Forecasting the Impact of Waste on Environmental Pollution

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Abstract

Reducing pollution of environment is an important aim of this study, Box-Jenkins models cannot predict volatility even if its residuals having ARCH effect, the GARCH (1,1) model have been used because the residuals of the mean equation has ARCH effect. Depending on GARCH (1,1) model we forecasted for sixty days respectively, the forecasted weight of waste is increasing it implies that the pollution of environment is also increased if the waste does not disposed of in a scientific way.

Key word: Time series analysis, Box-jenkins method, ARCH and GARCH method.

التنبؤ بتاثير كمية النفايات على تلوث البيئة

مقدم من

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المستخلص

ان الهدف من هذه الدراسة هو التنبؤ بتاثير كمية النفايات على تلوث البيئة,وعند دراسة هذا الموضوع كان لا بد من استخدام انموذج احصائي ياخذ بنظر الاعتبار التقلبات التي تحدث في كميات النفايات

حيث ان النفايات هي مجمل مخلفات الأنشطة الإنسانية المنزلية والزراعية والصناعية والإنتاجية، أي كل المنقولات المتروكة أو المتخلى عنها في مكان ما ، والتي تَرْكُها يهدد ويسيء إلى الصحة و السلامة العامة.

تم استخدام بيانات من الشركة الوطنية للتنظيف في محافظة البصرة في العراق وهي ثالث محافظة تحتوي على الاهوار وشط العرب وهي المنفذ المائي الى الخليج العربي

وان ادارة النفايات تعتمد على الاليات المستخدمةلنقل النفايات يوميا وعدد العمال المستخدمين في كل يوم كما ان عدد النفايات اليومية يعد امرا مهما اضافة الى وزن النقلة الواحدة

تم اخذ هذي المتغيرات بشكل يومي ولمدة 5سنوات يعني 1825يوم وحيث ان هناك تقلب في السلسة الزمنية ولمعالجة هذه المشكلة قدم الباحث Engle في عام 1982 نموذج ال ARCH وفي عام 1986 اضافة العالم Bollersley حدود الانحدار الذاتي ليتحول الى نموذج غارش ,يتم اختبار هذا النموذج ومعرفة فيما اذا يحقق الشروط او الكفائة الخاصة به حيث قمنا باستخدام برنامج Eviewلحساب المقدرات الاحصائية والاستنتاج بان اسلوب غارش افضل من الاساليب السابقة وكمية النفايات في زيادة مستمرة

نوصي لحل هذا الموضوع باستخدام اساليب علمية للتخلص من النفايات واعادة التدوير, استخدام اسلوب التوعية الصحية للمواطنين....لان التخلص من النفايات ليست مسؤولية الحكومة بحد ذاتها وانما هي مسؤولية مشتركة بين المواطن والحكومات ,عقد ندوات لطلاب الجامعات لزيادة الوعي الثقافي

1-1 Introduction

There are several definitions of the term waste. The Solid wastes include substances originating from both human and animal activities, usually disposed it because they are no longer required and these useless materials (solid waste) consist of industrial, non-industrial and domestic hazardous waste. For Examples of these solid waste are household organic rubbish, institutional rubbish, construction waste, and street surveys. The World Health Organization (WHO) has defined waste as some of the things that its owner does not want it, and which haven't any benefit, English law defines it as any material resulting from any production process, or any material, equipment, broken, damaged, idle, contaminated material or any excess clothing.

1-2 Type of Waste

1. Hazardous solid waste: Waste from different processes that retain the properties of a hazardous substance that does not have alternative uses. It is a source of danger to human health and the elements of the environment because it contains toxic or explosive materials. The sources of these wastes include industrial and agricultural sources, hospitals and health facilities. And pharmaceuticals
2. Non-hazardous solid waste: solid waste that does not contain substances or components that have the characteristics of hazardous substances, and they vary in their chemical and physical properties and include organic and inorganic substances such as:

a. Municipal waste: waste produced from the kitchens of houses, shops, markets, and restaurants through the preparation, cooking and serving of food. It is mainly composed of organic substances that can be rotted and damp, and contains free liquids in small quantities

b. Industrial waste: There are many industrial activities in the countries, resulting in waste such as industrial waste. The quality and quantity of industrial solid waste vary according to the quality of the industry and the method of production.
c. Agricultural Waste: Agricultural waste includes all waste or waste resulting from all agricultural, animal, and slaughterhouse activities. The most important of these wastes are animal secretions, fodder residues and plant harvesting waste. In general, these agricultural wastes are not an environmental problem if they are returned to normal
d. Health waste and laboratories are all solid, liquid and gaseous wastes that include sharp teeth, blood, body organs, chemicals, drugs, pharmaceuticals, medical instruments and radioactive materials from various health care institutions, medical laboratories, medical research centers, pharmaceutical factories and warehouses, hospitals and medical clinics.

1-3Factors influencing waste increase

1. The number of population: directly proportional to the amount of waste as the number of individuals increased the amount of waste produced by each individual and in the countryside where the waste generated in cities and urban areas are usually higher than in rural areas.
2. Industrial development: The increase in factories contributed to the provision of canned food, ready-made cups, spoons and plastic and paper dishes are not usable again made them a cause of accumulation of household waste.
3. Economic development: The waste generated by the economic level of the country and the rapid urbanization and income levels of the population, which are the main factors in the waste disposal process, are affected.
4. Social conditions: Adhering to tribal customs and traditions by providing large quantities of food and beverages during the occasions, holidays and orphanages

and the absence of canned foods, which results in increasing the volume of household waste, especially organic ones.

5. Climate conditions: The quantity of waste and the quality of waste generated vary according to the four seasons.

1-4 Waste management

The waste management principle is based on thinking not only on the disposal of waste, but also on finding solutions and ways of handling the huge amounts generated each day. Waste management has a set of foundations for applying this principle, including:

1. Reduce the use of raw materials.
2. Reuse of some solid waste components.
3. Extraction of energy from solid waste.
4. Recycling some solid waste elements.
5. Final disposal process.
6. Daily waste management.

Chapter Two

Methodology

2-1 Building a GARCH Model [1]

For building any ARCH or GARCH model in time series analysis the below steps are required:

1. Construct an appropriate first moment model using either an ARIMA, regression, or transfer function model, and use the residual series ($\hat{a}_t$) of the model to exam for the presence of GARCH effects.

2. Explain an appropriate GARCH model for a_t^2 and perform parameter estimation;
3. Study the fitted GARCH model and refine it if necessary.

2-2 Testing GARCH Effects (Test of heteroscedasticity) [6] [4] [2]

The availability of ARCH/GARCH effects may give serious model miss-specification if they are ignored. Logically ignoring ARCH effects will give the identification of ARMA models that are over-parameterized. In addition, as with all forms of heteroscedasticity,

Estimation assuming its absence will result in inappropriate standard errors of parameter estimates which are typically smaller than what they should be. Therefore it is important to check the presence of GARCH effects in time series modeling.

Two ways of testing GARCH effects are used. Number one is to check the Ljung-Box portmanteau Q statistics of a_t^2 . McLeod and Li show that the sample autocorrelations of a_t^2 have asymptotic variance n^{-1} and that portmanteau statistics calculated from them are asymptotically χ^2 if the a_t^2 are independent. Since the sample autocorrelations of a_t^2 are also useful for the identification of an GARCH model for a_t^2 .

Number two checking conditional heteroscedasticity is to use the Lagrange multiplier test of Engle. Consider the following regression model for

a_t^2 on a_{t-j}^2 j=1,2,…..m

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + ... + \alpha_m a_{t-m}^2 + v_t . \qquad t=m+1.......n \qquad (2\text{-}1)$$

Where vt denotes the error term, m is a pre-specified positive integer, and n is the total number of observations in the series. Using R^2 to denote the *coefficient of determination* from (2.1), Engle shows that under the null

hypothesis $H_0 : \alpha_1 = \alpha_2 = ... \alpha_m = 0$, nR^2 asymptotically follows a χ^2 -distribution with m degrees of freedom.

2-3 Normal Distribution [3]

Taking that a_t^2 follows a GARCH (1, 1) model and ε_t follows a Normal

distribution, the maximum likelihood estimates of the GARCH(1,1) model for series are.

$$y_t = c_1 + a_t$$
$$\sigma_t^2 = c_2 + GMA \ a_{t-1}^2 + GAR \ \sigma_{t-1}^2$$

2-4 Volatility

Volatility is an important factor in options trading. Here volatility means the conditionalvariance of the underlying asset return.

2-5 Identification of a GARCH Model [3]

If the Ljung-Box statistics and LaGrange multiplier (LM) test are significant, then conditional heteroscedasticity of a_t^2 is present, and we need to identify an appropriate GARCH model for a_t^2. However since the GARCH (1,1) model has been shown to be appropriate in many empirical studies, we may employ the GARCH(1,1) model at the beginning of the analysis. As the model is estimated, diagnostic checking procedures may be followed to see if the GARCH (1,1) model is okay, or if the orders of the GARCH model should be increased or decreased. Instead of using this trial-and-error approach, we may use the following procedure for the definition of a GARCH model for the { a_t^2 } series.

2-6 Ljung-Box Q-Statistic [1] [5] [4]

Adding to the visual inspection of the plotted autocorrelation, the Ljung-Box Q-Statistic is Used for diagnostic checking .The Ljung-Box Q-Statistic is defined by equation (2-2)

$$Q^* = n(n+2)\sum_{j=1}^{K}(n-j)^{-1} r_j^2(e_t) \qquad (2\text{-}2)$$

Where n is the number of observation, K is the largest lag used and rj is the sample autocorrelation function at lag j of an appropriate time series a_t, for example.

Statistic r_j for a_t is then defined as

$$r_j = \frac{\sum_{t=j+1}^{n}(a_t - \bar{a})(a_{t-j} - \bar{a})}{\sum_{t=1}^{n}(a_t - \bar{a})^2} \qquad (2\text{-}3)$$

The Q-Statistic is a modification of the Box-Pierce test statistic, this was suggested for testing ARIMA and ARMA models both the test statistics are determined by the calculation of the sample autocorrelation function for the residuals $\hat{\varepsilon}_t$ from those models .the similar test statistic based on different calculation using the autocorrelation function will be high benefit for small sample applicability, it is defined as

$$Q^* = n(n+2)\sum_{j=1}^{K}\frac{r_j^2(e_t)}{(n-j)} \sim \chi_k^{\ 2} \qquad (2\text{-}4)$$

And r_j^* is

$$r_j^* = \sum_{t=j+1}^{n} (a_t^{\wedge 2} - \bar{a})(a_{t-j}^{\wedge 2} - \bar{a}) / \sum_{t=1}^{n} (a_t^{\wedge 2} - \bar{a}) \qquad (2\text{-}5)$$

2.7 Likelihood Function of GARCH Models [3] [5]

By defining α = $[\alpha_0, \alpha_1, ... \alpha_m, B_1, ... B_r, \eta]'$, the log likelihood functions of α may be derived Under the Normality assumption of ε_t . If ε_t is assumed to follow a Normal distribution. However, practically, there

is substantial evidence showing that this assumption may not all the time be satisfactory.

For the GARCH (1.1) model, the joint density of the observations $a_1 ...... a_T$ can be calculated as the product of the conditional densities, conditioning on the last observations

$$fa_1,....,\ a_T(a_1,...,\ a_T) = \{\prod_{i=2}^{T} fa_i \left| a_1,... a_{i-1}(a_i \right| a_1,... a_{i-1})\} * fa_1(a_1) \qquad (2\text{-}6)$$

Easy way, the marginal density of a_1 will be dropped as for ARIMA (1.1) model. For k=2,…T the conditional density of a_k , conditioning on $a_1 ...... a_{k-1}$ is

$$fa_k \left| a_1,....,\ a_{k-1}(a_k \right| a_1,...,\ a_{k-1}) = \frac{1}{\sqrt{2\pi}\sqrt{\sigma_k^2}} \exp\left\{-\frac{a_k^2}{2\sigma_k^2}\right\}. \qquad (2\text{-}7)$$

And the conditional likelihood function given a_t and σ_t^2 is :

$$L(\alpha_0, \alpha_1, B_1) = fa_2,... a_T \left| a_1 \sigma_1^2 (a_2,... a_T \right| a_1 \sigma_1^2) \qquad (2\text{-}8)$$

$$\prod_{i=2}^{T} \frac{1}{\sqrt{2\pi}\sqrt{\sigma_i^{*2}}} \exp\left\{-\frac{a_i^2}{2\sigma_i^{*2}}\right\}.$$

Where $\sigma_i^{*2} = \alpha_0 + \alpha_1 a_{i-1}^2 + B_1$ are obtained recursively. We substitute σ_t^2 by its expected value $E(\sigma_t^2) = \dfrac{\alpha_0}{1-\alpha_1 - B_1}$ (2-9)

Using the logarithm and ignoring the constant term we find that the log likelihood function is:

$$l(\alpha_0, \alpha_1, B_1 \mid a, \sigma^2) = -\frac{1}{2}\left\{\sum_{i=2}^{T} \log \sigma_i^{*2} + \frac{a_i^2}{\sigma_i^{*2}}\right\} \qquad (2\text{-}10)$$

Where $a = (a_1, \ldots a_T)^-$ *and* $\sigma_t^2 = (\sigma_1^2, \ldots \sigma_T^2)$.

2-8 Model Checking of GARCH (r,m) [3]

For a GARCH model, the standardized shocks $\varepsilon_t^\wedge = a_t^\wedge / \sigma_t^\wedge$ are *i.i.d.* random errors following either a standard Normal or a non-Normal distribution such as the standardized Student-t distribution. Therefore, one can check the adequacy of a fitted GARCH model by examining the series $\{\varepsilon_t^\wedge\}$. In particular, the sample autocorrelations and the Ljung-Box Q statistics of $\varepsilon_t^\wedge$ can be used to check the adequacy of the mean (first moment) equation and those of ε_t^2 can be used to test the validity of the volatility (second moment) equation.

2-9 Existence of the GARCH (1,1) process [5]

The GARCH(1,1) model is:

$$a_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + B_1 \sigma_{t-1}^2 \qquad (2\text{-}11)$$

Where $\alpha_0 > 0$, $\alpha_1 \geq 0$ *and* $B_1 \geq 0$.

GARCH (r,m) processes are defined recursively and conditions are needed to guarantee the existence of stationary solutions. Now we derive such conditions for the GARCH (1,1) process Dividing by the square root of the conditional variance of a_t from (2-11) . We got

$$\varepsilon_t \sim N(0,1)$$

$$\sigma_t^{2} = \alpha_0 + \alpha_0 \sum_{k=1}^{\infty} (\prod_{j=1}^{k} (\alpha_1 E(a_{t-j}^{2} + B_1)) \qquad (2\text{-}12)$$

Theorem 2-1 [5]: if the expectation of an infinite sum of non-negative random variables is finite , then the sum converges almost surely.

(see Lucas 1975 ,theorem 4,2,1 ,p. 80.)

We will use this theorem to find a condition under which the equations in (2-12) exists. Using the unconditional expectation of both sides, resulting in

$$E(\sigma_t^{2}) = \alpha_0 + \alpha_0 \sum_{k=1}^{\infty} (\prod_{j=1}^{k} (\alpha_1 E(a_{t-j}^{2} + B_1))$$

$$= \alpha_0 + \alpha_0 \sum_{k=1}^{\infty} (\alpha_1 + B_1)^{k}$$

$$= \frac{\alpha_0}{1-\alpha_1 - B_1} \qquad (2\text{-}13)$$

So the unconditional expected value of σ_t^2 , is the finite and the infinite series for σ_t^2 in (2-12) converges to $\alpha_0 /(1-\alpha_1 - B_1)$ provided that $\alpha_1 + B_1 < 1$ .In summary, if $\alpha_1 + B_1 < 1 \ \ and \ \ \alpha_1 \geq 0 \ , B_1 \geq 0$, we can define σ_t^2 by (2-12) and $a_t = \varepsilon_t \sqrt{\sigma_t^2}$ the resulting process { a_t } is a stationary solution of (2-11).

2-10 Forecasting GARCH (1,1) Model [3]

Forecasts of a GARCH model can be found by using methods similar to those of an ARMA model. Consider the GARCH (1, 1) model in assume that the forecast origin is n. For one-step-ahead forecast, we have

$$\sigma_{n+1}^{2} = \alpha_0 + \alpha_1 a_n^{2} + B_1 \sigma_n^{2} \qquad (2\text{-}14)$$

Where $a_n^2 \ \ and \ \ \sigma_n^2$ are known at t=n .therefore, the one- step ahead forecast is

$$\sigma_n^2(1) = \alpha_0 + \alpha_1 a_n^2 + B_1\sigma_n^2 \qquad (2\text{-}15)$$

For multi-step ahead forecasts, we use $a_t^2 = \sigma_t^2 \varepsilon_t^2$

$$\sigma_{t+1}^2 = \alpha_0 + (\alpha_1 + B_1)\sigma_t^2 + \alpha_1\sigma_t^2(\varepsilon_t^2 - 1) \qquad (2\text{-}16)$$

When t=n+1 , the equation becomes

$$\sigma_{n+2}^2 = \alpha_0 + (\alpha_1 + B_1)\sigma_{n+1}^2 + \alpha_1\sigma_{n+1}^2(\varepsilon_{n+1}^2 - 1) \qquad (2\text{-}17)$$

since $E(\varepsilon_{n+1} - 1 | F_n) = 0$, the two –step ahead volatility forecast at the forecast origin n satisfies the equation

$$\sigma_n^2(2) = \alpha_0 + (\alpha_1 + B_1)\sigma_n^2(1) \qquad (2\text{-}18)$$

In general, we have

$$\sigma_n^2(\ell) = \alpha_0 + (\alpha_1 + B_1)\sigma_n^2(\ell - 1) \quad , \quad \ell > 1 \qquad (2\text{-}19)$$

This result is exactly the same as that of an ARMA (1, 1) model with an AR polynomial 1− ($\alpha_1 + B_1$) B. By repeated substitutions in (2-19),

the ℓ -step-ahead forecast can be written as

$$\sigma_n^2(\ell) = \frac{\alpha_0[1 - (\alpha_1 + B_1)^{\ell-1}]}{1 - \alpha_1 - B_1} + (\alpha_1 + B_1)^{\ell-1}\sigma_n^2(1) \qquad (2\text{-}20)$$

Therefore:

$$\sigma_n^2(\ell) \to \frac{\alpha_0}{1 - \alpha_1 - B_1} = \alpha_0^* , \quad as \quad \ell \to \infty \qquad (2\text{-}21)$$

Provided that $\alpha_1 + B_1 < 1$

Consequently, the multi-step-ahead volatility forecasts of a GARCH (1, 1)model converge to the unconditional variance of a_t as the forecast horizon increases to infinity provided that Var (a_t) exists.

Chapter Three

Applications

3-1 Fitting mean equation model

The series of the study should be stationary, therefore the ADF test of the stationarity have been used as it is shown below in table (1):

Table (1) Represents the stationarity test results.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.762935	0.0000
Test critical values:	1% level	-3.449797	
	5% level	-2.870004	
	10% level	-2.571349	

From the above table it is obviouse that the p-value is less than 0.05 that mean the series is stationary

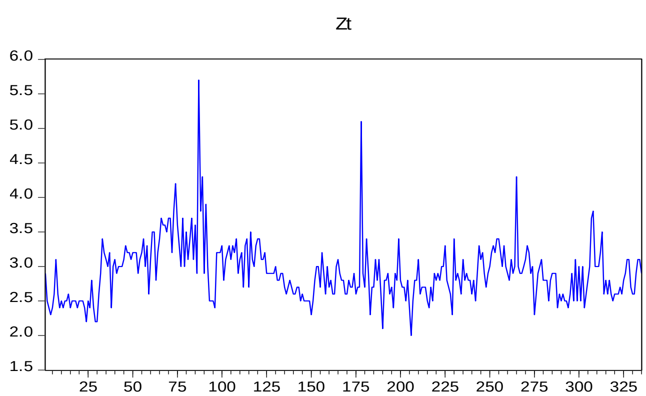


Figure (1) Represents the graph of the series

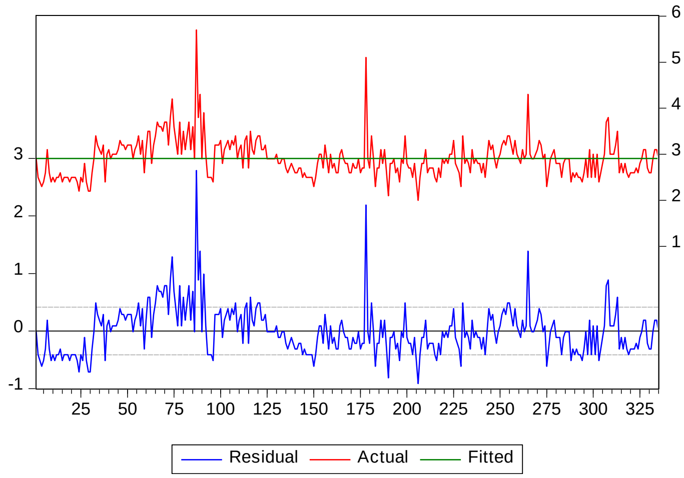
After achiving the stationarity condition of the series we should fit mean equation model as it is shown below:

Table (2) Represents the fit of mean equation model

Dependent Variable: ZT
Method: Least Squares
Date: 08/18/17 Time: 17:23
Sample: 1 335
Included observations: 335

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.911045	0.022659	128.4703	0.0000

Frome table (2) the p-value is less than 0.05 then one can say that the model is significant.



Figure(2) Represents the residuals of the mean equation

The hypothesis of ARCH has effect or not on the mean equation for this purpose heteroskedasticity test ARCH have been used and its results are shown in table (3):

H_0: There is no ARCH effect Vs H1: there is ARCH effect

Table (3) Represents the heteroskedasticity test ARCH

Heteroskedasticity Test: ARCH			
F-statistic	13.415662	Prob. F(1,332)	0.003

The P-value is less than 0.05 then the null hypothesis should be rejected, in another word there exist ARCH effect.

We achived two main assumptions of using GARCH model which are the stationary of the series and effect of ARCH in the mean equation mmodel then GARCH model can be used to forecat the volatility.

3-2 Fitting GARCH (1,1)

The GARCH (1,1) model have been runned, the results of its fit is shiown in table (4) below:

Table (4) Represents the fit of GARCH (1,1) model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.836153	0.018968	149.5258	0.0000
Variance Equation				
C	0.018268	0.008899	2.052893	0.0401
RESID(-1)^2	0.229532	0.102049	2.249229	0.0245
GARCH(-1)	0.649460	0.127342	5.100128	0.0000

From the above table it is obviouse that the estimators of the variance equation are significant depending the p-value which is less than 0.05.

The residuals of the GARCH (1,1) model should be tested in order to find out that the model is suffer from serial correlation of residuals or not

H_0: There is no serial correlation of residuals. Vs H_1: There is serial correlation of residuals.

Table (5) Represents testing of ACF and PACF

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.025	-0.025	0.2058	0.650
		2	-0.020	-0.020	0.3394	0.844
		3	-0.021	-0.022	0.4837	0.922
		4	-0.012	-0.014	0.5331	0.970
		5	-0.013	-0.014	0.5893	0.988
		6	-0.020	-0.022	0.7303	0.994
		7	-0.019	-0.021	0.8484	0.997
		8	-0.024	-0.027	1.0469	0.998
		9	-0.007	-0.010	1.0630	0.999
		10	-0.008	-0.011	1.0856	1.000
		11	-0.019	-0.022	1.2124	1.000
		12	0.026	0.022	1.4500	1.000
		13	0.007	0.005	1.4654	1.000
		14	-0.014	-0.015	1.5320	1.000
		15	-0.023	-0.025	1.7189	1.000
		16	-0.009	-0.012	1.7471	1.000
		17	-0.017	-0.020	1.8482	1.000
		18	-0.002	-0.006	1.8502	1.000
		19	-0.012	-0.014	1.8978	1.000
		20	-0.016	-0.019	1.9888	1.000
		21	0.035	0.031	2.4220	1.000
		22	-0.015	-0.018	2.5038	1.000
		23	-0.011	-0.014	2.5493	1.000
		24	-0.024	-0.028	2.7659	1.000
		25	-0.004	-0.010	2.7727	1.000
		26	-0.009	-0.014	2.8046	1.000
		27	0.005	0.003	2.8154	1.000
		28	0.050	0.047	3.7167	1.000
		29	0.004	0.005	3.7216	1.000
		30	-0.021	-0.022	3.8807	1.000
		31	-0.012	-0.014	3.9308	1.000
		32	-0.003	-0.004	3.9336	1.000
		33	-0.010	-0.015	3.9701	1.000
		34	-0.009	-0.011	3.9989	1.000
		35	-0.018	-0.019	4.1151	1.000
		36	-0.006	-0.006	4.1289	1.000

From the above table the p-value for the 36 laggs are greater than 0.05 then we can accept the null hypothesis.

The final test is heteroskedasticity test:ARCH to figure out that the postulated model is adequate or not , the results is shown in table (6) below:

H_0: ARCH has no effect. Vs H_1: ARCH has effect.

Table (6) Represents the test of ARCH effect.

Heteroskedasticity Test: ARCH			
F-statistic	0.093045	Prob. F(1,332)	0.7605
Obs*R-squared	0.093580	Prob. Chi-Square(1)	0.7597

From the above table it is clear that the P-value is greater than 0.05 then we can accept H_0 .

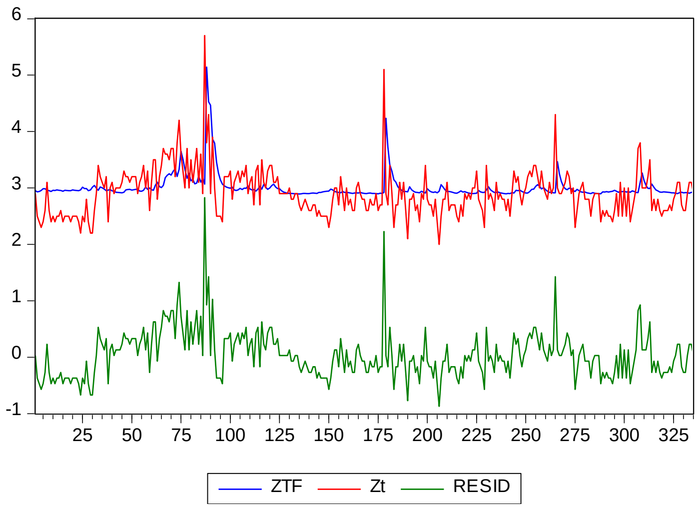


Figure (3) Represents the graph of actual, forecasted and residuals.

Table (7) Represents the forecasted values

Laggs	Forecasted	Laggs	Forecasted	Laggs	Forecasted
336	2.8	356	2.83	376	2.7
337	3.1	357	2.43	377	2.9
338	3.2	358	3.03	378	2.7
339	3.3	359	2.43	379	2.6
340	3	360	2.93	380	2.7
341	3	361	2.43	381	2.8
342	3	362	2.93	382	2.8
343	2.7	363	2.33	383	2.9
344	3	364	2.53	384	2.8
345	3.1	365	2.73	385	3
346	3.1	366	3.1	386	3.1
347	3.1	367	3.8	387	3.3

348	2.6	368	3.9	388	3.3
349	2.8	369	3.1	389	2.9
350	2.7	370	3.1	390	2.8
351	2.53	371	3.1	391	2.8
352	2.43	372	3.3	392	3.1
353	2.43	373	3.6	393	3.3
354	2.33	374	2.7	394	3.3
355	2.53	375	2.9	395	3.1

4-1 Conclusions

1- GARCH model is more adequate for the series that its residuals are affected by ARCH.
2- Any time series models after fitting its residuals should be tested to figure out that there exist any pattern in the residuals or not.
3- GARCH models provides the forecasting for volatility for each observation.

4-2 Recommendations

In this paper according to forecasted values there exist an increasing of the weight of waste which implies that the environment will be in danger, therefor the stack holders must warring citizens through posters, T.V programs and seminars at the colleges to raised people awareness towards pollution of environment.

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