SHORT TERM FORECASTING OF SULFATE CONCENTRATIONS IN BAGHDAD

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ABSTRACT

Water quality control is an important protection issue. The analysis of the water quality parameters and the prediction of their changes in future, are important in the planning for water pollution control program. This analysis and prediction are the important steps and functions that the environmental engineer must perform.

In this study, time series analysis was applied to model a short term forecasting for the minimum and the maximum values for both raw and produced water of Sulfate concentrations at seven water treatment plants serving Baghdad city (Karkh, Sharq Dijlah, Karama, Wathba, Qadisiya, Dora, and Rasheed).

Holt-Winters' method was used for the modeling. Three years (2001-2003) were used for building the model and the year (2004) was used for the verification, to check the model acceptability. Comparisons by (t-test) and (F-test) between means and variances of the observed concentrations and these generated by the Holt-Winters' model had reflected the applicability of this model. Hence, in future for operation purposes, it can be use for forecasting Sulfate concentrations.

Visual Basic Application (VBA) software was built for this short-term forecasting model. This software was built in away, which allows an automatic updating of the model parameters. Adding additional observed data usually performs the updating of such model.

INTRODUCTIONT

The idea of using a mathematical model to describe the behavior of a certain physical phenomenon is well established. In particular, it is some times possible to derive a model based on physical laws. This model is enabling to calculate the value of some time dependent quantity nearly exactly at any instant of time. If exact calculation were possible such a model would be entirely deterministic. Probably no phenomenon is totally deterministic because of the unknown factors that contribute to its variation. So it is not possible to use a deterministic model to describe this phenomenon. In this case, it may be possible to derive a model that can be used to calculate the probability of a future value lying between two specified limits. Such a model is called a stochastic model **[1]**.

Stochastic analysis of water quality parameters is a useful treatment of its' data for making quantitative decisions, such as whether water quality is improving or getting worse over time. The short-term forecasting can be useful for extrapolating the momentum that exists in the phenomena. As changes in established patterns are not likely over a short span, extrapolating them provides, most often, with accurate and reliable forecasters. Seasonality can also be predicted fairly well **[2]**.

Area and Objective of the Study

The Tigris River has a large importance in the present and in the future. This is because of the detrimental effect of pollutants resulting from human activities, industrial wastes, sewage wastes, and harmful effect of increasing drainage waters coming from agricultural lands upstream coupled with the decreasing in its discharge. So it has become necessary to make detailed studies and researches to evaluate the suitability of the river water for different purposes in a selected site of the river.

The reach of the river along Baghdad city and Sulfate concentration levels were chosen for this study. Time series analysis was applied to both raw water and treated water of the existing treatment plants that exists along the river in Baghdad. The running conventional water treatment plants are (Karkh, Sharq Dijlah, Karama, Wathba, Qadisiya, Dora, and Rasheed) as shown in Figure (1).

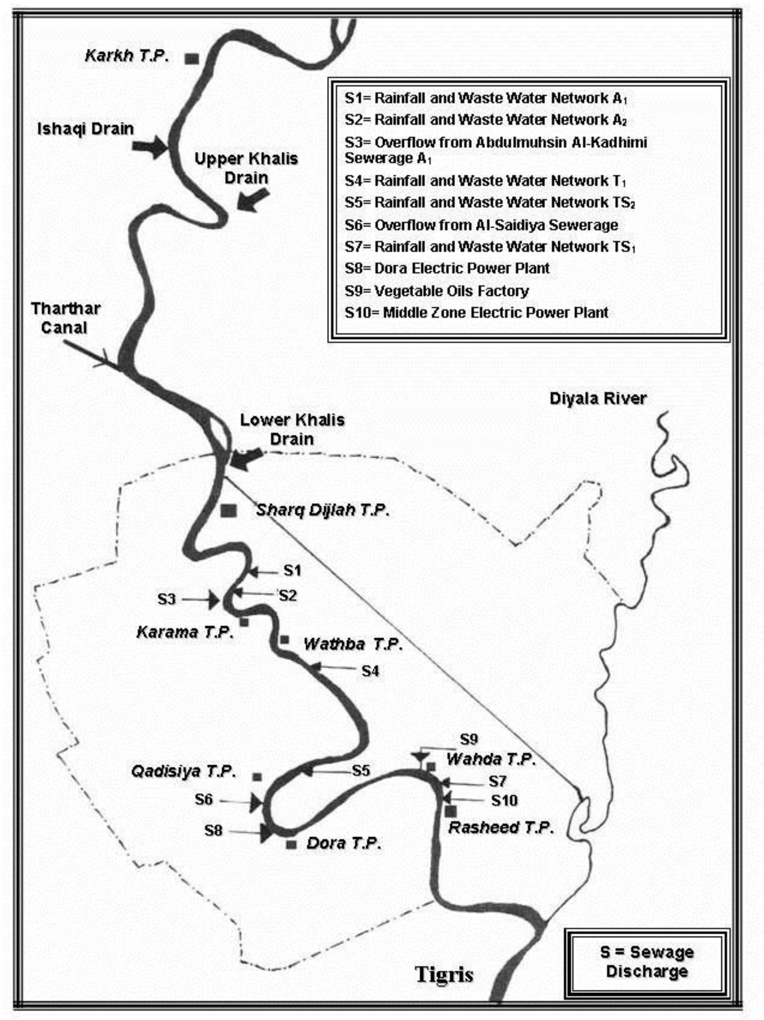


Figure (1) : Conventional water treatment plants and main sources of pollutions in Tigris River at Baghdad (from [3])

The main objective of this study is to arrive at a stochastic description of the time series of Sulfate water quality data for the (7) plants in Baghdad for both raw and treated water with its monthly maximum and minimum recoded values. This can be achieved by obtaining a short-term forecasting model, which can be used for operation purposes.

The analyzed time series for each plant is (3) years in length, during the period (2001-2003) of monthly maximum and minimum values for both raw and produced water. The records of year (2004) are used to check the model acceptability. The Sulfate concentration records were measured as SO_4 in (mg/L) units.

INTRODUCTION

Time series analysis is a major tool in assessing the state of pollution of water resources. A review of short-term forecasting models and related researches are presented here in historical sequence .

***Brown* [4]** in (1956) developed an extension to the weighted moving average forecasting by exponentially decreasing weights which known as exponential smoothing procedures. A flat forecast function was used because single exponential smoothing works best for data, which have no trend, no seasonality. The smoothing was modified by a factor known as the damping factor.

***Holt* [5]** in (1957) extended the single exponential smoothing to a linear exponential smoothing to allow forecasting of data with trends. Holt's method sometimes called double exponential smoothing. Two smoothing constant were modified, one for level and the other for trend.

***Winters* [6]** in (1960) extended Holt's method to capture seasonality directly. The Holt-Winters' method was based on three smoothing equations, one for level, one for trend, and one for seasonality.

***Harrison and Stevens* [7]** in (1976) developed a multi disturbance state space approach. They introduced, in the 'recipes' section of their papers, special cases that in today's terminology are called the local level, local trend and local seasonal models.

***Snyder* [8]** in (1985) developed a state space framework based on a single source of error, with equations closely resembling those of exponential smoothing, was proposed. For the first time, a statistical framework with clear, direct links with exponential smoothing had been found.

***Hyndman et. al.* [9]** in (2002) provided a statistical framework for the exponential smoothing. The framework incorporated stochastic models underlying the various forms of the exponential smoothing and enabled the calculation of maximum likelihood estimates of smoothing parameters.

***Baki et. al.* [10]** in (2005) showed that the applications of exponential smoothing to forecast time series usually rely on three basic methods: simple exponential smoothing, trend corrected exponential smoothing and a seasonal variation thereof. A common approach to select the method appropriate to a particular time series was based on prediction validation on a withheld part of the sample using criteria such as the mean absolute percentage error. A second approach was to rely on the most appropriate general case of the three methods. For annual series this is trend corrected exponential smoothing: for sub-annual series it is the seasonal adaptation of trend corrected exponential smoothing. The rationale for this approach is that a general method automatically collapses to its nested counterparts when the pertinent conditions pertain in the data.

THEORY OF SHORT-TERM FORECASTING

Generally, a time series can be expressed as a linear combination of four components depending on the type of variable and the averaging time interval. These components are represented in the form:

$$X_t = J_t + T_t + P_t + D_t \quad \text{......} \quad (1)$$

Where:

Xt : Time series observations at time t = 1,2,3 … N

Jt : Jump component.

Tt : Trend component.

Pt : Periodic component.

Dt: dependent stochastic component.

N: No. of observations

The first three components represent the deterministic part which is exactly determined by some mathematical function, while the fourth component represents the non-deterministic part (stochastic part) which is described only in terms of the probability distribution **[11]**.

Short-term forecasting is used in the water quality systems for operation purposes. Forecasting can be useful by extrapolating the momentum that exist in the phenomena because it provides, most often, an accurate and reliable forecasters. Seasonality can also be predicted fairly well **[2]**.

Exponential smoothing is a class of methods that imply exponentially decreasing weights as the observation get older. There are a variety of exponential smoothing methods, but they all have in common the property that recent values are given relatively more weight in forecasting than the older observations. Method of exponential smoothing takes the forecast for the previous period and adjusts it using the forecast error, then:

$$F_{1+1} = W\ X_t + (1-W)\ F_t \quad (2)$$

Where:
Xt : Observation at time (t)
Ft : Forecast value at time (t)
Ft+1 : Forecast value at time (t+1)
W : Damped factor in exponential smoothing method (between 0 and 1)

The new forecast will include a substantial adjustment for the error in the previous forecast. Conversely, when (W) is close to zero, the new forecast will include very little adjustment **[2]**. To find the optimal value for (W), It must minimize the mean square error (MSE) between the observation and the forecasted values.

$$MSE = \frac{\sum_{t=1}^{N}\left(X_t - F_t\right)^2}{N} \quad (3)$$

Exponential smoothing works best for data, which have no trend, no seasonality, or other underlying pattern.

Holt **[5]** extended the exponential smoothing to linear exponential smoothing to allow forecasting of data with trends. The forecast was found by using two smoothing factors (W1) for level and (W2) for trend. Each ranges between zero and one.

$$L_t = W1\ X_t + (1-W1)(L_{t-1} + T_{t-1}) \quad (4)$$

$$T_t = W2(L_t - L_{t-1}) + (1-W2)T_{t-1} \quad (5)$$

$$F_{t+1} = L_t + T_t \quad (6)$$

Where:
Xt : Observation at time (t)
Lt : Level at time (t) in Holt's linear method
Tt : Trend at time (t) in Holt's linear method

Ft+1 : Forecast value at time (t+1)
W1 : Smoothing factor for level in Holt's linear method
W2 : Smoothing factor for trend in Holt's linear method

The initialization process requires two estimations: one for finding (L1) and the other for finding (T1). This can be done by use the assumptions suggested by Holt **[5]**:

$$L_1 = X_1 \qquad (7)$$

$$T_1 = \left|X_2 - X_1\right| \qquad (8)$$

To find the optimal values for (W1) and (W2), we must minimize the mean square error (MSE) between the observation and forecast values by using equation (3).

Holt's method was extended by Winters **[6]** to capture seasonality directly. The method is based on three smoothing equations, one for the level, one for trend, and one for seasonality **[2]**. The basic equations for the method are:

$$L_t = W1\frac{X_t}{S_{t-s}} + (1-W1)(L_{t-1} + T_{t-1}) \qquad (9)$$

$$T_t = W2(L_t - L_{t-1}) + (1-W2)T_{t-1} \qquad (10)$$

$$S_t = W3\frac{X_t}{L_t} + (1-W3)S_{t-s} \qquad (11)$$

$$F_{t+1} = (L_t + T_t)S_{t+1-s} \qquad (12)$$

Where:
Xt : Observation at time (t)
Lt : Level at time (t) in Holt-Winters' method
Tt : Trend at time (t) in Holt-Winters' method
St : Seasonality at time (t) in Holt-Winters' method
Ft+1 : Forecast value at time (t+1)
W1 : Smoothing factor for level in Holt-Winters' method
W2 : Smoothing factor for trend in Holt-Winters' method
W3 : Smoothing factor for seasonality in Holt-Winters' method
s : Season interval (for monthly data: s=12)

To initialize the method, It needs initial values of the level (Lt), the trend (Tt), and the seasonal. To determine initial estimates of the seasonal indices it needs to use one complete season's data **[2]**. Therefore we initialize trend and level at period (s).

The level is initialized by taking the average of the first season:

$$L_s = \frac{1}{s}\left(X_1 + X_2 + \dots + X_s\right) \qquad (13)$$

To initialize trend, it is convenient to use two complete seasons as follows:

$$T_s = \frac{1}{s}\left[\frac{X_{s+1} - X_1}{s} + \frac{X_{s+2} - X_2}{s} + \dots + \frac{X_{s+s} - X_s}{s}\right] \qquad (14)$$

Finally, the seasonal indices are initialized using the ratio of the first few data values to the mean of the first year, so:

$$S_1 = \frac{X_1}{L_s}, \qquad S_2 = \frac{X_2}{L_s}, \qquad \ldots\ldots \qquad S_s = \frac{X_s}{L_s} \qquad (15)$$

To find the optimal values for (W1), (W2), and (W3) it must minimize the mean square error (MSE) between the observations and forecasted values by using equation (3) after two seasons **[2]**.

Modeling of the Sulfate Concentrations

The problem, which arises in the use of any statistical analysis, is the missing data values **[11]**. These gaps should be filled before starting the data analysis. Among many methods available to obtain a missing value, linear interpolation procedure was used for filling the gaps in the data series to complete the historical records of each station using the (SPSS) software. The parameters (W1, W2, and W3) of Holt-Winters' method are shown in Table (1). Were:

R : Raw water
S : Supply water
Min : Minimum
Max : Maximum

Table (1) : Holt-Winters' model parameters for sulfate parameter

Month	Prameters		Karkh T. P.	Sharq Dijlah T. P.	Karama T. P.	Wathba T. P.	Qadisiya T. P.	Dora T. P.	Rasheed T. P.
			Min	Min	Min	Min	Min	Min	Min
1	W1	R	0.5	0.3	0.3	0.9	1.0	0.8	0.3
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.3
	W3	R	0.2	0.1	0.4	1.0	0.0	0.4	0.4
2	W1	R	0.5	1.0	0.3	1.0	1.0	0.8	0.2
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.2	0.0	0.6	0.0	0.0	0.4	0.3
3	W1	R	0.5	0.3	0.3	1.0	0.6	1.0	0.3
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.9	0.4	0.8	0.0	0.9	0.0	0.1
4	W1	R	1.0	1.0	0.7	1.0	1.0	0.9	0.6
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.0	0.9	1.0	0.0	0.3	1.0	0.7
5	W1	R	0.6	1.0	0.6	0.9	1.0	1.0	0.7
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	0.2	1.0	1.0	0.0	0.0	0.7
6	W1	R	0.6	1.0	0.5	1.0	1.0	0.9	0.7
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.7	0.1	1.0	0.1	0.0	1.0	0.4
7	W1	R	0.6	0.5	0.5	0.7	0.8	0.8	0.6
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	0.7	1.0	0.8	1.0	0.0	0.7
8	W1	R	1.0	1.0	0.5	1.0	1.0	0.8	0.6
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.0	0.2	0.9	0.0	0.6	0.0	0.5
9	W1	R	0.9	0.9	0.5	1.0	1.0	0.7	0.5
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	1.0	0.9	0.0	0.0	0.0	0.4
10	W1	R	0.8	1.0	0.5	1.0	1.0	0.7	0.6
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	0.0	0.9	0.3	0.8	0.0	0.7
11	W1	R	0.8	1.0	0.5	1.0	0.8	0.5	0.9
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	0.2	0.8	0.0	1.0	0.4	0.1
12	W1	R	1.0	0.6	0.6	1.0	1.0	1.0	1.0
	W2	R	0.0	0.0	0.0	0.0	0.9	0.0	0.0
	W3	R	0.0	0.7	0.9	0.1	0.0	0.0	0.0

Month	Prameters		Karkh T. P. Max	Sharq Dijlah T. P. Max	Karama T. P. Max	Wathba T. P. Max	Qadisiya T. P. Max	Dora T. P. Max	Rasheed T. P. Max
1	W1	R	0.6	0.4	0.3	0.5	0.5	0.5	0.3
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.5	0.2	1.0	0.8	1.0	0.7	1.0
2	W1	R	0.5	0.5	0.3	0.5	0.9	0.5	0.4
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.4	0.1	1.0	0.9	1.0	0.6	1.0
3	W1	R	0.6	0.4	0.3	0.8	0.9	0.5	0.4
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.6	0.4	1.0	1.0	1.0	0.6	1.0
4	W1	R	1.0	0.3	0.3	0.7	0.8	0.5	0.3
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.0	0.7	1.0	1.0	1.0	0.5	1.0
5	W1	R	0.7	0.9	0.3	0.8	0.7	0.4	0.3
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.5	1.0	1.0	1.0	1.0	1.0	1.0
6	W1	R	0.6	0.6	0.3	0.6	0.9	0.7	0.4
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.2	0.7	0.9	1.0	1.0	1.0	1.0
7	W1	R	0.5	0.5	0.3	0.4	0.7	0.6	0.3
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.7	0.6	1.0	1.0	1.0	1.0	1.0
8	W1	R	1.0	0.6	0.3	0.5	0.7	0.5	0.4
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.0	0.8	1.0	1.0	1.0	1.0	1.0
9	W1	R	0.9	0.6	0.3	0.4	0.9	0.5	0.4
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	0.7	1.0	0.9	1.0	0.9	1.0
10	W1	R	1.0	0.6	0.3	0.4	0.8	0.5	0.4
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.0	0.8	1.0	0.8	1.0	0.7	1.0
11	W1	R	1.0	1.0	0.3	0.8	1.0	1.0	0.5
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	0.0	0.0	1.0	1.0	0.0	0.0	0.7
12	W1	R	0.8	1.0	0.5	1.0	1.0	0.3	0.6
	W2	R	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	R	1.0	0.0	1.0	0.0	0.0	0.6	0.6

Table (1) : Continued

Month	Prameters		Karkh T. P. Min	Sharq Dijlah T. P. Min	Karama T. P. Min	Wathba T. P. Min	Qadisiya T. P. Min	Dora T. P. Min	Rasheed T. P. Min
1	W1	S	0.7	0.3	0.3	0.9	1.0	0.7	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.0	0.1	0.8	1.0	0.0	0.7	0.4
2	W1	S	0.6	0.3	0.5	1.0	0.4	0.8	0.2
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.1	0.2	0.7	0.0	0.8	0.6	0.4
3	W1	S	0.5	0.3	0.3	0.9	0.3	0.8	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.4	0.4	0.7	1.0	1.0	0.7	0.5
4	W1	S	1.0	0.3	0.9	1.0	0.4	0.9	0.5
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.0	0.4	1.0	0.0	1.0	1.0	1.0
5	W1	S	0.6	1.0	0.8	0.9	0.4	0.7	0.7
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	0.0	1.0	1.0	1.0	1.0	1.0
6	W1	S	0.6	0.9	0.7	0.9	0.4	0.7	0.7
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.9	1.0	1.0	1.0	1.0	1.0	1.0
7	W1	S	0.5	0.6	0.6	0.7	0.4	0.5	0.6
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	1.0	1.0	1.0	0.8	1.0
8	W1	S	1.0	0.6	0.6	1.0	0.4	0.5	0.6
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.0	1.0	0.9	0.0	1.0	0.8	1.0
9	W1	S	0.8	0.7	0.7	1.0	0.4	0.4	0.6
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	1.0	0.0	1.0	0.6	0.8
10	W1	S	0.8	0.7	0.7	1.0	0.4	0.4	0.6
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	1.0	0.0	0.9	0.5	1.0
11	W1	S	0.7	0.7	0.7	1.0	0.4	0.4	0.7
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	1.0	0.6	1.0	0.7	0.8
12	W1	S	0.6	0.8	0.8	1.0	0.4	0.4	0.9
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	1.0	0.0	1.0	0.5	1.0

Month	Prameters		Karkh T. P.	Sharq Dijlah T. P.	Karama T. P.	Wathba T. P.	Qadisiya T. P.	Dora T. P.	Rasheed T. P.
			Max	Max	Max	Max	Max	Max	Max
1	W1	S	0.5	0.4	1.0	0.6	0.4	0.4	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.6	0.8	0.0	0.9	1.0	0.9	0.9
2	W1	S	0.5	0.4	0.3	0.6	1.0	0.4	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.4	0.5	0.8	1.0	0.0	0.8	0.8
3	W1	S	0.5	0.3	0.3	0.9	1.0	0.4	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.7	0.6	0.9	1.0	0.0	0.8	0.8
4	W1	S	1.0	0.3	0.3	0.9	1.0	0.5	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.0	0.6	0.9	1.0	0.0	0.7	0.9
5	W1	S	0.6	0.4	0.4	1.0	0.8	0.3	0.4
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	0.7	0.8	0.2	1.0	1.0	1.0
6	W1	S	0.6	0.5	0.3	0.7	1.0	0.6	0.5
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.8	0.6	0.7	1.0	0.6	1.0	1.0
7	W1	S	0.5	0.5	0.3	0.4	0.8	0.5	0.3
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.8	0.6	0.8	1.0	1.0	0.8	1.0
8	W1	S	0.7	0.6	0.2	0.5	1.0	0.4	0.5
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	0.8	0.7	1.0	0.0	1.0	1.0
9	W1	S	0.7	0.7	0.3	0.5	0.9	0.5	0.5
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	0.7	1.0	1.0	0.7	1.0
10	W1	S	0.7	0.8	0.3	0.5	0.7	0.4	0.4
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	0.7	1.0	1.0	0.5	0.9
11	W1	S	1.0	1.0	0.3	1.0	0.9	0.8	0.7
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	0.0	0.0	0.6	0.3	1.0	0.3	0.6
12	W1	S	0.6	0.9	0.4	1.0	1.0	0.2	0.6
	W2	S	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	W3	S	1.0	1.0	0.7	0.0	0.0	0.8	0.4

Results and Discussion

For checking the Holt-Winters' model, the generated data are tested with those of the observed series (2004) using (t-test) and (F-test) at 95% level of significant as shown in Table (2).

Table (2) : Comparison between means and standard deviations of observed data and generated by Holt-Winters' model for sulfate parameter

		Karkh T. P.	Sharq Dijlah T. P.	Karama T. P.	Wathba T. P.	Qadisiya T. P.	Dora T. P.	Rasheed T. P.
		Min	Min	Min	Min	Min	Min	Min
t calculate	R	1.18	1.46	0.98	0.87	1.33	2.55	1.68
t tabulate	R	2.07	2.07	2.07	2.07	2.07	2.07	2.07
t-Test Result	R	Homog.	Homog.	Homog.	Homog.	Homog.	Not Homog.	Homog.
F calculate	R	3.63	1.36	1.47	1.05	3.75	1.66	3.29
F tabulate	R	2.82	2.82	2.82	2.82	2.82	2.82	2.82
F-Test Result	R	Not Homog.	Homog.	Homog.	Homog.	Not Homog.	Homog.	Not Homog.
		Max	Max	Max	Max	Max	Max	Max
t calculate	R	1.65	2.10	0.86	1.96	1.17	0.64	0.96
t tabulate	R	2.07	2.07	2.07	2.07	2.07	2.07	2.07
t-Test Result	R	Homog.	Not Homog.	Homog.	Homog.	Homog.	Homog.	Homog.
F calculate	R	2.83	3.18	1.30	2.62	5.56	1.30	1.05
F tabulate	R	2.82	2.82	2.82	2.82	2.82	2.82	2.82
F-Test Result	R	Not Homog.	Not Homog.	Homog.	Homog.	Not Homog.	Homog.	Homog.
		Min	Min	Min	Min	Min	Min	Min
t calculate	S	1.28	1.05	1.27	0.46	1.97	1.34	1.24
t tabulate	S	2.07	2.07	2.07	2.07	2.07	2.07	2.07
t-Test Result	S	Homog.	Homog.	Homog.	Homog.	Homog.	Homog.	Homog.
F calculate	S	1.63	1.59	1.87	1.03	1.29	1.15	2.36
F tabulate	S	2.82	2.82	2.82	2.82	2.82	2.82	2.82
F-Test Result	S	Homog.	Homog.	Homog.	Homog.	Homog.	Homog.	Homog.
		Max	Max	Max	Max	Max	Max	Max
t calculate	S	1.10	1.86	1.53	2.04	1.41	0.52	1.07
t tabulate	S	2.07	2.07	2.07	2.07	2.07	2.07	2.07
t-Test Result	S	Homog.	Homog.	Homog.	Homog.	Homog.	Homog.	Homog.
F calculate	S	2.41	3.61	2.59	2.22	4.85	1.31	1.65
F tabulate	S	2.82	2.82	2.82	2.82	2.82	2.82	2.82
F-Test Result	S	Homog.	Not Homog.	Homog.	Homog.	Not Homog.	Homog.	Homog.

Figure (2) shows the comparison between monthly observed and generated Sulfate concentrations by Holt-Winters' model. The figure indicates that the Holt-Winters' model is capable of preserving the monthly means for all Sulfate quality parameter.

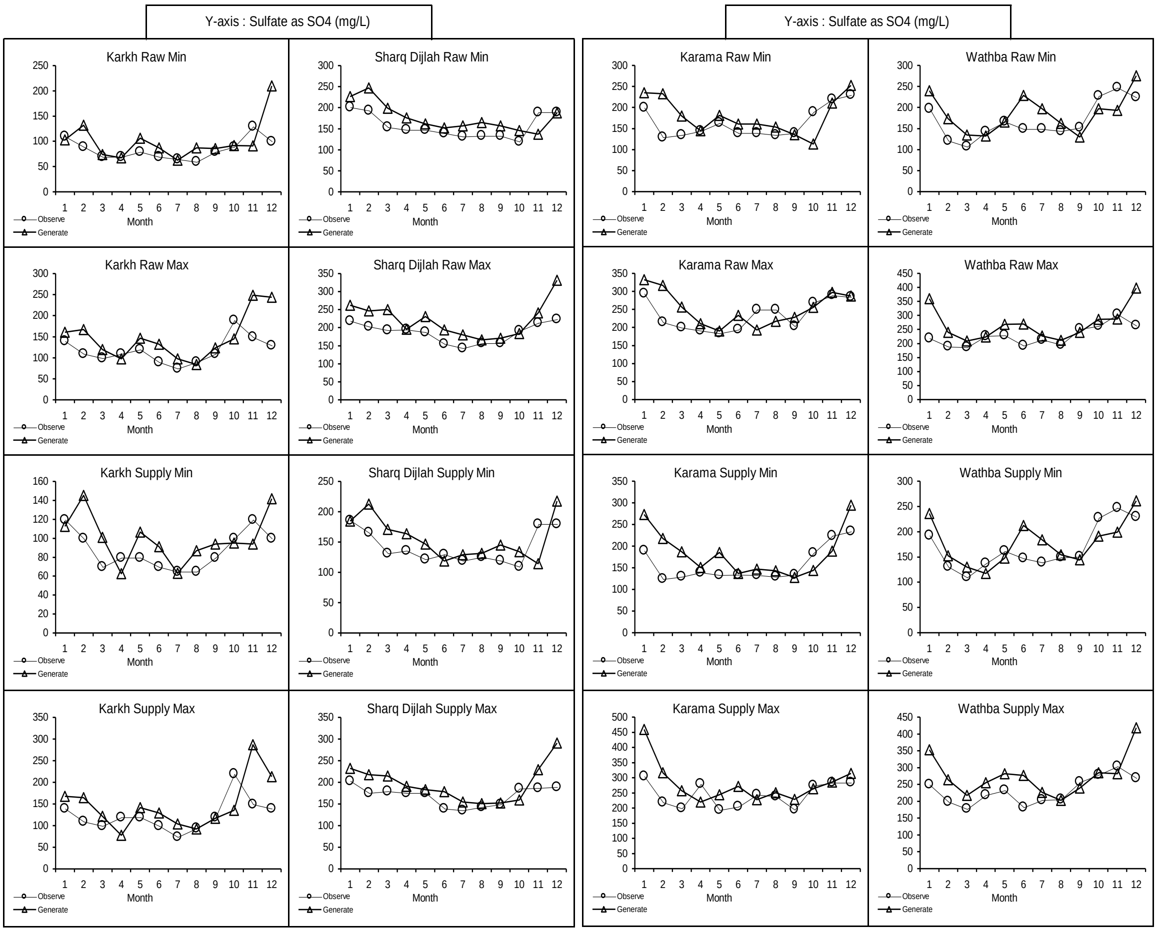
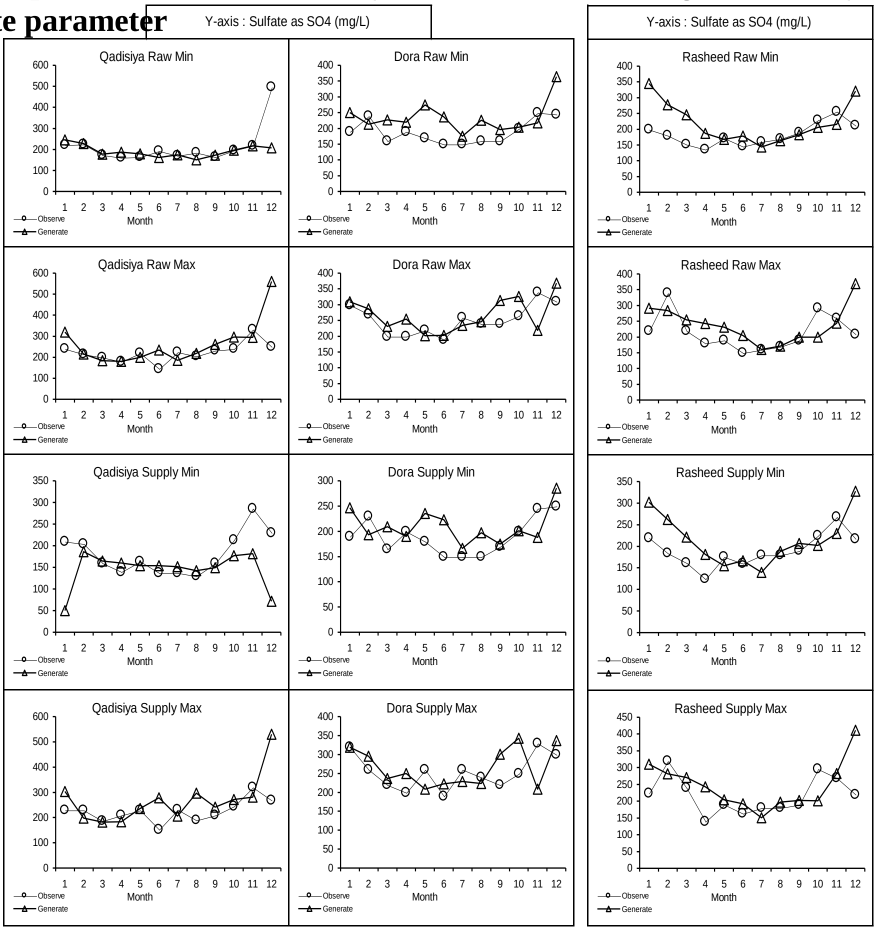


Figure (2) : Comparison between monthly observed data and generated by Holt-Winters' model for sulfate parameter



CONCLUSIONS

* Comparisons between means of observed data and generated series by Holt-Winters' model were reflected the applicability of this model for short-term forecasting, except the case of minimum records of Dora station and maximum records of Sharq Dijlah station due to the different sources of pollutions along the river which dispose their waste into it and change the concentrations in the water, therefore the randomness is increased.
* Comparisons between standard deviations of observed data and generated were reflected the applicability of this model for short-term forecasting, except some cases as shown in Table (3).

Table (3) : Failure cases of comparisons between standard deviations of observed and generated data.

Extreme Type	Water Type	Treatment Plant
Min	R	Karkh
Min	R	Qadisiya
Min	R	Rasheed
Max	R	Karkh
Max	R	Sharq Dijlah
Max	R	Qadisiya
Max	S	Sharq Dijlah
Max	S	Qadisiya

1. Most of the extreme values of the observed series and those of the generated series were found to exceed the allowable limits according to Iraqi and EEC specifications.

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