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ON forecasting by Dynamic Regression models

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ABSTRACT

This research include the application of some statistical technique for studying the time series of the average monthly humidity as an output series with one of the variables which affect on it, which is the series of the average monthly relative rainfall as an input which is measured at the meteorological station of Duhok the techniques used are the modeling by an(ARIMA) model as well as the dynamic regression model. So that the perfect dynamic regression model selected was suitable for determining the future forecasting values.

Introduction

The series of the humidity and relative rainfall were examined and determined that they are stationary in the mean and the variance, also both the auto correlation and partial auto correlation function were studied for the humidity and relative rainfall series and determined that there is an observed correlation for these phen35omena; therefore, a suitable model was determined for both series from order ARMA(1,1). Relative the dynamic regression models (it is that model which take the time into account),the modeling of the dynamic regression shows how is that output result from the input and that is depends upon:

1- the relation of the lag time with the input and output.
2- The time composition for the turbulence series.

Then the model which was identified by the statistical measures as well as the cross correlation function for the residual between the residual series (α_t) of the input series, it was found that these two series are independent and the model of the transformation function was suitable. As well as the examination of the auto correlation for the residuals series (a_t) by the statistical test shows that all values were insignificant and it is prove that the turbulence series is a white noise series. In this paper we compare between series ($\hat{\alpha}_t$) and series ($\hat{a}_t$) and we conclusion that the correlation between two series ($\hat{\alpha}_t$) and series ($\hat{a}_t$) is significant.

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DYNAMIC REGRESSION (DR)

Preliminary

A Dynamic Regression model is a regression model which allows lagged value of the explanatory variable(s) to be included, the relationship between the forecast variable and the explanatory variable is model using a transfer function. A DR model states how an output (Y_t) is linearly related to current and past value of one or more input ($X_{1,t}$, $X_{2,t}$, $X_{3,t}$,…), it is usually assumed that observations of the various series occur at equally spaced time intervals. While the output may be affected by the inputs, a crucial assumption is that the inputs are not affected by the outputs this means that we are limited to single equation models [6].

1.1 TRANSFER FUNCTION [1],[2],[6]

For simplicity we will discuss just one input. The ideas which developed here are easily extended to multiple inputs if Y_t depends on X_t in some way we may write this as

$$Y_t=f(X_t) \qquad (1)$$

Where f(.) is some mathematical function. The function f(.) is called a transfer function. The effect of a change in X_t is transferred to Y_t in some way specified by the function f(.).In general, however, there are other factors causing variation in Y_t besides changes in the specified input, we capture those other factors with an additive stochastic disturbance (N_t) that may be auto correlated N_t represents the effects of all excluded inputs on the variability of Y_t . The input – output relationship may also have an additive the constant term(C) .This is a buffer term that captures the effect of excluded inputs on the overall level of Y_t, thus we are considering models of the form:

$Y_t = C + f(X_t) + N_t$ (2)

Where Y_t : is the output

X_t: is the input

C: is the constant term.

$f(X_t)$: is the transfer function

N_t: is the stochastic disturbance which may be auto correlated

N_t is assumed to be independent of X_t

input N_t output

$X_t \rightarrow$[transfer function]$\rightarrow Y_t$

1-2 IMPULSE RESPONSE FUNCTION [5],[6]

We can write a linearly distributed lag transfer function in back shift form by defining v(B) as

$v(B)=v_0+v_1B+v_2B^2+v_3B^3+\ldots$ (3)

where B is the backshift operator defined such that $B^kX_t= X_{t-k}$

We can write the transfer function $f(X_t)$ as a liner combination of current and past X_t value:

$Y_t= f(X_t) = v_0X_t+v_1X_{t-1}+v_2X_{t-2}+v_3X_{t-3}+\ldots$ (4)

Using equation (5),(4) may be rewritten as

$Y_t= v(B)\, X_t\ldots.$ (5)

Equation (5) is a compact way of saying that there is a linearly distributed lag relationship between change in X_t andchanges in Y_t .The individual v_k weights in v(B), (v_0 , v_1, v_2, v_3, …) are called the impulse response weights we canestimate that the V_{k-b}weights as follows

$$V_k=\frac{\hat{\sigma}_\beta}{\hat{\sigma}_\alpha}\hat{\rho}_{\alpha\beta}(k) \quad (6)$$

Where $\hat{\rho}_{\alpha\beta}(k)$ estimates the cross correlation between α,β

$\hat{\sigma}_\beta$: standard deviation of β

$\hat{\sigma}_\alpha$: standard deviation of α

1-3 DEAD TIME[5],[6]

Y_t might not react immediately to a change in X_t, some initial v weights may be zero. The number of v weight sequal to zero (starting with v_0) is called dead time denoted as b, starting with $v_{0,}$ there is one v weight equal to zero ($v_0 = 0$), so b=1.Alternatively if $v_0 =v_1 =v_2 = 0$ and $v_3 \neq 0$ then b=3.

1-4 THE RATIONAL DISTRIBUTED LAG FAMILY[5],[6]

The Koyck impulse response function is just one member of the family of rational polynomial distributed lag models. This family is a set of impulse response functions v(B) given by

$$v(B) = \frac{w(B)B^b}{\delta(B)} \quad \text{where} \quad (7)$$

$$w(B) = w_0 + w_1B + w_2B^2 + \ldots+w_hB^h \quad (8)$$

$$\delta(B)=1-\delta_1B-\delta_2B^2-\ldots-\delta_rB^r \quad (9)$$

Where h: represents the order of (w)

r: represents the order of (δ)

Extending this frame work to m inputs, i=1,2,…,m, is straight forward. The result may be written compactly as

$$Y_t= \sum_{i=1}^{m} v_i(B)X_{i,t}$$

$$=\sum_{i=1}^{m}\frac{w_i(B)B^{bi}}{\delta_i(B)}X_{i,t} \quad (10)$$

1-5 BUILDING DYNAMIC REGRESSION MODELS(DR) [3],[5], [6].

A dynamic regression (DR) model with one input consists of a transfer function plus a disturbance. This may bewritten as:

$Y_t= c + v(B) + N_t$

Where

$$N_t= \frac{\theta(B^s)\theta(B)}{\phi(B^s)\phi(B)\Delta_s^D\Delta^d}a_t$$

and

a_t : is zero mean and normally distributed white noise

1-6 PREPARATION AND PREWHITENING OF THE INPUTS AND OUTPUTS SERIES [1],[2],[5]

Rewriting this process, we may think of AR and MA operators as a filter that, when applied to X_t, produces an uncorrelated residual series

$$\alpha_t = \theta_x^{-1}(B)\phi_x(B)X_t$$

The series α_t (in practice $\hat{\alpha}_t$) is called the pre whitened $X_t$series now suppose we apply the same filter to Y_t: this will produce another residual series

$$\beta_t = \theta_x^{-1}(B)\phi_x(B)Y_t$$

1-7 IDENTIFICTION

a) ESTIMATION OF THE IMPULSE RESPONSE WEIGHTS [5]

Equation (7) shows that if we prewhiten the input, and apply the same filter to the output, then the v weights are proportion to the cross correlations of the residuals from these two filtering procedures. in practice we don't know the parameters on the right side of equation (7). Instead we substitute estimates of these parameters obtained from the data to arrive at the following estimated v weights.

$$\hat{v}_k = \frac{r_{\alpha\beta}(k)\hat{\sigma}_\beta}{\hat{\sigma}_\alpha}$$

b) IDENTIFICATION OF (r,s,b) FOR THE TRANSFER FUNCTION[6]

We obtain the identity

$v_j = 0;$ j<b

$v_j = \delta_1 v_{j-1} + \delta_2 v_{j-2} + \ldots \delta_r v_{j-r} + w_0;$ j = b

$v_j = \delta_1 v_{j-1} + \delta_2 v_{j-2} + \ldots \delta_r v_{j-r} - w_{j-b};$ j = b +1, b+2, …,b+s

$v_j = \delta_1 v_{j-1} + \delta_2 v_{j-2} + \ldots \delta_r v_{j-r};$ j> b + s

c)DISTURBANCE SERIES [5].

We generate an estimate of the N_t series denoted by $\hat{N}_t$, the estimate disturbance series and it is computed as:

$\hat{N}_t = Y_t - v_1(B)X_t$

$= Y_t - \frac{w_s(B)}{\delta_r(B)}B^b X_t$

–

This disturbance series (N_t) in a dynamic regression will often be autocorrelated.

$\phi_N(B)N_t = \theta_N(B)a_t$ where

a_t : is zero mean and normally distributed white noise

1-8 ESTIMATION [2],[3],[4]

At the identification stage we tentatively specify a rational from transfer function model of orders (b,r,s), and a disturbance series ARIMA model of orders (p,d,q) We identified the following DR model

$$Y_t = \frac{w(B)B^b}{\delta(B)}X_t + \frac{\theta_N(B)}{\varphi_N(B)}a_t \quad (11)$$

At the second stage of our modeling strategy we estimate the parameters of the identified DR model using the available data. To estimate (11) we will use initial values to refer to coefficient values can often be found from identification stage information to estimate the coefficients in w(B) and $\delta(B)$ the next step in estimation is to compute the SSR(sum of squared residua

$$SSR = \sum_{i=1}^{n} a_i^2$$

Is used to choose better model coefficients, by taking the minimum SSR

1-9 DiagnosticCheck[1],[6]

We can Diagnostic Check time series model by examining

a)Residuals Cross Correlation function (RCCF)$r_{k(\hat{\alpha})}$ where

$$r_{k(\hat{a})} = \frac{\rho_{\alpha a(k)}}{\hat{\sigma}_a\hat{\sigma}_a} \text{k=1,2,3,…} \quad (12)$$

Where

$\rho_{\alpha a(k)}$: the cross correlation between a,α

$\hat{\sigma}_a$: standard deviation

$\hat{\sigma}_\alpha$: standard deviation ofα

$$\rho_{\alpha a(k)} = \frac{\sum_{t=1}^{n-k}(\hat{\alpha}_t - \bar{\alpha})(\hat{a}_{t+k} - \bar{a})}{n} \text{k=1,2,3,…} (13)$$

Where $\hat{r}_k$ is only an estimate of parameter ρ_k , we may test the null hypothesis

H_o:$\rho_k = 0$

H_A :$\rho_k \neq 0$

If α_t and a_t are uncorrelated and normally distributed, and one of these two series is white noise, than $\hat{r}_k$ has the following approximate standard error

$S(\hat{r}_k)=n^{-1/2}$ (14)

Wheren is the smaller of the number of observation for $\hat{a}_t$ or $\hat{\alpha}_t$

Another useful statistic involves a test on all K residual CCF coefficients as a set. Consider the joint null hypothesis

$H_o: \rho_1 = \rho_2 = \rho_3 = \ldots = \rho_k = 0$

$H_A: \rho_1 \neq \rho_2 \neq \rho_3 \ldots \neq \rho_k \neq 0$

By using Ljung and Box(1978) below

$s = n^2 \sum_{k=0}^{K} (n-k)^{-1} (r_k)^2$ (15)

Wheren: is the smaller of the number of observation for $\hat{a}_t$ or $\hat{\alpha}_t$

$s \sim \chi^2$ for degree of freedom (K+1-m)

m: is the number of parameters estimated in the transfer function part of the DR model. If the critical value less than the χ^2 for degree of freedom (K+1-m), we accepted the H_0 .it means that the two series $\hat{a}_t$ and $\hat{\alpha}_t$ are independent.

b) Autocorrelation Check

we also check the adequacy of the ARIMA model for the disturbance series in the DR model by examine autocorrelation and partial autocorrelation of series $\hat{a}_t$ we test the null hypothesis

$H_o: \rho_k = 0$

$H_A: \rho_k \neq 0$ k=1,2,3,…K

Wrong transfer function model will also tend to produce significant residual autocorrelations, even if the disturbance ARIMA model is correct. We may also perform a joint test with the null hypothesis

$H_o: \rho_0(a) = \rho_1(a) = \rho_2(a) = \rho_3(a) = \ldots = \rho_k(a) = 0$

$H_A: \rho_0(a) \neq \rho_1(a) \neq \rho_2(a) \neq \rho_3(a) \ldots \neq \rho_k(a) \neq 0$

The test statistic proposed by Ljung and Box(1978) is

$Q^* = n(n+2)\sum_{k=1}^{K}(n-k)^{-1} r_k^2(\hat{a})$

Under the null hypothesis Q^* is approximately χ^2 distributed with K-m degrees of freedom, where m is the total number of parameters estimated in the disturbance ARIMA model. After calculate theCritical value we compare it with the tabulated value if Critical value is less than the tabulated value it means that the good model.

1-10 forecasting [1] ,[6]

We explain how forecasts of future value of Y_t are produced from the following DR model with M=1 input:

$$Y_t = \frac{w(B)B^b}{\delta(B)} X_t + \frac{\theta_N(B)}{\varphi_N(B)} a_t \qquad (16)$$

Now equation(16) may be written

$\delta^*(B)\, Y_t = w^*(B)\, X_{t-b} + \theta^*(B)\, a_t$

where

$\delta^*(B) = 1 - \delta^*_1 B - \ldots - \delta^*_{p+q+r} B^{p+q+r} = \delta(B)\nabla^d \varphi(B)$ (17)

$w^*(B) = w_0 + w_1^* B + \cdots + w^*_{p+d+h} B^{p+d+h} = \nabla^d \varphi(B) w(B)$

$\theta^*(B) = 1 - \theta_1^* B - \cdots - \theta^*_{q+r} B^{q+r} = \delta(B)\theta(B)$

Suppose the current time period from which forecasts are to be made is period t=n called the forecast origin. suppose also that we want to forecasts the future value Y_{n+I} , where $I \geq 1$ is called the forecast lead time. Using (17) write the value for Y_{n+I} as

$Y_{n+I} = \delta_1^* Y_{n+I-1} + \cdots + \delta^*_{p+d+r} Y_{n+I-p-d-r} + w_0^* X_{n+I-b} + \ldots + w^*_{p+d+h} X_{n+I-b-p-d-h} - \theta_1^* a_{n+I-1} - \cdots - \theta^*_{q+r} a_{n+I-q-r} + a_{n+I}$ (18)

Forecasts are made using only information available through the forecast origin t=n. denote the information in the set of data available at time n(Y_n , Y_{n-1} ,…,X_n, X_{n-1},…) as I_n. the forecast of Y_{n+I} given I_n. denoted a conditional expectation with square brackets. The from (18) the DR model forecast of Y_{n+I} is

$\hat{Y}_n(I) = E(Y_{n+I} \mid I_n) = [Y_{n+I}] = \delta^*_1[Y_{n+I-1}] + \ldots + \delta^*_{p+q+r}[Y_{n+I-p-d-r}] + w_0^*[X_{n+I-b}] + \ldots + w^*_{p+d+h}[X_{n+I-b-p-d-h}] - \theta_1^*[a_{n+I-1}] - \cdots - \theta^*_{q+r}[a_{n+I-q-r}] + [a_{n+I}]$ (19)

The value of $[Y_{n+j}]$ and $[X_{n+j}]$ for $j \leq 0$ are the observed values of each series. Similar the value of $[a_{n+j}]$ for $j \leq 0$ are estimated by the residuals $(\hat{a}_{n+j})$ of the DR model. On the other hand, the value of $[Y_{n+j}]$ and $[X_{n+j}]$ for $j > 0$

Are their forecasts $\hat{Y}_n(j)$ and $\hat{X}_n(j)$, which are their respective condition expected values. And for $j > 0$,$[a_{n+j}]$ =0: At time n we have no estimate of a_{n+j} in the form of the DR model residual$\hat{a}_{n+j}$, so its expected value is zero.

If the DR model in rational form has a constant term we compute the forecast as:

F = C(1-$\sum_{i=1}^{p} \varphi_i\big)\big(1-\sum_{i=1}^{p} \varphi_{is}\big)\big(1-\sum_{i=1}^{r1} \delta_{i1}\big) \dots (1-\sum_{i=1}^{rm} \delta_{im}) \dots$ (20)

(1.11) forecast error variance[1],[6]

To find the variance of the forecast errors, we first write the ARIMA model for X_t

$$X_t = [\theta_x(B)/\nabla^{dx}\emptyset_x(B)] \quad (21)$$

Use (21) to substitute for X_t in (16) we obtain

$$Y_t = \eta(B)\alpha_t + \psi(B)a_t \quad (22)$$

where

$$\eta(B) = \eta_0 + \eta_1 B + \eta_2 B^2 + \cdots = \omega(B)\theta_x(B)B^b/\delta(B)\nabla^d \emptyset_s(B)$$

and

$$\psi(B) = \psi_0 + \psi_1 B + \psi_2 B^2 + \cdots = \theta(B)/\nabla^d \emptyset(B)$$

where $\psi_0 = 1$

Both $\eta(B)$ and$\psi(B)$ may be of infinitely high order. Using the definition of (B) , the η weights are found by equating coefficients of like powers of B on either side of this expression:

$$\delta(B)\nabla^d\emptyset_s(B)\eta(B) = \omega(B)\theta_x(B)B^b \quad (23)$$

Similarly, using the definition of (B) , the ψ weights are found by equating coefficients of like power of B on either side of this expression:

$$\nabla^d\emptyset\big(B\psi(B)\big) = \theta(B) \quad (24)$$

Now use (22) to write the future value Y_{n+I} , where t=n is the forecast origin, as

$$Y_{n+I} = \eta_0\alpha_{n+I} + \eta_1\alpha_{n+I-1} + \eta_2\alpha_{n+I-2} + \cdots + a_{n+I} + \psi_1 a_{n\pm I-1} + \psi_2 a_{n\pm I-2} + \cdots \quad (25)$$

The forecast of Y_{n+I} is

$$\hat{Y}_n(I) = [Y_{n+I}] = \eta_I\alpha_n + \eta_{I+1}\alpha_{n-1} + \cdots + \psi_I a_n + \psi_{I+1}a_{n-1} + \cdots \quad (26)$$

That is, any a_t or α_t value for t > n is neither known nor estimated from a model residual, given the data available through t = n. The expected value of these terms is zero;(26) shows the remaining nonzero terms. The lead I forecast error from origin n is

$$e_n(I) = Y_{n+I} - \hat{Y}_n(I)$$

thus, subtracting (26) from (25) gives the forecast error

$$e_n(I)=\eta_0\alpha_{n+1} + \eta_I\alpha_{n+I-1} + \cdots + \eta_{I-1}\alpha_{n+I} + \alpha_{n+I} + \psi_I a_{n+I-1} + \cdots + \psi_{I-1}a_{n+1} \quad (27)$$

The forecast error variance for lead I from origin n is the mathematical expectation

$V(I) = E[e_n(I)]^2$.

2-1 Wherethe expected value of the forecast error is zero. Therefore squaring (27) and taking expected values gives **preparation and prewhitening of the inputs and outputs series**

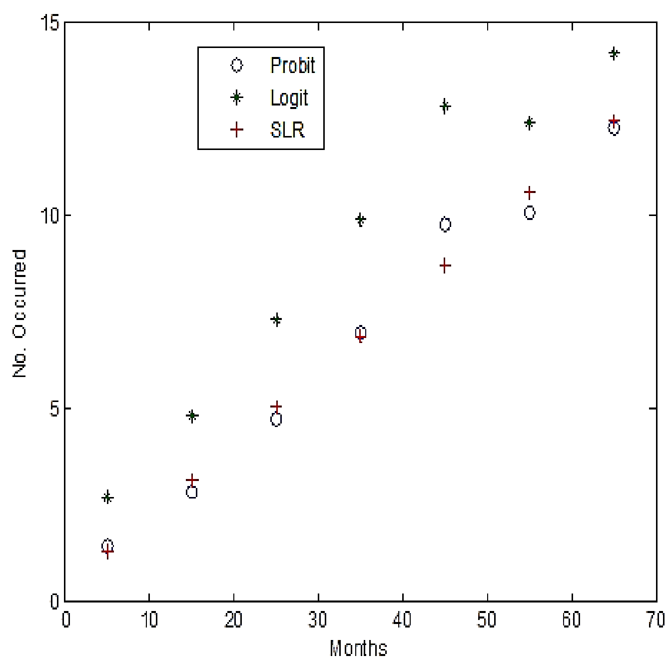
1)cross-correlation between output RH(Y_t) and input rainfall (X_t). we plot the time series of it by using software of Minitab (13.2) as in figures(1),(2) respectively we show that the series is stationary in mean and variance

$$V(I) = \sigma_\alpha^2 \sum_{j=0}^{I-1}\eta_j^2 + \sigma_\alpha^2 \sum_{j=0}^{I-1}\eta_j^2 \quad (28)$$

In finding this result we use the fact that a_t and α_t are mutually independent and not auto correlated.

2) APPLICATION

This section contains applying section two. The first method is testing of cross-correlation function between prewhitening of the input denoted by rainfall and of the output denoted by humidity (RH). We take the monthly average of the meteorological station of Duhok for the period (1992) to (2006), all data are shown in the tables(1) in the appendix (A). The second method is it used to test χ^2between two series of input and output by using equation.



Figure(1):the time series plot of(RH)

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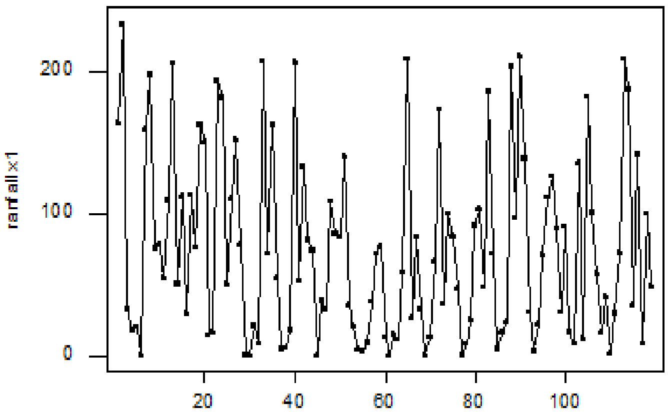
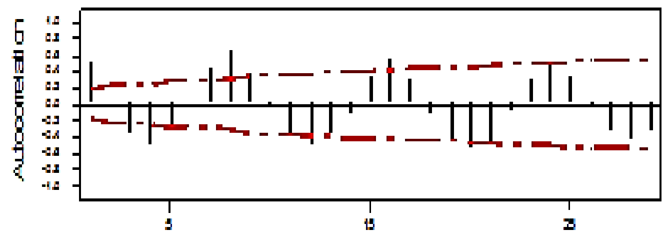
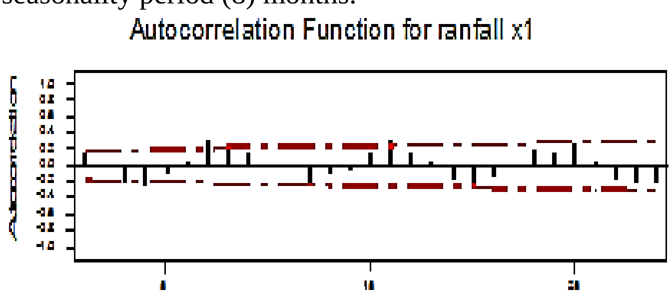


Figure(2):the time series plot of rainfall



Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T		Lag	Corr	T	LBQ
1	0.53	5.77	34.15	10	-0.05	-0.28	191.84	19	-0.41	-1.81	352.49	28	-0.42	-1.57	552.67
2	0.05	0.47	34.50	11	-0.40	-2.16	212.95	20	-0.54	-2.32	405.15	29	-0.32	-1.15	565.79
3	-0.33	-2.90	48.28	12	-0.49	-2.57	245.45	21	-0.44	-1.78	432.99				
4	-0.51	-4.14	80.45	13	-0.37	-1.81	263.59	22	-0.07	-0.28	433.72				
5	-0.32	-2.33	92.72	14	-0.10	-0.46	264.84	23	0.32	1.28	445.77				
6	0.00	0.01	92.72	15	0.33	1.55	279.74	24	0.52	2.05	480.27				
7	0.44	3.02	115.40	16	0.55	2.60	321.90	25	0.34	1.28	507.65				
8	0.65	4.21	171.27	17	0.32	1.43	335.28	26	-0.04	-0.16	507.94				
9	0.36	2.04	191.49	18	-0.11	-0.45	337.97	27	-0.32	-1.21	521.34				

We plot (Autocorrelation function) ACF for the RH and rainfall series in figures (3),(4) we show that the seasonality period (8) months.



Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ
1	0.17	1.83	3.33	10	-0.00	-0.04	44.84	19	-0.18	-1.38	78.27	28	-0.30	-1.38	122.42
2	-0.00	-0.08	3.34	11	-0.03	-0.27	44.98	20	-0.22	-1.64	83.39	29	-0.31	-1.38	128.18
3	-0.33	-3.40	9.88	12	-0.21	-1.77	47.88	21	-0.18	-1.07	88.88				
4	-0.27	-2.71	18.81	13	-0.09	-0.77	48.03	22	0.01	0.08	88.80				
5	-0.08	-0.87	19.88	14	-0.07	-0.88	48.87	23	0.21	1.81	93.30				
6	0.04	0.41	19.91	15	0.17	1.38	83.48	24	0.18	1.14	97.13				
7	0.32	3.03	33.04	16	0.33	2.81	68.08	25	0.39	2.08	110.31				
8	0.31	1.88	38.74	17	0.18	1.14	71.33	26	0.03	0.19	110.43				
9	0.18	1.31	41.30	18	0.03	0.24	71.37	27	-0.19	-1.28	118.83				

Figure(4):(Autocorrelation function) ACF for rainfall (4)

We take first difference for the data as shown in the figures(5),(6) and plot ACF again for the differenced time series about rainfall and (PACF) in a figures(7),(8).

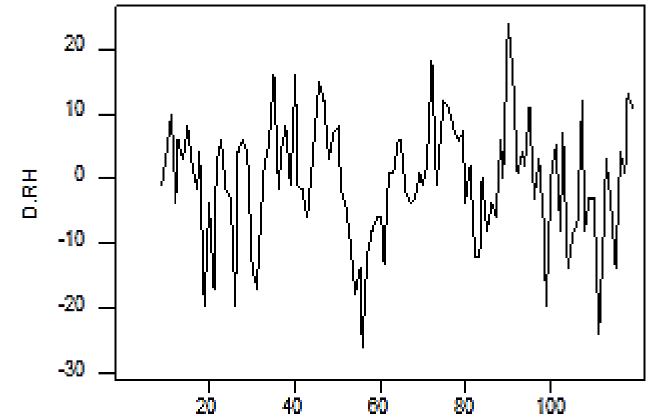
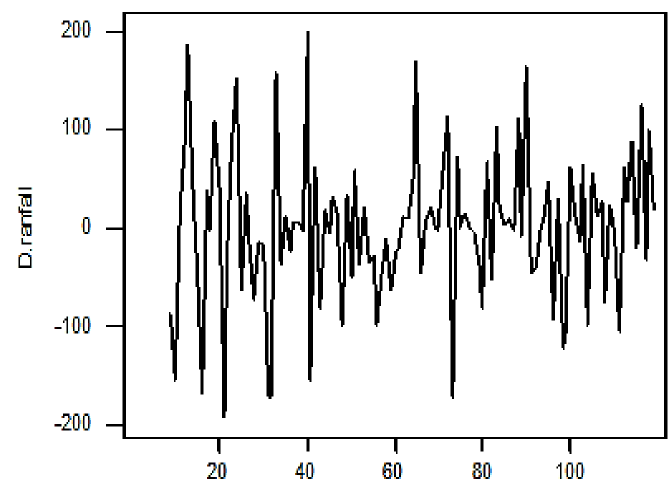
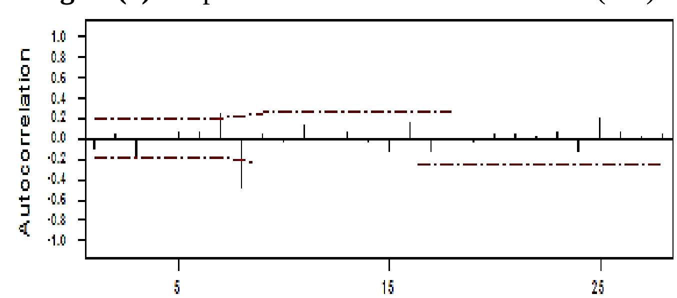


Figure (5): the plot for differenced timeseries of(rainfall)

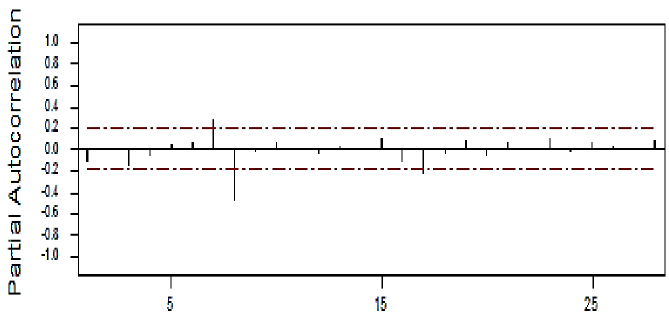


Figure(6):the plot for differenced time series of(RH)



Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ
1	-0.12	-1.28	1.67	10	-0.06	-0.46	46.43	19	-0.04	-0.31	58.20	28	0.03	0.21	68.49
2	0.03	0.30	1.77	11	0.14	1.08	48.76	20	0.03	0.20	58.30				
3	-0.18	-1.88	5.58	12	-0.01	-0.05	48.77	21	0.03	0.26	58.46				
4	-0.02	-0.24	5.65	13	0.05	0.39	49.09	22	0.01	0.08	58.48				
5	0.05	0.49	5.94	14	-0.05	-0.37	49.37	23	0.08	0.57	59.29				
6	0.07	0.75	6.60	15	-0.14	-1.11	51.99	24	-0.14	-1.08	62.26				
7	0.25	2.50	14.12	16	0.15	1.19	55.10	25	0.20	1.48	67.96				
8	-0.51	-4.84	45.90	17	-0.15	-1.12	57.97	26	0.05	0.37	68.35				
9	0.03	0.25	46.01	18	0.00	0.02	57.97	27	0.01	0.06	68.36				

Figure (7): (Autocorrelation function) ACF for differenced time series of(rainfall)



Lag	PAC	T	Lag	PAC	T	Lag	PAC	T	Lag	PAC	T
1	-0.12	-1.28	10	0.07	0.75	19	0.09	0.96	28	0.08	0.83
2	0.01	0.16	11	-0.01	-0.15	20	-0.07	-0.71			
3	-0.18	-1.88	12	-0.06	-0.63	21	0.07	0.78			
4	-0.07	-0.73	13	0.03	0.29	22	-0.00	-0.00			
5	0.04	0.46	14	0.01	0.12	23	0.10	1.04			
6	0.06	0.60	15	0.10	1.10	24	-0.03	-0.33			
7	0.26	2.78	16	-0.13	-1.33	25	0.06	0.66			
8	-0.49	-5.14	17	-0.25	-2.62	26	0.03	0.32			
9	-0.04	-0.38	18	-0.05	-0.56	27	-0.02	-0.16			

Figure (8): (PACF)differenced time series of(rainfall)

The figures (7) and (8) suggest that the tentative model for the differenced series is ARMA(1,1) as shown in the equation below:

$$(1-\phi B)X_t = (1-\theta B)\alpha_t$$

$$X_t - \phi X_{t-1} = \alpha_t - \theta\alpha_{t-1}$$

$$\alpha_t = X_t - \phi X_{t-1} + \theta\alpha_{t-1}$$

$\alpha_1 = X_1$ where $X_0 = 0$

The researcher writes the program through the use of macro within Minitab just as program (1) in the ppendix (B).we can find the results of series($\hat{\alpha_t}$) are the same as in the table (1).

Table(1) :the values of ($\hat{\alpha_t}$) variable input (rainfall) with (ϕ =0.7955)and (θ =0.9142)

t	$\hat{\alpha_t}$	t	$\hat{\alpha_t}$	t	$\hat{\alpha_t}$	t	$\hat{\alpha_t}$	t	$\hat{\alpha_t}$	T	$\hat{\alpha_t}$
1	-88.000	21	-15.491	41	20.914	61	3.090	81	13.621	101	17.454
2	-166.95	22	-19.263	42	-57.810	62	0.825	82	181.321	102	-10.213
3	-6.126	23	-177.78	43	45.285	63	57.945	83	-11.341	103	-110.586
4	68.599	24	-199.08	44	-43.399	64	124.244	84	-14.421	104	44.623
5	176.766	25	114.991	45	11.351	65	-151.397	85	19.309	105	18.369
6	63.841	26	-60.162	46	-40.951	66	73.494	86	23.930	106	83.730
7	-29.107	27	-12.916	47	-39.515	67	8.862	87	64.763	107	-14.519
8	-158.20	28	-44.079	48	-111.860	68	21.545	88	-71.480	108	130.171
9	26.933	29	-16.623	49	-71.630	69	8.559	89	38.555	109	-14.929
10	-6.771	30	-13.595	50	-38.523	70	3.025	90	-110.418	110	111.542
11	104.042	31	-20.304	51	-88.810	71	-35.216	91	-113.352	111	42.656
12	49.465	32	183.923	52	-54.554	72	-81.143	92	43.921		
13	-180.41	33	-146.21	53	-52.158	73	58.409	93	5.146		
14	-46.325	34	52.027	54	-20.257	74	-52.560	94	-19.396		
14	-46.325	34	52.027	54	-20.257	74	-52.560	94	-19.396		
16	148.764	36	8.166	56	25.589	76	31.220	96	-98.705		
17	-48.434	37	-12.367	57	155.796	77	13.113	97	45.794		
18	40.497	38	25.794	58	-39.659	78	16.667	98	8.398		

19	-1.822	39	12.152	59	6.239	79	7.493	99	25.509		
20	-64.697	40	-99.762	60	21.392	80	120.885	100	-73.079		

by same method we can find the output series (RH) as below:

$$(1-\phi B)Y_t = (1-\theta B)\beta_t$$

$$Y_t - \phi Y_{t-1} = \beta_t - \theta\beta_{t-1}$$

$$\beta_t = Y_t - \phi Y_{t-1} + \theta\beta_{t-1}$$

$$\beta_1 = Y_1 \text{ where } Y_0 = 0$$

We can find the series ($\overset{\wedge}{\beta_t}$) by using program (2) in the appendix (B)

Table (2): values ($\overset{\wedge}{\beta_t}$) for output (RH)

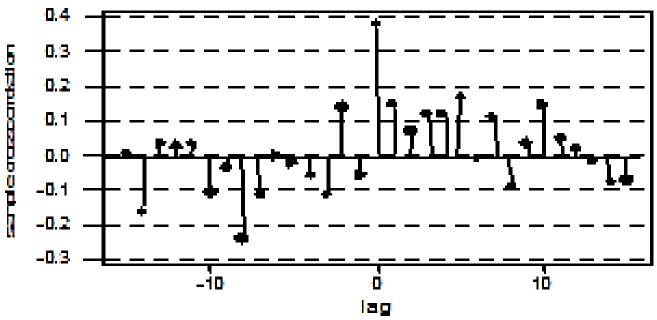
t	($\overset{\wedge}{\beta_t}$)	t	($\overset{\wedge}{\beta_t}$)	t	($\overset{\wedge}{\beta_t}$)	t	($\overset{\wedge}{\beta_t}$)	T	($\overset{\wedge}{\beta_t}$)	T	($\overset{\wedge}{\beta_t}$)
1	-1.0000	21	1.9371	41	11.5237	61	-2.7684	81	-0.8323	101	-4.9184
2	3.8813	22	-15.411	42	12.9664	62	-4.3263	82	23.2391	102	-5.1099
3	10.3663	23	-19.951	43	3.4899	63	-1.1596	83	19.1532	103	-26.2850
4	-2.4781	24	-14.717	44	0.7815	64	15.3489	84	4.9863	104	-12.9377
5	6.9165	25	-3.4988	45	-6.1036	65	-1.2871	85	7.7630	105	-2.4636
6	4.5500	26	0.2104	46	-15.6249	66	7.6189	86	5.9149	106	-8.6388
7	9.7732	27	12.2148	47	-13.9653	67	12.6012	87	14.8164	107	-18.7156
8	4.5706	28	-3.5612	48	-27.6301	68	12.9740	88	1.7947	108	-1.9728
9	0.5875	29	2.3354	49	-16.5764	69	11.1103	89	7.0272	109	-3.9855
10	6.1281	30	6.9530	50	-13.6081	70	9.7931	90	-2.9622	110	8.5610
11	-17.579	31	-1.0076	51	-12.0766	71	11.1798	91	-17.1396	111	8.4849
12	-4.1614	32	15.8744	52	-12.2674	72	0.6521	92	0.2410		
13	-17.622	33	0.7843	53	-19.4418	73	5.7781	93	5.2203		
14	-0.5868	34	-0.4875	54	-6.4322	74	-8.3086	94	-7.2051		
15	3.8725	35	-4.8546	55	-5.6759	75	-10.0498	95	6.7771		
16	-3.2328	36	2.3349	56	0.0156	76	0.3585	96	-13.3729		
17	-4.3644	37	11.5436	57	1.2413	77	-7.6722	97	-10.0885		
18	-21.603	38	16.8026	58	-5.6382	78	-4.6500	98	-9.0634		
19	0.1602	39	15.4285	59	-7.5635	79	-7.0690	99	9.2828		
20	2.9644	40	7.5587	60	-6.7325	80	4.3105	100	-9.0597		

1) correlation coefficient between ($\overset{\wedge}{\alpha_t}$)and ($\overset{\wedge}{\beta_t}$) by using equation (1) we can find the values of correlation coefficient in the table (3)

Table (3): the values of correlation coefficient between ($\overset{\wedge}{\alpha_t}$) and ($\overset{\wedge}{\beta_t}$)

t	$r_{\alpha\beta}$	T	$r_{\alpha\beta}$	t	$r_{\alpha\beta}$	T	$r_{\alpha\beta}$
0	0.378	6	-0.004	12	0.025	18	-0.214
1	0.147	7	0.110	13	-0.011	19	-0.135
2	0.068	8	-0.090	14	-0.078	20	-0.062
3	0.122	9	0.038	15	-0.071	21	

4	0.118	10	0.148	16	-0.019	22	
5	0.171	11	0.048	17	-0.128	23	



Figure(9): correlation coefficient between ($\hat{\alpha_t}$) and ($\hat{\beta_t}$) determines the dead time for input(RH).It is clear from the figure (9) that the dead time is (b=0) close to zero which explains $\rho_{\alpha\beta}(0) \neq 0$ significant and all of values near to zero, we can say that there is feedback between output series (Y_t) and input (X_t). We find ACF between residual series and series ($\hat{\alpha_t}$).we can clear that below.

2) identification

2.1- estimation of the impulse response weights

We estimate of the impulse response weights between input (X_t) and output series (Y_t) in the table (4) below.

Table (4): the values of the impulse response of input variable (rainfall X_t)

t	V	T	v	t	V	t	v
0	0.0499	6	-0.0005	12	0.0033	18	-0.0282
1	0.0194	7	0.0145	13	-0.0014	19	-0.0178
2	0.0089	8	-0.01188	14	-0.0103	20	-0.00819
3	0.0161	9	0.0050	15	-0.0093	21	
4	0.01558	10	0.0195	16	-0.0025	22	
5	0.0225	11	0.00634	17	-0.0169	23	

2)identification of (r,s,b) for the transfer function

It is clear from the figure (9) taking one change point will continue toward itself for a few periods(s=5). It transfer to the other side thus than (r=1) .the pattern can be written as:

$$Y_t = \frac{(w_0 - w_1 B - w_2 B^2 - w_3 B^3 - w_4 B^4 - w_5 B^5)}{(1 - \delta_1 B)} X_t + N_t \quad (29)$$

3) disturbance series

We find disturbance series by using the equation

$$N_t = Y_t - v_0 X_t - v_1 X_{t-1} - \ldots - v_{20} X_{t-20} \quad (30)$$

By using equation (30) we can obtain the number of disturbance series which their values less than the input and output series values(t=21) so, we can apply them in program (3) in appendix(B) the values in the table (5).

Table(5) :estimate values of disturbance series N_t

t	$\hat{N_t}$	T	$\hat{N_t}$	T	$\hat{N_t}$	t	$\hat{N_t}$	t	$\hat{N_t}$
1	8.3067	19	8.4527	37	1.8966	55	-17.218	73	-27.8116
2	-13.3977	20	10.6442	38	11.867	56	11.4734	74	2.2931
3	-20.1134	21	-6.2558	39	-10.634	57	5.6367	5	-2.0726
4	0	22	-6.8021	40	6.6606	58	-7.2843	76	2.2749
5	-0.3655	23	4.6793	41	14.2883	59	-2.0547	77	-6.8147
6	13.8634	24	13.9806	42	-1.8847	60	-7.7965	78	14.2572
7	0.8759	25	-21.235	43	-3.686	61	-2.2512	79	-5.2206
8	24.6778	26	-12.021	44	-3.2112	62	8.8708	80	-3.3320
9	15.1076	27	-14.395	45	0.5373	63	28.049	81	-1.8584
10	1.3322	28	7.7617	46	1.8966	64	-9.6713	82	-11.5726
11	15.0231	29	2.2580	47	11.867	65	-10.100	83	7.4928
12	7.1083	30	-0.346	48	-12.615	66	8.5172	84	2.5678
13	3.5126	31	1.6847	49	-4.1235	67	-4.315	85	-19.049
14	-1.2732	32	-10.0583	50	7.4006	68	4.4084	86	-6.5645
15	11.7306	33	7.6015	51	1.6043	69	6.57	87	-0.8425
16	-16.373	34	2.5706	52	3.009	70	-14.985	88	5.2194
17	-4.3515	35	4.4363	53	4.5073	71	-11.229	89	5.5882
18	9.382	36	-7.8483	54	-5.3716	72	8.9425	90	-11.5726

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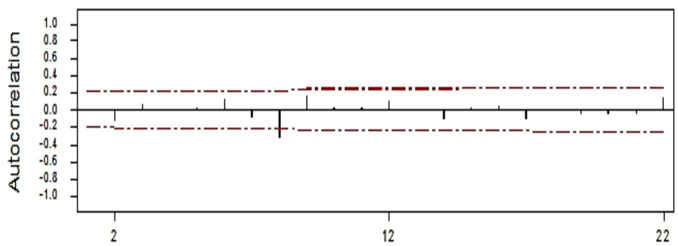
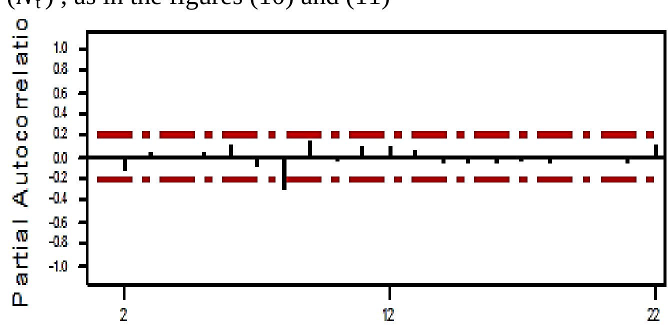
2013,(7), (3) :152-165



Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ
1	-0.02	-0.15	0.02	8	-0.32	-2.94	15.13	15	0.03	0.23	21.15	22	0.15	1.16	26.62
2	-0.13	-1.23	1.60	9	0.17	1.42	18.12	16	0.03	0.25	21.27				
3	0.05	0.51	1.88	10	0.01	0.11	18.14	17	-0.12	-0.98	22.97				
4	-0.00	-0.00	1.88	11	0.02	0.15	18.18	18	-0.01	-0.08	22.98				
5	0.02	0.21	1.93	12	0.11	0.89	19.45	19	-0.05	-0.43	23.32				
6	0.13	1.22	3.63	13	0.00	0.01	19.45	20	-0.06	-0.48	23.76				
7	-0.10	-0.88	4.55	14	-0.12	-0.98	21.06	21	-0.04	-0.32	23.97				

Figure (10): ACF and from the disturbance series ($\widehat{N}_t$)

We plot ACF and PACF from the disturbance series ($\widehat{N}_t$) , as in the figures (10) and (11)



Lag	PAC	T	Lag	PAC	T	Lag	PAC	T	Lag	PAC	T
1	-0.02	-0.15	8	-0.31	-2.93	15	-0.07	-0.70	22	0.11	1.07
2	-0.13	-1.23	9	0.14	1.36	16	-0.08	-0.78			
3	0.05	0.48	10	-0.05	-0.49	17	-0.05	-0.47			
4	-0.02	-0.15	11	0.09	0.84	18	-0.06	-0.58			
5	0.04	0.35	12	0.10	0.95	19	-0.00	-0.02			
6	0.13	1.23	13	0.06	0.53	20	0.02	0.17			
7	-0.09	-0.83	14	-0.07	-0.68	21	-0.08	-0.72			

Figure (11): PACF and from the disturbance series ($\widehat{N}_t^{\wedge}$)

It is clear from the figure(11) that the disturbance series ($\widehat{N}_t$) is equal residual series

$N_t = a_t$, thus the model of dynamic regression as shown in the equation below:

$$Y_t = \frac{(w_0 - w_1 B - w_2 B^2 - w_3 B^3 - w_4 B^4 - w_5 B^5)}{(1-\delta_1 B)} X_t + a_t \quad (31)$$

We estimate the values of the model by using equation (31)

By using table(4) we find

$v_0 = \delta_1 v_1 + w_0$ j =b

$v_0 = w_0$

$v_1 = \delta_1 v_0 - w_1$

$v_2 = \delta_1 v_1 - w_2$ j =b +1,…,b+s

$v_3 = \delta_1 v_2 - w_3$

$v_4 = \delta_1 v_3 - w_4$

$v_5 = \delta_1 v_4 - w_5$

$v_6 = \delta_1 v_5$

$\delta_1 = v_6 / v_5 = -0.0005/0.0225 = -0.222$

$w_0 = v_0 = 0.0499$

$w_1 = \delta_1 v_0 - v_1 = (-0.222)(0.0499) - (0.0194) = -0.0304778$

$w_2 = \delta_1 v_1 - v_2 = (-0.222)(0.0194) - (0.0089) = -0.0132066$

$w_3 = \delta_1 v_2 - v_3 = (-0.222)(0.0089) - (0.0161) = -0.01808$

$w_4 = \delta_1 v_3 - v_4 = (-0.222)(0.0161) - (0.01558) = -0.01915$

$w_5 = \delta_1 v_4 - v_5 = (-0.222)(0.01558) - (0.0225) = -0.025958$

Search to Minimize Sum of Squared Residuals

The next step in estimation is to compute the SSR (Sum of Squared Residuals).

$$SSR = \sum_{t=1}^{n} a_t^2$$

$$Y_t = \frac{(0.0499 + 0.0305B + 0.0132066B^2 + 0.01808B^3 + 0.01915B^4 + 0.02595B^5}{(1+0.222B)}$$

$\hat{a}_t = Y_t + 0.222Y_{t-1} - 0.0499\,X_t - 0.0305\,X_{t-1} - 0.0132066\,X_{t-2} - 0.01808\,X_{t-3} - 0.01915\,X_{t-4} - 0.02595\,X_{t-5} - 0222a_{t-}$ (32)

We find the values of series ($\hat{a}_t$) by using equation (32) and program (4) in appendix (B),The value as in the table(6).

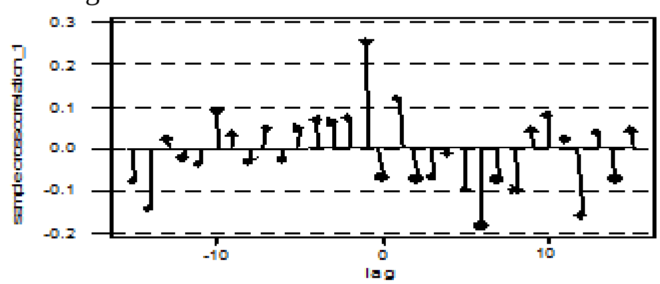
Table (6): the values of series ($\hat{a}_t$)

t	$\hat{a}_t$	t	$\hat{a}_t$	t	$\hat{a}_t$	t	$\hat{a}_t$	T	$\hat{a}_t$	T	$\hat{a}_t$
1	0.0000	20	-0.9160	39	-3.3955	58	1.1386	77	14.6687	96	-1.4370

2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0.7422	9.5889	4.9520	-3.4498	0.9387	-21.9821	-5.2100	-9.8956	4.5466	3.3031	-8.3265	-2.3224	-17.5623	2.1247	6.3294	3.7500	-12.1944	-11.5427
21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
1.6774	5.2860	19.1778	1.2919	5.5449	5.3637	0.0144	9.9616	0.5953	-1.6047	-6.0637	2.3747	8.6837	16.8753	10.2357	6.8976	6.9511	8.7745
40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57
-8.4087	-17.9861	-11.8717	-23.2960	-8.0296	-6.5819	-2.2575	-2.6486	-9.9744	2.2018	1.4054	5.6577	0.3474	-3.4559	-4.2761	-5.5386	-1.1261	-3.1218
59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76
13.2296	1.9000	8.1710	9.5838	10.0785	6.9647	8.3027	6.7636	-0.7813	1.2307	-11.0673	-13.1957	-1.6501	-7.6427	-5.8736	-6.2127	0.7505	-1.9606
78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95
2.0145	1.8387	1.2348	7.7183	0.3255	4.0698	-4.2324	-14.4481	-0.0109	5.9083	-6.6499	7.5821	-11.2824	-10.1545	-8.6454	11.4132	-6.8504	14.6687
97	98	99	100	101	102	103	104	105	106								
-4.4783	-20.4011	-8.0027	2.3374	-6.7431	-14.3211	1.3423	-2.1231	9.6593	6.6924								

4) Diagnostic Check

a) Residuals Cross Correlation function(RCCF) $r_{k(\widehat{a})}$.We plotcross correlation between series $(\hat{\alpha}_t)$ and series $(\hat{a}_t)$as in the figure (12), it is clear that there are significant values, this means that the correlation between two series $(\hat{\alpha}_t)$ and series $(\hat{a}_t)$ is significant.



Figure(12):cross correlation between series $(\hat{\alpha}_t)$ and series $(\hat{a}_t)$

By using Ljung and Box(1978) below

$$s = n^2 \sum_{k=0}^{K}(n-k)^{-1}(r_k)^2 = 8.1$$

This value is less than the χ^2 critical value (11.07) for K+1-m=10+1-6=5 degrees of freedom at the 5% level. Therefore we do not reject the stated H_0.

b) Autocorrelation Check

The test statistic proposed by Ljung and Box(1978) is

$$Q^* = n\,(n+2)\sum_{k=1}^{K}(n-k)^{-1}\, r_k^2(\hat{a}) = 11.9$$

this value is less than the χ^2 critical value (37.65) for K - m=26-1= 25 degrees of freedom at the 5% level. Therefore we do not reject the stated H_0.

4)Forecasting

We explain how forecasts of future value of Y_t are produced from the following DR model with equation below

$y_t = \delta_1^* y_{t-1} + w_0x_t - w_1x_{t-1} - w_2x_{t-2} - w_3x_{t-3} - w_4x_{t-4} - w_5x_{t-5} + a_t$

the forecast is

$\hat{y}_n(I) = \delta_1^* [y_n] + w_0[x_{n+1}] - w_1[x_n] - w_2 [x_{n-1}] - w_3 [x_{n-2}] - w_4 [x_{n-3}] - w_5 [x_{n-4}] + a_{n+1}$

$\delta_1^* = 1+\delta_1$ =1-0222 Where t=n = 119

for I = 1, the forecast is

$\hat{y}_{119}(1) =$
$0.778[y_{119}]+0.0499[x_{120}]+0.0304778[x_{119}]+0.0132066[x_{118}]+0.01808[x_{117}]$
$+0.01915[x_{116}]+0.025958[x_{115}] + a_{120}$

Therefore squaring (29) and taking expected values gives

$V(I) = \sigma_\alpha^2 \sum_{j=0}^{I-1} \eta_j^2 + \sigma_a^2 \sum_{j=0}^{I-1} \eta_j^2$

$\eta(B) = \eta_0 + \eta_1 B + \eta_2 B^2 + \cdots$
$= \omega(B)\theta_x(B)B^b/\delta(B)\nabla^d \emptyset_s(B)$

$\eta_0 = w_0 = 0.0499$

$\eta_1 = w_1 = -0.0304778$

$V(I) = \sigma_\alpha^2 \sum_{j=0}^{I-1} \eta_j^2 + 0$

$\sigma_\alpha^2 = 5433.89$

$V(I) = \sigma_\alpha^2 \eta_0^2 = 13.53$

SE= 3.6

$V(2) = \sigma_\alpha^2(\eta_0^2 + \eta_1^2) = 18.577$

SE = 4.31

The forecast for x_t is

$X_{t+I} = \alpha_{t+I} - \theta\alpha_{t+I-1} + \emptyset X_{t+I-1}$

$X_{t+I} = \alpha_{t+I} - 0.9142\alpha_{t+I-1} + 0.7955X_{t+I-1}$

And The forecast for Y_t is

$Y_{t+I} = \beta_{t+I} - \theta\beta_{t+I-1} + \emptyset Y_{t+I-1}$

$Y_{t-I} = \beta_{t+I} - 0.9142\beta_{t+I-1} + 0.7955Y_{t+I-1}$

Table (7): forecasting X_{t+I} and Y_{t+I} and Dynamic regression

time	time	Actual X_t	Forecasting X_t	Actual Y_t	Forecasting Y_t	Forecasting dynamic y_t
2006.	Jan.	72.9	101.463	66	60.6535	41.3421
	Feb.	209.3	100.494	60	63.6289	53.2040
	Mar.	188.6	92.162	47	61.5696	69.7538
	Apr.	35.9	94.081	56	55.4739	58.9298
	May.	142.6	49.055	40	54.4772	53.2323
	Oct.	8.2	9.542	44	37.8449	58.1119
	Nov.	100.4	4.061	55	38.1801	47.9720
	Des.	48.9	58.028		53.0353	48.0064
2006 /2007	Des.		90.406	55	62.9801	53.9366
	Jan.		106.214	61	65.3804	63.3803
	Feb.		91.721	65	63.0423	62.9003
	Mar.		88.656	56	56.8185	62.8561
	Apr.		44.103	57	54.7555	55.2476
	May.		11.214	43	38.2354	51.7219
	Oct.		2.226	40	37.6134	36.9045
	Nov.		53.536	59	52.1672	37.0295
	Des.		87.022	59	62.6513	49.9403

Conclusion

1) ACF for the RH and rainfall series , we show that the seasonality period (8) months, we. suggest that the tentative model for the differenced series is ARMA(1,1)
2) After using cross- correlation between series ($\hat{\alpha}_t$) and series ($\hat{a}_t$), it is clear that there are significant values, which mean that the correlation between the two series ($\hat{\alpha}_t$) and series ($\hat{a}_t$) is significant, this is special case in dynamic regression.
3) to examine the value is less than the χ^2 critical value (37.65) for K - m=26-1= 25 degrees of freedom at the 5% level. Therefore we do not reject the stated H_0.

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Appendix (A)

monthly average of the humidity and rainfall of the meteorological station of Dohuk for the period (1992) to (2006)

Year	Month	humidity	rainfall	year	month	RH	rainfall	year	month	RH	rainfall
1992	Jan.	72	164.0	1997	Jan.	67	53.0	2002	Jan.	69	103.8
	Feb.	69	234.7		Feb.	60	133.7		Feb.	54	48.0
	Mar.	60	32.8		Mar.	64	82.0		Mar.	52	186.8
	Apr.	63	18.2		Apr.	61	74.5		Apr.	59	72.1
	May.	47	19.8		May.	55	0.5		May.	33	4.3
	Oct.	42	0.0		Oct.	56	39.1		Oct.	40	16.1
	Nov.	52	159.9		Nov.	60	33.0		Nov.	50	23.7
	Des.	66	198.4		Des.	75	108.8		Des.	75	204.9
1993	Jan.	71	76.0	1998	Jan.	74	86.6	2003	Jan.	69	96.8
	Feb.	73	78.2		Feb.	68	83.5		Feb.	78	211.3
	Mar.	70	54.8		Mar.	62	140.2		Mar.	69	139.6
	Apr.	59	109.9		Apr.	57	36.0		Apr.	60	30.5
	May.	53	206.8		May.	45	20.9		May.	37	3.7
	Oct.	45	51.0		Oct.	38	4.0		Oct.	42	21.9
	Nov.	60	113.0		Nov.	46	3.0		Nov.	61	71.2
	Des.	68	29.5		Des.	49	9.2		Des.	72	112.0
1994	Jan.	69	113.2	1999	Jan.	62	38.0	2004	Jan.	72	126.8
	Feb.	77	76.4		Feb.	60	71.8		Feb.	71	89.5
	Mar.	50	163.6		Mar.	56	77.3		Mar.	49	30.3
	Apr.	55	150.8		Apr.	51	12.6		Apr.	60	91.1
	May.	36	13.7		May.	32	0.0		May.	42	16.9
	Oct.	47	16.0		Oct.	39	14.8		Oct.	34	8.3
	Nov.	66	194.1		Nov.	47	11.2		Nov.	68	136.2
	Des.	66	181.9		Des.	55	58.6		Des.	58	11.9
1995	Jan.	66	51.0	2000	Jan.	68	209.7	2005	Jan.	63	183.2
	Feb.	57	110.9		Feb.	58	26.3		Feb.	64	100.9
	Mar.	54	152.2		Mar.	52	83.6		Mar.	61	57.2
	Apr.	61	78.7		Apr.	48	33.3		Apr.	52	16.1
	May.	40	0.0		May.	33	0.0		May.	39	41.5
	Oct.	33	0.0		Oct.	38	12.8		Oct.	31	1.7
	Nov.	49	21.2		Nov.	49	66.8		Nov.	44	29.7
	Des.	56	7.8		Des.	73	174.1		Des.	50	72.9
1996	Jan.	68	218.5	2001	Jan.	67	36.6	2006	Jan.	66	219.3
	Feb.	62	71.7		Feb.	66	100.5		Feb.	60	188.6
	Mar.	70	163.1		Mar.	64	84.3		Mar.	47	35.9
	Apr.	59	55.1		Apr.	59	47.3		Apr.	56	142.6
	May.	44	4.9		May.	41	0.0		May.	40	8.2
	Oct.	41	5.5		Oct.	44	8.0		Oct.	44	100.4
	Nov.	40	17.7		Nov.	56	25.0		Nov.	55	48.9
	Des.	72	207.5		Des.	69	91.9		Des.		

Appendix (B)

The software Minitab(13.2) is used in the following macro programs.

Program (1): the values of ($\hat{\alpha}_t$) variable input (rainfall)

```
gmacro
aa.macro
let c4(1)=-88
do k3=2:111
let c4(k3)=c2(k3)- 0.7955*c2(k3-1)+
0.9142*c4(k3-1)
enddo
endmacro
```

Program (2): values ($\hat{\beta}_t$) for output (RH)

```
gmacro
aa.macro
let c5(1)=-1
do k3=2:111
let c5(k3)=c1(k3)- 0.7955*c1(k3-1)+
0.9142*c5(k3-1)
enddo
endmacro
```

Program (3): estimate values of disturbance series N_t by using matlab program

```
For i=1:111
For k=1:21
Z(I,k)= v(k)*ul(i+21)-k);
end;
end
for i=1:111
s(i)=0;
for j=1:21
s(i)=s(i)-z(i,j);
end
end
for i=22:111
n(i)=y(i)+s(i-20)
end
```

program (4): the values of series ($\hat{a}_t$)

```
gmacro
aa.macro
let c3(5)=0
do k1=6:111
let c3(k1)=c1(k1)+ 0.222*c1(k1-1)-
0.0499*c2(k1)-0.0304778*c2(k1-1)-
0.0132066*c2(k1-2)- 0.01808*c2(k1-3)-
0.01915*c2(k1-4)- 0.025958*c2(k1-5)-
0.222*c3(k1-1)
enddo
let k4=sum(c3(k1)**2)
print k4
endmacro
```

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الخلاصة

يتضمن هذا البحث تطبيقات على بعض التقنيات الاحصائية لدراسة السلسلة الزمنية لمعدلات الرطوبة الشهرية كسلسلة مخرجات مع احد المتغيرات التي تؤثر عليها وهو سلسة معدلات الامطار الشهرية التي تم قياسها في محطة دهوك للانواء الجوية والتقنيات التي استخدمت هي نموذج ARIMA والنمذجة بالانحدار الحركي . وبذلك يكون نموذج الانحدار الحركي التام المختار ملائماً لايجاد القيم التنبوئية للقيم المستقبلية.