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Climatic Temperature Data Forecasting in Nineveh Governorate Using the Recurrent Neutral Network Method

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***Abstract*— The forecasting of maximum climatic temperature is essential by using some statistical and intelligent techniques. Iraqi maximum temperature data collected monthly in several cities due to the Nineveh government will be studied in this paper. This study aims to forecast maximum climatic temperature as univariate time series and obtain the best results with minimum forecasting error. The non-linearity of climatic datasets is the main reason for data complexity, which needs to use some nonlinear methods for obtaining satisfactory results. In this paper, the maximum climatic temperature data will be forecasted by using traditional and intelligent methods. Single and double exponential smoothing (SES and DES) models have been used as traditional linear methods to forecast climatic temperature. The forecasting results reflected that the hybrid methods outperformed the traditional methods. The proposed hybrid methods can forecast climatic temperature in more accurate results. The hybrid methods SES-RNN and DES-RNN combine the SES and DES as a linear model with RNN as a nonlinear method to be one method that can handle any data, especially the nonlinear type. Recurrent neural network (RNN) as the nonlinear intelligent method is combined with SES and DES in hybrid SES-RNN and DES-RNN methods to forecast climatic temperature data and handle the non-linearity of datasets. The results reflect that the proposed hybrid methods outperformed the traditional methods for forecasting climatic temperature data. The proposed hybrid methods can be used to forecast climatic temperature in more accurate results.**

***Keywords*— SES; DES; RNN; forecasting; GIS.**

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I. INTRODUCTION

Maximum temperature data with its nonlinear nature make forecasting a complicated process. Most climate data have a non-linearity nature makes forecasting become a complicated process [1]. The quality of forecasting accuracy of maximum temperature data is essential to control and plan different activities every day. The fluctuation in the pattern of climate temperature is often the reason for the non-linearity. Temperature forecasting is essential for different activities such as climate nature generation, tourism, maintenance, and investment schedule. The temperature forecasting can be studied for many seasonal cycles such as monthly, daily, hourly, or other periods. The temperature data is time-series data, and its observations are often by the nearest previous observation [2]. A previous study suggested forecasting temperature data in the literature using exponential smoothing models [3]. In this study, single exponential smoothing (SES) and double exponential smoothing (DES) models will be used to model the univariate climate temperature data.

However, using classical statistical models to forecast temperature data may produce inaccuracy in forecasting because this type of data often contains nonlinear patterns. Some researchers suggested forecasting temperature data using different types of neural networks such as [4], [5]. In this study, the non-linearity pattern of temperature data will be handled using the recurrent neural network (RNN) method, an artificial neural network algorithm to get more accurate forecasting results. Using RNN as a modern approach will improve temperature forecasting comparing with temperature forecasting using SES and DES models [6]. Choosing the best model can be measured using the mean absolute percentage error (MAPE) measurement. For the current study, temperature data has been collected from four different Nineveh government regions (Mosul, Rabea, Talafar, and Senjar cities) to get a more comprehensive view of the temperature's seasonality effects data.

II. Materials And Methods

A. Data and framework of the study

In this study, four datasets of monthly Iraqi climate temperature were collected from four cities inside the Nineveh government (Mosul, Rabea, Talafar, and Senjar cities). Iraqi climate temperature will be studied for 31 years (January 1980–December 2010), including 372 monthly observations. The full period will be divided into two periods for training and testing. The framework of this study includes the following:

- Dividing the full period into two groups for training and testing.
- Modeling training data by using SES and DES models.
- Simulating testing data by using same SES and DES models.
- Modeling training data by using the proposed SES-RNN and DES-RNN methods.
- Simulating testing data by using same proposed methods.
- Comparing the error measurements of SES and DES models as traditional methods and the proposed SES-RNN and DES-RNN as intelligent methods to determine what method would provide the best adequacy.

B. Traditional methods for temperature forecasting.

Exponential smoothing methods are often used to smooth time series data to obtain more fitted forecasted series. SES is an exponential smoothing model within the exponential smoothing family. In exponential smoothing, a new observation will be forecasted on a previous observation in the present time in addition to the random error $(\mathrm{Y_t} - \hat{\mathrm{Y}}_\mathrm{t})$ such as in the following equation.

$$\hat{Y}_{t+1} = \hat{Y}_t + \alpha(e_t) \quad (1)$$

where $\hat{Y}_{t+1}, \hat{Y}_t$ are the next and current forecasted observations, respectively, and e_t is the random error, while α is a smoothing constant which will be determined to minimize the sum of squares of errors when $(0 < \alpha < 1)$.
After re-symbolizing $\hat{Y}_{t+1}, \hat{Y}_t$ by F_{t+1}, F_t, the equation can be reformulated as SES model such as follows.

$$F_{t+1} = F_t + \alpha(Y_t - F_t) \quad (2)$$

where F_{t+1}, F_t are the next and current forecasted observations, Y_t is current original series. The initial value of F_t is missing.

In other words, SES equation can be written as follows [7].

$$\hat{Y}_{t+1} = F_{t+1} = \alpha \mathrm{Y}_t + (1-\alpha)F_t \quad ; t > 1 \quad (3)$$

Double or Holt's exponential smoothing is improved from the SES model when there is a series trend. DES is also an exponential smoothing model within the exponential smoothing family. Double means there are two smoothing constants $(0 < \alpha < 1,\ \text{and}\ 0 < \beta < 1)$. The forecasted observation with m steps can be formulated as follows.

$$F_{t+m} = L_t + \mathrm{m}b_t \quad (4)$$

where $L_t = \alpha \mathrm{Y}_t + (1-\alpha)(L_{t-1} + b_{t-1})$ and $b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$.

The initial value $L_1 = Y_1$, and the initial value $b_1 = (Y_4 - Y_1)/3$.

C. Hybrid Methods

In this study, two-hybrid methods, SES-RNN and DES-RNN are proposed to improve Iraqi climate temperature data forecasting results. The framework steps of these proposed methods are detailed, such as follows [8].

- Constructing the best SES and DES models those are suitable for dataset.
- Constructing RNNs by Depending on the SES and DES models' structures to obtain the proposed SES-RNN and DES-RNN hybrid methods.
- Performing the training and testing stages to obtain the training and testing forecasted series of the hybrid SES-RNN and DES-RNN methods.
- Comparing the hybrid methods SES-RNN and DES-RNN to the traditional methods SES and DES for training and testing forecasting results.

A hybrid SES-RNN and DES-RNN methods will be proposed for forecasting the training and testing series in high-quality results because RNN is a nonlinear method and can be handled the nonlinear pattern in data and improved the forecasting results. RNN contains one or more layers and this may handle the non-linearity of data. RNN also contains a delay layer that may solve data heterogeneity because it contains more extended memory than other algorithms.

In this study, RNN will contain two layers and the input layer with R inputs weighted randomly. The first layer is hidden with M neurons, and the second one is the output layer with one output. The number of neurons can be calculated usually by depending on the number of inputs such as $(M = (R \times 2) + 1)$. The sum of input variables in the transfer function F can be formatted as follows.

$$\mathrm{SUM} = \sum_{i=1}^{M} \sum_{j=1}^{R} w_{i,j} z_j + b \quad (5)$$

where z_j is the input variable and $w_{i,j}$ is the weight of input variable z_j which will enter to the neurons i while b is the biased value [9]

The common transfer functions in the hidden and the output layers are (tan-sigmoid, log-sigmoid, and linear function) such as in fig.1 below.

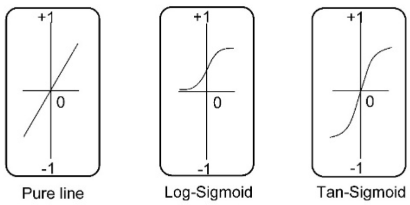


Fig. 1 The types of the transfer function

The formula of pure line, log-sigmoid, and tan-sigmoid transfer functions, respectively, are as follows. $f(SUM) = SUM$, $f(SUM) = \frac{1}{1+e^{-SUM}}$, and $f(SUM) = \frac{2}{1+e^{-2SUM}} - 1$. where SUM was defined in equation (5) Fig.2 below demonstrates the structure of RNN.

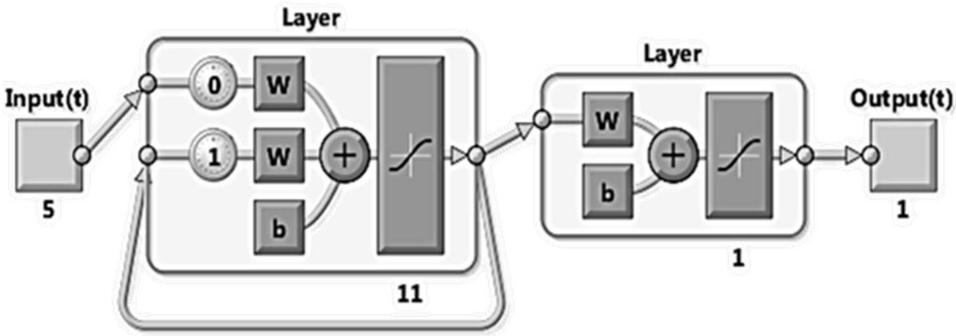


Fig. 2 The structure of RNN

Determining the suitable training algorithms, training function, and other requirements of RNN are very important to construct RNN structure and control by the goodness of forecasting results [10]. After constructing the RNN structure based on the SES and DES model, the output of training and testing processes is the training and testing forecasted series using the hybrid SES-RNN and DES-RNN methods.

Mean absolute percentage error (MAPE) is used in this study as forecasting error criteria, it can be written such as follows.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| \times 100 \qquad (6)$$

where e_i is the random error of forecasting, n is the total number of observations, and y_i is the original series [11].

III. Results and Discussion

Four monthly Iraqi climate temperatures were taken from four cities inside the Nineveh government (Mosul, Rabea, Talafar, and Senjar cities). The governorate of Nineveh is located in northwestern Iraq, 402 Km north of Baghdad. The Tigris river extends from the governorate's northwest to the south. According to the the geographical information system (GIS), the study area is extended from latitude of (34^0:59':9.40" to 37^0:05':31.48") and between longitude of (42^0:01':50.85" to 43^0:32':30.15") as shown in Fig.3. It is covered an area of (32.308 km^2).

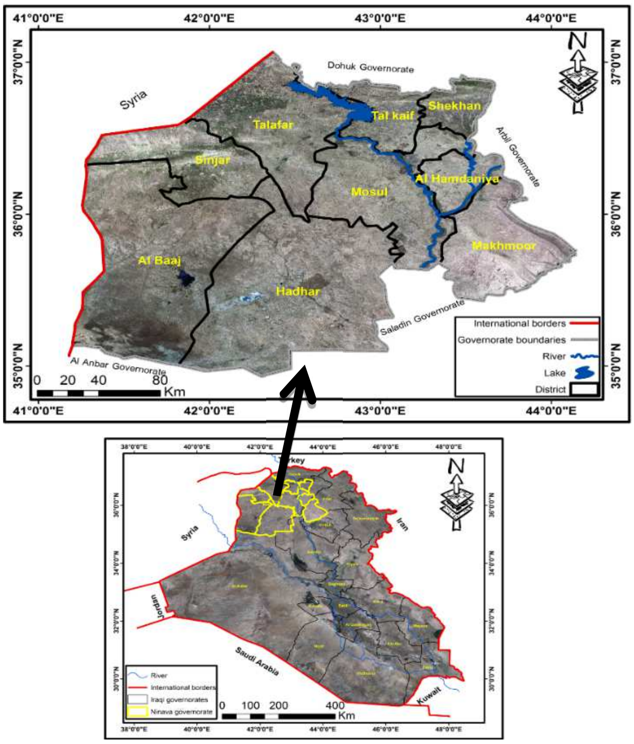


Fig. 3 Location of the study area

The prevailing climate in Nineveh is hot and dry in summers while cool and rainy in winter. This location is classified as Csa (Hot-summer Mediterranean climate) [12]. The climate of the governorate is affected by the variation of surface topography. The average temperature in the winter varies between (-5 to +8 degrees Celsius) while in the summer varies between (30 to 46 degrees Celsius). The average annual temperature is about 11.4 °C in Nineveh, and the average annual rainfall is 1053 mm. Fig.4 demonstrates the average monthly behavior of the temperature in Nineveh.

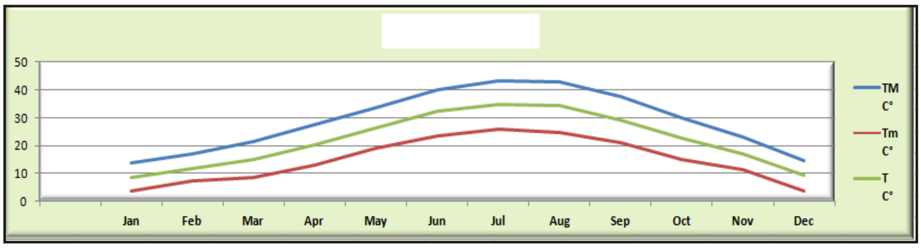


Fig. 4 The temperature variation of Nineveh Governorate

In this study, the datasets of monthly Iraqi climate temperature were collected from four meteorological stations inside the Nineveh government (Mosul, Rabea, Talafar, and Senjar cities), by using GIS, the location of the stations was shown in Fig.5.

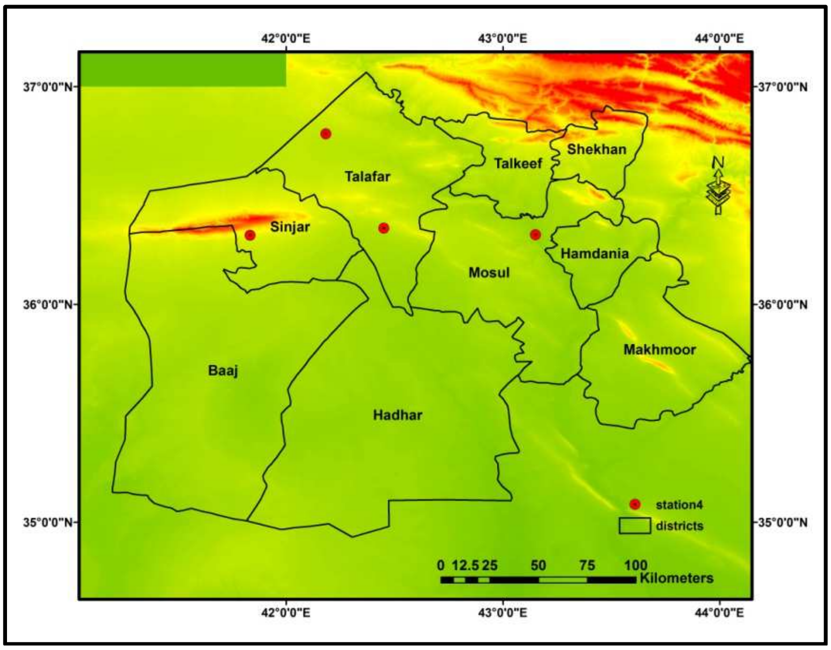


Fig. 5 The geographical locations of the selected stations

Iraqi climate temperature datasets have been taken for 31 years, including 372 monthly observations (January 1980 – December 2010). The full datasets have been divided into two sub-periods for training and testing. The training period includes around 90% of observations, while 10% of observations remained for testing. The training period is (January 1980 – December 2007), while the testing period is (January 2008 – December 2010) with 36 observations. Training data used for modeling, while testing data left for simulating. Full different datasets have been plotted, such as in Fig.6 below.

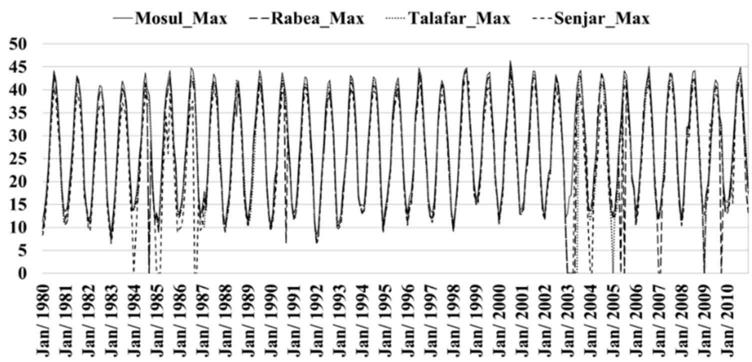


Fig. 6 Full original maximum temperature series of Mosul, Rabea, Talafar, and Senjar cities.

Fig.6 shows monthly seasonal periods based on data line behavior. The data was recorded monthly, and it exhibited peaks or valleys seasonally.

A. SES and DES models

After trying all possible values of smoothing constants and check MAPE values, the best SES model of Iraqi maximum temperature series of Mosul, Rabea, Talafar, and Senjar cities were satisfy where the smoothing constant α values are equaled to 0.95 for all cities for training and testing processes [13], [14]. The best DES model of the Iraqi maximum temperature series of Mosul, Rabea, Talafar, and Senjar cities were satisfied where α and β values are equated to 0.95 for all cities for training and testing processes except α=0.05 for Senjar data in the testing process.

TABLE I
MAPE OF TRAINING FORECASTS ACCURACIES BY USING SES AND DES FOR DIFFERENT DATASETS

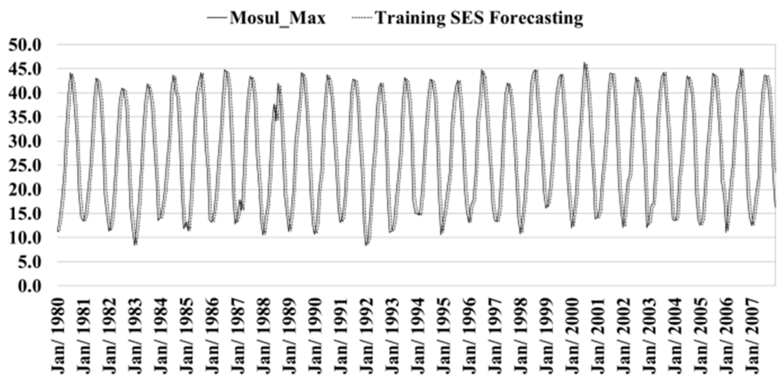
Method	City	MAPE
SES	Mosul	23.34
	Rabea	25.67
	Talafar	25.06
	Senjar	25.03
DES	Mosul	18.00
	Rabea	20.97
	Talafar	19.07
	Senjar	19.45

Table 1 and Table 2 below present the MAPE values of SES and DES model for Mosul, Rabea, Talafar, and Senjar cities in training process. Table 1 and Table 2 refer that DES model is better than SES model because MAPE values of DES are less than MAPE values of SES model for training and testing stages.

TABLE II
MAPE OF TESTING FORECASTS ACCURACIES BY USING SES AND DES FOR DIFFERENT DATASETS

Method	City	MAPE
SES	Mosul	20.2144
	Rabea	21.8617
	Talafar	21.2189
	Senjar	21.9385
DES	Mosul	15.7728
	Rabea	17.1895
	Talafar	16.3168
	Senjar	22.2399

Fig.7 and Fig.8 below present the fitness function between the original maximum temperature variable and training and testing forecasted series, respectively, using the SES model for different datasets. Fig.9 and Fig.10 below present the fitness function between the original maximum temperature variable and the training and testing forecasted series using the DES model for different datasets.



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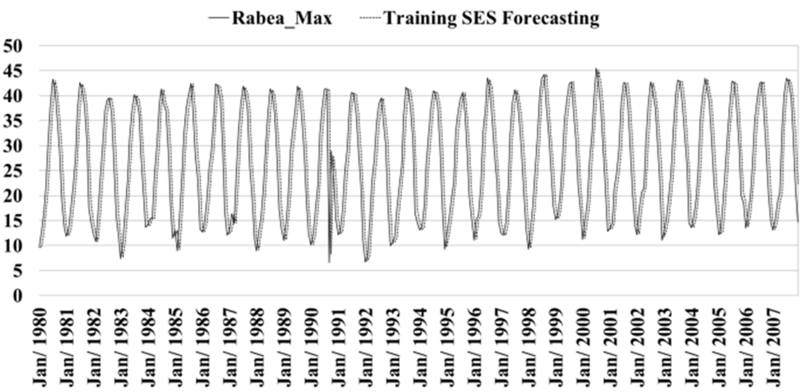

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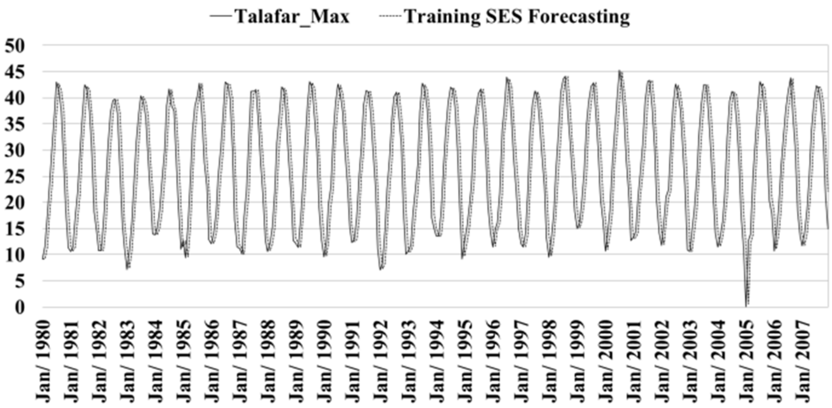

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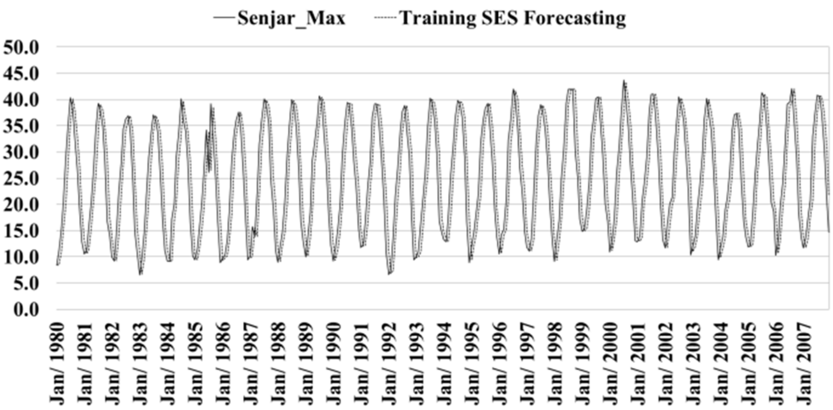

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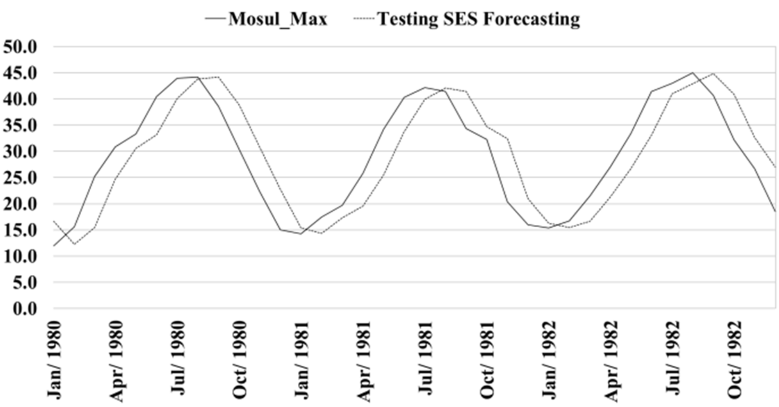
Fig. 7 The fitness function between the training forecast using the SES model and the original maximum temperature series of a. Mosul, b. Rabea, c. Talafar, and d. Senjar cities respectively



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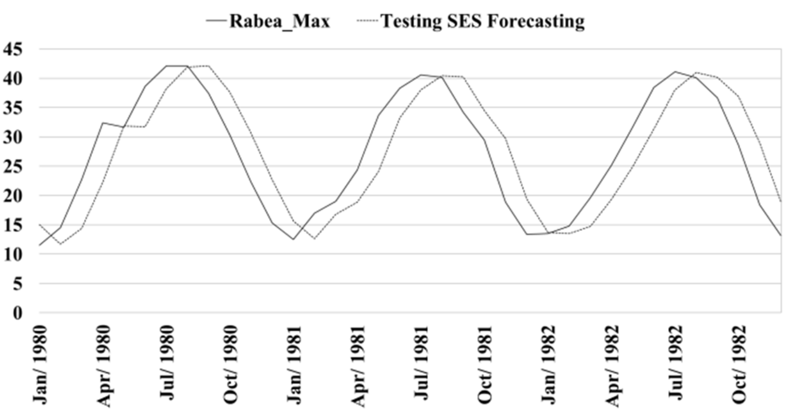

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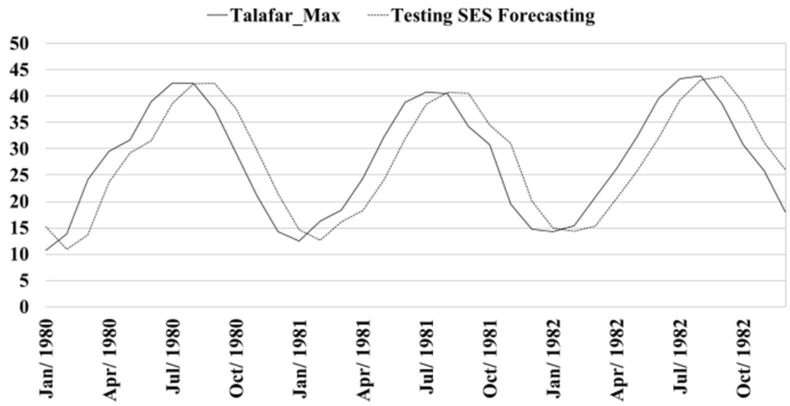

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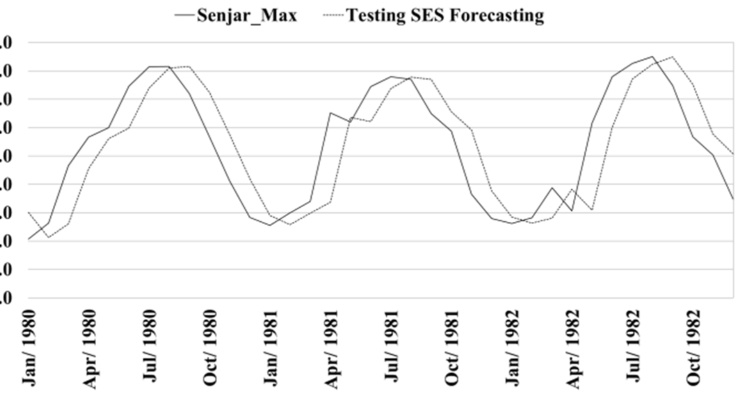

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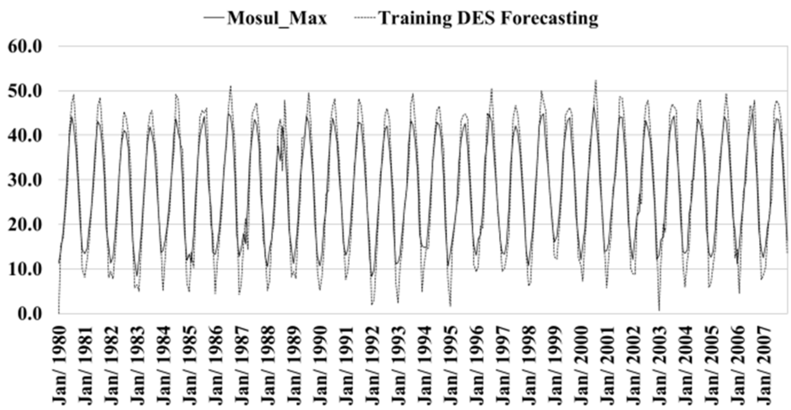
Fig. 8 The fitness function between the testing forecast using the SES model and the original maximum temperature series of a. Mosul, b. Rabea, c. Talafar, and d. Senjar cities, respectively.



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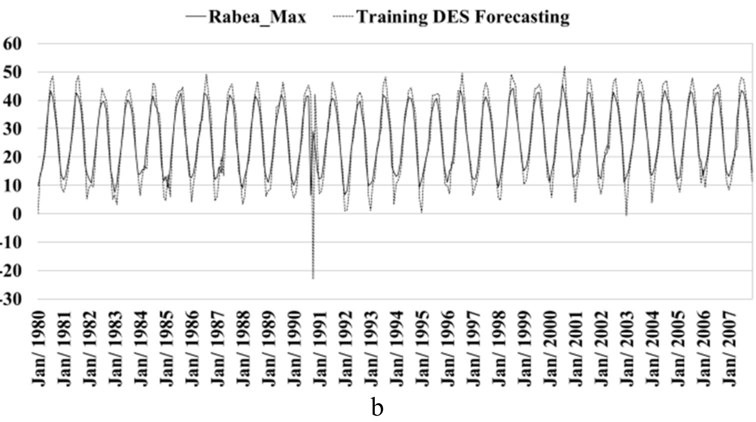

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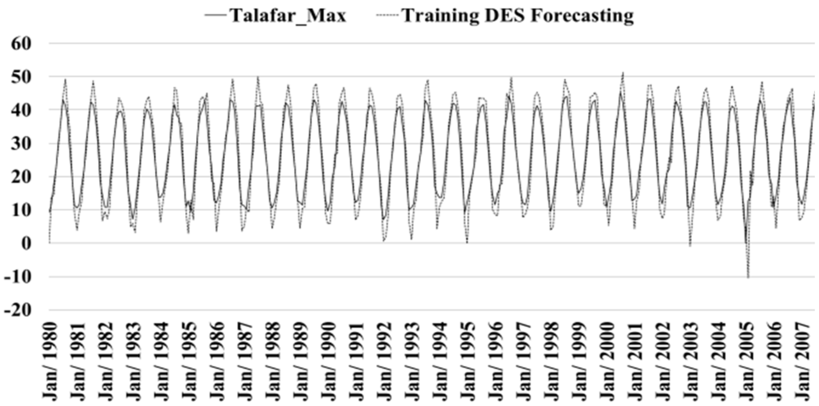

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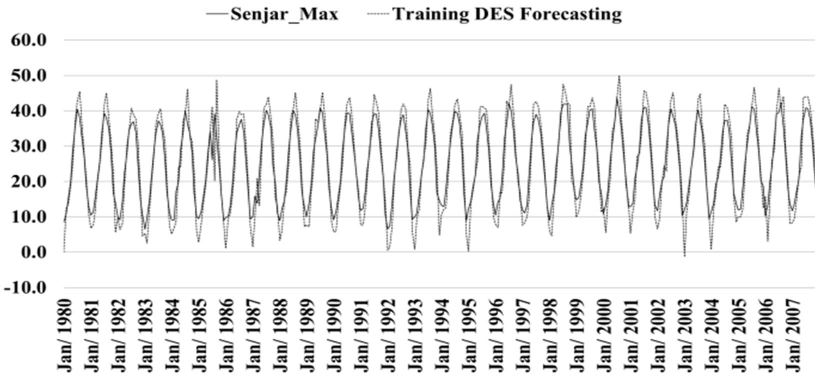

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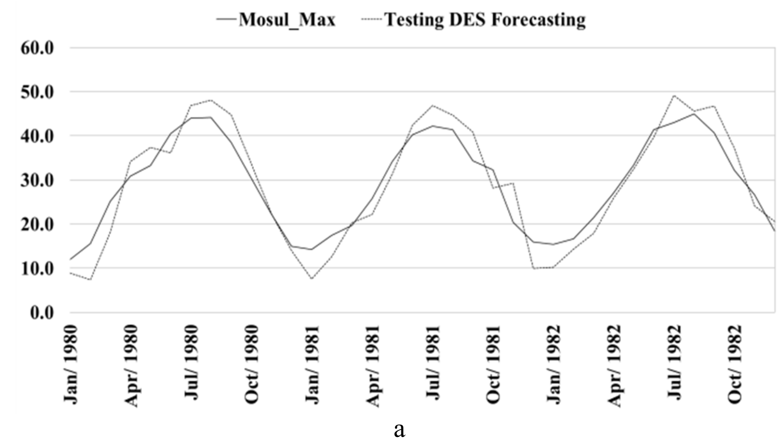
Fig. 9 The fitness function between the training forecast using the DES model and the original maximum temperature series of a. Mosul, b. Rabea, c. Talafar, and d. Senjar cities, respectively.



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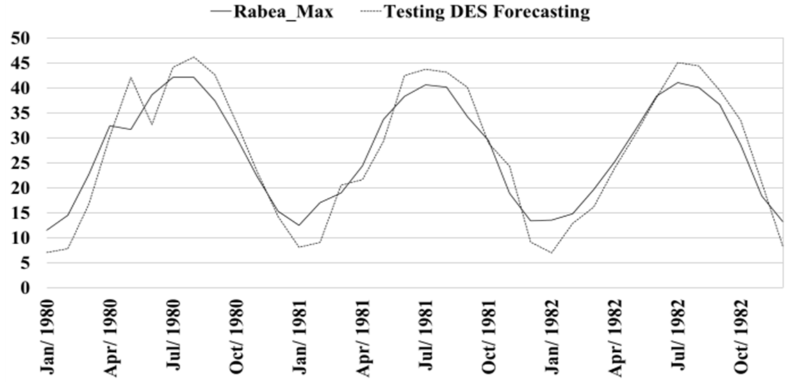

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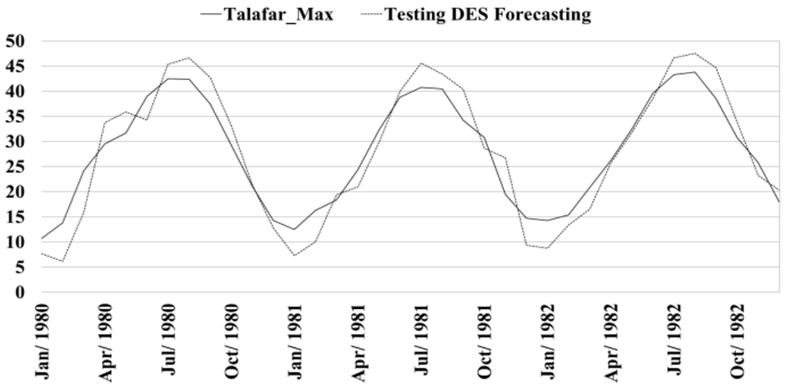

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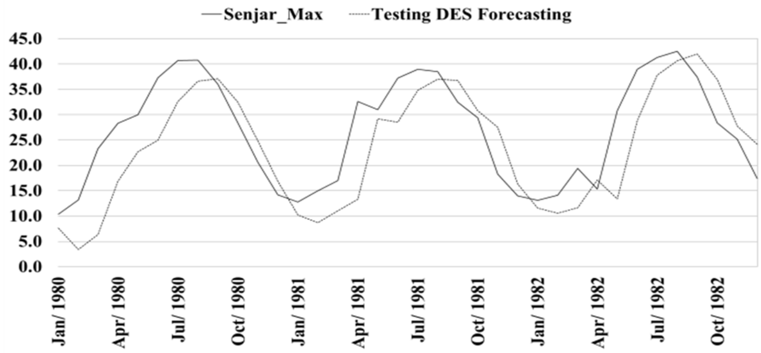

d

Fig. 10 The fitness function between the testing forecast using the DES model and the original maximum temperature series of a. Mosul, b. Rabea, c. Talafar, and d. Senjar cities, respectively.

Fig.7, Fig.8, Fig.9, and Fig.10 confirm that DES model is better than SES model because the lines of original and forecasted variables in Fig.9, and Fig.10 are more fitted than these two lines in Fig.7, and Fig.8. The main reason belongs to the trend effect, which improves the forecasting results of DES to be better.

B. Hybrid SES-RNN and DES-RNN methods

Combining linear and nonlinear methods in one hybrid method can be proposed to forecast any type of datasets in high accuracy results. Hybridizing SES and DES with RNN will generate strong approaches that can handle the non-linearity of datasets. The framework for forecasting maximum climate temperature datasets using SES-RNN and DES-RNN hybrid methods can be summarized as follows.

- The inputs variable and target variable should be entered into the workspace in MATLAB separately.
- The inputs are the same as the terms in the right hand of SES and DES models.
- The target is the original maximum temperature of Mosul, Rabea, Talafar, and Senjar cities.
- The inputs variable and target variable should be imported framework space to the neural network toolbox.
- There are several essential requirements to perform the RNN construction, such as determining the training function, the number of hidden neurons, and the transfer functions of hidden and output layers.
- The number of neurons in the hidden layer is $((2 \times 2) + 1 = 5)$.
- RNN that constructed in the previous stage is used to perform the training and testing process.
- The training and testing process's output variable are the training and testing forecasted variable using the SES-RNN and DES-RNN hybrid method.

Table 3 and Table 4 below present the MAPE values of SES-RNN and DES-RNN methods for Mosul, Rabea, Talafar, and Senjar cities in the training process.

TABLE III
MAPE OF TRAINING FORECASTS ACCURACIES BY USING SES-RNN AND DES-RNN.

Method	City	MAPE
SES	Mosul	7.64
	Rabea	9.92
	Talafar	8.51
	Senjar	9.25
DES	Mosul	7.61
	Rabea	10.39
	Talafar	7.59
	Senjar	10.27

TABLE IV
MAPE OF TESTING FORECASTS ACCURACIES BY USING SES-RNN AND DES-RNN.

Method	City	MAPE
SES	Mosul	7.55
	Rabea	6.50
	Talafar	8.66
	Senjar	12.81
DES	Mosul	8.00
	Rabea	6.87
	Talafar	7.21
	Senjar	20.74

Table 3 and Table 4 refer that the hybrid SES-RNN method is better than the SES model because MAPE values of SES-RNN are less than MAPE values of the SES model for training and testing stages. Also, the hybrid DES-RNN method is better than the DES model because MAPE values of DES-RNN are less than MAPE values of the DES model for training and testing stages. Fig.11 and 12 below present the fitness function between the original maximum temperature variable and the training and testing forecasted series using the hybrid SES-RNN method for different datasets. Fig.13 and 14 below present the fitness function between the original maximum temperature variable and the training and testing forecasted series, respectively, using the hybrid DES-RNN method for different datasets.

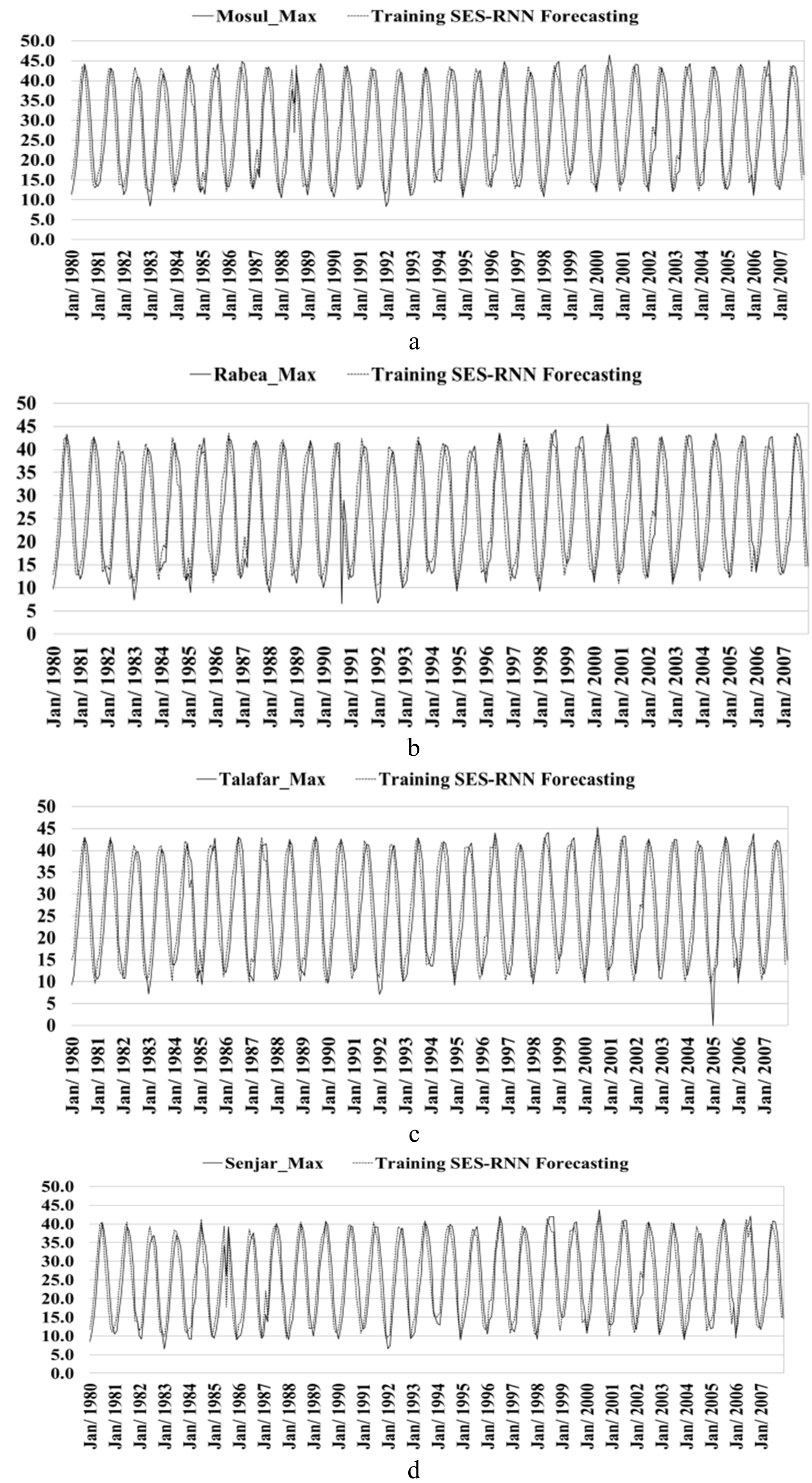

Fig. 11 The fitness function between the training forecast using the hybrid SES-RNN and original maximum temperature of a. Mosul, b. Rabea, c. Talafar, and d. Senjar cities.

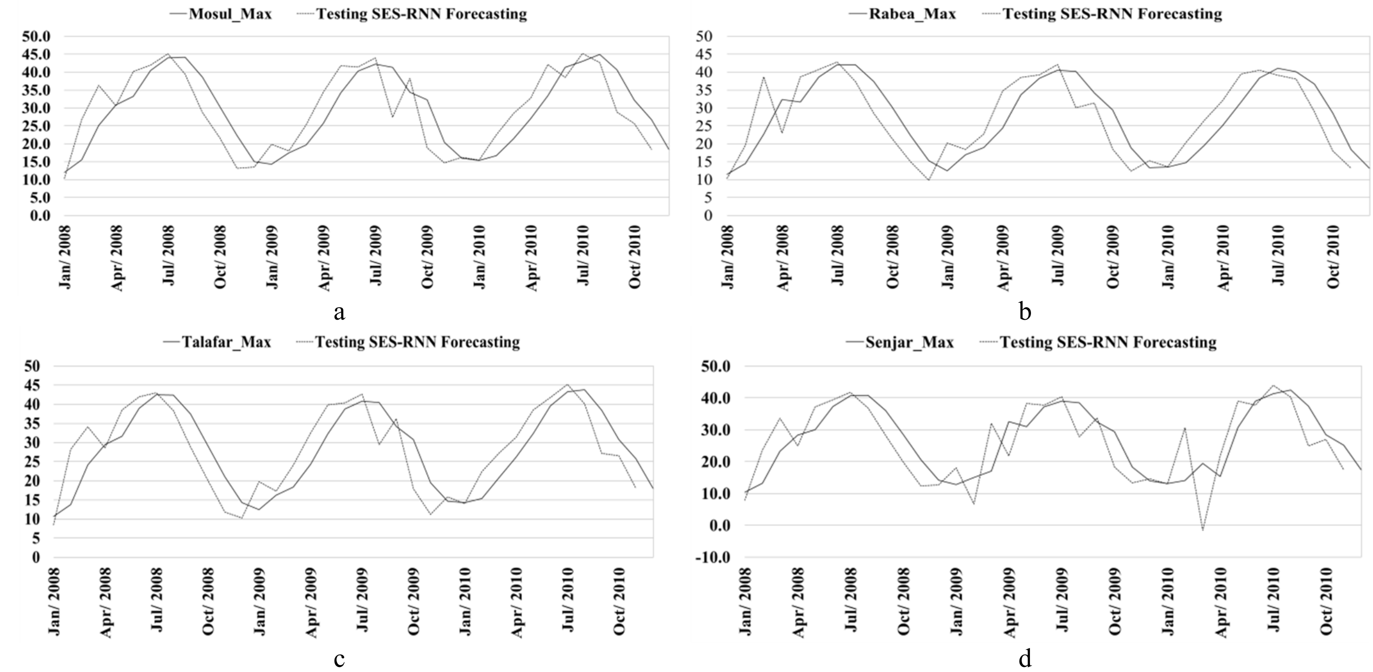

Fig. 12 The fitness function between the testing forecast by using the hybrid SES-RNN and original maximum temperature series of a. Mosul, b. Rabea, c. Talafar, and d. Senjar cities.

Fig.11, Fig.12 confirm that the hybrid SES-RNN method is better than the SES model. The hybrid DES-RNN method is better than the DES model because the lines of original and forecasted variables, as in Fig.13 and Fig.14, are more fitted than these two lines in Fig.11 and Fig.12. RNN is a nonlinear method and can handle the non-linearity of datasets. The hybrid methods SES-RNN and DES-RNN combine the SES and DES as a linear model with RNN as a nonlinear method to be one method that can handle any data, especially the nonlinear type, that is another critical reason for current forecasting results.

IV. CONCLUSION

SES and DES models were used as traditional linear methods to forecast maximum climatic temperature. RNN as a nonlinear intelligent method is proposed combining with SES and DES in hybrid SES-RNN and DES-RNN methods to forecast and handle the non-linearity of datasets. The forecasting results reflected that the hybrid methods outperformed the traditional methods. The proposed hybrid methods can be used to forecast climatic temperature in more accurate results. The hybrid methods SES-RNN and DES-RNN combine the SES and DES as a linear model with RNN as a nonlinear method to be one method that can handle any data, especially the nonlinear type.

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