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Predicting Time Series of Temperature in Nineveh Using The Conversion Function Models

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Abstract—**Prediction of time series is one of the topics that receive significant interest because of its importance in various fields, especially when studying natural phenomena. In this research, the transformation function model was reconciled where it aims to use the genetic algorithm to estimate the parameters of the final transformation function model. Also, it was used to predict future values for the time series of monthly averages of temperatures in Nineveh Governorate for the period (1985-2000) as an output series and wind speed as an input series. In Nineveh Governorate, they are not stable in average and variance; when taking the square root of the data and taking the first seasonal difference as well as the first normal difference, stability was achieved, and then showed a model of the transformation function as shown in the equation (17). This research showed that the model's final parameters were estimated using the genetic algorithm based on the standard error squares average. The best estimate was chosen for the parameters that correspond to the lowest value of the average error squares, and by using this model, monthly temperature rates were predicted. Predictive values were shown to be consistent with the original values of the series. By depending on the transformation function model shown in the above equation, monthly averages of the temperature were predicted for the next four months, and the prediction results were consistent with the original time series values, which indicates the efficiency of the model.**

Keywords—**Transformation function; genetic algorithm; forecasting; bleaching; TFM.**

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I. INTRODUCTION

The importance of time series, many works can be seen in the literature on these topics, especially those that depend on statistical models, and there are many possible methods for describing temporal behavior. The Box Jenkins method is attractive in time series analysis as it provides us with a comprehensive statistical modeling methodology that covers a wide variety of patterns from stability to non-stability and seasonality of time series. The prediction for using ARIMA models is based on using a single time series without using the information package available in other linked time series. Moreover, in many prediction situations, other events lead to a regular impact on the time series that we want to predict (dependent variables), so we need to use multivariate prediction models, and here we must build a prediction model that includes more than one-time series and shows the dynamic characteristics of the system. Such a model is called a transformation function model(TFM) [1], [2].

The research aims to estimate the parameters of the best model for the transformation function models using the genetic algorithm and then predict the appropriate model and apply that to real data, which represents monthly averages of temperatures in Nineveh Governorate for the period (1985-2000) as a series of outputs and the wind speed measured (m/hour) as a series inputs.

II. MATERIALS AND METHOD

A. *Mathematical Formula of the (TFM) and its Construction Steps*

Assuming that Z_t, U_t represent two stable series, these two series are connected by a linear filter [3]:

$$Z_t = V(\zeta)U_t + N_t \quad (1)$$

Whereas: $V(\zeta) = v_0 + v_1\zeta + v_2\zeta + \ldots$ The conversion function, the coefficients $v_0, v_1, v_2, \ldots$ represent the impulse response weights, (ζ) the back displacement factor, and N_t represents white noise and follows the ARMA pattern [4].

We assumed in the previous equations that the change in U leads to an immediate change in Z, as a delay time in the system's response to changes is likely to occur. It has been assumed (k) that the number of periods that elapse before U starts affecting the dependent variable in this case Equ.1 can be rewritten as follows:

$$Z_t = \frac{\varpi_s(\zeta)}{\gamma_r(\zeta)} U_{t-k} + \frac{\vartheta(\zeta)}{\varphi(\zeta)} a_t \quad (2)$$

$$\varpi(\zeta) = \varpi_0 - \varpi_1\zeta - \ldots - \varpi_s\zeta^s$$
$$\gamma(\zeta) = 1 - \gamma_1\zeta - \ldots - \gamma_r\zeta^r$$
$$\vartheta(\zeta) = 1 - \vartheta_1\zeta - \ldots - \vartheta_{q_n}\zeta^{q_n}$$
$$\varphi(\zeta) = 1 - \varphi_1\zeta - \ldots - \varphi_{p_n}\zeta^{p_n}$$

There are three stages to building a transform function model through the Box Jenkins algorithm. These stages can be summarized as follows:

B. Diagnosing the TFM

The first step is to determine the chain's stability or not and whether there are seasonal changes or not. After confirming the stability of the chain, the weights of the TFM are estimated depending on the cross-correlation function; pre-bleaching of the input and output chains is made by assuming that both series are they follow the ARMA model and can be expressed as:

$$\varphi(\zeta)U_t = \vartheta(\zeta)\varepsilon_t \Rightarrow \varepsilon_t = \frac{\varphi(\zeta)}{\vartheta(\zeta)} U_t \quad (3)$$

$$\varphi(\zeta)Z_t = \vartheta(\zeta)\partial_t \Rightarrow \partial_t = \frac{\varphi(\zeta)}{\vartheta(\zeta)} Z_t \quad (4)$$

After obtaining the two residual chains ε_t and ∂_t two interviews for each of the input and output series, respectively, the two ovarian series' cross-linking is calculated according to the following formula [5].

$$\rho_{\varepsilon\partial}(h) = \frac{cov(\varepsilon,\partial)}{\sqrt{var(\varepsilon)}\sqrt{var(\partial)}} \quad (5)$$

Where $\rho_{\varepsilon\partial}(h)$ the cross-correlation function ε_t and ∂_t the delay Lagging represent h. Pulse response weights are found according to the following formula [6].

$$v_l = \frac{\sqrt{var(\partial)}}{\sqrt{var(\varepsilon)}} \rho_{\varepsilon\partial}(h) \quad (6)$$

C. Determination of the ARMA model for white noise N_t

Before identifying the N_t model, the interference chain Nt's estimated values must first be calculated using the following equation and then estimating the ARMA model of the white noise chain [7].

$$N_t = Z_t - V(\zeta)U_t \quad (7)$$

D. Estimation and Validation of Model Diagnostic Accuracy

After the diagnostic stage in which the function of the TFM rank (r, s, k) is determined and the chain of disturbance of the ARMA model, the parameters of the TFM described in equation (2) are evaluated as follows:

E. Initial Values for Parameters

The following relationships determine initial values for parameters for the TFM:

$$\left.\begin{array}{ll} v_l = 0 & ,l < k \\ v_l = \gamma_1 v_{l-1} + \gamma_2 v_{l-2} + \ldots + \gamma_r v_{l-r} + \varpi_o, & l = k \\ v_l = \gamma_1 v_{l-1} + \gamma_2 v_{l-2} + \ldots + \gamma_r v_{l-r} - \varpi_{l-k}, & l = k+1 \\ v_l = \gamma_1 v_{l-1} + \gamma_2 v_{l-2} + \ldots + \gamma_r v_{l-r}, & l > k+s \end{array}\right\} \quad (8)$$

F. Final Values of Parameters

The genetic algorithm is used in the final estimation of the parameters, and tests are performed to determine the suitability of the model with the final parameters. The estimator function that achieves the smallest value for the mean error squared standard is used. The proposed steps for a genetic algorithm are as follows [8]:

1) Creation of the primary generation: The single chromosome in this generation represents the parameter values for the TFM. The true value of the parameter has been placed in the chromosome gene, meaning that the coding was real coding [9].

2) Fitness function: The value of the fitness function in this algorithm represents the value of the standard mean error squares and at the same time checking the randomness of the residual chain by using the (Box-Pierce) test according to the following formula:

$$\psi = c \sum_{l=1}^{h} \Re_{aa}^2 (l) \quad (9)$$

Whereas, c = n-r-s-k and $\Re$ the values auto-correlation function of the a_t series, ψ is almost followed Kay Square distribution with a degree of freedom ($h-p_n-q_n$) and h represents the largest studied displacement. And checking the independence of the bleached input chain with the remaining residual chain by using the (Box -Pierce) test according to the following formula:

$$\Omega = c \sum_{l=0}^{h} \Re_{\varepsilon a}^2 (l) \quad (10)$$

Whereas, c = n-1-n *, n * = max (p_u, s + k + p_n) and p_u are the autoregressive order of the input chain, and Ω is almost followed Kay Square distribution with a degree of freedom (h +1-r-s) [10].

3) Selection: the process of selecting parents in the community for mating and producing a new generation, and the roulette wheel was chosen for the choice of parents.

4) Transit: This process is represented by a change between the corresponding values of the two sections of the parents elected to form the new individual, and the transit has been chosen with two cutting points [11].

5) Mutation: The process of switching between one individual's values to form individuals that give new solutions to the next generation that was not previously formed in previous generations to expand possible solutions. The mutation process was done using the uniform function [12], [13]. After the TFM fits into the data, it can be used to predict the output chain Z_t by using the previous date of the output string Z_t and the input string U_t. The step prediction formula m can be written as:

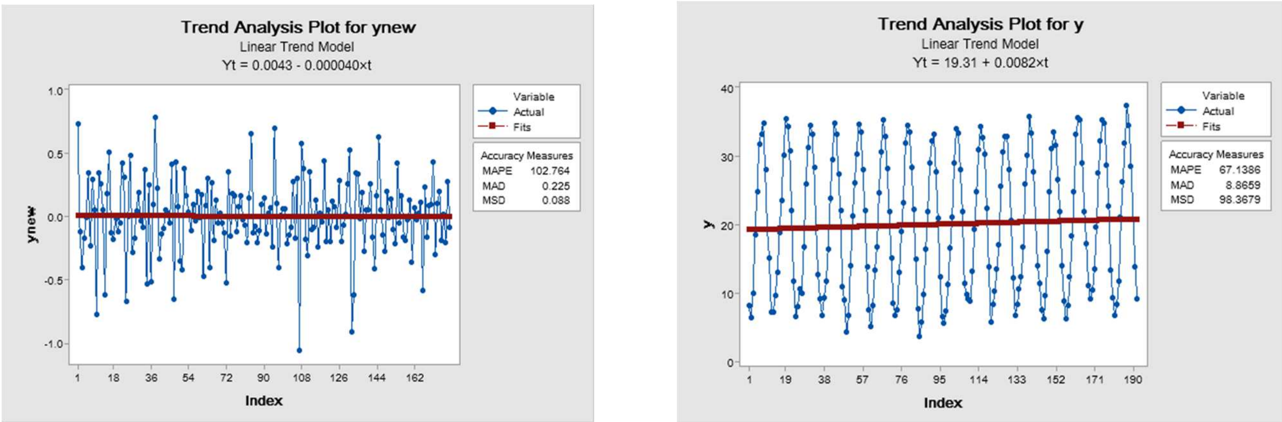
$$Z_{t+m} = \gamma_r^{-1}(\zeta)\varpi_s(\zeta)U_{t+m-k} + \varphi^{-1}(\zeta)\vartheta(\zeta)a_{t+m} \quad (11)$$

III. Results and Discussion

In this paragraph of the research, two-variable time series models were applied using a single-input- single-output TFM on real data that represents monthly averages of temperatures in Nineveh Governorate for the period (1985-2000) as a series of outputs and the wind speed measured (m/hour) As an input series. The stages of creating the transformation function model are as follows:

A. Initializing the Data

The first essential step is to know whether the data is stable or not for the input and output series. We note that the input and output series are unstable in the mean and variance, and in order to make them stable, one of the transformations was used, which is taking the square root of the contrast variance and the seasonal difference to remove the effect of the season from this series. The first difference was taken to make it stable in the mean, as shown in the following Figure 1.



Output series after stabilization

The original output series

Fig.1 Illustrates drawing the general direction of the input and output series after their stability is proven

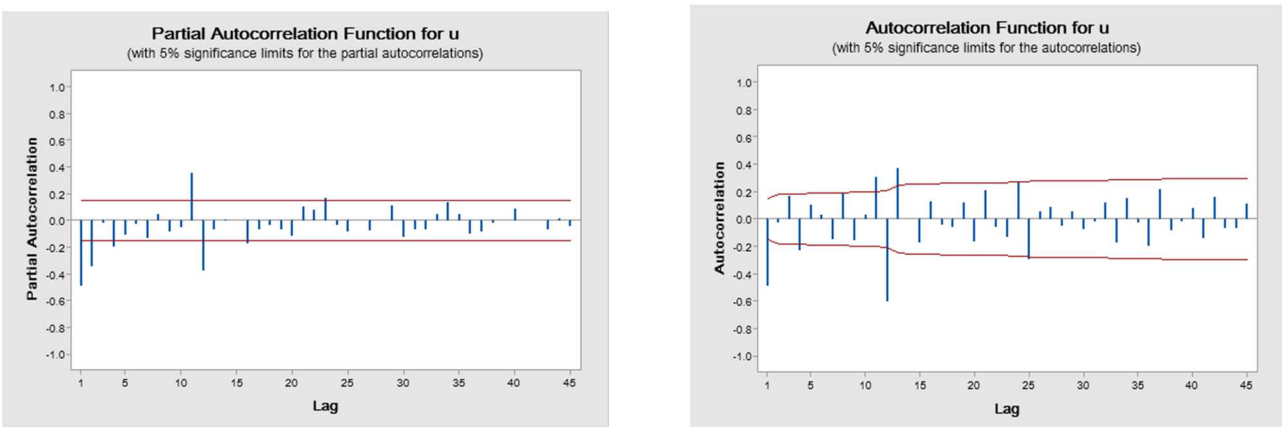


Fig.2 Shows the graph of the ACF and the PACF of the input series after after stability is achieved

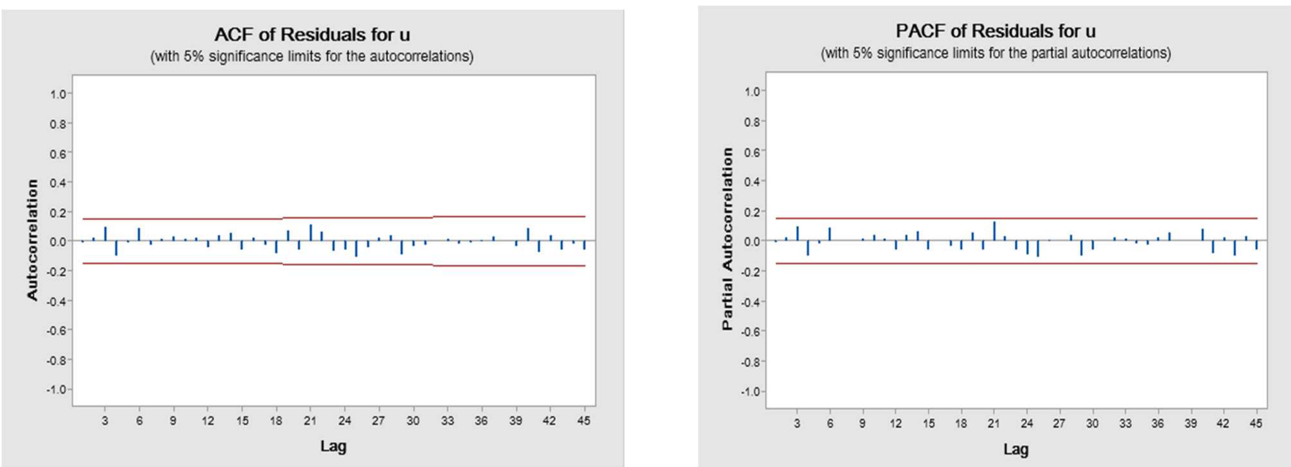


Fig. 3 Shows the graph of the ACF and the PACF for a series residue model SARIMA(2,1,1)(2,1,3)$_{12}$.

B. Purify the Input U_t and Z_t Output Series

After initializing the input and output chains, they were bleached by specifying the appropriate model for them to obtain a series of independent residues by noting the behavior of the ACF and PACF, as it was evident from Figure 2 that the chain follows the SARIMA (2,1,1), $(2,1,3)_{12}$ model, having less MSE = 0.0281 Likewise, the residues were random, as shown in Figure 3, which represents the graph of both the ACF and PACF for the residues of the appropriate model and the estimated values of the parameters is $\varphi_1 = 0.0989$, $\varphi_2 = 0.0296$, $\emptyset_1 = -1.215$, $\emptyset_2 = -0.634$, $\vartheta_1 = 0.8635$, $\theta_1 = -0.237, \theta_2 = 0.374, \theta_3 = 0.699$. The general formula for the model is shown in Table 1. To maintain the semantic relationship between inputs and outputs, the input chain is purified on the output chain. Table 2 shows the error chain values ∂_t.

TABLE I

VALUES ε_t FOR THE INPUT VARIABLE

t	ε_t	t	ε_t	t	ε_t	t	ε_t	t	ε_t
1	0.498120	37	-0.393251	73	0.360085	109	-0.141922	145	-0.061399
2	0.884663	38	0.599732	74	0.102317	110	0.141894	146	0.287686
3	0.499046	39	0.029300	75	0.046100	111	0.254833	147	0.175468
4	0.762652	40	0.466817	76	0.387465	112	0.343662	148	0.215171
5	0.204545	41	0.042197	77	-0.183038	113	-0.038347	149	0.134937
6	0.121971	42	0.045467	78	0.031139	114	0.067151	150	-0.027980
7	0.373431	43	0.120327	79	0.177160	115	0.127725	151	-0.040712
8	-0.091480	44	-0.154220	80	-0.253200	116	-0.178096	152	-0.007475
9	-0.214389	45	-0.227104	81	-0.517602	117	-0.199731	153	-0.071996
10	0.229705	46	0.169186	82	0.355857	118	0.113654	154	-0.177266
11	-0.205437	47	-0.155790	83	0.125481	119	-0.260843	155	-0.218456
12	0.237249	48	0.223675	84	0.271502	120	0.628991	156	0.256291
13	0.142695	49	0.314969	85	0.193366	121	0.056190	157	0.015234
14	0.682390	50	0.452405	86	0.309239	122	0.508134	158	0.488197
15	0.509071	51	0.284273	87	0.226719	123	0.237392	159	0.251315
16	0.414193	52	0.387645	88	0.211759	124	0.214525	160	0.423183
17	0.003322	53	-0.123891	89	-0.127048	125	0.058693	161	-0.044763
18	-0.094328	54	0.017535	90	-0.052418	126	0.185873	162	0.237306
19	0.044619	55	-0.024953	91	-0.065646	127	-0.036388	163	0.121221
20	-0.476283	56	-0.096343	92	-0.197148	128	-0.043273	164	-0.143632
21	-0.293718	57	-0.299356	93	-0.281486	129	-0.114904	165	-0.278497
22	-0.061859	58	-0.304895	94	-0.027333	130	-0.339746	166	-0.267685
23	0.556640	59	0.061252	95	-0.114836	131	0.272284	167	-0.126395
24	0.501938	60	0.237627	96	0.283466	132	0.215503	168	0.554009
25	-0.010214	61	0.029984	97	-0.086968	133	-0.028421	169	-0.090935
26	0.420960	62	0.511822	98	0.403503	134	0.388946	170	0.241338
27	0.099327	63	0.347506	99	0.351416	135	0.237277	171	0.521145
28	0.132832	64	0.397739	100	0.286403	136	0.214420	172	0.162524
29	-0.007686	65	-0.113384	101	0.109332	137	-0.096411	173	0.051100
30	-0.000648	66	0.125001	102	-0.010700	138	0.133215	174	0.150161
31	0.023728	67	0.099776	103	-0.063911	139	0.220204	175	0.265546
32	-0.245978	68	-0.114875	104	0.137138	140	-0.228046		
33	-0.242385	69	-0.295024	105	-0.419668	141	-0.211941		
34	-0.190463	70	0.154342	106	0.313446	142	-0.266587		
35	0.201226	71	0.057091	107	0.257655	143	-0.025114		
36	0.720294	72	0.677589	108	0.164679	144	0.312524		

TABLE II

VALUES ∂_t FOR THE OUTPUT VARIABLE

t	∂_t	t	∂_t	t	∂_t	t	∂_t	t	∂_t
1	0.730280	37	0.290682	73	0.000285	109	0.557807	145	0.230120
2	0.433082	38	0.860596	74	0.149706	110	0.285817	146	0.233940
3	-0.043889	39	0.379137	75	0.040776	111	-0.215295	147	0.027786
4	-0.170726	40	0.064188	76	-0.115900	112	0.123452	148	0.060464
5	-0.128316	41	-0.123693	77	-0.016722	113	-0.109031	149	0.208206
6	0.235844	42	0.164503	78	0.073634	114	-0.122539	150	0.081815
7	-0.059740	43	-0.074365	79	0.093053	115	-0.125473	151	0.075898
8	0.252390	44	0.045305	80	0.142980	116	-0.004269	152	0.018955
9	0.243628	45	0.339499	81	0.263764	117	0.010447	153	0.099857
10	-0.577676	46	-0.209397	82	-0.236186	118	-0.267844	154	0.305099
11	-0.078226	47	-0.019219	83	-0.078848	119	-0.186070	155	0.322599
12	0.180604	48	-0.383446	84	-0.083827	120	0.316673	156	0.230366
13	0.880409	49	0.461807	85	0.392315	121	0.672533	157	0.479839
14	-0.061145	50	0.477478	86	0.207052	122	0.093680	158	0.178562
15	-0.219487	51	-0.203971	87	-0.140886	123	-0.319239	159	-0.078081
16	0.183129	52	0.099241	88	-0.135765	124	0.163942	160	0.072717
17	-0.011497	53	0.006581	89	0.032397	125	-0.096345	161	-0.135911
18	0.143098	54	0.186633	90	0.241912	126	0.208447	162	-0.003744
19	-0.130381	55	-0.134265	91	0.065898	127	-0.087050	163	-0.091883
20	0.065921	56	0.062383	92	0.134815	128	-0.092491	164	-0.115100
21	0.041794	57	0.227694	93	0.294854	129	0.018483	165	0.083897
22	-0.308573	58	0.131304	94	-0.309292	130	-0.034840	166	-0.279609
23	0.409612	59	0.185078	95	0.611431	131	0.824940	167	0.316425
24	-0.114376	60	-0.045894	96	0.583009	132	-0.000945	168	-0.213087
25	0.534445	61	0.183816	97	0.385248	133	-0.298536	169	-0.017234
26	0.193388	62	0.352787	98	0.382100	134	-0.141847	170	-0.010528
27	-0.250918	63	-0.055451	99	0.071455	135	-0.088459	171	0.310009
28	0.009602	64	-0.206216	100	-0.064583	136	0.110172	172	0.026968
29	-0.098092	65	0.088286	101	-0.049903	137	0.057679	173	-0.089647
30	0.192695	66	0.080481	102	0.035938	138	0.029269	174	0.149711
31	-0.088369	67	-0.083391	103	-0.184594	139	-0.180354	175	-0.150429
32	-0.044727	68	0.023606	104	0.203628	140	-0.034678		
33	0.320005	69	0.273480	105	0.207971	141	0.293588		
34	-0.488667	70	-0.026341	106	-0.167881	142	0.022029		
35	0.451085	71	0.031127	107	-0.378575	143	0.146070		
36	-0.638840	72	-0.782508	108	0.213932	144	-0.273265		

C. *Cross-Correlation Function (CCF) between Series (ε_t) and (∂_t)*

Using equation (5), the cross-correlation values between the two (ε_t) and (∂_t) series are obtained, and the cross-correlation values are drawn to determine the system delay time as well as determine the TFM ranks (s, r). The following Figure 4 shows the CCF graph between the two strings (ε_t) and (∂_t), and Table 3 shows the values of the CCF between them.

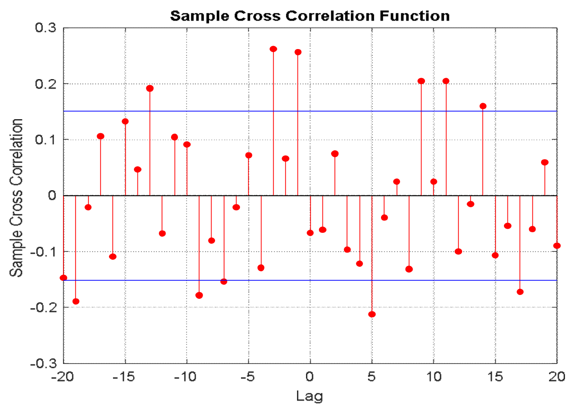


Fig. 4 Shows the graph of the cross-link function between the series (ε_t) and (∂_t).

TABLE III
VALUES OF THE CROSS-CORRELATION FUNCTION BETWEEN SERIES (ε_t) AND (∂_t)

t	$\rho_{\varepsilon\partial}$	t	$\rho_{\varepsilon\partial}$	t	$\rho_{\varepsilon\partial}$	t	$\rho_{\varepsilon\partial}$	t	$\rho_{\varepsilon\partial}$
1	-0.066843	6	-0.211899	11	0.024691	16	-0.107010	21	-0.0898681
2	-0.061267	7	-0.039612	12	0.204591	17	-0.054091		
3	0.074771	8	0.024740	13	-0.099650	18	-0.172258		
4	-0.096836	9	-0.131466	14	-0.014954	19	-0.060100		
5	-0.121444	10	0.204960	15	0.159757	20	0.059681		

D. Diagnosis

Pulse response weights were estimated according to equation (6) and as shown in Table 4. The order of the transformation function model (s, r, k) is determined from Figure 4, which represents the values of the cross-linking of the two series (ε_t) and (∂_t).

TABLE IV
VALUES OF PULSE RESPONSE WEIGHTS

t	v	t	v	t	v	t	v	t	v
1	-0.065799	6	-0.208590	11	0.024305	16	-0.105339	21	-0.0884644
2	-0.060310	7	-0.038993	12	0.201395	17	-0.053246		
3	0.073603	8	0.024353	13	-0.098094	18	-0.169567		
4	-0.095324	9	-0.129412	14	-0.014720	19	-0.059162		
5	-0.119547	10	0.201759	15	0.157262	20	0.058749		

We note that the first significant correlation is at the fifth deficiency, and this means that (k = 5) (r = 0)) And (s = 1), and the formula for the conversion function model is as follows:

$$Z_t = (\varpi_0 - \varpi_1 \zeta) U_{t-5} + N_t \quad (12)$$

When substituting the initial values for the pulse response weights, we obtain the initial values for the parameters:

$$N_t = Z_t - \sum_{i=0}^{20} v_i U_{t-i} \quad (13)$$

To estimate the values of the noise chain N_t, we use the following equation. Table 5 shows the obtained N_t noise string values.

TABLE V
THE NT NOISE VALUES

t	N_t	t	N_t	t	N_t	t	N_t	t	N_t
1	0.763056	37	-0.094591	73	0.19538	109	0.417826	145	0.489481
2	-0.062099	38	0.850668	74	-0.14042	110	-0.261614	146	0.221122
3	-0.428088	39	0.237827	75	0.22102	111	-0.251174	147	-0.271074
4	-0.157123	40	-0.319817	76	0.18995	112	0.335221	148	-0.241050
5	0.103400	41	-0.053534	77	-0.07958	113	-0.255383	149	0.247854
6	0.429821	42	-0.361963	78	-0.01339	114	0.009102	150	-0.171904
7	-0.055868	43	0.120893	79	-0.00926	115	0.031681	151	0.327981
8	0.250855	44	0.184382	80	0.05466	116	-0.193692	152	-0.089340
9	0.048014	45	-0.209755	81	-0.24140	117	0.031935	153	-0.283963
10	-0.824248	46	0.661166	82	-0.16826	118	-0.071617	154	0.533906
11	0.166238	47	-0.875889	83	0.26200	119	0.617085	155	-0.299097
12	0.200053	48	0.625850	84	0.55319	120	-0.275735	156	0.313290
13	-0.159593	49	0.028878	85	0.05120	121	0.063467	157	-0.089585
14	-0.552264	50	-0.354432	86	-0.16265	122	-0.180793	158	-0.392367
15	0.216655	51	-0.502067	87	-0.07833	123	0.054661	159	0.069963
16	0.414159	52	0.333475	88	-0.08254	124	0.085043	160	0.051396
17	-0.016515	53	0.189100	89	-0.02219	125	0.079901	161	-0.296747
18	-0.151297	54	0.147590	90	0.28283	126	0.126055	162	0.125920
19	0.125415	55	-0.256705	91	-0.21911	127	-0.048291	163	-0.183757
20	-0.054395	56	0.182004	92	-0.04486	128	-0.089416	164	0.176421
21	-0.346325	57	0.062696	93	0.12106	129	-0.063070	165	0.127835
22	0.706236	58	-0.051081	94	-0.20703	130	0.399834	166	-0.631121
23	0.144551	59	0.160119	95	0.60917	131	0.147935	167	0.296067
24	-0.588176	60	-0.111308	96	0.06119	132	-0.588696	168	-0.251815
25	-0.115997	61	-0.224987	97	-0.44359	133	-0.781612	169	0.051513

26	0.398595	62	0.021393	98	0.04341	134	0.344638	170	0.153513
27	0.058817	63	0.148946	99	0.09757	135	0.315038	171	0.354127
28	-0.187875	64	-0.197633	100	-0.07346	136	-0.055234	172	-0.209759
29	0.041552	65	0.048949	101	-0.15530	137	0.264939	173	0.016519
30	0.087384	66	0.021662	102	0.17189-	138	-0.247279	174	0.270358
31	-0.016360	67	0.259677	103	-0.02517	139	0.081305	175	-0.093713
32	-0.306604	68	-0.174933	104	0.43258	140	-0.139967		
33	0.393227	69	0.124428	105	-0.23151	141	0.458041		
34	-0.682945	70	-0.127230	106	0.34167	142	-0.384373		
35	0.382304	71	-0.081672	107	-1.10073	143	-0.106694		
36	-0.393990	72	-0.459595	108	0.55603	144	0.033809		

The ARMA model for the N_t series has been determined by drawing the ACF and the PACF, and it has been found that the best model is SARMA(2,0,2)(1,0,2)$_{12}$ because it has the lowest value MSE=0.0367, and the estimated values of the parameters are $(\varphi_1 = 0.003, \varphi_2 = 0.084, \emptyset_1 = -0.799, \vartheta_1 = 0.574, \vartheta_2 = 0.391, \theta_1 = 0.081, \theta_2 = 0.799)$, the final model of the TF can be illustrated according to the formula following:

$$Z_t = (\varpi_0 - \varpi_1 \zeta) U_{t-5} \quad (14)$$

The genetic algorithm described in 2.3.2 was used by applying it with the MATLAB program to estimate the parameters' final values. On repeat (202) the genetic algorithm was stopped, and the final values of the model were obtained, and the minimum means squared error MSE = 0.048533 correspondings to the parameters$(\varpi_0 = -0.079, \varpi_1 = 0.06, \varphi_1 = -0.547, \varphi_2 = 0.05, \emptyset_1 = -0.3, \vartheta_1 = 0.103, \vartheta_2 = 0.615, \theta_1 = 0.266, \theta_2 = 0.393)$ and Table 6 shows the values of The residual a_t is calculated using the following estimated formula:

The Autocorrelations and partial auto- correlations of the residual are calculated as in Figure 5. These correlations seem small and fall within the confines of confidence, and accordingly, it can be said that the residual series has random fluctuations. And to determine whether the values of auto-correlations are significant or not, the calculated value of the (Box-Pierce) test by using the equation (9) is $\psi = 18.2905$ less than the tabular value $\chi^2_{(0.05,13)} = 22.362$ at the level of significance 0.05. Thus, the series of residues is considered a random series, and the calculated value of the (Box-Pierce) test by using the equation (10) is $\Omega = 16.5502$ less than the tabular value $\chi^2_{(0.05,20)} = 31.41$ at the level of significance 0.05. This indicates the independence of the bleached input series with the residual series.

TABLE VI
THE RESIDUAL SERIES VALUES a_t

t	a_t	t	a_t	t	a_t	t	a_t	t	a_t
1	0.730280	37	0.082353	73	-0.135267	109	0.268636	145	0.221632
2	0.349392	38	0.504460	74	-0.251570	110	0.095976	146	0.153492
3	-0.028568	39	0.440523	75	-0.039013	111	-0.284825	147	0.136826
4	-0.182273	40	0.101945	76	-0.044029	112	0.195920	148	-0.066065
5	-0.123194	41	0.018068	77	0.051174	113	-0.119270	149	0.212630
6	0.258044	42	-0.008914	78	0.066321	114	-0.133547	150	0.065478
7	-0.001306	43	-0.057592	79	0.160816	115	-0.086949	151	0.173628
8	0.357569	44	-0.021854	80	0.060975	116	-0.106703	152	-0.007009
9	0.272757	45	0.128439	81	0.101626	117	-0.109463	153	-0.046691
10	-0.522532	46	0.133826	82	-0.143847	118	-0.159205	154	0.419282
11	-0.007829	47	-0.121008	83	-0.035924	119	0.072003	155	0.254129
12	0.162046	48	-0.196106	84	0.286744	120	0.280925	156	0.150058
13	0.589208	49	0.203657	85	0.165540	121	0.262315	157	0.038919
14	-0.334449	50	0.181664	86	0.094897	122	0.098904-	158	-0.045816
15	-0.118382	51	-0.326278	87	-0.017977	123	0.093649-	159	-0.039831
16	0.198958	52	0.026102	88	-0.141965	124	0.120365	160	0.038738
17	0.035170	53	-0.017131	89	0.057267	125	-0.081312	161	-0.217114
18	0.047488	54	0.180817	90	0.119213	126	0.204648	162	-0.141177
19	-0.094660	55	-0.070901	91	0.070405	127	-0.066261	163	-0.105842
20	0.010063	56	0.095122	92	0.089018	128	-0.042247	164	-0.113858
21	-0.049275	57	0.151202	93	0.150748	129	-0.108989	165	0.036280
22	-0.065319	58	0.169345	94	-0.237290	130	0.197927	166	-0.363065
23	0.421833	59	0.087547	95	0.521480	131	0.548071	167	-0.032661
24	-0.258421	60	0.065289	96	0.452591	132	-0.196943	168	-0.281188
25	0.315252	61	-0.152934	97	0.096438	133	-0.565943	169	-0.046236
26	0.169089	62	0.168510	98	0.066581	134	-0.317898	170	-0.109936
27	-0.170762	63	0.080505	99	0.067493	135	-0.096538	171	0.368133

28	-0.054775	64	-0.211458	100	0.023778	136	0.114532	172	-0.105296
29	-0.052338	65	0.133792	101	-0.086232	137	0.114500	173	0.073668
30	0.195792	66	-0.098566	102	-0.110193	138	-0.101196	174	0.173825
31	-0.050023	67	0.012425	103	-0.177641	139	-0.075977	175	-0.022766
32	0.005499	68	0.000483	104	0.161876	140	-0.080281		
33	0.331650	69	0.128345	105	-0.046125	141	0.189830		
34	-0.486898	70	0.086773	106	0.072234	142	0.043856		
35	0.347627	71	-0.142190	107	-0.654399	143	0.021081		
36	-0.647690	72	-0.616677	108	0.374395	144	-0.144315		

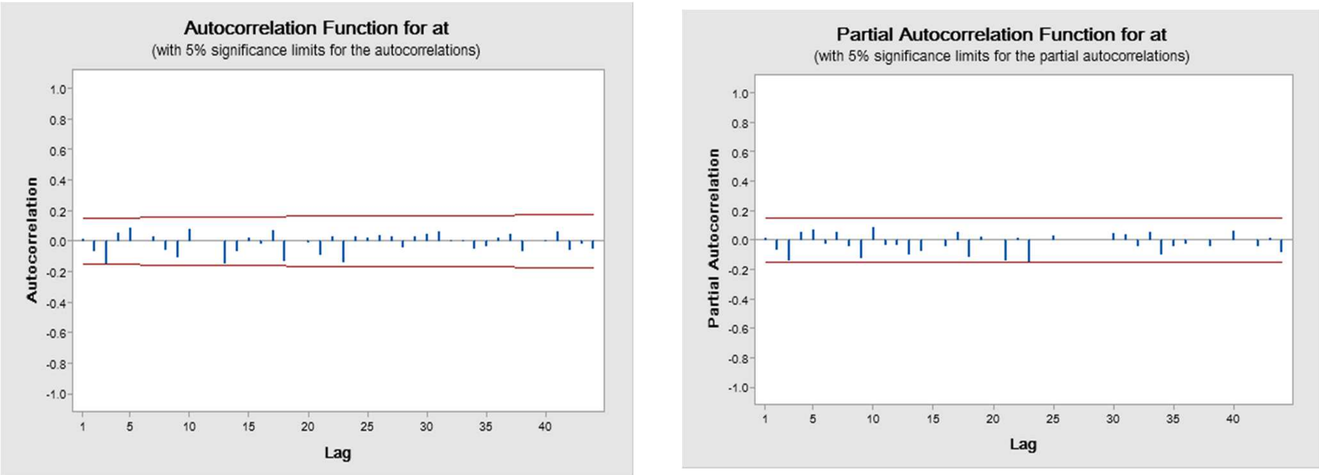


Fig.5 Shows the graph of the ACF and the PACF for a series residue a_t.

The prediction at period (m) can be obtained from the TFM by using the following equation:

$$\text{TFM} = (m_0 - m_1\zeta)U_z \tag{15}$$

To find the predictive value of the output series Z_t requires determining a_{t+m} values is the predicted value of a future step of m and this value is not predictable and therefore is equal to zero, and the following Table 7 shows the original values and prediction values.

TABLE VII
PREDICTIVE VALUES FOR ZT TIME SERIES USING THE TF.

t	actual	forecasting
176	0.016141	0.0261363
177	-0.204892	-0.008901
178	0.268467	0.1078065
179	-0.087026	-0.1029681

IV. CONCLUSIONS

Through studying each of the series of inputs and outputs represented by wind speed and temperature respectively in Nineveh Governorate, they are not stable in average and variance, when taking the square root of the data and taking the first seasonal difference as well as the first normal difference of data, stability was achieved. Then a model of the transformation functioned shown in the equation (17), and it was found the final parameters of the model were estimated using the genetic algorithm based on the standard error squares average, where the best estimate was chosen for the parameters that correspond to the lowest value of the average error squares. By using this model, monthly temperature rates were predicted, and predictive values were shown to be consistent with the original values of the series; and The appropriate model of data can be formulated as follows:

$$Z_t = (\varpi_0 - \varpi_1\zeta)U_{t-5} + \frac{(1-\vartheta_1\zeta-\vartheta_2\zeta^2)(1-\theta_1\zeta^{12}-\theta_2\zeta^{24})}{(1-\varphi_1\zeta-\varphi_2\zeta^2)(1-\emptyset_1\zeta^{12})}a_t \tag{16}$$

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