

Forecasting rainfall using transfer function

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ABSTRACT

This research includes the application of some statistical techniques for studying the time series of the average monthly rainfall as an output series with two of the variables which affect on to, which are the series of the average monthly relative temperature and humidity as an input which is measured at the meteorological station of Ninawah. 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.

KEYWORDS: *Output, series, input, ARIMA, dynamic, regression, forecasting.*

التكهن بالأمطار باستخدام الدالة التحويلية

الملخص

يتضمن هذا البحث تطبيق لبعض التقنيات الاحصائية في دراسة السلسلة الزمنية لمعدلات الامطار الشهرية كسلسلة مخرجات مع سلسلتى المدخلات التي تؤثر فيها وهما سلسلة معدلات الرطوبة الشهرية ودرجة الحرارة التي تم قياسها في محطة نينوى للانواء الجوية باستخدام الانحدار الحركي . حصل الباحث على هذا الاستنتاج وهو ان يكون نموذج الانحدار الحركي التام المختار ملائماً لايجاد القيم التنبؤية للقيم المستقبلية.

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INTRODUCTION

The series of the rainfall and relative temperature and humidity were examined and determined that they were stationary in the mean and the variance, also both the autocorrelation and partial autocorrelation function were studied for the rainfall and relative temperature and humidity series and determined that there is an observed correlation for these phenomena; therefore, a suitable model was determined there three series from order AR(1). Relative to the dynamic regression models (it is that model which takes the time into account) is the modeling of the dynamic regression which shows how that output results 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 autocorrelation for the residuals series (α_t) by the statistical test shows that all values were insignificant and it is prove that the turbulence series (α_t).

1- Dynamic Regression (DR)

1.1 transfer function:[1],[3],[7]

For simplicity we will discuss just one input. The ideas we develop here are easily extended to

multiple inputs if Y_t depends on X_t in some way we may write this as

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

Where $f(\cdot)$ is some mathematical function. The function $f(\cdot)$ 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 $f(\cdot)$. In general,

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 autocorrelated.

N_t represents the effects of all excluded inputs on the variability of Y_t . The input – output

relationship may also have an additive 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

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

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 autocorrelated and it is assumed to be independent of X_t

Input X_t \rightarrow N_t output

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

1-2 IMPULSE RESPONSE FUNCTION:[6],[7]

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

$$v(B) = v_0 + v_1 B + v_2 B^2 + v_3 B^3 + \dots \quad (3)$$

Where B is the backshift operator defined such that

$$B^k X_t = X_{t-k}$$

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

$$Y_t = f(X_t) = v_0 X_t + v_1 X_{t-1} + v_2 X_{t-2} + v_3 X_{t-3} + \dots \quad (4)$$

Using equation (3),(4) may be rewritten as

$$Y_t = v(B) X_t \quad (5)$$

Equation (5) is a compact way of saying that there is a linearly distributed lag relationship between change in X_t and changes in Y_t . The individual v_k weights in $v(B)$, ($v_0, v_1, v_2, v_3, \dots$) are called the impulse response weights, we can estimate that the v_k weights as follows

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

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:[6],[7]

Y_t might not react immediately to a change in X_t , some initial v weights may be zero. The number of v weights equal to zero (starting with v_0) is called dead time denoted as b , starting with v_0 , if 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:[2],[6],[7]

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

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

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

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

Where h : represents the order of (w)

r : represents the order of (δ)

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

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

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

(10)

1-5 BUILDING DYNAMIC REGRESSION MODELS (DR).[4],[6],[7].

A Dynamic Regression (DR) model with two inputs consists of a transfer function plus

a disturbance. This may be written as

$$Y_t = c + v_1(B)X_{1,t} + v_2(B)X_{2,t} + N_t$$

$$= \frac{w_1(B)B^{b_1}}{\delta_1(B)} X_{1,t} + \frac{w_2(B)B^{b_2}}{\delta_2(B)} X_{2,t} + N_t$$

Where

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

a_t : is zero mean and normally distributed white noise

1-6 preparation and prewhitening of the inputs and outputs series:[1],[3]

Rewriting the 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 prewhitened X_t series, known suppose we apply the

same filter to Y_t : this will produce another residual series

$$\beta_t = \theta_y^{-1}(B)\phi_y(B)Y_t$$

1-7 IDENTIFICATION

a) Estimation of the impulse response weights:[2],[6]

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

$$v_k^{\wedge} = \frac{r_{\alpha\beta}(k)\sigma_{\beta}^{\wedge}}{\sigma_{\alpha}^{\wedge}}$$

b) Identification of (r,s,b) for the transfer function:[2],[7]

We obtain the identity

$$v_j = 0; \quad j < b$$

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

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

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

c) Disturbance series:[6]

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

$$\begin{aligned} \hat{N}_t &= Y_t - v_1(B)X_{1,t} - v_2(B)X_{2,t} \\ &= Y_t - \frac{w_1(B)B^{b_1}}{\delta_1(B)}X_{1,t} - \frac{w_2(B)B^{b_2}}{\delta_2(B)}X_{2,t} \end{aligned}$$

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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:[3],[4],[5]

At the identification stage we tentatively specify a rational form 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

$$Y_t = \frac{w_1(B)B^{b_1}}{\delta_1(B)} X_{1,t} + \frac{w_2(B)B^{b_2}}{\delta_2(B)} X_{2,t} + \frac{\theta_N(B)B^b}{\varphi_N(B)} a_t \quad (11)$$

At the second stage of our modeling strategy we estimate the parameters of the identified DR

model using the available data .To estimate the coefficients in $w(B)$ and $\delta(B)$ the next step in

estimation is to compute the SSR(sum of squared residual)

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

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

1-9 Diagnostic Check:[1],[6]

We can Diagnose Check time series model by examining

a)Residuals Cross Correlation function (RCCF) $r_k(\hat{a})$

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

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

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

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

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

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

$$H_0: \rho_k = 0$$

$$H_A: \rho_k \neq 0$$

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

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

Where n is smaller number of observation for $\hat{\alpha}_t$ or $\hat{\alpha}_t$.

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

$$H_0: \rho_1 = \rho_2 = \rho_3 = \dots = \rho_k = 0$$

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

By using Ljung and Box(1978) below

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

Where n : is smaller number of observation for $\hat{\alpha}_t$ 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 is less than the χ^2 for degree of freedom $(K+1-m)$, we accept the H_0 . it means that the two series $\hat{\alpha}_t$ 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 examining autocorrelation and partial autocorrelation of series $\hat{\alpha}_t$ we test the null hypothesis

$$H_0: \rho_k = 0$$

$$H_A: \rho_k \neq 0 \quad k=1,2,3,\dots,K$$

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

$$H_0: \rho_0(a) = \rho_1(a) = \rho_2(a) = \rho_3(a) = \dots = \rho_k(a) = 0$$

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

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

$$Q^* = n(n+2) \sum_{k=1}^K (n-k)^{-1} r_k^2(\hat{\alpha}) \quad (16)$$

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 calculating the Critical value we compare it with the tabulated value if the Critical value is less than the tabulated value it means that will be a good model

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1-11 forecasting:[1],[7]

We explain how forecasts of future value of Y_t are produced from the following DR model with $M=2$ input: $Y_t = v_1(B)X_{1,t} + v_2(B)X_{2,t}$

$$Y_t = \frac{w_1(B)B^{b_1}}{\delta_1(B)}X_{1,t} + \frac{w_2(B)B^{b_2}}{\delta_2(B)}X_{2,t} \quad (17)$$

Now equation(17) may be written

$$v_i(B) = v_{i,0} + v_{i,1}B + v_{i,2}B^2 + \dots = w_i(B)B^{b_i}/\delta_i(B) \quad i=1,2$$

$$b_i = \text{dead time for input} \quad i=1,2$$

$$w_i(B) = w_{i,0} + w_{i,1}B + \dots + w_{i,h_i}B^{h_i} \quad \text{for } i=1,2$$

$$\delta_i(B) = 1 - \delta_{i,1}B - \delta_{i,2}B^2 - \dots - \delta_{i,r_i}B^{r_i} \quad \text{for } i=1,2$$

$$h_i = \text{order of } w_i(B) \quad i=1,2$$

$$r_i = \text{order of } \delta_i(B) \quad i=1,2$$

Extending this framework to M inputs, $i=1,2,\dots,m$, is straightforward. The result may be written compactly as :

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

$$= \sum_{i=1}^M \frac{w_i(B)B^{b_i}}{\delta_i(B)}X_{i,t}$$

Equation (17) shows the rational form of a model with M inputs and M transfer functions. A complete dynamic may also include a constant term (C),and it has a disturbance series (N_t)

$$Y_t = C + \sum_{i=1}^M \frac{w_i(B)B^{b_i}}{\delta_i(B)}X_{i,t} + N_t \quad (18)$$

The disturbance may have a time structure that can be described by an ARIMA mechanism. This is written as

$$\phi(B^s)\phi(B)\nabla_s^D\nabla^d N_t = \theta(B^s)\theta(B)a_t \quad \text{or}$$

$$N_t = \frac{\theta(B^s)\theta(B)}{\phi(B^s)\phi(B)\nabla_s^D\nabla^d} a_t \quad (19)$$

Substitute (19) into (18); then the combined multiple input transfer function plus disturbance model (i.e. the complete dynamic regression model) is

$$Y_t = C + \sum_{i=1}^m \frac{w_i(B)B^{b_i}}{\delta_i(B)} X_{i,t} + \frac{\theta(B^s)\theta(B)}{\phi(B^s)\phi(B)\nabla_s^p \nabla^d} a_t \quad (20)$$

Using the initial values, recursively compute (for periods $t, t+1, t+2$) the following two series:

$$y_{1,t}^* = [w_1(B)B^{b_1}/\delta_1(B)]x_{1,t} \\ = \delta_{1,1}y_{1,t-1}^* + \dots + \delta_{1,r_1}y_{1,t-r_1}^* + w_{1,0}x_{1,t-b_1} + \dots + w_{1,h_1}x_{1,t-b_1-h_1} \quad (21)$$

$$y_{2,t}^* = [w_2(B)B^{b_2}/\delta_2(B)]x_{2,t} \\ = \delta_{2,1}y_{2,t-1}^* + \dots + \delta_{2,r_2}y_{2,t-r_2}^* + w_{2,0}x_{2,t-b_2} + \dots + w_{2,h_2}x_{2,t-b_2-h_2} \quad (22)$$

These two series are the outputs from the $M=2$ transfer function components of model (18), given the initial values of the coefficients. In other words, $y_{1,t}^*$ is the set of values predicted by the transfer function $[w_1(B)B^{b_1}/\delta_1(B)]x_{1,t}$ in (20), conditional on the initial coefficient values; and $y_{2,t}^*$ is the set of values predicted by the transfer function $[w_2(B)B^{b_2}/\delta_2(B)]x_{2,t}$ in (18), also conditional on the initial coefficient values.

Because of the recursive nature of (20), computation of $y_{1,t}^*$ requires r_1 starting values of $y_{1,t}^*$ prior to $t=k_1$, where $k_1 = \max[r_1 + 1, b_1 + h_1 + 1]$. Similarly, computation of $y_{2,t}^*$ in (20) requires r_2 starting values for $y_{2,t}^*$ prior to $t=k_2$, where $k_2 = \max[r_2 + 1, b_2 + h_2 + 1]$.

$$F = C(1 - \sum_{i=1}^p \varphi_i)(1 - \sum_{i=1}^p \varphi_{is})(1 - \sum_{i=1}^{r_1} \delta_{i1}) \dots (1 - \sum_{i=1}^{r_m} \delta_{im}) \dots \quad (21)$$

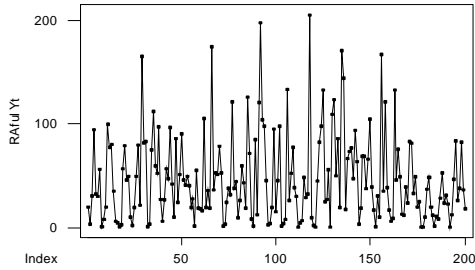
2) Application

2-1 Introduction

This section deals with the application of section one. The first method is testing of cross-correlation function between prewhitening of the input denoted by humidity (RH) and temperature and of the output denoted by rainfall. We take the monthly average of the meteorological station of Ninawah for the period (1976) to (2000), all data are shown appendix (A). The second method is used to test χ^2 between two series of input and output by using equations (15), (16)

2.2 preparation and prewhitening of the inputs and outputs series

1) cross-correlation between output rainfall (Y_t) and input temperature (X_{1t}), RH (X_{2t}). We plot the time series of it by using software of Minitab (13.2) as in figures (1), (2), (3), respectively. We show that the series is stationary in mean and variance



Figure(1):the time series plot of rainfall

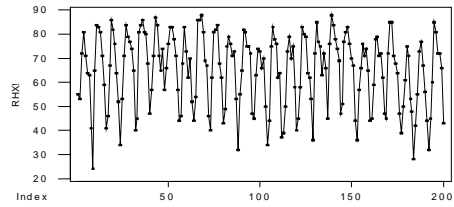
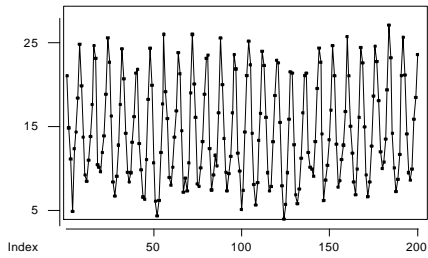
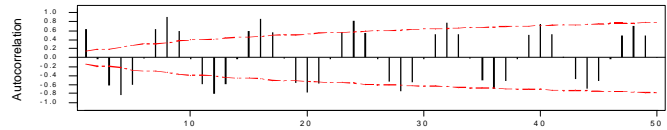


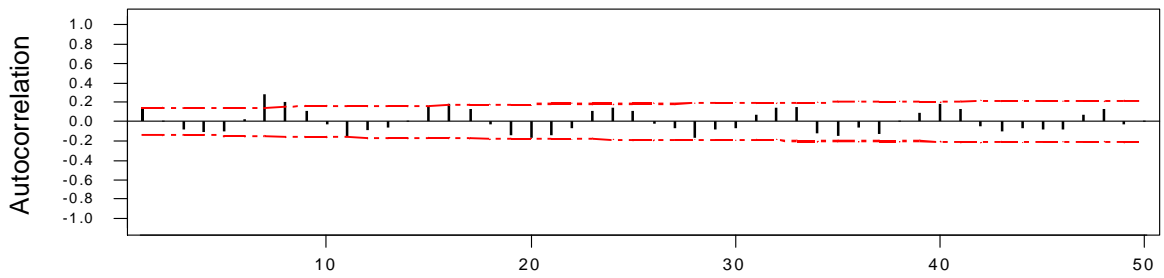
Figure (2):the time series plot of temperature



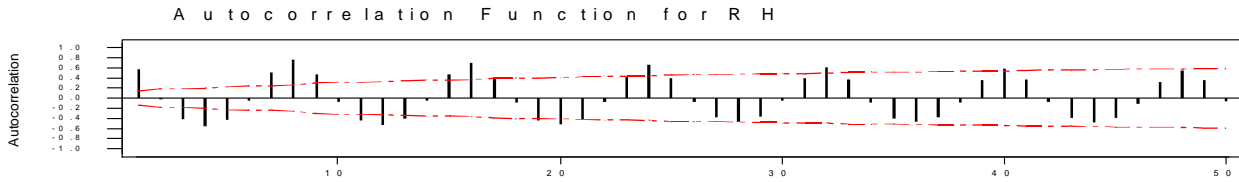
Figure(3):the time series plot of (RH)



Figure(4): ACF for the rainfall



Figure(5): ACF for the temperature



Figure(6) :ACF for the RH

We plot above (Autocorrelation function) ACF for the rainfall, temperature and RH series in figures (4),(5),(6) we show that the seasonality period is(8) months. We take the first difference for the data as shown in the figures(7),(8) ,(9) and plot ACF again for the difference time series about temperature and RH in figures(10,11) and (PACF) in figures(12,13)

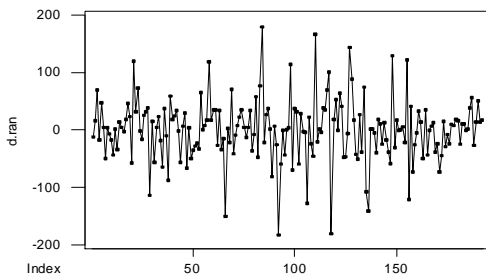


Figure (7): the plot for difference time series of(rainfull)

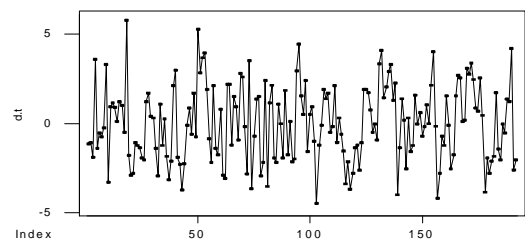


Figure (8): the plot for difference time series of (temperature)

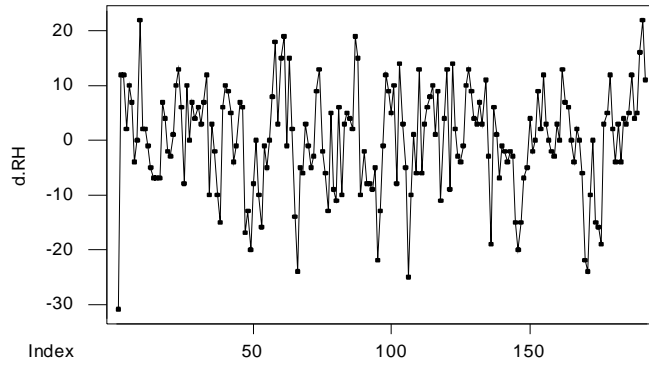


Figure (9): The plot for difference time series of(RH)

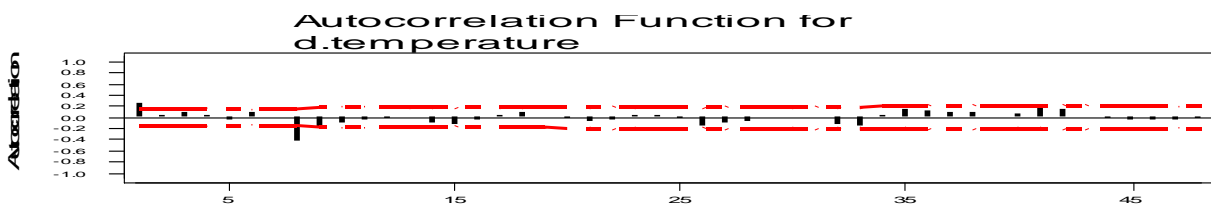


Figure (10): ACF for differenced time series of(temperature)

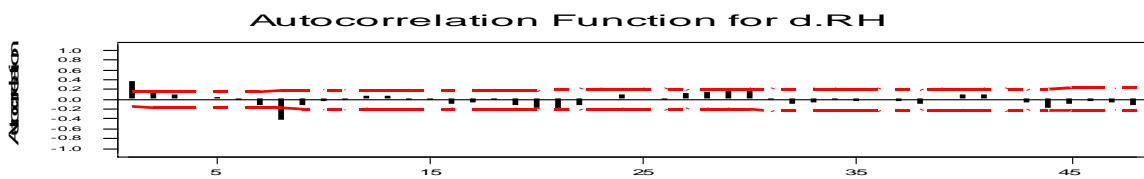


Figure (11):(ACF)differenced time series of(RH)

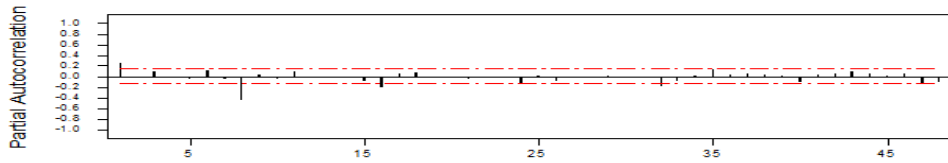


Figure (12):(PACF)differenced time series of temperature)

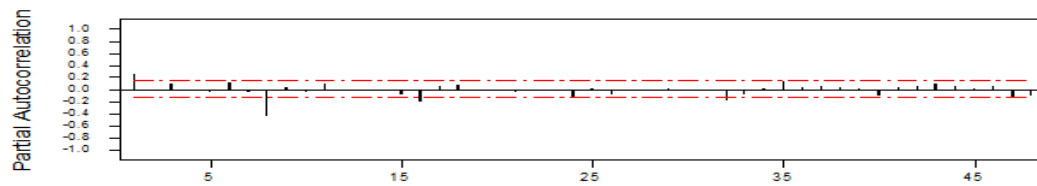


Figure (13):(PACF)differenced time series of(RH)

The figures (10) and (12),by using $(AIC=-2\log L + 2m)$ we suggest that the tentative model for the differenced series is AR(1) as shown in the equation below:

$$\alpha_t = (1 - \phi B)X_{1,t}$$

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

The researcher writes the program through the use of macro within Minitab just as program (1) in the appendix (B).we can find that the results of series(α_t^{\wedge}) are the same as in the table (1).

Table(1) :the values of (α_t^{\wedge}) variable input (temperature) with ($\phi=0.2518$)

T	α_t^{\wedge}	t	α_t^{\wedge}	T	α_t^{\wedge}	T	α_t^{\wedge}	T	α_t^{\wedge}	t	α_t^{\wedge}
1	-1.15000	33	1.84281	65	-1.75396	97	0.10971	129	0.07590	161	1.86475
2	-0.81043	34	-1.52698	66	1.80216	98	2.27410	130	-0.93741	162	-0.49029
3	-1.62302	35	0.56475	67	0.57230	99	-2.20432	131	3.58921	163	-2.52482
4	4.07842	36	-1.91295	68	-1.18921	100	0.90288	132	3.25647	164	-1.10791
5	-2.30648	37	-2.68417	69	3.03921	101	0.82410	133	0.41762	165	1.99065
6	-0.19748	38	-1.30683	70	1.89496	102	-1.23921	134	1.68489	166	2.30971
7	-0.61151	39	2.62878	71	-0.85468	103	-4.24820	135	2.38381	167	1.87014
8	-0.06115	40	2.47122	72	-2.79964	104	-0.06690	136	2.56978	168	-0.54209
9	3.36295	41	-2.65540	73	4.21763	105	0.20216	137	0.46906	169	0.17482
10	-4.13094	42	-1.82158	74	-4.53130	106	1.92518	138	1.92266	170	3.04964
11	1.78094	43	-3.17086	75	0.21907	107	0.92158	139	-4.56655	171	1.96942
12	0.91079	44	-1.30575	76	1.52626	108	1.34748	140	-0.34280	172	2.70755
13	0.61043	45	0.46655	77	1.16007	109	-0.92806	141	1.73993	173	1.59388
14	-0.12662	46	0.87518	78	-3.32770	110	-0.07410	142	-0.15252	174	0.23309
15	1.17482	47	-0.81403	79	-1.45719	111	2.15036	143	-2.60036	175	0.48597
16	0.69784	48	1.85108	80	2.95396	112	-1.57878	144	0.94209	176	2.37374
17	-0.75180	49	-1.17806	81	-4.15432	113	0.56439	145	-1.67554	177	-0.19209
18	5.92590	50	5.48885	82	2.04389	114	-0.67554	146	-0.84712	178	-3.96331
19	-3.26044	51	1.51546	83	1.86043	115	-1.39892	147	1.91475	179	-0.98057
20	-2.44676	52	2.98237	84	-2.49137	116	-3.00971	148	-0.45288	180	-2.30899

[30]

Forecasting rainfall using transfer function

21	-2.06978	53	3.01834	85	-1.70899	117	-1.29388	149	0.61259	181	-1.39496
22	-0.39496	54	0.90539	86	1.65396	118	-3.15863	150	-0.85108	182	-1.32122
23	-0.97302	55	-1.32842	87	-0.27698	119	-1.86834	151	-0.02374	183	2.21583
24	-1.03525	56	-1.98597	88	-1.95000	120	-0.64496	152	1.10036	184	-1.89065
25	-1.61007	57	2.65396	89	2.34101	121	-0.86007	153	-0.26439	185	-1.68489
26	-1.55899	58	-1.92878	90	-2.21583	122	-2.34784	154	2.15000	186	0.46619
27	1.71619	59	-1.39748	91	0.54065	123	-0.43273	155	3.50863	187	-0.53741
28	1.39784	60	1.24065	92	-2.17518	124	2.17698	156	-1.16979	188	1.48849
29	-0.02806	61	-3.10144	93	-1.45863	125	1.42158	157	-4.16223	189	0.91007
30	0.19928	62	-2.36978	94	3.45360	126	1.27158	158	-1.74244	190	3.88525
31	-1.47554	63	2.98058	95	3.70719	127	0.30935	159	0.00504	191	-3.65756
32	-2.59748	64	1.64604	96	0.42949	128	-0.68885	160	-1.07374	192	-1.39532

And We can find the series (β_t^{\wedge}) by using program (2) in the appendix (B).

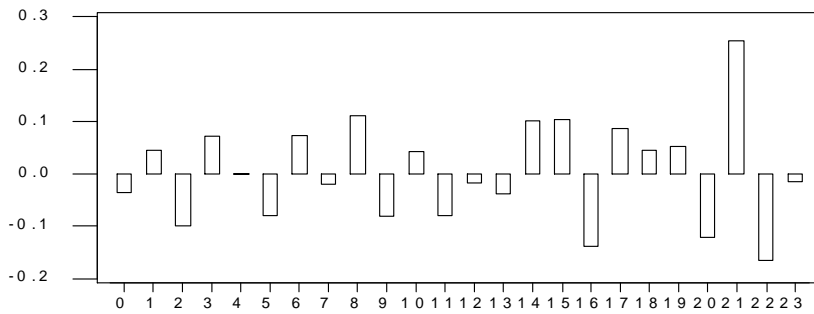
Table (2): values (β_t^{\wedge}) for output (rainfall)

T	(β_t^{\wedge})	T	(β_t^{\wedge})	T	(β_t^{\wedge})	T	(β_t^{\wedge})	T	(β_t^{\wedge})	t	(β_t^{\wedge})
1	-12.000	33	22.216	65	-6.864	97	11.954	129	-5.235	161	34.059
2	19.522	34	-24.517	66	-146.622	98	3.473	130	-46.806	162	6.341
3	65.145	35	-60.117	67	39.996	99	113.768	131	-40.099	163	-53.576
4	-34.350	36	53.917	68	-21.529	100	-98.381	132	39.491	164	48.065
5	52.055	37	-19.668	69	75.988	101	55.000	133	-45.323	165	-52.239
6	-6.936	38	-84.732	70	-58.802	102	22.557	134	84.719	166	10.703
7	-51.584	39	80.782	71	1.524	103	-67.358	135	-126.585	167	6.650
8	16.066	40	3.794	72	10.116	104	43.332	136	-114.081	168	11.638
9	-7.456	41	19.717	73	21.011	105	-10.251	137	36.654	169	-42.149
10	-15.538	42	27.656	74	29.709	106	-2.519	138	1.623	170	-13.430
11	-39.069	43	-9.811	75	-3.739	107	-126.469	139	-4.978	171	-67.458
12	12.328	44	-56.173	76	-14.509	108	54.154	140	-38.167	172	-25.843
13	-34.653	45	21.527	77	7.924	109	-29.465	141	28.296	173	26.755
14	22.937	46	28.362	78	32.842	110	-39.482	142	6.267	174	-32.628
15	0.599	47	-74.604	79	-44.261	111	178.457	143	-27.445	175	-0.573
16	-3.458	48	20.171	80	0.889	112	-62.751	144	19.819	176	-21.636
17	19.004	49	-50.831	81	60.740	113	7.012	145	-20.924	177	16.342
18	42.467	50	-22.910	82	-62.181	114	-4.253	146	-33.993	178	5.481
19	11.540	51	-18.861	83	89.435	115	39.357	147	-48.831	179	16.260
20	-63.392	52	-15.700	84	160.486	116	25.031	148	144.430	180	11.192
21	134.279	53	-27.584	85	-67.224	117	60.563	149	-63.458	181	-28.478
22	2.334	54	73.685	86	32.114	118	83.350	150	24.655	182	17.469
23	64.816	55	-16.443	87	30.102	119	-206.381	151	-4.555	183	7.755
24	-19.481	56	7.700	88	-8.066	120	63.776	152	0.076	184	-3.569
25	-15.823	57	15.461	89	-81.402	121	48.717	153	5.400	185	2.127
26	29.754	58	115.219	90	27.221	122	-13.621	154	-22.860	186	38.022
27	25.729	59	-12.315	91	-27.212	123	64.650	155	128.214	187	46.006
28	29.992	60	30.218	92	-176.979	124	25.034	156	-152.221	188	-40.725
29	-122.994	61	26.263	93	-12.620	125	-58.399	157	71.543	189	20.923
30	43.754	62	-35.513	94	14.506	126	-34.814	158	-83.224	190	47.824
31	-59.827	63	40.723	95	-43.824	127	6.009	159	-7.444	191	0.957
32	19.201	64	-42.461	96	11.954	128	145.660	160	1.496	192	13.800

Correlation coefficient values between (α_t^{\wedge}) and (β_t^{\wedge}) can be found by using equation (12) as in table(3).

Table (3): the values of correlation coefficient between $(\hat{\alpha}_t)$ and $(\hat{\beta}_t)$

T	$r_{\alpha\beta}$	T	$r_{\alpha\beta}$	T	$r_{\alpha\beta}$	T	$r_{\alpha\beta}$
0	-0.036	6	0.073	12	-0.018	18	0.045
1	0.045	7	-0.020	13	-0.038	19	0.052
2	-0.100	8	0.111	14	0.102	20	-0.122
3	0.071	9	-0.082	15	0.105	21	0.256
4	-0.001	10	0.043	16	-0.140	22	-0.166
5	-0.080	11	-0.080	17	0.087	23	-0.015



Figure(14): cross correlation coefficient between $(\hat{\alpha}_t)$ and $(\hat{\beta}_t)$

It is clear from figure (14) that the dead time is $(b=0)$ close to zero which explains $\rho_{\alpha\beta}(0) \neq 0$, reading the graph from left to right, there are no initial zero value weights (because $v_0 \neq 0$), and there is an eventual simple exponential decay pattern.

2.3 Identification for y_t and x_{1t}

a- Estimation of the impulse response weights

We estimate 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 (temperature $X_{1,t}$)

T	V	t	V	T	V	t	V
0	-0.980	6	1.988	12	-0.490	18	1.220
1	1.220	7	-0.540	13	-1.030	19	1.410
2	-2.700	8	3.020	14	2.770	20	-3.320
3	1.900	9	-2.230	15	2.800	21	6.970
4	-0.027	10	1.170	16	-3.810	22	-4.520
5	-2.170	11	-2.170	17	2.370	23	-0.400

b) Identification of (r,s,b) for the transfer function

It is clear from the figure (14) of (r,s,b) equal $(2,2,0)$. the pattern can be written as:

$$Y_t = \frac{(w_0 - w_1B - w_2B^2)}{(1 - \delta_1B - \delta_2B^2)} X_{1t} + a_t \quad (31)$$

c) Disturbance series

We find disturbance series by using the equation

$$N_t = Y_t - v_0X_t - v_1X_{t-1} - \dots - v_{23}X_{t-23} \quad (32)$$

By using equation (32) we can obtain the number of disturbance series which their values are less than the input and output series values($t=23$) so, we can apply them in program (3) in appendix(B) ,the values are in table (5)

Table(5) :estimate values of disturbance series N_t

T	N_t^A	T	N_t^A	T	N_t^A	t	N_t^A	t	N_t^A	t	N_t^A
1	13.365	31	10.901	61	147.725	91	29.868	121	2.03	151	-21.446
2	-31.641	32	35.253	62	-30.333	92	-3.813	122	-35.799	152	-4.474
3	6.611	33	-0.382	63	52.868	93	46.077	123	-51.845	153	-41.222
4	54.277	34	33.167	64	18.616	94	127.691	124	-38.218	154	40.844
5	31.804	35	108.622	65	-17.067	95	-156.801	125	124.675	155	45.27
6	-80.144	36	38.022	66	-24.033	96	-11.406	126	-21.48	156	9.855
7	-31.143	37	-0.049	67	-55.589	97	80.595	127	-22.942	157	-29.622
8	-17.244	38	24.683	68	-17.151	98	-14.855	128	7.415	158	-5.815
9	-28.431	39	23.632	69	-182.988	99	71.533	129	-29.11	159	-1.084
10	-0.27	40	34.248	70	0.591	100	34.748	130	-5.655	160	17.514
11	0.871	41	-18.947	71	-61.522	101	-13.25	131	11.296	161	-5.045
12	-59.391	42	-32.597	72	-14.96	102	-73.314	132	92.202	162	-0.353
13	13.981	43	-147.168	73	32.97	103	-1.652	133	-125.625	163	24.038
14	-25.183	44	-46.851	74	-37.958	104	132.26	134	50.583	164	35.708
15	-43.969	45	-10.365	75	116.984	105	81.207	135	-15.209	165	-13.952
16	24.472	46	56.519	76	-37.351	106	12.39	136	-59.037	166	4.87
17	74.275	47	-25.199	77	67.257	107	-30.118	137	48.495	167	47.988
18	-5.746	48	-52.361	78	-35.903	108	-33.99	138	28.447	168	-35.856
19	36.336	49	-2.244	79	-12.999	109	0.865	139	-23.989	169	44.456
20	-29.206	50	40.356	80	9.85	110	-2.283	140	-45.368		
21	-39.696	51	11.621	81	-41.741	111	74.674	141	62.079		
22	4.019	52	36.622	82	22.486	112	-102.218	142	-51.065		
23	36.398	53	4.295	83	-107.222	113	-107.77	143	14.645		
24	-69.85	54	14.151	84	36.119	114	38.386	144	21.651		
25	-27.85	55	3.439	85	-40.364	115	-4.607	145	-8.623		
26	-12.357	56	-20.087	86	-35.045	116	-20.542	146	-61.668		
27	-13.303	57	24.121	87	144.68	117	-30.373	147	-33.479		
28	-4.782	58	7.383	88	21.282	118	-3.758	148	-46.209		
29	2.524	59	10.358	89	-32.411	119	3.314	149	-22.5		
30	-20.55	60	51.908	90	3.156	120	-7.261	150	-14.829		

We plot ACF and PACF from the disturbance series (\hat{N}_t), as in the figures (15) and (16)

Autocorrelation Function for N_t

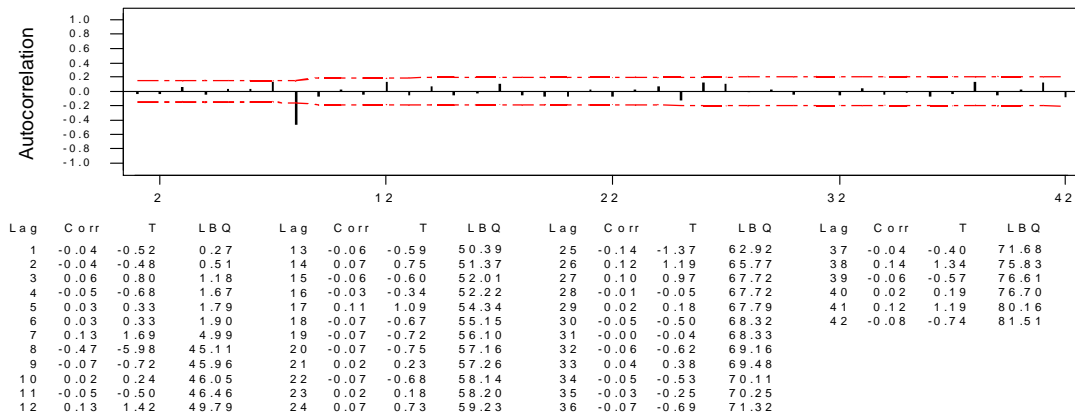


Figure (15): ACF and from the disturbance series (\hat{N}_t)

Figure(15) Shos the outline because we have the value (-59.39) in table(5) outlier.

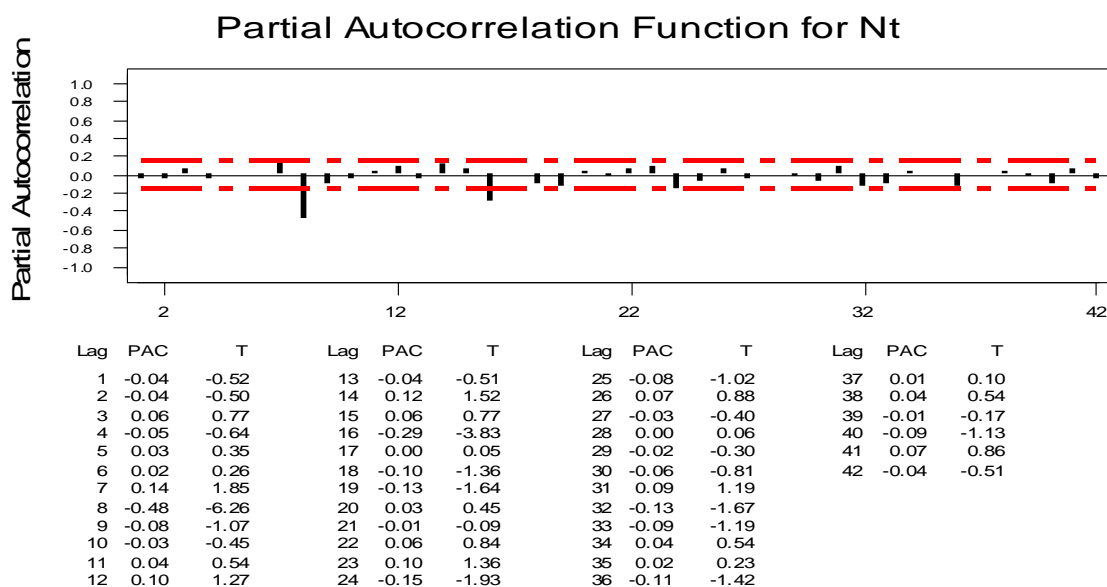


Figure (16): PACF and from the disturbance series (\hat{N}_t)

It is clear from figure (16) that the disturbance series (\hat{N}_t) is equal residual series $N_t = a_t$ (the series N_t does not follow any model because it is independent random), thus the model of dynamic regression is as shown in the equation below

$$Y_t = \frac{(w_0 - w_1B - w_2B^2)}{(1 - \delta_1B - \delta_2B^2)} X_{1t} + a_t \tag{33}$$

We estimate the values of the model by using equation (33)

$$v_0 = w_0$$

$$v_1 = \delta_1 v_0 - w_1$$

$$v_2 = \delta_1 v_1 + \delta_2 v_0 - w_2 \quad j = b + 1, \dots, b+s$$

$$v_3 = \delta_1 v_2 + \delta_2 v_1$$

$$v_4 = \delta_1 v_3 + \delta_2 v_2$$

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

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

$$\hat{Y}_t = \frac{(-2.667 + 1.422B + 4.451B^2)}{(1 - 1.048B - 0.7266B^2)} X_{1t} + a_t$$

$$\hat{a}_t = Y_t - 1.048Y_{t-1} - 0.7266Y_{t-2} + 2.667X_{1,t-1} - 1.422X_{1,t-1} - 4.451X_{1,t-2} + 1.048a_{t-1} + 0.7266a_{t-2} \tag{34}$$

We find the values of series (\hat{a}_t) by using equation (34) and program (4) in appendix (B), We have shown that all value of series (\hat{a}_t) is equal to zero

d) Diagnostic Check

a) Residuals Cross Correlation Function(RCCF) $r_k(\hat{a}_t)$. We that the cross correlation between series ($\hat{\alpha}_t$) and (\hat{a}_t), It is clear that there are no correlation between two series ($\hat{\alpha}_t$) and series (\hat{a}_t). We can find the cross correlation between rainfall and RH as the same way between rainfall and temperature.

The figures (11) and (13) suggest that the tentative model for the differenced series is AR(1) as shown in the equation below:

$$\alpha_t = (1 - \phi B)X_{2,t}$$

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

The researcher writes the program through the use of macro within Minitab just as program (1) in the appendix (B). We can find that the results of series ($\hat{\alpha}_t$) are the same as in table (6).

Table(6) :the values of ($\hat{\alpha}_t$) variable input (RH) with ($\phi = 0.3882$)

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	-31.0000	33	9.2826	65	-14.7764	97	-20.0590	129	3.9534	161	-1.1646
2	24.0342	34	-14.6584	66	-18.5652	98	-4.4596	130	0.5062	162	13.0000
3	7.3416	35	6.8820	67	4.3168	99	4.0466	131	1.4472	163	1.9534
4	-2.6584	36	-3.1646	68	-4.0590	100	12.3882	132	5.8354	164	3.2826
5	9.2236	37	-9.2236	69	5.3292	101	4.3416	133	0.2826	165	-2.3292
6	3.1180	38	-11.1180	70	-2.1646	102	1.5062	134	9.8354	166	-4.0000
7	-6.7174	39	11.8230	71	-4.6118	103	8.0590	135	-7.2702	167	3.5528
8	1.5528	40	7.6708	72	-1.0590	104	-11.8820	136	-17.8354	168	-0.7764
9	22.0000	41	5.1180	73	10.1646	105	17.1056	137	13.3758	169	-6.0000
10	-6.5404	42	1.5062	74	9.5062	106	-2.4348	138	-1.3292	170	-19.6708
11	1.2236	43	-5.9410	75	-7.0466	107	-6.1646	139	-7.3882	171	-15.4596
12	-1.7764	44	0.5528	76	-5.2236	108	-23.0590	140	1.7174	172	-0.6832
13	-4.6118	45	7.3882	77	-10.6708	109	-0.2950	141	-1.6118	173	3.8820
14	-5.0590	46	3.2826	78	10.0466	110	4.8820	142	-3.2236	174	-15.0000
15	-4.2826	47	-19.3292	79	-10.9410	111	-6.3882	143	-0.4472	175	-10.1770
16	-4.2826	48	-6.4006	80	-7.5062	112	15.3292	144	-2.2236	176	-12.7888
17	9.7174	49	-14.9534	81	10.2702	113	-11.0466	145	-13.8354	177	10.3758
18	1.2826	50	-0.2360	82	-12.3292	114	5.3292	146	-14.1770	178	3.8354
19	-3.5528	51	3.1056	83	6.8820	115	4.8354	147	-7.2360	179	10.0590
20	-2.2236	52	-10.0000	84	3.8354	116	5.6708	148	-1.1770	180	-2.6584
21	2.1646	53	-12.1180	85	2.0590	117	6.8944	149	-2.2826	181	-4.7764
22	9.6118	54	5.2112	86	0.4472	118	-2.8820	150	5.9410	182	4.5528
23	9.1180	55	-4.6118	87	18.2236	119	8.6118	151	-3.5528	183	-5.1646
24	0.9534	56	1.9410	88	7.6242	120	-14.4938	152	0.7764	184	5.5528
25	-10.3292	57	8.0000	89	-15.8230	121	8.2702	153	9.0000	185	1.4472
26	13.1056	58	14.8944	90	1.8820	122	11.4472	154	-1.4938	186	3.8354
27	-3.8820	59	-3.9876	91	-7.2236	123	-14.0466	155	11.2236	187	10.0590
28	7.0000	60	13.8354	92	-4.8944	124	17.4938	156	-1.6584	188	-0.6584
29	1.2826	61	13.1770	93	-5.8944	125	-3.4348	157	-1.1646	189	3.4472
30	4.4472	62	-8.3758	94	-1.5062	126	-3.7764	158	-2.0000	190	14.0590
31	0.6708	63	15.3882	95	-14.7764	127	-2.8354	159	-2.2236	191	15.7888
32	5.8354	64	-3.8230	96	-18.5652	128	0.5528	160	4.1646	192	2.4596

And we can find the series (β_t^{\wedge}) by using program (2) in the appendix (B)

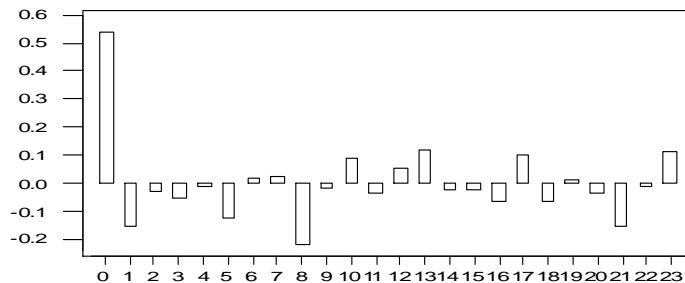
Table (7): values (β_t^{\wedge}) for output (rainfall)

T	(β_t^{\wedge})	T	(β_t^{\wedge})	T	(β_t^{\wedge})	t	(β_t^{\wedge})	T	(β_t^{\wedge})	t	(β_t^{\wedge})
1	-12.000	33	21.520	65	21.520	97	3.351	129	-17.333	161	34.741
2	21.158	34	-27.723	66	-27.723	98	113.264	130	-49.138	162	1.867
3	62.895	35	-57.579	67	-57.579	99	-114.027	131	-34.302	163	-55.568
4	-43.802	36	62.755	68	62.755	100	64.480	132	46.421	164	54.871
5	54.361	37	-24.796	69	-24.796	101	17.443	133	-48.965	165	-57.081
6	-13.456	38	-83.340	70	-83.340	102	-71.722	134	89.985	166	16.609
7	-52.280	39	92.690	71	92.690	103	51.420	135	-136.815	167	6.678
8	22.926	40	-4.226	72	-4.226	104	-14.125	136	-99.391	168	10.738
9	-7.920	41	17.179	73	17.179	105	-2.097	137	55.914	169	-43.963
10	-14.638	42	24.328	74	24.328	106	-126.019	138	1.473	170	-8.138
11	-36.723	43	-14.421	75	-14.421	107	71.518	139	-5.238	171	-64.294
12	18.248	44	-55.995	76	-55.995	108	-32.479	140	-37.553	172	-15.845
13	-34.843	45	29.233	77	29.233	109	-36.222	141	33.656	173	32.797
14	27.615	46	27.366	78	27.366	110	184.663	142	3.757	174	-34.756
15	-1.351	47	-78.724	79	-78.724	111	-85.529	143	-28.931	175	3.341
16	-4.030	48	29.309	80	29.309	112	9.836	144	23.189	176	-20.572
17	19.332	49	-51.281	81	-51.281	113	-4.499	145	-22.780	177	19.562
18	39.957	50	-16.090	82	-16.090	114	39.875	146	-31.606	178	4.063
19	5.116	51	-14.019	83	-14.019	115	19.793	147	-43.593	179	15.156
20	-66.584	52	-11.908	84	-11.908	116	55.829	148	152.410	180	8.696
21	142.122	53	-24.488	85	-24.488	117	73.898	149	-81.150	181	-30.634
22	-14.006	54	78.227	86	78.227	118	-220.131	150	28.857	182	20.811
23	60.383	55	-25.349	87	-25.349	119	88.464	151	-6.861	183	6.213
24	-29.439	56	7.700	88	7.700	120	46.235	152	0.116	184	-5.015
25	-15.673	57	14.411	89	14.411	121	-20.891	153	5.400	185	2.249
26	31.950	58	112.845	90	112.845	122	64.678	154	-23.596	186	37.762
27	22.223	59	-28.629	91	-28.629	123	16.222	155	131.146	187	40.754
28	25.600	60	27.790	92	27.790	124	-64.033	156	-168.971	188	-48.323
29	-128.190	61	21.529	93	21.529	125	-28.266	157	88.089	189	24.565
30	59.222	62	-40.287	94	-40.287	126	12.407	158	-88.816	190	45.888
31	-61.901	63	44.365	95	44.365	127	146.452	159	2.500	191	-6.053
32	26.839	64	-47.099	96	-47.099	128	32.722	160	5.016	192	11.904

e)Correlation coefficient between (α_t^{\wedge}) and (β_t^{\wedge}) by using equation (12) we can find the values of correlation coefficient in the table (8)

Table (8): the values of correlation coefficient between (α_t^{\wedge}) and (β_t^{\wedge})

T	$r_{\alpha\beta}$	t	$r_{\alpha\beta}$	t	$r_{\alpha\beta}$	t	$r_{\alpha\beta}$
0	0.541	6	0.017	12	0.056	18	-0.064
1	-0.154	7	0.026	13	0.120	19	0.012
2	-0.032	8	-0.221	14	-0.022	20	-0.038
3	-0.056	9	-0.021	15	-0.022	21	-0.155
4	-0.012	10	0.089	16	-0.064	22	-0.014
5	-0.126	11	-0.038	17	0.101	23	0.115



Figure(17):cross correlation coefficient between $(\hat{\alpha}_t)$ and $(\hat{\beta}_t)$

It is clear from figure (17) that the dead time is (b=0) close to zero which explains $\rho_{\alpha\beta}(0) \neq 0$, reading the graph from left to right, there are no initial zero value v weights (because $v_0 \neq 0$), and there is an eventual simple exponential decay pattern.

2.4)Identification for Y_t and x_{2t}

a) Estimation of the impulse response weights

We estimate of the impulse response weights between input (X_{2t}) and output series (Y_t) in table (9) below

Table (9): the values of the impulse response of input variable (RH $X_{2,t}$)

T	V	T	V	t	V	t	V
0	3.4868	6	0.078	12	0.3519	18	-0.443
1	-1.016	7	0.215	13	0.769	19	0.0782
2	-0.267	8	-1.466	14	-0.1042	20	-0.247
3	-0.306	9	-0.130	15	-0.221	21	-0.990
4	-0.052	10	0.606	16	-0.351	22	-0.1042
5	-0.827	11	-0.2990	17	0.651	23	0.775

b)Identification of (r,s,b) for the transfer function

It is clear from figure (17) of (r,s,b) equals(1,4,0) the pattern can be written as:

$$Y_t = \frac{(w_0 - w_1B - w_2B^2 - w_3B^3 - w_4B^4)}{(1 - \delta_1B)} X_{2,t} + N_t \tag{35}$$

c)Disturbance series

We find disturbance series by using the equation

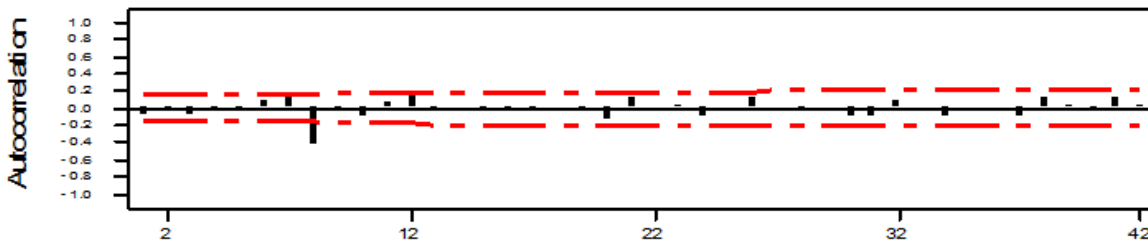
$$N_t = Y_t - v_0X_t - v_1X_{t-1} - \dots - v_{23}X_{t-23} \tag{36}$$

By using equation (36) we can obtain the number of disturbance series which their values is less than the input and output series values (t=23) so,

we can apply them in program (3) in appendix(B), the values are in the table (10)

Table(10) :estimate values of disturbance series N_t

T	N_t^{\wedge}	T	N_t^{\wedge}	t	N_t^{\wedge}	t	N_t^{\wedge}	t	N_t^{\wedge}	t	N_t^{\wedge}
1	28.613	31	48.29	61	142.505	91	-27.889	121	-15.644	151	5.353
2	37.799	32	-26.884	62	-53.047	92	1.357	122	20.184	152	9.002
3	-4.912	33	-29.15	63	-6.867	93	61.531	123	16.92	153	9.528
4	64.620	34	-35.358	64	-73.859	94	56.834	124	-54.694	154	-42.586
5	11.535	35	14.585	65	-41.58	95	-83.122	125	155.17	155	-43.309
6	-112.436	36	24.826	66	23.028	96	59.807	126	-2.326	156	-76.594
7	23.379	37	14.483	67	16.817	97	15.616	127	-28.331	157	2.882
8	-29.135	38	6.115	68	-5.876	98	54.553	128	-24.571	158	-4.407
9	-18.565	39	29.213	69	-131.606	99	18.965	129	-8.101	159	4.887
10	-17.032	40	-4.362	70	-23.163	100	48.033	130	-30.087	160	47.208
11	29.12	41	-28.575	71	10.271	101	-26.102	131	-56.512	161	-6.14
12	-89.822	42	64.341	72	54.304	102	-7.176	132	83.506	162	-2.095
13	37.059	43	-7.306	73	31.851	103	-48.157	133	-124.696	163	21.646
14	37.423	44	-11.606	74	-64.811	104	63.41	134	19.564	164	43.923
15	-11.027	45	-23.646	75	23.724	105	80.266	135	-24.15	165	-4.469
16	14.801	46	52.51	76	-86.81	106	-8.572	136	17.788	166	5.317
17	-21.378	47	-78.918	77	-23.933	107	-26.532	137	-19.742	167	-15.377
18	-29.934	48	-19.443	78	-29.27	108	-17.112	138	45.418	168	-78.165
19	14.658	49	37.887	79	5.893	109	-5.346	139	-27.959	169	-16.994
20	11.552	50	-62.899	80	-27.532	110	-41.305	140	-57.219		
21	-18.165	51	-60.43	81	-14.486	111	54.457	141	29.328		
22	-40.238	52	22.992	82	45.548	112	-55.424	142	-43.046		
23	-17.26	53	17.84	83	3.863	113	-52.061	143	-6.476		
24	25.547	54	49.121	84	39.841	114	-27.107	144	-28.45		
25	62.791	55	44.317	85	6.302	115	20.879	145	12.916		
26	48.802	56	46.758	86	0.832	116	0.277	146	-8.207		
27	-14.201	57	1.702	87	61.255	117	-44.527	147	67.796		
28	-27.227	58	37.108	88	-34.269	118	17.533	148	13.316		
29	-32.854	59	13.342	89	-6.008	119	29.546	149	-40.976		
30	4.071	60	55.595	90	-44.886	120	-15.576	150	-7.83		



Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ	Lag	Corr	T	LBQ
1	-0.06	-0.77	0.60	13	-0.05	-0.50	48.01	25	0.00	0.05	58.81	37	-0.08	-0.84	69.38
2	-0.01	-0.17	0.63	14	0.00	0.03	48.01	26	0.12	1.18	59.50	38	0.13	1.32	73.38
3	-0.06	-0.79	1.28	15	-0.05	-0.50	48.43	27	0.00	0.03	59.50	39	0.03	0.33	73.62
4	-0.04	-0.52	1.56	16	-0.03	-0.35	48.64	28	-0.01	-0.15	59.54	40	-0.05	-0.45	74.10
5	-0.03	-0.39	1.72	17	-0.01	-0.12	48.66	29	0.01	0.07	59.55	41	0.12	1.13	77.16
6	0.11	1.36	3.71	18	0.01	0.05	48.67	30	-0.08	-0.88	61.05	42	0.03	0.30	77.39
7	0.15	1.87	7.57	19	-0.00	-0.02	48.67	31	-0.10	-1.03	63.25				
8	-0.43	-5.33	40.30	20	-0.13	-1.39	52.10	32	0.09	0.94	65.12				
9	-0.04	-0.42	40.58	21	0.12	1.24	54.90	33	0.03	0.25	65.26				
10	-0.09	-0.99	42.12	22	0.01	0.09	54.91	34	-0.11	-1.05	67.65				
11	0.08	0.87	43.32	23	0.04	0.41	55.23	35	0.01	0.10	67.67				
12	0.15	1.62	47.58	24	-0.09	-0.91	56.80	36	0.03	0.26	67.82				

Figure (18): ACF of disturbance series (\hat{N}_t)

We figure(18) shows the outline we have the value (-89.822) in table(6) outlier

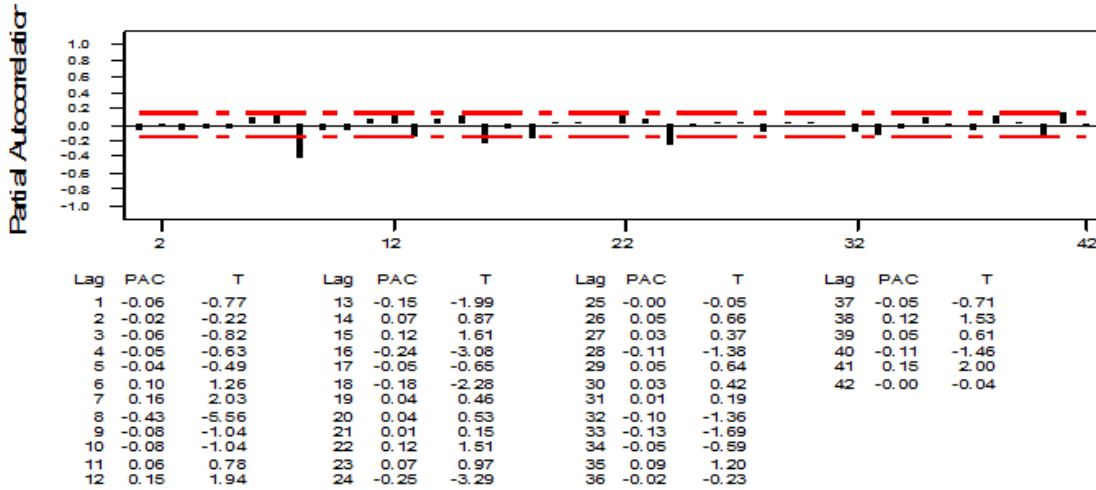


Figure (19): PACF of disturbance series (\hat{N}_t)

It is clear from figure (18) that the disturbance series (\hat{N}_t) is equal residual series

$N_t = a_t$ (because N_t independent no model to thus the model of dynamic regression as shown in the equation below:

$$Y_t = \frac{(w_0 - w_1B - w_2B^2 - w_3B^3 - w_4B^4)}{(1 - \delta_1B)} X_{2,t} + a_t$$

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

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

$$Y_t = \frac{(3.911 - 2.228B + 1.291B^2 + 1.077B^3 + 0.4532B^4)}{(1 - 0.9309B)} X_{2,t} + a_t$$

$$a_t = Y_t - 0.9309Y_{t-1} - 3.911X_{2,t} + 2.228X_{2,t-1} - 1.291X_{2,t-2} - 1.077X_{2,t-3} - 0.4532X_{2,t-4} - 0.9309a_{t-1} \quad (37)$$

We find the values of series (a_t) by using equation (37) and program (4) in appendix(B),

The value is as in table(11)

Table (11): the values of series (a_t)

T	a_t	T	a_t	T	a_t	T	a_t	t	a_t	T	a_t
1	50.365	32	17.214	63	1.672	94	48.311	125	37.305	156	-82.711
2	-90.235	33	9.267	64	27.954	95	-7.721	126	-36.165	157	-11.085
3	-70.627	34	-4.637	65	25.321	96	-38.909	127	22.769	158	-36.029

4	-92.189	35	27.389	66	-46.286	97	-48.405	128	-92.528	159	39.536
5	70.200	36	-10.187	67	-20.277	98	-0.497	129	-60.434	160	34.025
6	-114.237	37	-70.976	68	-12.659	99	8.282	130	-2.785	161	17.844
7	160.600	38	-26.341	69	56.899	100	80.297	131	-10.002	162	-36.150
8	280.070	39	30.149	70	77.632	101	-25.895	132	-3.329	163	50.648
9	61.636	40	25.470	71	13.540	102	-70.116	133	-58.201	164	19.161
10	-159.349	41	65.383	72	-52.913	103	91.315	134	28.313	165	-7.360
11	95.367	42	13.519	73	9.592	104	6.997	135	36.838	166	0.953
12	143.262	43	-53.584	74	41.188	105	7.823	136	-7.920	167	10.333
13	-30.895	44	-20.828	75	-12.424	106	-0.698	137	10.690	168	38.846
14	181.607	45	6.230	76	89.463	107	-2.385	138	30.009	169	46.669
15	-130.834	46	67.477	77	171.036	108	-8.595	139	11.914	170	-23.288
16	240.304	47	62.504	78	-71.415	109	48.501	140	-6.551	171	-36.614
17	10.798	48	-3.787	79	12.279	110	63.762	141	140.643	172	-66.124
18	40.784	49	-54.902	80	-30.939	111	-129.493	142	-22.666	173	28.415
19	-12.151	50	-11.923	81	-34.212	112	-5.555	143	-10.967	174	-5.426
20	23.883	51	62.623	82	-23.518	113	15.895	144	2.907	175	-90.206
21	0.118	52	41.013	83	46.625	114	20.722	145	-1.762	176	-16.801
22	-10.565	53	-6.733	84	-12.270	115	20.300	146	-16.224	177	12.358
23	-6.392	54	-18.974	85	-185.105	116	33.982	147	-26.870	178	-5.054
24	-40.202	55	-58.342	86	-55.763	117	-35.398	148	101.249	179	3.947
25	-46.941	56	-7.003	87	19.832	118	4.818	149	-112.047	180	3.069
26	-18.892	57	-3.776	88	77.998	119	0.314	150	19.355	181	2.609
27	27.512	58	61.987	89	67.879	120	104.485	151	-88.526	182	8.366
28	-51.267	59	-47.600	90	-11.399	121	16.639	152	-33.098	183	3.916
29	57.579	60	-4.957	91	13.581	122	-16.085	153	-3.738	184	3.656
30	-8.086	61	-42.081	92	-119.634	123	-41.270	154	52.494	185	11.909
31	-42.822	62	27.025	93	20.001	124	-28.408	155	-11.893	186	19.877

By using Ljung and Box(1978) below

$$s_{x_2}^2 = n^2 \sum_{k=0}^K (n-k)^{-1} (r_k)^2$$

$$= 20.1225$$

The value is less than the χ^2 critical value(31.4) for $K+1-m=24+1-5=20$ degrees of freedom at the 5% level. Therefore we do not reject the stated H_0 (H_0 :the two series a_t and α_t are independent)

d- Autocorrelation Check

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

$$Q_{x_2}^2 = n(n+2) \sum_{k=1}^K (n-k)^{-1} r_k^2(\bar{a})$$

$$= 34.43$$

We get the value (34.43) by using software of Minitab (13.2)

This value is less than the χ^2 critical value (55.8) for $K - m=41-1= 40$ degrees of freedom at the 5% level. Therefore we do not reject the stated H_0 . (H_0 : series a_t independent)

The next step to compute two input temperature and RH and compute the SSR (Sum of Squared Residuals)

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

$$Y_t = \frac{(-2.667 + 1.422B + 4.451B^2)}{(1 - 1.048B - 0.7266B^2)} X_{1,t} + \frac{(3.911 - 2.228B + 1.291B^2 + 1.077B^3 + 0.4532B^4)}{(1 - 0.9309B)} X_{2,t} + a_t$$

Table (12): the values of series (a_t^{\wedge})

T	a_t^{\wedge}	t	a_t^{\wedge}	t	a_t^{\wedge}	T	a_t^{\wedge}	t	a_t^{\wedge}	T	a_t^{\wedge}
1	30.365	32	17.214	63	1.672	94	48.311	125	37.305	156	-82.711
2	-86.235	33	9.267	64	27.954	95	-7.721	126	-36.165	157	-11.085
3	-36.627	34	-4.637	65	25.321	96	-38.909	127	22.769	158	-36.029
4	-77.189	35	27.389	66	-46.286	97	-48.405	128	-92.528	159	39.536
5	146.200	36	-10.187	67	-20.277	98	-0.497	129	-60.434	160	34.025
6	-142.237	37	-70.976	68	-12.659	99	8.282	130	-2.785	161	17.844
7	66.600	38	-26.341	69	56.899	100	80.297	131	-10.002	162	-36.150
8	80.070	39	30.149	70	77.632	101	-25.895	132	-3.329	163	50.648
9	211.636	40	25.470	71	13.540	102	-70.116	133	-58.201	164	19.161
10	-39.349	41	65.383	72	-52.913	103	91.315	134	28.313	165	-7.360
11	50.367	42	13.519	73	9.592	104	6.997	135	36.838	166	0.953
12	48.262	43	-53.584	74	41.188	105	7.823	136	-7.920	167	10.333
13	-45.895	44	-20.828	75	-12.424	106	-0.698	137	10.690	168	38.846
14	86.607	45	6.230	76	89.463	107	-2.385	138	30.009	169	46.669
15	-31.834	46	67.477	77	171.036	108	-8.595	139	11.914	170	-23.288
16	24.304	47	62.504	78	-71.415	109	48.501	140	-6.551	171	-36.614
17	0.798	48	-3.787	79	12.279	110	63.762	141	140.643	172	-66.124
18	44.784	49	-54.902	80	-30.939	111	-129.493	142	-22.666	173	28.415
19	-12.151	50	-11.923	81	-34.212	112	-5.555	143	-10.967	174	-5.426
20	23.883	51	62.623	82	-23.518	113	15.895	144	2.907	175	347
21	0.118	52	41.013	83	46.625	114	20.722	145	-1.762	176	-235
22	-100.565	53	-6.733	84	-12.270	115	20.300	146	-16.224	177	-127
23	-6.392	54	-18.974	85	-185.105	116	33.982	147	-26.870	178	
24	-49.202	55	-58.342	86	-55.763	117	-35.398	148	101.249	179	
25	-46.941	56	-7.003	87	19.832	118	4.818	149	-112.047	180	
26	-18.892	57	-3.776	88	77.998	119	0.314	150	19.355	181	
27	27.512	58	61.987	89	67.879	120	104.485	151	-88.526	182	
28	-59.267	59	-47.600	90	-11.399	121	16.639	152	-33.098	183	
29	57.579	60	-4.957	91	13.581	122	-16.085	153	-3.738	184	
30	-8.086	61	-42.081	92	-119.634	123	-41.270	154	52.494	185	
31	-44.822	62	27.025	93	20.001	124	-28.408	155	-11.893	186	

By using equation (15) Ljung and Box(1978) below

$$s^2 = 19.6743$$

The value is less than the χ^2 critical value(27.6) for $K+1-m=24+1-8=17$ degrees of freedom at the 5% level. Therefore we do not reject the stated H_0 (H_0 :the two series a_t and α_t are independent)

e)Autocorrelation Check

The statistic test proposed by equation (16) Ljung and Box(1978) is

$$Q^2 = 40.16$$

this value is less than the χ^2 critical value (55.8) for $K - m=41-1= 40$ degrees of freedom at the 5% level. Therefore we do not reject the stated H_0 (H_0 : series a_t is independent).

Forecasting \hat{Y}_{201}

We explain how forecasts of future value of Y_t are produced from the following DR model with equation below ,where $t=n = 200$

for $I = 1$, the forecast is

$$\hat{y}_{201} = 0.978y_{200} + 0.0723y_{199} - 0.6726y_{198} - 2.667x_{1,201} - 3.904x_{1,200} + 3.126x_{1,199} - 0.124x_{1,198} + 3.911x_{2,201} - 0.87x_{2,200} - 0.5067x_{2,199} + 1.342x_{2,198} + 0.643x_{2,197} - 0.252x_{2,196} - 0.329x_{2,195} + \alpha_{200} - 0.978\alpha_{200} - 0.0723\alpha_{199} + 0.672\alpha_{198} = 8.2$$

$$\alpha_t = y_t - 0.978y_{t-1} - 0.0723y_{t-2} + 0.6726y_{t-3} + 2.667x_{1,t} + 3.904x_{1,t-1} - 3.126x_{1,t-2} + 0.124x_{1,t-3} - 3.911x_{2,t} + 0.87x_{2,t-1} + 0.5067x_{2,t-2} - 1.342x_{2,t-3} - 0.643x_{2,t-4} + 0.252x_{2,t-5} + 0.329x_{2,t-6} + 0.978\alpha_{t-1} + 0.0723\alpha_{t-2} - 0.672\alpha_{t-3}$$

The forecast for x_t is

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

And The forecast for Y_t is

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

We find the values of forecasting X_{t+1} and Y_{t+1}

Table (13): forecasting X_{t+1} and Y_{t+1} and Dynamic regression

Year	Time	Forecasting temperature	Forecasting RH	Forecasting dynamic y_t
2001-2002	Oct.	20.5395	52.0114	8.2
	Nov.	18.5030	57.2962	25.4
	Des.	17.1697	60.3956	91.656
	Jan.	16.2968	62.2133	149
	Feb.	15.7254	63.2793	58
	Mar.	15.3512	63.9045	196
	Apr.	15.1063	64.2712	75.4
	May.	14.9459	64.4862	8.3

Conclusions

- 1) ACF for the rainfall from series temperature and RH, we show that the seasonality period (8) is months, we suggest that the tentative model for the differenced series is AR(1)
- 2) After using cross-correlation between series (α_t) and series (a_t), it is clear that there are significant values, which mean that the correlation between the two series (α_t) and series (a_t) is significant, we suggest the best way to forecast using dynamic regression.

3) To examine that the value is less than the χ^2 critical value for K - m 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 Nineveh for the period (1976) to (2001)

Year	Month	RH	rainfall	Tm	year	month	RH	rainfall	tm	Year	month	RH	rainfall	Tm
76-77	Oct.	55	19.4	21.05		Feb.	81	50.9	7.25		Oct.	45	17.1	21.35
	Nov.	53	3.0	14.85		Mar.	69	78.6	10.65		Nov.	76	66.7	11.90
	Des.	72	30.6	11.10		Apr.	67	52.9	19.05		Des.	88	73.1	10.15
	Jan.	81	94.3	4.85		May.	46	1.5	26.05		Jan.	84	76.5	9.90
	Feb.	71	32.2	12.35	85-86	Oct.	40	3.0	20.10		Feb.	78	47.3	9.00
	Mar.	64	30.0	14.35		Nov.	62	23.9	16.05		Mar.	74	93.8	13.25
	Apr.	63	56.2	18.40		Des.	81	38.1	8.10	94-95	Apr.	69	63.7	19.55
	May.	41	0.8	24.90		Jan.	82	31.5	7.85		May.	47	2.9	24.40
77-78	Oct.	24	7.4	19.90		Feb.	84	121.6	10.05		Oct.	51	18.2	22.65
	Nov.	65	19.5	13.75		Mar.	68	37.6	13.25		Nov.	77	68.6	14.15
	Des.	84	99.9	9.20		Apr.	62	44.1	18.85		Des.	81	68.6	6.15
	Jan.	83	77.4	8.45		May.	43	9.4	23.20		Jan.	83	37.2	8.55
	Feb.	81	80.0	10.95	86-87	Oct.	49	26.0	23.60		Feb.	76	65.7	10.40
	Mar.	71	35.1	13.80		Nov.	75	59.4	12.40		Mar.	70	104.7	13.45
	Apr.	59	5.9	17.65		Des.	79	43.3	7.40	95-96	Apr.	67	39.0	17.00
	May.	41	4.2	24.65		Jan.	76	18.3	9.20		May.	44	16.5	24.70
78-79	Oct.	46	0.8	23.20		Feb.	71	126.2	11.55		Oct.	36	0.7	21.05
	Nov.	67	2.3	10.45		Mar.	73	71.6	10.30		Nov.	57	30.2	12.90
	Des.	86	56.5	10.15		Apr.	53	8.4	16.65		Des.	66	10.1	7.75
	Jan.	82	78.8	9.60		May.	32	1.3	25.60		Jan.	76	166.9	8.50
	Feb.	76	45.7	11.85	87-88	Oct.	55	84.7	20.05		Feb.	71	34.9	11.00
	Mar.	64	49.4	13.90		Nov.	65	12.0	13.55		Mar.	74	121.6	12.75
	Apr.	52	10.1	18.85		Des.	82	120.8	9.55	96-97	Apr.	65	38.7	16.80

	May.	34	1.8	25.65		Jan.	81	198.3	7.25		May.	44	16.5	25.75
79-80	Oct.	53	19.2	22.70		Feb.	75	104.3	9.35		Oct.	45	6.1	21.05
	Nov.	71	49.4	16.25		Mar.	75	98.2	11.40		Nov.	59	8.7	15.05
	Des.	84	79.9	8.35		Apr.	72	45.2	16.65		Des.	78	132.9	11.80
	Jan.	79	21.3	6.70		May.	47	2.5	23.65		Jan.	79	45.6	8.35
	Feb.	77	165.5	9.05	88-89	Oct.	45	3.6	21.90		Feb.	71	75.9	6.80
	Mar.	74	81.9	12.80		Nov.	63	18.8	11.80		Mar.	72	48.7	9.95
	Apr.	65	83.1	17.60		Des.	74	95.3	9.65	97-98	Apr.	62	12.9	16.10
	May.	40	0.7	24.30		Jan.	73	14.9	5.10		May.	47	11.5	24.50
80-81	Oct.	45	3.1	20.75		Feb.	66	45.5	7.35		Oct.	45	38.9	22.60
	Nov.	81	75.1	14.20		Mar.	70	97.9	14.35		Nov.	72	23.3	14.95
	Des.	84	112.1	9.55		Apr.	50	1.3	21.10		Des.	85	83.0	9.25
	Jan.	86	59.4	8.40		May.	34	3.4	25.20		Jan.	85	81.1	6.60
	Feb.	81	52.1	9.45	89-90	Oct.	44	7.3	22.40		Feb.	71	32.6	8.35
	Mar.	80	97.1	13.10		Nov.	75	133.5	14.20		Mar.	68	48.5	12.65
	Apr.	68	27.1	16.20		Des.	83	25.8	8.05	98-99	Apr.	64	19.5	18.65
	May.	47	5.8	21.35		Jan.	78	52.4	5.60		May.	47	24.8	24.60
81-82	Oct.	57	26.6	21.85		Feb.	76	77.5	8.30		Oct.	39	0.1	22.80
	Nov.	71	56.5	12.95		Mar.	62	38.6	13.35		Nov.	50	0.1	18.05
	Des.	87	47.3	9.80		Apr.	64	29.7	16.60		Des.	61	9.7	12.00
	Jan.	84	97.0	6.55		May.	37	0.3	24.00		Jan.	75	36.8	10.00
	Feb.	71	41.9	6.30	90-91	Oct.	39	4.0	22.30		Feb.	71	48.2	10.80
	Mar.	65	9.8	11.00		Nov.	50	6.2	16.10		Mar.	53	19.8	13.50
	Apr.	74	85.9	18.30		Des.	73	47.9	9.45		Apr.	48	11.7	19.35
	May.	57	24.4	24.35		Jan.	79	28.5	7.30		May.	28	1.2	27.15
82-83	Oct.	66	51.0	19.95		Feb.	70	32.0	7.80		Oct.	42	10.5	23.25
	Nov.	76	90.3	10.65		Mar.	75	205.6	13.15	2000	Nov.	55	8.2	14.20
	Des.	83	46.0	6.05		Apr.	58	9.0	18.70		Des.	73	28.0	10.05
	Jan.	83	40.5	4.30		May.	40	2.1	22.95		Jan.	77	52.6	7.20
	Feb.	78	49.2	6.20	91-92	Oct.	45	0.2	22.60		Feb.	67	23.7	8.70
	Mar.	71	40.0	11.85		Nov.	58	44.6	15.50		Mar.	56	31.1	11.65
	Apr.	57	18.9	17.70		Des.	83	82.6	7.90		Apr.	44	22.3	21.10
	May.	44	27.7	26.05		Jan.	80	97.8	3.90		May.	32	0.3	25.70
83-84	Oct.	46	1.0	19.20		Feb.	79	132.8	5.65		Oct.	45	12.4	21.20
	Nov.	68	54.8	15.95		Mar.	64	24.6	9.45	2001	Nov.	60	46.7	14.15
	Des.	83	18.2	8.90		Apr.	62	27.2	15.90		Des.	85	83.7	9.50
	Jan.	73	17.8	8.00		May.	53	55.4	21.60		Jan.	81	25.9	8.55
	Feb.	62	15.9	10.15	92-93	Oct.	36	0.0	21.40		Feb.	72	37.9	9.95
	Mar.	70	105.3	13.75		Nov.	72	109.2	12.85		Mar.	72	82.5	15.85
	Apr.	52	18.9	16.85		Des.	85	123.9	6.80		Apr.	66	36.2	18.50
	May.	44	35.4	23.85		Jan.	77	49.8	5.80		May.	43	17.6	23.65
84-85	Oct.	54	18.4	21.30		Feb.	75	85.9	7.55					
	Nov.	86	174.4	14.55		Mar.	63	18.8	11.20					
	Des.	86	36.0	7.15	93-94	Apr.	72	171.4	16.65					
	Jan.	88	52.5	8.80		May.	66	144.1	21.10					

Appendix (B)

he software Minitab(13.) is used in the following macro programs.

Program (1): the values of (α_t^{\wedge}) variable input (temperature)

```
gmacro
aa.macro
let c4(1)=-1.15
do k3=2:192
let c4(k3)=c2(k3)- 0.2518*c2(k3-1)
enddo
endmacro
```

Program (2): values (β_t^{\wedge}) for output (Rainfall)

```
gmacro
aa.macro
let c5(1)=-12
do k3=2:192
let c5(k3)=c1(k3)- 0.2518*c1(k3-1)
enddo
endmacro
```

[44]

Forecasting rainfall using transfer function

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

```
For i=1:192
```

```
For k=1:23
```

```
Z(I,k)= v(k)*ul(i+21)-k);
```

```
end;
```

```
end
```

```
fori=1:192
```

```
s(i)=0;
```

```
for j=1:21
```

```
s(i)=s(i)-z(i,j);
```

```
end
```

```
end
```

```
fori=24:192
```

```
n(i)=y(i)+s(i-20)
```

```
end
```

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

```
gmacro
```

```
aa .macro
```

```
let c3(8)=0
```

```
do k1=9:192
```

```
let c3(k1)=c1(k1)-1.048*c1(k1-1)- 0.7266*c1(k1-2)+2.667*c2(k1)-
```

```
1.422*c2(k1-1)-4.451*c2(k1-2)+1.04*c3(k1-1)+0.7266*c3(k1-2)
```

```
enddo
```

```
let k4=sum(c3(k1)**2)
```

```
print k4
```

```
endmacro
```