Forecasting of Air Maximum Temperature on Monthly Basis Using Singular Spectrum Analysis and Linear Autoregressive Model

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Abstract. In this research, the singular spectrum analysis technique is combined with a linear autoregressive model for the purpose of prediction and forecasting of monthly maximum air temperature. The temperature time series is decomposed into three components and the trend component is subjected for modelling. The performance of modelling for both prediction and forecasting is evaluated via various model fitness function. The results show that the current method presents an excellent performance in expecting the maximum air temperature in future based on previous recordings.

Keywords: Autoregressive Model; Baghdad City; prediction model; temperature.

1. Introduction

The ecosystem has faced significant problems resulting from the variability of climate and global warming. These problems are likely to go worst depend on various climate change's scenarios (i.e., the temperature increased)[1, 2]. The natural disaster (e.g., volcanoes), industrialisation, and rapid increase of urbanisation led to Enormous greenhouse gases emission that in the last influence adversely climate change [3, 4]. It has set a considerable influence on the environment of residential areas in many places of the world [5-7]. These impacts differ in relation to the region, the type, and the importance.

The factors of climatic have directly and indirectly impacted both inhabitants and their residential environment along with short-, medium-, and long-terms [8]. Temperature is considered the most vital climatic variable that influences the growth, development and yield of crops [9]. In Addition, the system of houses is advanced in relation to factors of climatic [10, 11].
Different areas have faced a damaging impact of climate change that causes diminishing the quantity [12-16] and quality [17-22] of drinking water resources. High temperatures (i.e., dry days) lead to the growing urban water needed [23]. In addition, various studies presented that urban water needed was driven by maximum temperature [24-28]. Lately, a precise estimate of maximum temperature is a problem that has attracted the attention of researchers, since it has several various usages in the applications such as industry, agriculture or energy. Many approaches and methods are utilised in several fields [29-33], and research simulate the maximum temperature by different techniques [34-36]. The AR technique employed efficiently in several applications [37-39]. In this study, Auto-regressive (AR) approach will be applied to estimate the monthly maximum temperature.

2. Area of study and data set
Iraq is one of the Arab countries that lies in arid to the semi-arid area, and Baghdad is the capital of Iraq and locates in the centre of the country [40]. The weather is wet and cold in winter and dry and hot in summer (i.e., the temperature reaches 45 C). Iraq faced an acute climate change cased adversely impact the people, residential area, and freshwater sources [41-43]. The historical monthly data if maximum temperature along twelve years (2003-3014) used to build and assess the model.

![Figure 1. Location map of Baghdad city.](image)

3. Methodology
The technique of this study divides into, data pre-processing, and auto-regressive approach.

3.1 Data Pre-processing
This technique has a significant effect on the precision of the prediction techniques. It can be separated here into two stages: normalisation and cleaning. Normalisation time series assistance to reduction the influence of outliers and makes the data to be normal or near-normal distribution [44, 45]. In this study, a natural logarithm is used for normalising the data due to its capability to reduction the influence of multicollinearity among predictor factors [28, 46].
3.2 Autoregressive Model (AR)

In autoregressive (AR) model, the output pertaining to a particular variable can be predicted from the past observations of that variable [47]. This model has a linear form. As such, the simplicity of this model coupled with its powerful prediction increases the popularity of this model in different disciplines in which time series data need to be analysed. In water demand forecasting, city engineers and water authorities are working collectively to maintain the balance between the demand and supply of drinking water to residents in their city. Hence, to achieve this goal, a sound statistical method should be used. Accordingly, there is a growing interest in applying autoregressive model in water demand forecasting. The outputs in this model are merely dependent on the previous observations of the same variable [37, 38].

To mathematically formulate autoregressive models, Eq. (1) is used to relate the current observation with the past ones in a linear relationship as illustrated [37, 38]:

\[
X_t = \theta_0 + \sum_{i=1}^{p} k_i X_{t-1} + \epsilon_t
\]

Where; \(X_t\) and \(X_{t-1}\) are the observations in periods \(t\) and \(t-1\), \(p\) is the order of the AR model considered, \(k_i\) is the autoregressive parameters, \(\theta_0\) is the constant term, and \(\epsilon_t\) is the disturbance term for period \(t\). A least-square algorithm using MATLAB is utilised to accurately predict the unknown coefficients in the AR model.

4. Results and discussion

Initially, the maximum temperature data are normalised and cleaned. Afterwards, the time series of maximum temperature was analysis. Figure 2 visualises the temperature time series components obtained from the singular spectrum analysis. The first component represents the trend component, which follows the same fluctuation of the original time series. It is clear that this component, i.e. trend component, has the greatest portion of the variance of the original time series.

The data of trend then categorised into training set (70%, 101 data points) and testing set (30%, 43 data points). The AR approach fitness criteria, i.e., \(R^2\), MAE, MSE, and RMSE are shown in Table 1 for the training and testing stages. The table presents the model fitness at order 10 for both the prediction of the training sample and forecasting the testing sample. The comparison shows that the use of the combined technique outperforms the use of AR alone for both the prediction and forecasting processes. This can be clearly seen from the reduction in the MAE, MSE, and RMSE values when the SSA-AR is used.
Figure 2. The normalised and the first three signals of maximum temperature time series.

![Normalised and first three signals of maximum temperature time series](image)

Table 1: Model fitness for AR and SSA-AR methods

|                | Training sample | Testing sample |                |
|----------------|-----------------|----------------|----------------|
|                | $R^2$ | MAE  | MSE  | RMSE | $R^2$ | MAE  | MSE  | RMSE |
| AR             | 0.92  | 7.67 | 1.03 | 1    | 0.94  | 2.92 | 0.3  | 0.55 |
| SSA-AR         | 0.98  | 3.16 | 0.17 | 0.41 | 0.94  | 2.36 | 0.19 | 0.44 |

Additionally, Figure 3 represents the visual comparison between the measured and forecasted values of the testing sample. As it was mentioned earlier that the testing sample includes 44 recordings. It is clearly seen how precise the model forecasting is.

![Comparison between measured and forecasted maximum temperature time series](image)

Figure 3. The comparison between measured and forecasted maximum temperature time series.

Moreover, Figure 4 illustrates the model forecasting error histogram. It can be seen that the absolute error value is 0.15 as a maximum while the majority of the errors range in between [-0.1 +0.1].
Based on the above statistical tests, the suggested methodology has the ability for simulating efficiently the monthly maximum temperature considering the previous data.

5. Conclusions

Maximum temperature estimate is an important component in dynamic modern city planning and management because it helps to find suitable tools that utilised in building and industrials. In this research, the combined model includes the SSA and AR techniques employed for forecasting the monthly time series of temperature in Baghdad City over twelve years. The SSA used to denoise the time series of maximum temperature. The AR technique used to simulate the time series of maximum temperature. The outcomes reveal that the SSA is a suitable technique for noise removal. Also, the suggested methodology is effective to forecast the maximum temperature data in the testing stage (i.e., it is yield coefficient of determination 0.98 and 0.94 for training and testing stage, respectively). These results can be considered as an initial base of combined techniques for additional research in future.

6. References

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