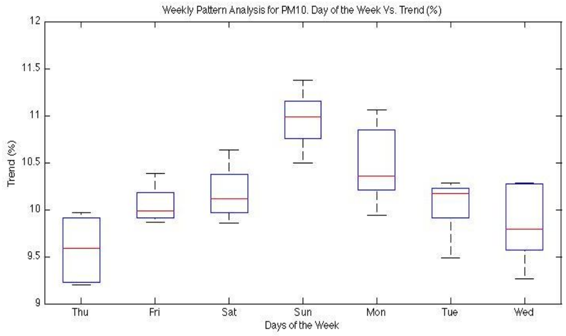
This approach explores the feasibility of using RQA to extract information from the Recurrence Plots by day of the week. In this approach, all monitoring sites were considered (Northwest, Northeast, Downtown (City Center), Southwest and Southeast). The results were compared with a statistical analysis already discussed by other authors (Stephens [35]) as shown on Figure 4.



(a)



(b)



(c)

Figure 4. Comparison between PM10 results between RQA for Day of the Week Long-term patterns. a) Weekly Patterns for PM10 Separated by Monitoring Zone 1992-2007 (Stephens Fig. 3d). b) Recurrence rate for PM10 Weekly Patterns Years 1999-2010, c) Trend for PM10 Weekly Patterns Years 1999-2010.

In figure 4 is shown the recurrence rate and the trend separated by day of the week. Figure 4a shows the work published by Stephens [35] where is seen that Sunday shows the lowest PM10 concentration of all days of the week in a V-shaped figure regardless of the monitoring zone. In comparison, Figures 4b and 4c shows the recurrence rate and trend, respectively. In figure 4b is shown the recurrence rate. Although it is shown starting on Thursday like Figure 4a, for consistency and a V-shaped figure is mildly appreciated in the box plots for median (inverted, though), it is not clear whether the same trend is maintained at this point.

For this reason, other RQA tools were analyzed to see whether a better representation of the behavior is observed. For Determinism, Entropy, Trapping Time and Linearity do not give a clear indication of the overall behavior according to day of the week. However, trend gives a much better representation of the behavior of an inverted "v". This is shown on figure 4c. This might indicate that although it is not linearly related, an overall trend for day of the week is maintained regardless of the monitoring zone.

5 Experimental Results

A number of experiments have been carried out for PM10. This particle is particularly non-linear due to the combination of different gases and their behavior, this makes more difficult to model its behavior.

However, this contribution has shown that even though PM10 is highly non-linear, long-trend behavior can be modelled with relatively moderate accuracy.

The experiments show that it is feasible to model this for long term behavior and days of the week patterns emerge similar to the ones shown in other works, which make these results accurate.

Recurrence rate is useful, when combined with other Recurrence Quantification Tools, such as Trend. Also, this work has shown that for this particular purpose, other RQA tools were not useful.

Trends could be identified using these tools and preliminary conclusions suggest that important information could be drawn using Recurrence Plots.

As a conclusion, the results suggests that recurrence and trend may give a moderately accurate representation of the overall model for long-term PM10 behavior. Further investigation may lead to the usefulness of other RQA tools, such as determinism, entropy, trapping time, etc. At this point, a relationship between PM10 model and such tools were not found.

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