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Full Length Research Paper

Stochastic approaches for time series forecasting of rate of dust fall: A case study of northwest of Balochistan, Pakistan

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The atmospheric rate of dust fall has been reported to be the pollution indicator of urban area of Northwest of Balochistan, Pakistan. The multiplicity and complexity of sources of atmospheric dusts in urban regions has put forward the need of distribution of these sources indicating their contribution to specific environmental receptor. The present study is focused on investigation of the rate of dust fall in Quetta valley. The prediction equations were developed by using auto regressive integrated moving average (ARIMA) modeling to forecast the rate of dust fall at three different locations out of selected sites in Quetta from 2004 to 2008. Such a study would help us decide about controlling the pollutants particularly heavy and toxic metals present in the particulate matters. All the stochastic models have been critically analyzed on various climatic parameters and ARIMA model was found a relatively better forecaster for the rate of dust fall.

Key words: Particulate matter, heavy metals, auto regressive integrated moving average (ARIMA), Stochasting modeling, Markov transition matrix (MTM).

INTRODUCTION

Quetta valley is about 1650 m above sea level and is bounded by the Murdar mountain ranges; Chiltan peak almost parallels it by 10 to16 km on the eastwest of the valley. Somewhat, farther are the mountain ranges of Zarghoon ranges and Takato ranges enclosing the valley along the northeast-northwest directions. Quetta is sited at 30°12′38″N, 67°1′8″E, having an area of around 2653 km^2 (SMEDA, 2005). Climate of Quetta is cold and dry; minimum temperature in winter reaches below freezing point while in summer it can reach as high as 40°C. As compared to the rest of Balochistan, Quetta district was also affected by drought (2000 to 2004). However, in recent years, the rain increased by 105.9 mm which was much better in 2005 with 310.5 mm (SMEDA, 2005). Mainly, valley landscape has plains. Limestone is the major part of the sedimentary rocks around the valley.

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The population of Quetta was recorded to be 1.5 million officially, yet unofficially it is claimed that it has even crossed 2.5 million. Rickshaws are the major public transport (≥ 5000), besides the local buses and the haphazard population of both humans and traffic, and lack of planning trigger the pollution from bad to worst (Sami, 2009).

In the present investigation, settling dust particulates samples were collected for the period of 5 years (2004 to 2008) from ten different sites of Quetta city depending upon their locations, traffic situation, height, developed and underdeveloped areas. The sampling locations have been reported previously (Sami et al., 2006, 2011).

Stochastic time series model such as autoregressive–moving-average (ARMA) (p,q), non-seasonal auto regressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) models were developed to simulate and forecast hourly averaged wind speed (HAWS), and average annual and monthly rate of dust fall sequences on 5 year data, that is, 2004 to 2008 of

Quetta, Pakistan. Stochastic time series models take into consideration numerous fundamental features of wind rate including autocorrelation, non-Gaussian distribution and non-stationary. The positive correlation between consecutive wind speed observations is taken into account by fitting ARMA process to wind speed data. The data are normalized to make their distributions approximately Gaussian and standardized to remove scattering of transformed data (stationary, that is, without chaos). A diurnal variation has been taken into account to observe forecasts and its reliance on time. Though, the ARMA (p,q) model is suitable for prediction interval and probability forecasts; nevertheless this model is only suitable for both long ranges (1 to 6 h) and short range (1 to 2 h). This indicates that forecast values are the deciding components for an appropriate wind energy conversion system (WECS). ARMA processes cannot be applied for non-stationary (chaotic) and random data. Non-seasonal ARIMA models and the prediction equations for each month and indeed for each season of 5 meteorological years 2004 to 2008 rate of dust fall data is predicted. The SARIMA and its prediction equations for each month of 5 years data were also studied. With non-stationary or chaos in data, stochastic simulator in the ARIMA processes even though its prediction equations do not effectively work, yet ARIMA is good enough to forecast relatively short range reliable values. Various statistical techniques are used on 5 years that is, 2004 to 2008 data of dust fall, average humidity, rainfall, maximum and minimum temperatures, respectively. The relationships to regression analysis time series (RATS) are developed for determining the overall trend of these climate parameters on the basis of which forecast models can be corrected and modified. Badescu (2001) made use of ARIMA models to forecast daily average surface pressures. Our study is relevant to him for reasons that the surface pressure would certainly affect the dust fall rate and indeed the concentration of pollutants at various locations. We shall, however, give due considerations of this study in later stages while looking into a more generalized ARIMA model. However, our SARIMA model will take into account such considerations indirectly; Badescu (2001) performed the statistical study of ambient air pollution in Delhi. A state space model was developed by using Kalmin filter formulation for the prediction of various pollutants and repairable suspended particulate matter. The approach was found quite pertinent. They used the auto-regressive (ARX) model with exogenous input, which to our analysis are not adequate. We discarded ARMA modeling for reasons that the dust fall rate and the concentration of various pollutants follow random nature or non-stationarity. The ARMA modeling could be used only if the data is standardized. This unfortunately had not been done by Chelani et al. (2001). Instead we developed ARIMA and SARIMA models for dust fall rate and indeed their forecasters are provided with prediction equations. It was established by us that the ARIMA and SARIMA models could be considered relatively better than artificial neural network (ANN) models due to diurnal (seasonal) variations. It was taken into account in our studies, the diurnal variations by considering interrelationship between ARIMA and SARIMA. To our surprise, ARMA model did not work for our data, as a consequence of which, the ACF would not be considered. The regression analysis is, of course important too, but we avoided it because there are diverse statistical tests needed to support the analysis. Kolehanainen (2000) coined a new technique by developing hybrid neural network modeling for air quality forecasting. They followed self-organized map algorithm (SOM), Sammon's mapping and fuzzy distance metrics. They categorized the clusters of data by overlapping multilayer perceptron (MLP) models. Needless to mention their work was logically pertinent and could be used for our data too. We shall look into such kind of models in near future but we are handicap due to non-availability of diverse algorithms. Hamdi et al. (2008) developed crop evapotranspiration time series simulation model by using ARIMA. This reflects the strength and validity of ARIMA model in most of the reported literature (Othman and Naseri, 2011; Li et al., 2011; Kamarposhti, 2011).

Stochastic time series modeling, simulation and prediction

A technique of predicting dust fall yield a few hours before, from a dust fall collector with which suspended/-settled dust fall under 'g' (gravity force) is required to ensure efficient measures, which might be taken in order to avoid its maximum calamity. Time series modeling of dust fall has been the subject of much discussion because of the interest in its rate of deposition, which proves mostly to be catastrophic. When the records of dust fall are incomplete or of too short duration or the handling and storage of large values of the data are not desirable, then a time series model is needed. Since dust fall is a manifestation of wind velocity, atmospheric pressure, geography and topography of the area, etc., generally the simulation is derived from simulations of wind speed. Dust fall simulations can be done with Monto Carlo techniques that depend upon exclusively on the anticipated factors of the trivial distribution of wind speeds.

Aguiar and Collares-Pereira (1992) and Mora-Lopez and Sidrach-de-Cardona (1998) made some important contributions from modeling and simulation point of view, having used stochastic simulation by ARIMA modeling of solar irradiation, a time dependent autoregressive Gaussian model (TAG) for generating synthetic hourly radiation and the multiplicative ARMA models simultaneously to generate hourly series of global radiation. An ARMA process on hourly global radiation data was used by Kamal et al. (1997). Stochasting modeling through Markov transition matrix (MTM) was performed by them and synthetic sequences of hourly global solar irradiation for Quetta, Pakistan were produced as well. Kamal and Jafri (1997) found MTM approach relatively better as a simulator compared to ARMA modeling. But, their analysis for ARMA process to simulate and forecast HAWS for Quetta, Pakistan produced good results as well.

Jafri (1996a) found that the hierarchical unsystematic procedure is a Markovian random process, which can be portrayed by a scaling probability division. A breeding function for such a procedure was acquired. Jafri (1996b) proved that these observations can be fruitfully applied to muddle time series to surmount the non-stationarity in ARMA method but it would need practical stochastic simulation techniques. Jafri (1996a) recommended that the chaotic time series both in Bayesian and non-Bayesian statistics is deterministic. Jafri (1995) built up a first order MTM for non-Gaussian character of wind velocity of Quetta for 1985 and suggested a Gaussian form of MTM order to produce HAWS series. The similar effort was extended more on wind and rate of dust fall data for a period of 5 years. Needless to state, the simulation of wind data using MTM is rather hard contrast to simulation on solar radiation data as was earlier considered by Kamal and Jafri (1999). The number of iterations went beyond a specific boundary therefore causing for HAWS and daily average wind speed (DAWS) series to become awkward and entwined. Jafri (1995) also established autocorrelation coefficient for wind data, which shows stages of determination in wind velocity frequencies and of wind velocity enormities when compared with diurnal variations over DAWS orders.

A class of parametric time series models called ARMA processes engaged by Blanchard and Desrochers, (1984), Box et al. (1976) and Katz and Skaggs (1981) worked on such procedures, which have been in use to form many meteorological time series. The form of Blanchard and Desrochers, (1984) takes into consideration elevated autocorrelation and permits a time series to be produced which deduces all the main distinctiveness of the statistics; and it does not require any hypothesis about the wind velocity division. Actually, a larger class of seasonal models contains ARIMA models and was proved by Blanchard and Desrochers, (1984). Sfetsos (2002) studied the linear ARIMA models and feed forward artificial neural networks (FFANN). He discovered that the model arrangement is chosen from the minimization of the assessment set error in the ARIMA process. He proposed the multi-step forecasting and the consequent averaging to produce mean hourly prediction of wind statistics. The ARIMA models have been significantly examined by Jain and Lungu (2002). They considered equally non- seasonal and seasonal ARIMA models by using stochastic parts. The perseverance patterns if any of the stochastic components were also calculated to decide by them.

The model of Chou and Corotis (1981) is based upon Weibull distribution and does not need stationarity in the statistics. McWilliams and Sprevak (1982) explained a new description of an existing time series modeling method of Box et al. (1976) from which the distribution of wind velocities and wind directions are obtained by McWilliams and Sprevak (1982). Their model incorporated diurnal variations observed in wind speed in such a manner that the time series of wind speed component remain stationary; the sample autocorrelation functions for the series have identical stochastic behavior as far as the second order statistics are concerned, consequently plummeting the problem to modeling single Gaussian series. This model is accurate for auto-correlation functions, to account for diurnal variations. There is one point which is clear: transformation of HAWS was not used by them. In its place, they measured annual deterministic variation μ (t) and σ^2 (t) which is modeled by harmonic series representation to justify diurnal variation of wind velocity. Diurnal variation applied by Brown et al. (1984) ought to be engaged in model development in a way analogous to McWilliams and Sprevak (1982) with reference to our inference.

The approach of Daniel and Chen (1991) was adopted by us which consists of first fitting ARMA processes of various orders to HAWS data which have been transformed to make their distribution approximately Gaussian and standardize to remove the so called diurnal stationarity. The main benefit of including more than 1 year of data in the model development is the increased trustworthiness of the estimates of the model parameter. The methods of changing and standardization were not likened but favored this approach for the grounds that the model had the tendency of using wind data of more than 1 year.

MINITAB (version 11) for, non-seasonal ARIMA modeling and simulation was used by us. ARIMA models are used to model a special class of non-stationary series. SARIMA models are used to incorporate cyclic components in models. In other words, ARIMA models are in theory, the most general class of models (Parsimonious) for forecasting a time series which can be stationarized by transformations such as differencing and logging. SARIMA has the same structure as ARIMA. The non-seasonal model on monthly and annually averaged rate of dust fall data for 2004 to 2008 was used. For non-seasonal ARIMA modeling and simulation, the six options that is, random walk ARIMA (0,1,0), differenced first order autoregressive model ARIMA (1,1,0), constant ARIMA (0,1,1), linear exponential smoothing (LES) without constant ARIMA (0,2,1) or (0,2,2) and mixed ARIMA (1,1,1) are tried for each month and on four seasons. Non-seasonal ARIMA (0,1,1) which deals with exponential growth and constant incorporates simple exponential smoothing (SES) model. MA (1) coefficients correspond to 1-α in the SES formula. The term α is called

called training parameter. For LES without constant, MA (1) coefficient corresponds to 2^{α}. The greatest choice is chosen by bearing in mind the mainly minimum chi-squared value at 5% confidence gap.

Theory

ARIMA models are used to model a special class of non-stationary series. SARIMA model are used to incorporate cyclic components in models. We can split the time series into deterministic and stochastic components. The proportion of variance for each component can be modeled through Monto Carlo simulations. The stochastic component can be analyzed for persistence in time series by using Box et al. (1976).

The general non-seasonal ARIMA model is auto-=regressive to order p and moving average to order q , and operator on the dth differences of Z_t, where $\{Z_t\}$ are time series values for t = 1,2,…, N and N is number of observations. Defining

$$B^s Z_t = Z_{t-s}, \ \nabla_s = (1-B^s), \ \nabla_s^d = (1-B^s)^d \quad (1)$$

where d = 0,1,…, B is the backward shift operator, s is the period of the season (s = 12 in our present case for each month) and ∇ is the difference operator. The general non-seasonal ARIMA model can be written as:

$$\Phi p\ (B)\ Z_t = \theta_q\ (B)\ a_t \quad (2)$$

where $\{ a_t\}$ are residuals, and

$$\Phi_p (B) = 1 - \Phi_1 B - \Phi_2 B^2 - ,\ldots,- \Phi_p B^p \quad (3)$$

$$\theta_q (B) = 1- \theta_1 B- \theta_2 B^2 - ,\ldots,- \theta_q B^q \quad (4)$$

where p and q are the order of polynomials respectively. The error 'e' in our prediction equation is adjustable automatically with lead times, t.

Time series prediction with harmonic analysis can also be accomplished in the similar fashion of and Lungu, (2002). Theories on RATS have long been established by Gujarati (2003), Chapra and Canale (2010) and Rawlings et al. (1998).

We considered locations such as Gawalmandi and T.B. Sanatorium on the basis of optimum dust fall rate, that is, the most maximum in Gawalmandi and the second most minimum in the T.B. Sanatorium. To reflect the statistical variations in between the optimum values, we considered a third location C.G.S. Colony, which will provide statistical variations with respect to mean values of the optimum dust fall rate. Table 1 for non-seasonal ARIMA is shown on the basis of categorization for seasons such as the spring of Quetta, which comprises of February, March and April, and so is the case for other seasons, for Gawalmandi, T.B. Sanatorium and C.G.S. Colony, respecttively. Each table for different locations for each month of the season for (Tables 1 to 12) non-seasonal ARIMA provides prediction equations obtained for each month of the season from ARIMA model, which is beneficial to predict the dust fall rate for larger as well as shorter lead times.

Derived statistical equations/results

We inferred from the statistical non-seasonal ARIMA modeling equations of our maximum dust fall receiving site 'Gawalmandi' for spring [February (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)- x(t-2)}- θe(t-1), March (1,1,1) yields x(t)=a+ x(t-1)+Φ{x(t-1)- x(t-2)}- θe(t-1) and April (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)-x(t-2)}-θe(t-1)]; summer [May (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}, June (1,1,1) yields x(t)=a+ x(t-1)+Φ{x(t-1)- x(t-2)} and July (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)-x(t-2)}-θe(t-1)]; autumn [August (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)-x(t-2)}-θe(t-1), September (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)- x(t-2)}- θe(t-1) and October (1,1,1) yields x(t)=a+ x(t-1)+Φ{x(t-1)-x(t-2)}-θe(t-1))]; winter are [November (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)-x(t-2)}, December (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)-x(t-2)}-θe(t-1) and January (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)-x(t-2)}-θe(t-1)].

Similarly, the statistical modeling ARIMA equations of our second minimum dust fall receiving site 'T.B. Sanatorium' for spring [February (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)} –θe(t-1), March (1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)} and April (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}–θe(t-1)]; summer [May (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}–θe(t-1), June (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1) and July (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}–θe(t-1)]; autumn [August (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)}–θe(t-1), September (1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)} and October (1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}]; winter are [November (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}–θe(t-1), December (1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}–θe(t-1) and January x(t)=a+x(t-1)+Φ{x(t-1)–x(t-2)}]

Finally, the statistical modeling ARIMA equations of our moderate (in a comparative with other sites of the Quetta city though it received very huge amount of average rate of dust fall including most of cities of the world) dust fall receiving site 'C.G.S. Colony' for spring [February x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1), March x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) and April x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1)]; summer [May x(t)=a+x(t-1)-θe(t-1), June x(t) =a+x(t-1)+Φ(x(t-1)-x(t-2) and July x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1)]; autumn [August x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1), September x(t) =a+x(t-1)+Φ(x(t-1)-x(t-2) and October x(t)=a+x(t-1)-θe(t-1)]; winter are [November x(t) =a+x(t-1)+Φ(x(t-1)-x(t-2), December x(t)=a+x(t-1)+Φ(

Table 1. ARIMA Gawalmandi (spring).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
February	(0,1,0)	-	-	-	-	-
	(1,1,0)	11.4	11	-0.8939	-	-0.2319
	(0,1,1)	112.5	11	-	0.9360	-0.0376
	(1,1,1)	9.5	10	-0.7304	.9082	-0.0459
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						
March	(0,1,0)	-	-	-	-	-
	(1,1,0)	14.8	11	-0.9959	-	-0.0180
	(0,1,1)	167.5	11	-	0.9408	-0.00698
	(1,1,1)	5.8	10	-0.9283	0.9629	-0.00668
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						
April	(0,1,0)	-	-	-	-	-
	(1,1,0)	4.4	11	-	-	2.016
	(0,1,1)	6.1	11	-0.3236	0.2552	1.439
	(1,1,1)	3.3	10	-1.0054	-0.8638	3.324
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						

Table 2. ARIMA Gawalmandi (summer).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
May	(0,1,0)	-	-	-	-	-
	(1,1,0)	9.7	11	-0.2623	-	0.531
	(0,1,1)	18.2	11	-	0.9852	0.1252
	(1,1,1)	9.8	10	0.2470	1.0576	-0.0870
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}						
June	(0,1,0)	-	-	-	-	-
	(1,1,0)	17.1	11	-0.9977	-	-0.001
	(0,1,1)	127.2	11	-	0.9549	0.00405
	(1,1,1)	-	-	-	-	-
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}						
July	(0,1,0)	-	-	-	-	-
	(1,1,0)	28.2	11	-0.9232	-	-0.2403
	(0,1,1)	129.7	11	-	0.9446	-0.0413
	(1,1,1)	11.4	10	-0.8417	0.9095	-0.0503
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						

x(t-1)-x(t-2))-θe(t-1) and January x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1)]

CONCLUSIONS AND SUGGESTIONS

(1) The area under present study is one of the cities of globe having very high level of lead (Pb) in its suffocating atmosphere. The major contributors of pollutants are automobiles running on Pb contaminated fuel/gas, a large part of which is adulterated before its distribution in order to gain more and more profit.

2) Due to scarcity of industries, luckily the concentrations of other heavy and toxic elements in air were not on an alarming level. That is why the phenomenon of photochemical smog has not been experienced so far. Though, the occurrence of thermal inversion spells, Quetta has been completed wrapped/blanketed in dust

Table 3. ARIMA Gawalmandi (autumn).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
August	(0,1,0)	-	-	-	-	-
	(1,1,0)	0.4	11	-1.000	-	-3.237
	(0,1,1)	1.4	11	-1.009	0.8981	-0.5870
	(1,1,1)	0.1	10	-	-0.0325	-3.223
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						
September	(0,1,0)	-	-	-	-	-
	(1,1,0)	22.7	11	-0.9579	-	-0.0075
	(0,1,1)	146.1	11	-	0.9373	-0.0141
	(1,1,1)	16.6	10	-0.9430	1.0574	0.0072
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						
October	(0,1,0)	-	-	-	-	-
	(1,1,0)	10.1	11	-0.4231	-	0.762
	(0,1,1)	10.0	11	-	0.4519	0.437
	(1,1,1)	6.8	10	-0.9981	-0.8879	1.049
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						

Table 4. ARIMA Gawalmandi (winter).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
November	(0,1,0)	-	-	-	-	-
	(1,1,0)	6.0	11	0.0695	-	0.316
	(0,1,1)	6.1	11	-	0.0663	0.333
	(1,1,1)	6.5	10	0.2787	0.2068	0.253
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}						
December	(0,1,0)	-	-	-	-	-
	(1,1,0)	55.1	11	-0.9413	-	-0.5028
	(0,1,1)	158.0	11	-	0.9409	-0.0067
	(1,1,1)	45.1	10	-0.8374	0.9419	0.0027
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						
January	(0,1,0)	-	-	-	-	-
	(1,1,0)	20.0	11	-0.9988	-	-0.001
	(0,1,1)	116.9	11	-	0.9332	-0.0193
	(1,1,1)	16.1	10	-0.9595	1.0206	0.245
Prediction equation for ARIMA (1,1,1) yields x(t)=a+ x(t-1)+ Φ{x(t-1)- x(t-2)}- θe(t-1)						

cloud time and again continuously for three to four days which, of course, triggered the particulates associated diseases (for instance, asthma, bronchitis, blood pressure, nuisance causing depression and anxiety etc).

(3) Statistical non-seasonal ARIMA modeling reflects that our ARIMA and the prediction equations, which we developed, are beneficial to look into design and engineering consideration to make environment of Quetta clean from dust fall rate. With these predictions equations, we could suggest remedial solutions to minimize the dust fall and indeed to make our environment clean by evolving natural eco system.

(4) The prediction equations for dust fall rate for each month categorized with respect to seasons, for non-seasonal ARIMA are given in their corresponding tables.

(5) Above all, a sense of ownership should be cultivated in the hearts and minds of the sons of the soil by emancipating them politically, economically and, last but

Table 5. ARIMA T.B. Sanatorium (spring).

Month	ARIMA(p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
February	(0,1,0)	-	-	-	-	-
	(1,1,0)	10.8	11	-0.9589	-	-0.1864
	(0,1,1)	145.6	11	-	0.9457	-0.0361
	(1,1,1)	9.3	10	-0.8623	0.9169	-0.2331
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						
March	(0,1,0)	-	-	-	-	-
	(1,1,0)	8.1	11	-0.7167	-	-0.227
	(0,1,1)	29.8	11	-	0.9819	-0.1933
	(1,1,1)	9.2	10	-0.3349	0.9662	-0.2152
Prediction equation for ARIMA(1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)}						
April	(0,1,0)	-	-	-	-	-
	(1,1,0)	10.1	11	-.2068	-	2,431
	(0,1,1)	12.2	11	-	.1736	1.967
	(1,1,1)	3.2	10	-1.0009	-.9839	4.954
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						

Table 6. ARIMA T.B. Sanatorium (summer).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
May	(0,1,0)	-	-	-	-	-
	(1,1,0)	22.4	11	-0.3259	-	0.991
	(0,1,1)	14	11	-	0.9467	0.0329
	(1,1,1)	13.3	10	0.0547	0.9682	0.0179
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						
June	(0,1,0)	-	-	-	-	-
	(1,1,0)	15.7	11	0.9978	-	-0.0002
	(0,1,1)	277.6	11	-	0.9525	-0.0212
	(1,1,1)	6.6	9	-0.9774	1.0138	-0.2010
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						
July	(0,1,0)	-	-	-	-	-
	(1,1,0)	15.7	11	-0.9978	-	-0.0002
	(0,1,1)	227.6	11	-	0.9525	-0.0212
	(1,1,1)	6.6	10	-0.9774	1.0138	-0.0106
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						

Table 7. ARIMA T.B. Sanatorium (autumn).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
August	(0,1,0)	-	-	-	-	-
	(1,1,0)	14.9	11	-0.9737	-	-0.0927
	(0,1,1)	152.0	11	-	0.9672	-0.01507
	(1,1,1)	11.3	10	-0.9745	0.5331	-0.0414
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						

Table 7. Contd

September	(0,1,0)	-	-	-	-	-
	(1,1,0)	39.4	11	-0.9958	-	-.003
	(0,1,1)	198.2	11	-	0.9505	-0.0071
	(1,1,1)	-	-	-	-	-
Prediction equation for ARIMA(1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)}						
October	(0,1,0)	-	-	-	-	-
	(1,1,0)	6.9	11	-0.6200	-	0.87
	(0,1,1)	14.6	11	-	0.6243	1.89
	(1,1,1)	8.5	10	-0.4879	0.2264	0.82
Prediction equation for ARIMA(1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)}						

Table 8. ARIMA T.B. Sanatorium (winter).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
November	(0,1,0)	-	-	-	-	-
	(1,1,0)	4.5	11	0.1147	-	0.684
	(0,1,1)	4.6	11	-	-0.1049	0.771
	(1,1,1)	4.5	10	0.1351	0.0206	0.668
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						
December	(0,1,0)	-	-	-	-	-
	(1,1,0)	9.4	11	-0.6817	-	0.0697
	(0,1,1)	10.5	11	-	0.9975	0.01124
	(1,1,1)	7.0	10	0.2424	0.9605	-0.0247
Prediction equation for ARIMA(1,1,1) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)} –θe(t-1)						
January	(0,1,0)	-	-	-	-	-
	(1,1,0)	23.6	11	-0.9966	-	0.0278
		28.3	23	-	-	-
	(0,1,1)	164.4	11	-	-0.9950	-0.0144
		274.5	23	-	-	-
	(1,1,1)	26.8	10	-0.9589	0.9513	-0.00411
		31.2	22	-	-	-
Prediction equation for ARIMA(1,1,0) yields x(t)=a+x(t-1)+Φ{x(t-1) – x(t-2)}						

Table 9. ARIMA CGS Colony (spring).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1)Φ	MA (1) Θ	Constant (a)
February	(0,1,0)	-	-	-	-	-
	(1,1,0)	3.9	11	-0.5163	-	-0.298
	(0,1,1)	111.9	11	-	0.9490	0.4492
	(1,1,1)	2.1	10	-0.0952	0.9451	0.5138
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						

Table 9. Cont'd

March	(0,1,0)	-	-	-	-	-
	(1,1,0)	8.7	11	-0.9355	-	-0.2360
	(0,1,1)	121.1	11	-	0.9491	-0.0375
	(1,1,1)	2.8	10	-0.8315	0.8979	-0.02664
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						
April	(0,1,0)	-	-	-	-	-
	(1,1,0)	6.0	11	-0.3438	-	2.078
	(0,1,1)	9.0	11	-	0.2812	1.436
	(1,1,1)	3.9	10	-0.10005	-1.0180	5.143
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						

Table 10. ARIMA CGS Colony (summer).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
May	(0,1,0)	-	-	-	-	-
	(1,1,0)	17.9	11	-0.3328	-	1.504
	(0,1,1)	9.6	11	-	0.9817	0.2541
	(1,1,1)	11.6	10	-0.1476	0.9721	0.4379
The prediction equation for non-seasonal ARIMA (0,1,1) yields x(t)=a+x(t-1)-θe(t-1) where a is constant, e is the error at period (t-1)and θ=MA(1)						
June	(0,1,0)	-	-	-	-	-
	(1,1,0)	48.5	11	-0.9601	-	-0.0427
	(0,1,1)	185.0	11	-	0.9549	-0.195
	(1,1,1)	Not working	-	-	-	-
The prediction equation for non-seasonal ARIMA(1,1,0) yields x(t) =a+x(t-1)+Φ(x(t-1)-x(t-2) where a is constant and Φ=AR(1)						
July	(0,1,0)	-	-	-	-	-
	(1,1,0)	13.3	11	-0.9187	-	-0.0429
	(0,1,1)	138.3	11	-	0.9844	-0.02995
	(1,1,1)	7.2	10	-0.8464	0.9538	-0.02241
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						

Table 11. ARIMA CGS Colony (autumn).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
August	(0,1,0)	-	-	-	-	-
	(1,1,0)	47.7	11	-0.9345	-	-0.1356
	(0,1,1)	129.6	11	-	0.9852	-0.05185
	(1,1,1)	20.5	10	-0.8327	.9324	-0.0185
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						
September	(0,1,0)	-	-	-	-	-
	(1,1,0)	10.7	11	-0.9961	-	-0.0002

Table 11. Cont'd

	(0,1,1)	167.2	11	-	0.0692	0.0492
	(1,1,1)	Not working	-	-	-	-
The prediction equation for non-seasonal ARIMA(1,1,0) yields x(t) =a+x(t-1)+Φ(x(t-1)-x(t-2) where a is constant and Φ=AR(1)						
October	(0,1,0)	-	-	-	-	-
	(1,1,0)	11.1	11	-0.4207	-	0.548
	(0,1,1)	8.0	11	-	0.5835	0.3576
	(1,1,1)	9.3	10	0.3272	-.9827	0.0341
The prediction equation for non-seasonal ARIMA (0,1,1) yields x(t)=a+x(t-1)-θe(t-1) where a is constant, e is the error at period (t-1)and θ=MA(1)						

Table 12. ARIMA CGS Colony (winter).

Month	ARIMA (p.d.q.)	$\chi^2_{0.05}$	d.f	AR (1) Φ	MA (1) Θ	Constant (a)
November	(0,1,0)	-	-	-	-	-
	(1,1,0)	5.7	11	0.0074	-	-7.63
	(0,1,1)	5.7	11	-	-0.0074	-7.69
	(1,1,1)	5.8	10	-0.9358	-1.0248	-0.2979
The prediction equation for non-seasonal ARIMA(1,1,0) yields x(t) =a+x(t-1)+Φ(x(t-1)-x(t-2) where a is constant and Φ=AR(1)						
December	(0,1,0)	-	-	-	-	-
	(1,1,0)	40.0	11	-0.9600	-	-0.1570
	(0,1,1)	94.2	11	-	1.055	-0.0818
	(1,1,1)	11.5	10	-0.8360	0.9141	0.0386
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						
January	(0,1,0)	-	-	-	-	-
	(1,1,0)	21.7	11	-0.9336	-	-0.2413
	(0,1,1)	99.8	11	-	0.9427	-0.0421
	(1,1,1)	8.5	10	-0.7906	-0.9047	-.03788
The prediction equation for non-seasonal ARIMA (1,1,1) yields x(t)=a+x(t-1)+Φ(x(t-1)-x(t-2))-θe(t-1) where a is constant, e is the error at period (t-1), Φ=AR(1) and θ=MA(1)						

not least, linguistically and culturally. So that they may get on board and ultimately could counter the corruption eventually to make the environment of their city peaceful, clean and tranquilizing.

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