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Time Series Analysis of Air Pollution in Al-Hashimeya Town Zarqa, Jordan

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Abstract

Different time series analysis of yearly air pollution at Al-Hashimeya Town, central of Jordan, has been performed in this study. Descriptive analysis showed different long-term variation of yearly air pollution. High persistence in yearly air pollution time series were identified using autocorrelation function. Autoregressive, integrated, and moving average (ARIMA) models were also calculated to predict future values of time series variable.. It was found that time series analysis of Al -Hashimeya yearly air pollution data for the period 1992–2004 showed an overall decreasing trend in ambient air pollutants NO_2, CO, H_2S, NO and TSP. This is likely due to regulatory measures implemented by the government in the preceding 13 years. There was an increasing trend in PM_{10} , NO_x and Pb, whereas SO_2 did not change much.

Key words: Air pollution, time series, ARIMA Autoregression , Autucorrelation

1. Introduction

Development and use of statistical and other quantitative methods in the environmental sciences have been a major communication between environmental scientists and statisticians (Hertzberg and Frew, 2003). In recent years, many statistical analyses have been used to study air pollution as a common problem in urban areas (Lee, 2002). The common descriptive statistical approach used for air quality measurement and modeling is rather limited as a method to understand behavior and variability of air quality (Voigt ,2004). Many investigators have used probability models to explain temporal distribution of air pollutants (Bencala and Seinfeld, 1979, Yee and Chen, 1997). Time series analysis is a useful tool for better understanding of cause and effect relationship in environmental pollution (Schwartz and Marcus, 1990, Salcedo *et a*l., 1999, Kyriakidis and Journel, 2001). The main aim of time series analysis is to describe movement history of a particular variable in time. Many authors have tried to detect changing behavior of air pollution through time using different techniques (Salcedo *et a*l., 1999, Hies *et a*l., 2000, Kocak *et a*l., 2000, among others). Many others have tried to relate air pollution to human health through time series analysis (Gouveia and Fletcher, 2000, Roberts, 2003, Touloumi *et a*l., 2004). Therefore, this study aims at extending time series analysis to give both qualitative and quantitative information about air pollution at Al -Hasimeya town, the most polluted city in Jordan, and to predict future concentrations of air pollutant.

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2. Methodology

2.1. Study Site:

Al-Hashimeya area is located north of Zarqa city, 35 km northeast of Amman. It is bounded by Longitude 36° 04′ to 39º 09′ east and Latitude 32º 04′ to 32 10 north (Figure 1). This town is the most polluted sity in Jordan. The air pollution has resulted from many factories and companies in the vicinity .Potential air pollution sources include Jordan Oil Refinery, Khirbit Al-Samra Waste water treatment plant, and Al-Hussein Thermal Power station. These sources are called "Triange of Pollution". And each source has a different impact on air quality. Asemi-arid Mediterranean type climate is dominant in Al-Hashimeya town, which characterized by hot and dry weather conditions in summer and lack of rain in winter. The average annual rate of rainfall is 142 mm. Low precipitation rate worsens air quality in Al-Hashimeya, because rain is a natural process that help washing out soluble substances from the air (Shehadeh, Noaman, 1991).

2.2. Data Collection:

There have been several studies conducted by both Royal Scientific Society (RSS) and Ministry of Environment to monitor basic pollutants in the area, from 1992 to 2004 (Table1 and Figure1). Instruments installed in the monitoring sites samples ambient air continuously and analyze it automatically, (Table 2 illustrate the instruments).

Table1: Monitoring sites and their positions from pollution sources in Al-Hashimeya.

Monitoring sites	Distance and direction of station from pollution sources
IBN EL ANBARY SCHOOL	6 km south west from SWTP 0.5 km north from HTPS 1.5km east from JOR
UM SOLEH	3 km from Al Hashymia town
THERMAL PLANT	5.5km southwest from SWTP 0.5 km south /southeast from HTPS 2km southeast from JOR
ELEMENTARY SCHOOL	4 km west from SWTP
SECONDARY SCHOOL	1 km northeast from JOR
ELECTRICAL TRAINING CENTER	0.5 km south from HTPS
HASHIMYEH MUNICIPALITY	Main highway of Irbid- Al Hashymia-Azarqa
POLICE STATION/ZARQA	Main highway zarqa Amman
PROJECT SITE	2km south east from SWTP 2 km north from HTPS 2km northeast from JOR
E. SCHOOL/ KHERBEH	2 km from south east from SWTP 6.8 km from northeast HTPS 7 km northeast from JOR
UM SHURYK	2 km south /southwest from SWTP 2.5 km north from HTPS 3km from northeast JOR

Table 2 : Instruments and their uses.

Instruments	USES
Sulfure Dioxide Analyser UV-Flourescence	Analyses Sulfure Dioxide continously
Hydrogen Sulfide Analyser UV-Flourescence	Analyses Hydrogen Sulfide continuously
Carbon Monoxide Analyser Non- Dispersive Infrared	Carbon Monoxide continously
High Volume Sampler with Selective PM10 Inlet, Gravimetric.	Collects PM10
Portable Calibrator Permeation Oven.	Calibrates instruments of pollutants measurement.
Wind Recorder Mechanical.	Measures wind direction and wind speed.

2.3. Preparing for the Data Analysis

We used the yearly mean concentration of seven criteria pollutants PM_{10} ,, TSP, CO, NOx SO_2,H_2S and Pb. The data were obtained from unpublished sources (RSS). Missing values were substituted. For example, if for a particular year the value was missing, then it was substituted by considering the average of the preceding and succeeding years. This was done to preserve seasonal patterning (as opposed to the effect of the procedure of substituting by the annual average.).

2.4. Time Series Analysis

In statistics, a time series is a sequence of data points measured typically at successive times, and spaced at (often uniform) time intervals. Three broad classes of partical importance for time series models can take many forms - these are Autoregressive (AR) models, integrated (I)models ,and moving average (MA) MODELS. It is generally referred to as an ARIMA (p,d,q) model where the p,d and q are integers greater than or equal to zero; and refer to the order of the Autoregressive, integrated, and moving average parts of the model respectively (Yee and Chen,1997).An ARMA (p,q) model is given by:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right) X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

Where L is the lag operator, the φ_i are the parameters of the autoregressive part of the model ,the θ_i are the parameters of the moving average part and the ε_t are error terms. The error terms ε_t are generally assumed to be variables sampeld from a normal distribution with zero mean: $\varepsilon_t \sim N(0,\sigma^2)$ where σ^2 is the variance (www.wikipedia.og).

2.5. Autocorrelation Correlogram

Seasonal patterns of time series can be examined via correlograms. The correlogram (autocorrelogram) displays the autocorrelation function (*ACF*) graphically and numerically - that is, serial correlation coefficients (and their standard errors) for consecutive lags in a specified range of lags (e.g., 1 through 30). Ranges of two standard errors for each lag are usually marked in correlograms, but typically the size of autocorrelation is of more interest than its reliability because we are usually interested only in very strong and thus highly significant autocorrelations.

2.6. Partial Autocorrelations:

Another useful method to examine serial dependencies is to examine partial autocorrelation function (*PACF*) - an extension of autocorrelation, where the dependence on the intermediate elements (those *within* the lag) is removed. In other words, partial autocorrelation is similar to autocorrelation, except that when calculating it, (auto) correlations with all the elements within the lag are partially out (Hay, 1980). If a lag of 1 is specified (i.e., there are no intermediate elements within the lag), then partial autocorrelation is equivalent to autocorrelation. In a sense, partial autocorrelation provides a "cleaner" picture of serial dependencies for individual lags (not confounded by other serial dependencies). (Sall and Lee 2001).

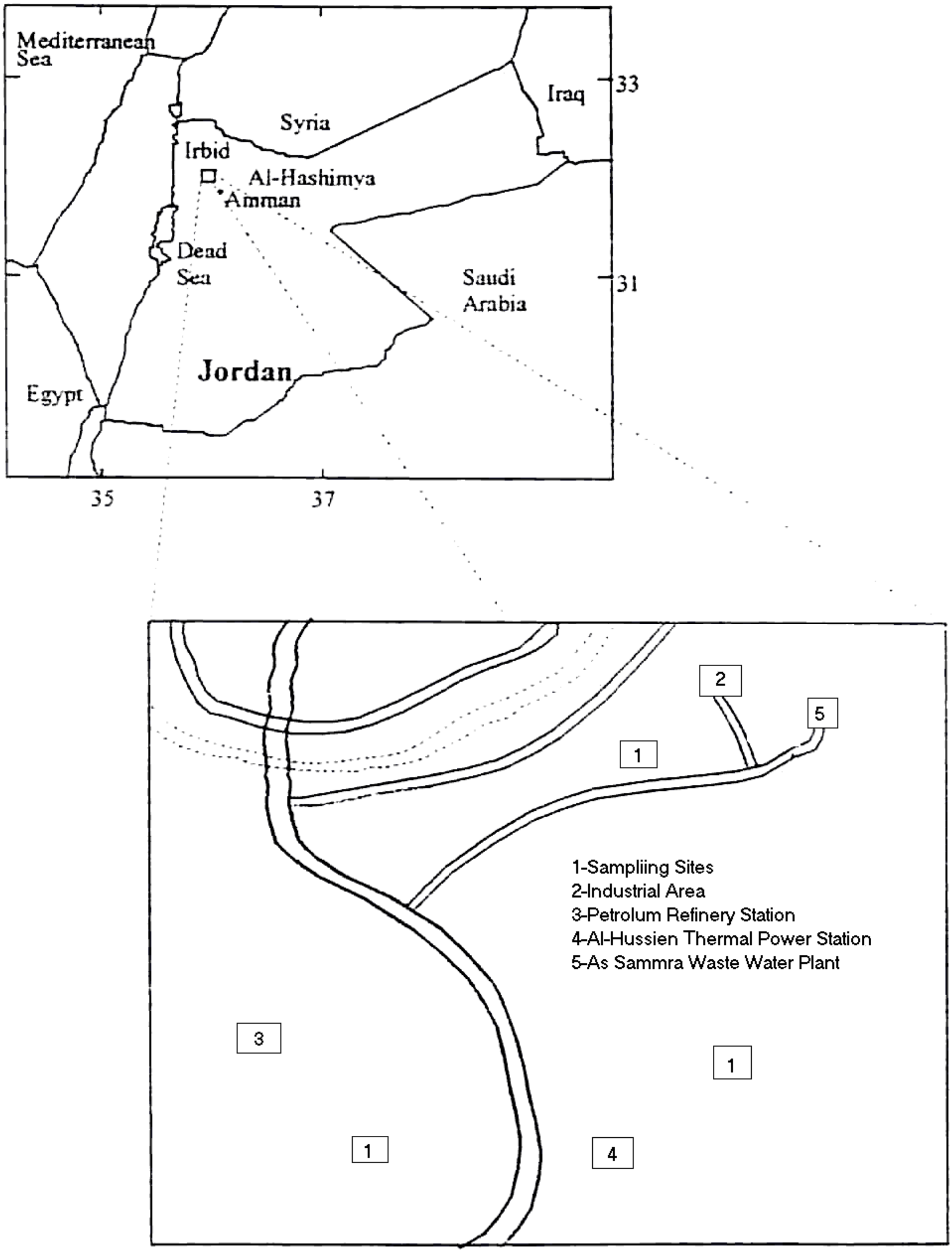


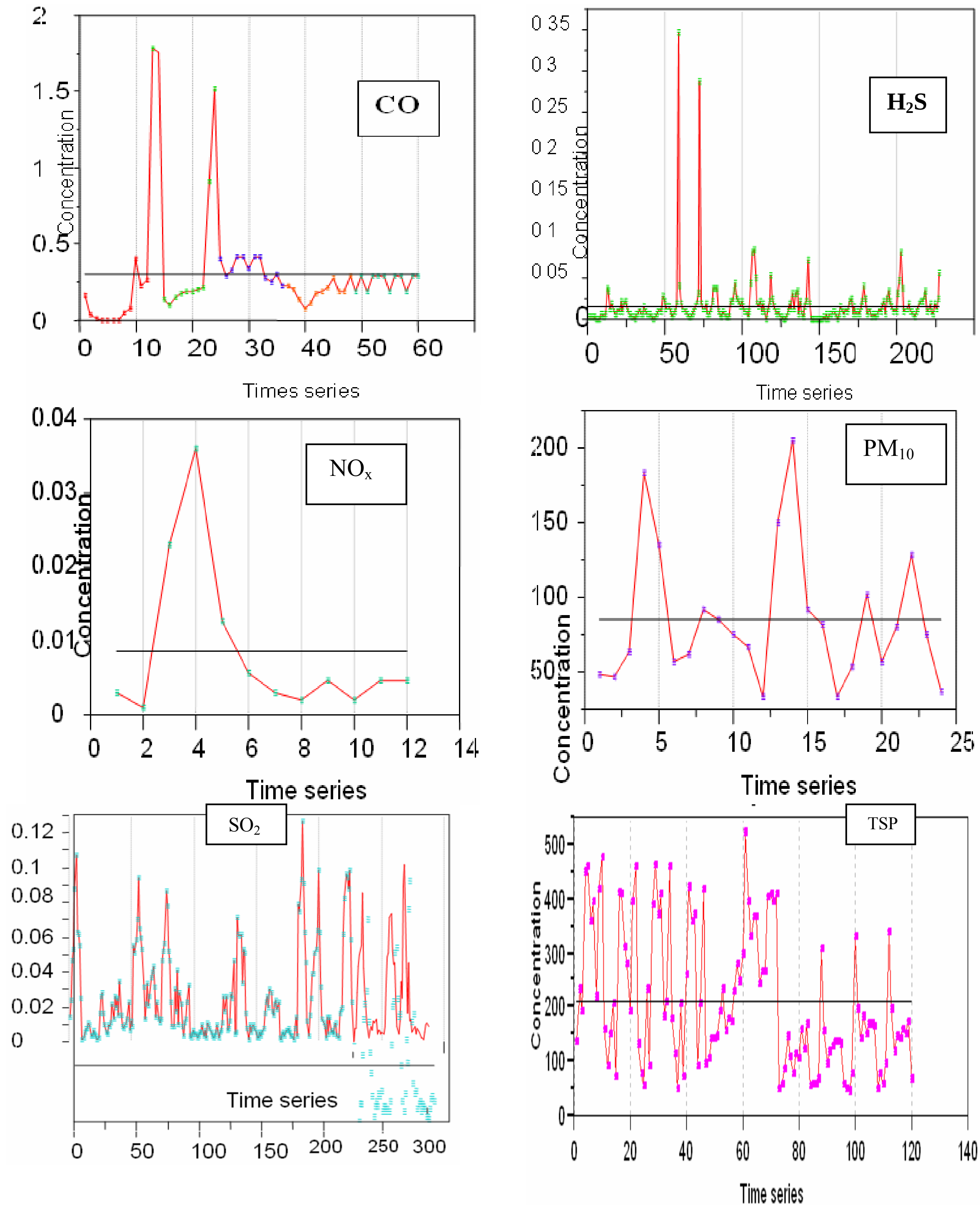
Figure 1: The locations of sampling sites

3. Results

3.1. Time Series

The first step in time series analysis is to draw time series plot. Time series plot provide a preliminary understating of time behavior of the series. Figure2. shows time series plot of selected time series air pollution concentration. This Figure shows different time behavior of air pollutants. For example, the concentration of SO_2 and TSP seems to have a similar trend from the beginning to the end of the year, but maximum and minimum concentrations occur in different times.

It is also obvious that H_2S and CO have not a significant trend through time. The fluctuations of Pb are more irregular at the end of the year, but the fluctuation of NOx and PM_{10} are more obvious at the beginning of the year.The autocorrelation functions of the selected time series also show different time stationary of the series. The autocorrelation functions of them are presented in Figure 3. The significant models of ARMA lags for all selected pollutants are also presented in Table 3. all pollutants show non stationary (long serial correlation). The amplitude of autocorrelation functions does not become less pronounced for most of the series.



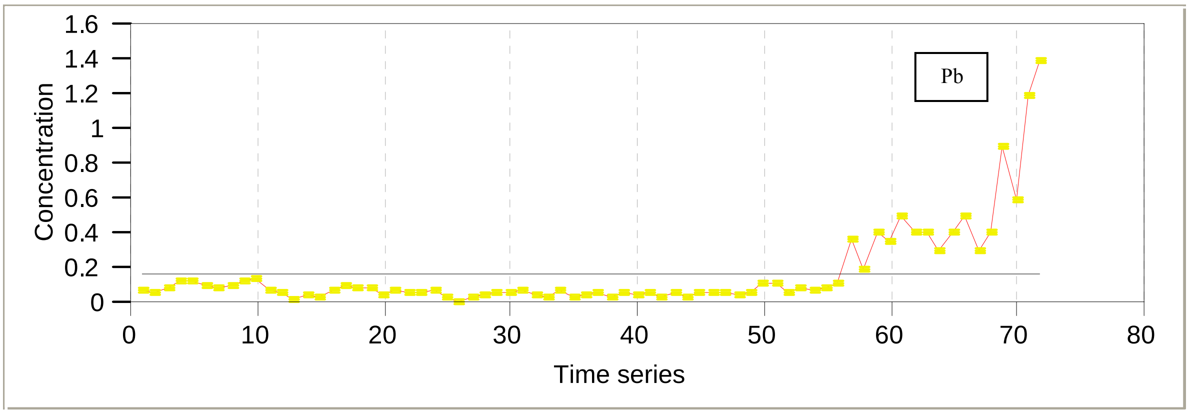


Figure 2: Time series plots of selected air pollutions.

Table 3: Models of ARMA (p, q) of pollutants concentrations.

Variables	-2LogLH	R^2	SBC	AIC.	Variance.	DF	Model
PM10	161.73	0.55	201.10	186.96	888.96	12	ARMA (1, 10)
TSP	1055.75	0.57	1181.1741	1108.69	6673.02	94	ARMA (12, 13)
CO	-178.09	0.55	-74.05	-122.23	0.061	37	ARMA(11, 11)
NOx	-118.64	0.49	-99.11	-102.01	0.0000748	6	ARMA (1, 4)
SO_2	-2456.72	0.70	-2376.71	-2424.33	0.0002018	275	ARMA(6, 6)
H_2S	-1655.30	0.29	-1488.40	-1587.80	0.00073	199	ARMA (14, 14)
Pb	-349.08	0.89	-282.92	-319.34	0.0075984	56	ARMA(2, 13)

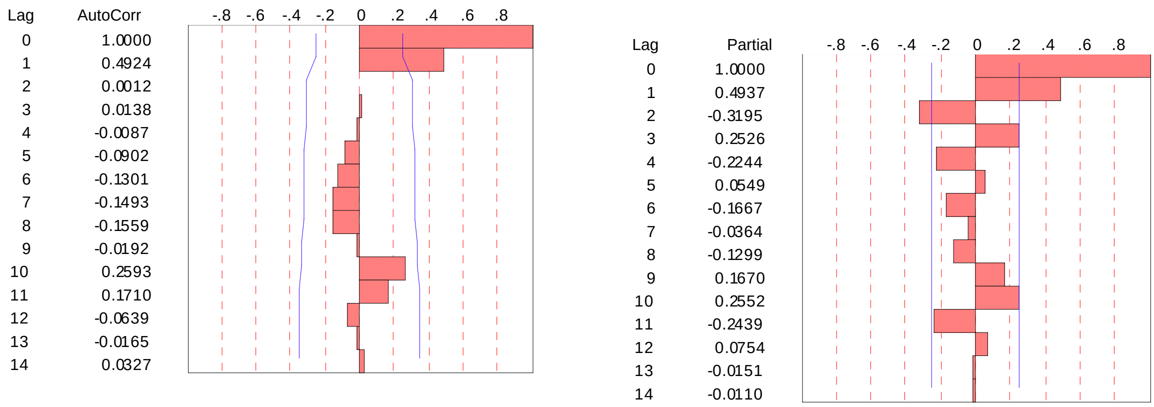


Figure 3a: Autocorrelation and partial auto correlation correlogram of CO.

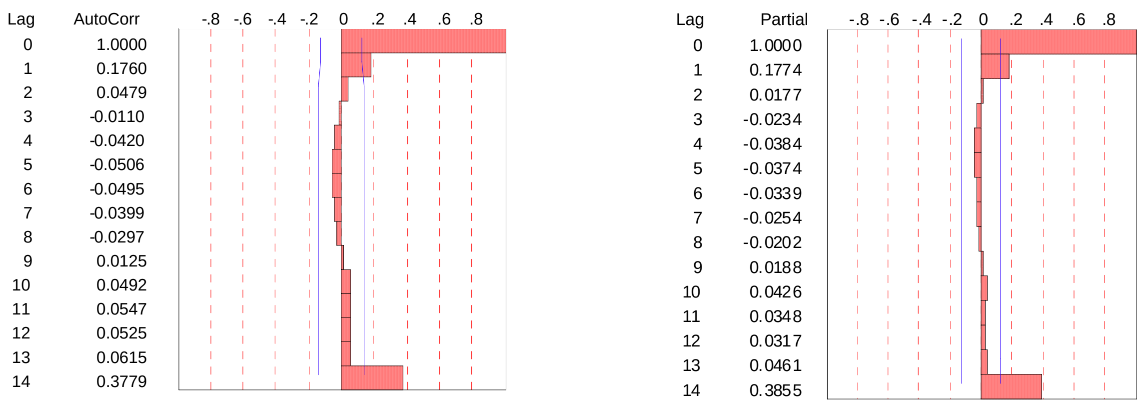
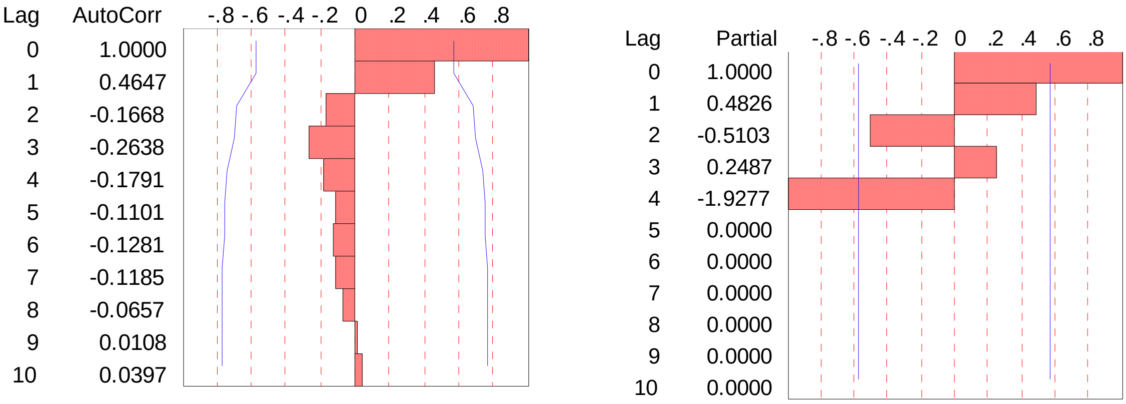
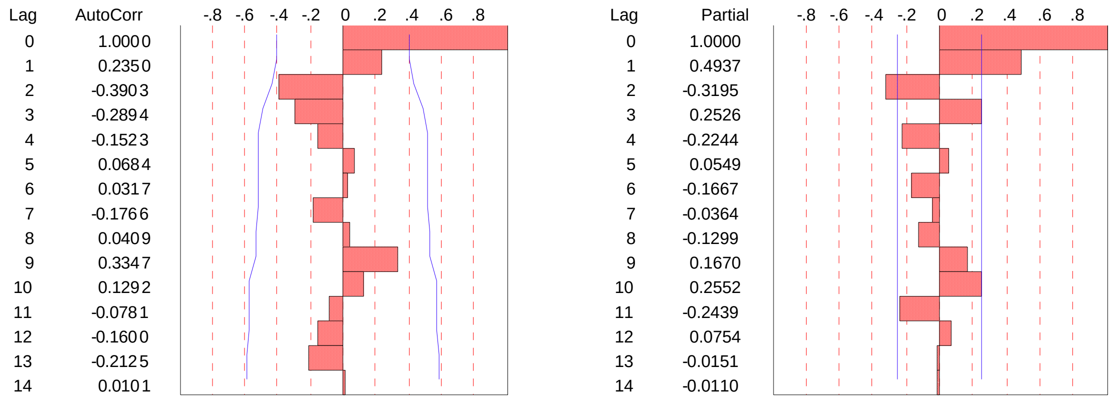


Figure 3b : Auto correlation and partial Auto correlation correlogram of H_2S.



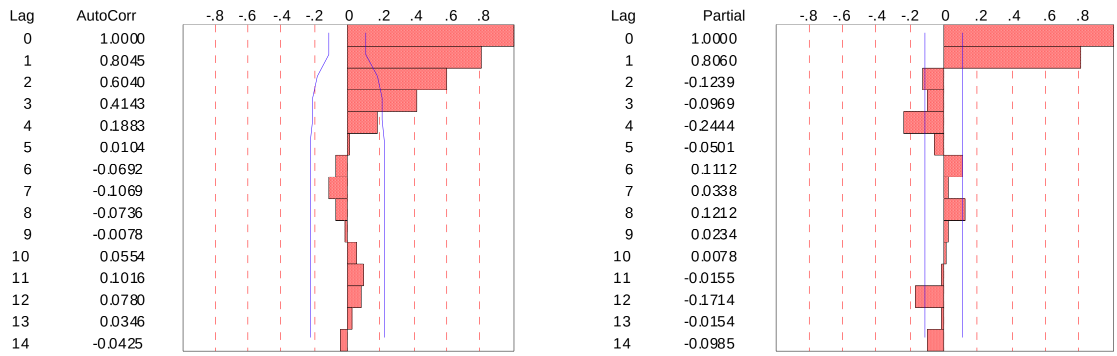
Lag	AutoCorr	Partial
0	1.0000	1.0000
1	0.4647	0.4826
2	-0.1668	-0.5103
3	-0.2638	0.2487
4	-0.1791	-1.9277
5	-0.1101	0.0000
6	-0.1281	0.0000
7	-0.1185	0.0000
8	-0.0657	0.0000
9	0.0108	0.0000
10	0.0397	0.0000

Figure 3c: Auto correlation and partial Auto correlation correlogram of NO_x.



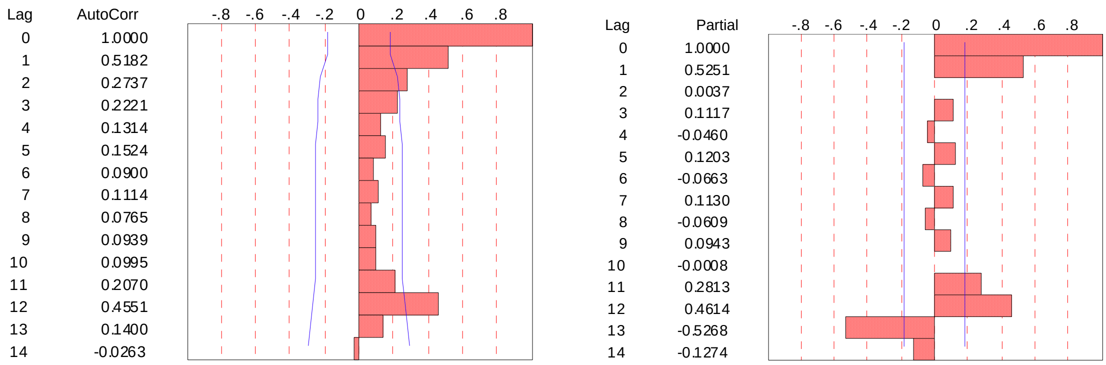
Lag	AutoCorr	Partial
0	1.0000	1.0000
1	0.2350	0.4937
2	-0.3903	-0.3195
3	-0.2894	0.2526
4	-0.1523	-0.2244
5	0.0684	0.0549
6	0.0317	-0.1667
7	-0.1766	-0.0364
8	0.0409	-0.1299
9	0.3347	0.1670
10	0.1292	0.2552
11	-0.0781	-0.2439
12	-0.1600	0.0754
13	-0.2125	-0.0151
14	0.0101	-0.0110

Figure 3d : Autocorrelation and partial Auto correlation correlogram of PM_{10}.



Lag	AutoCorr	Partial
0	1.0000	1.0000
1	0.8045	0.8060
2	0.6040	-0.1239
3	0.4143	-0.0969
4	0.1883	-0.2444
5	0.0104	-0.0501
6	-0.0692	0.1112
7	-0.1069	0.0338
8	-0.0736	0.1212
9	-0.0078	0.0234
10	0.0554	0.0078
11	0.1016	-0.0155
12	0.0780	-0.1714
13	0.0346	-0.0154
14	-0.0425	-0.0985

Figure 3e : Auto correlation and partial Auto correlation correlogram of SO_2.



Lag	AutoCorr	Partial
0	1.0000	1.0000
1	0.5182	0.5251
2	0.2737	0.0037
3	0.2221	0.1117
4	0.1314	-0.0460
5	0.1524	0.1203
6	0.0900	-0.0663
7	0.1114	0.1130
8	0.0765	-0.0609
9	0.0939	0.0943
10	0.0995	-0.0008
11	0.2070	0.2813
12	0.4551	0.4614
13	0.1400	-0.5268
14	-0.0263	-0.1274

Figure 3f : Auto correlation and partial Auto correlation correlogram of TSP.

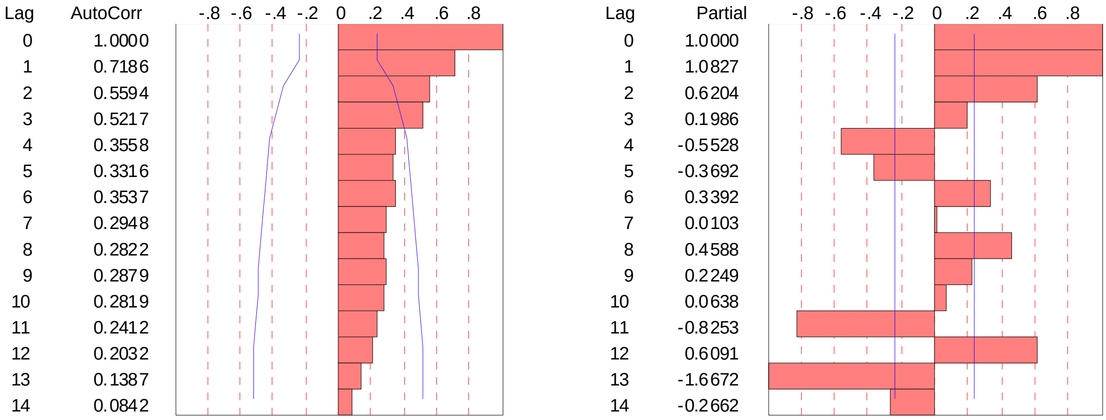


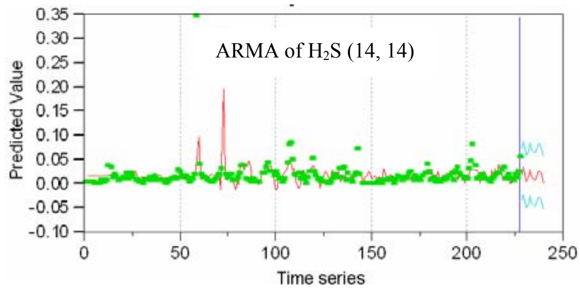
Figure 3g : Auto correlation and partial Auto correlation correlogram of Pb.

4. Scenarios:

Using an ARMA model calibrated on annual time scales, interannual monthly of pollutants were estimated for one year unit , 5 years, and 10 years , respectively,(Table 4). Time series models estimation for predicted yearly air pollutants data showed an overall decreasing trend in ambient air pollutants CO, H_2S, and TSP), likely due to regulatory measures implemented by the government in the preceding 13 years. There was an increasing trend in PM10,NO_x and Pb, whereas SO_2 did not change much.

Table 4: The mean of actual and predicted concentration of pollutants for predicted one year, 5 years, and 10 years.

Pollutants	Actual Concentration	Predicted con. For 1 year	Predicted con. For 5 years	Predicted con. For 10 years
CO	0.308	0.306	0.303	0.302
H_2S	0.0187	0.0186	0.0185	0.0184
NO_x	0.0086	0.0087	0.0088	0.0088
SO_2	0.024	0.0250	0.0248	0.0249
PM_{10}	85.9	89.3	89.6	89.7
TSP	214.5	211.4	209.5	209.6
Pb	0.173	0.376	0.529	0.524



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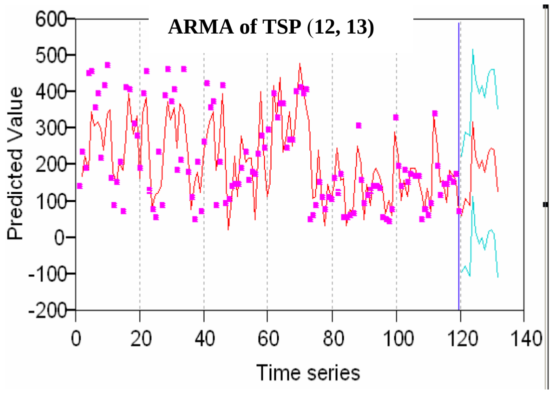

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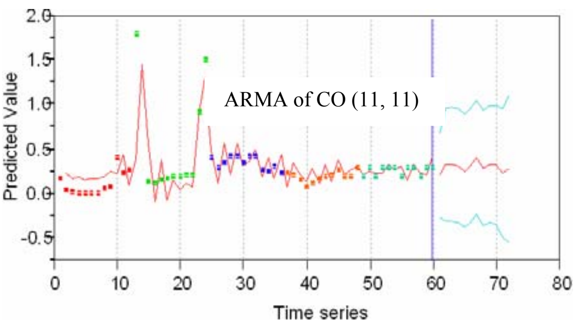
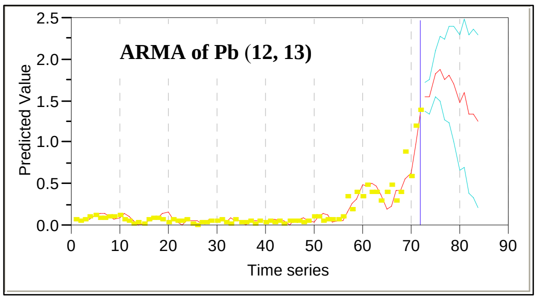


(a)



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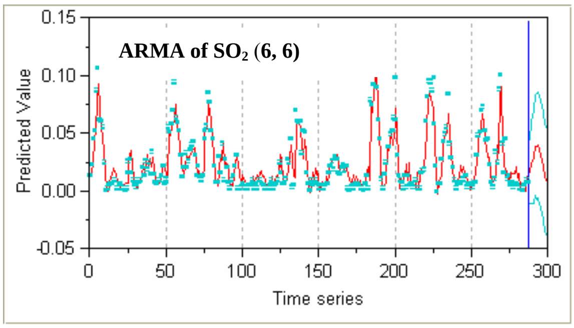

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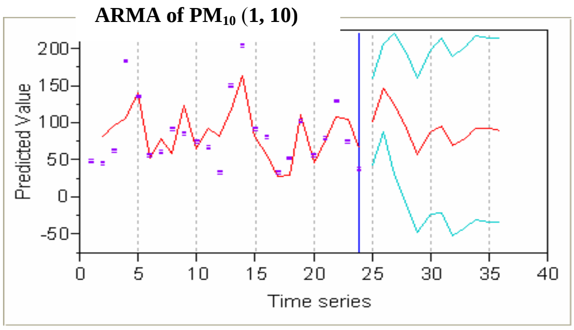

(f)

Figure 4: Forecast for Model of ARMA (q,p) of pollutants concentrations.

5. Discussion

Annual air pollution time series analysis of Al-Hashimeya area has been performed in this study; and has shown different temporal behavior of different air pollutants. This different time behavior is not only the reason of correlation of different pollutants with each other, but the seasonal variation on increasing or decreasing air pollutants as well. It was also shown that most annual air pollution time series have high persistence of air pollution conditions through time. This persistence is not only harmful for public health but also makes air pollution management and control very demanding.

The best fitted model of SO_2 concentration at 95% CIs were given for the current ARMA (6,6). This ARMA model shows the smallest AIC ,SBC ,Variance and DF values, and largest value of R^2 with a significant parameters. Time-series analysis showed that SO_2 does not change through the predicted years at all. The best fitted model of H_2S , TSP and CO concentrations were given for the current ARMA (14,14) ARMA (12,13) and ARMA (11, 11) ,respectively. Time-series analysis has shown decreasing trend in the predicted years for these pollutants.

6. Conclusion

Rresults have shown that pollution becomes more elastic to the inter-annual perturbations over time at Al-Hashimeya area. Furthermore, it has also shown that forecasted pollution could be identified with the help of ARIMA analysis. Time series analysis of Al -Hashimeya annual air pollution data for the period 1992–2004 showed an overall decreasing trend in ambient air pollutant for TSP. This is likely attributable to regulatory measures implemented by the government in the preceding 13 years. There was an increasing trend in PM_{10} , NO_x and Pb,

7. Acknowledgments

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References

[1] Bencala, K.E.,and Seinfeld,J.H.,1979..On frequency distribution of air pollutant concentrations. Atmos.Environ.,10:941-950.

[2] Brockwell,P.J.,and Davis,R.A..,2001.Introduction to Time Series and orecasting Springer -Verlag, NewYork.

[3] Gouveia, N.,and Fletcher T.,2000. Time series analysis of air pollution and mortality:Effects by cause,age and socioeconomic status J.Epidemoil.Commun.H., 54:750-755.

[4] Hertzberg,A.M, and Frew,L., 2003..Can public policy be influenced Environmentrics, 14: 1-10.

[5] Hies, T.,Treffeisen R.,Sebald L.,and Reimer E.,2003.Spectral analysis of air pollutants. Part I:elemental carbon time series. Atmospheric Environment,34:3495-3502.

[6] Kocak K.,Saylan L.,and Sen O.,2000.Nonlinear time series prediction of o3 concentration in Istanbul. Atmospheric Environment,34:1267-1271..

[7] Kyriakidis, P.C.,and Journal,A.G., 2001.Stochastic modeling of atmospheric pollution: a special time series framework. Part II: application to monitoring monthly sulfate deposition over Europe.Atmos.Environ., 35:2339-2348.

[8] Lee, C. K., 2002. Multiracial characteristics in air Pollutant concentration time series. Water Air Soil Poll., 135**:** 389-409.

[9] Roberts, S.,2003.Combining data from multiple monitors in air pollution mortality time series studies.Atmos.Environ.,37:3317-3322.

[10] Sall J., Lehman A., and Lee Creighton. (2001). JMP Start Statistics ,Using JMP and JMP IN Software. Copyright:2001 by SAS Institute Inc.Duxbury Thomson LEARNING.

[11] Salcedo R.L.R.,Alvim Ferraz M.,Alves C., and Martins F.,1999.Time series analysis of air pollution data.Atmos Environ.,33:2361-2372.

[12] Schwartz J.,and Marcus A., 1990.Mortality and air pollution in London: a time series analysis.Am.J. Epidem.,131:85-194.

[13] Smith, R.L.,1998. Extreme value analysis of environmental time series: an application to trend detection in ground-level ozone, Statistical Science 4:367–383.

[14] Touloumi, G.,Atkinson R.,and Terte A.L.,2004. Analysis of health oytcome time series data in epidemiological studies.Environmetrics,15:101-117.

[15] Voigt, K., Welzl G. ,and Bruggemann, R.,2004. Data analysis of environmental air pollutant monitoring.

[16] http://en.wikipedia.org/wiki/Autoregressive_integrated_moving_average (cited 24 March 2008).

[17] Yee E., and Chen, R.,1997.A simple model for the probability density functions of concentration fluctuations in atmospheric plumes.Atmos.Environ.,31:991-1002