ANALYSIS AND FORECASTING OF TEMPERATURE USING TIME SERIES FORECASTING METHODS
A Case Study of Mus

by

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The aim of this study is to forecast the daily average temperature of Mus province in Turkey using time series methods. The performance of three time series forecasting models is compared: LSTM, PROPHET, and ARIMA. The behavior of these models in temperature data is also investigated. It is found that these methods give accurate results according to the MAE, MSE, and RMSE error metrics. However, LSTM produces slightly better results. The temperature data used in this study was obtained from the Mus Meteorology Provincial Directorate. Accurate temperature forecasting is important for many different areas, from energy, agriculture to water resource management. This study is an important research step in temperature analysis and forecasting, and it will contribute to relevant decision-making processes.

Key words: *time series, prophet, LSTM, ARIMA, temperature forecasting*

Introduction

Temperature forecasting is the process of predicting future temperature values based on historical data. It is a valuable tool that can be used to improve decision-making in a variety of sectors. It is a critical for understanding and responding to climate change. Temperature forecasting is used in planning and decision-making processes across a variety of industries. It provides advantages in all aspects to sectors such as agriculture and industry [1]. In the agricultural sector, temperature forecasts can be used to manage water resources, plan planting and harvest seasons, and make other decisions about crop production. Forecasting air temperature can influence energy policy, human activities, and employment [2]. In the energy sector, temperature forecasts can be used to efficiently manage energy resources, such as by predicting solar radiation and wind speeds to ensure that solar panels and wind turbines are operating at peak efficiency. Temperature forecasts can also be used to plan travel, as they can help to predict weather conditions that may impact travel, such as snow and ice. Additionally, temperature forecasts can be used to protect human health by warning people about potential health risks associated with extreme heat or cold weather conditions.

In this study, three different models were used to forecast future temperature values: ARIMA, PROPHET, and LSTM. The models were chosen because each has strengths and weaknesses. The ARIMA is good for short-term forecasting, PROPHET is good for forecast-

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ing trends and seasonality, and LSTM is good for forecasting long-term dependencies. By using all three models, a more complete picture of future temperature values was obtained.

This study investigated the temperature changes using 12-year daily average temperature data of Mus province and tried to predict the temperature values with these data. The climate and temperature changes in Mus province are unique to the region, so this study can be a valuable resource for local residents, government officials, and other researchers. The daily average temperature data for Mus province between January 1, 2010, and December 31, 2022, was obtained from the Mus Provincial Directorate of Meteorology. This data was used to analyze past temperature trends and predict future temperature changes. The results were evaluated and the accuracy of the methods was compared using various error metrics.

The remainder of the article will include sections such as literature review, time series analysis and forecasting methods, dataset, results and discussion, conclusions, and future research recommendations.

Literature review

Time series forecasting models can be used for many purposes in many areas of daily life such as finance, agriculture, marketing, health, energy, meteorology. It is observed that artificial neural network based models are mostly used for forecasting.

Malakouti [3] used ANN to predict average air temperature for smart agriculture. The results show that the method can be used in smart agriculture to predict temperatures with fewer errors than those achieved with traditional approaches. Tran *et al.* [4] optimized the hyperparameters of the ANN, LSTM, and RNN models using genetic algorithm and applied these models at Cheongju station in South Korea to calculate the maximum temperature prediction. Abhishek *et al.* [5] forecasted the maximum daily air temperature of a station area between 1999 and 2009 using a feed-forward neural network. The input data used consists of the maximum air temperature for the last 10 years. According to the calculations, it was determined that the ANN with the tan-sigmoid transfer function made the best maximum temperature predictions. Qui *et al.* [6] used deep learning method for river water temperature prediction. In their study, they estimated daily river water temperatures using the LSTM method. They stated that the results of the method gave more accurate results than other methods in forecasting the average daily water temperature in rivers.

Zhengxin and Yue [7] designed a PID fuzzy controller with a time series prediction algorithm. The stability of the main steam temperature in thermal power plants is especially important for boiler operation. The time series algorithm enables the prediction of the main steam temperature for the upcoming time step and facilitates the calculation of the input value for the PID fuzzy controller based on the predicted value. Wei and Du [8] introduced a temperature forecasting approach utilizing the autoregressive moving average (ARMA) model to mitigate the risk of insulated gate bipolar transistor (IGBT) module failures and enhance their operational efficiency. The autoregressive model is constructed using historical and current temperature data to estimate the temperature trends in IGBT chips. Zang *et al.* [9] proposed a temperature forecasting model using urban temperature data and a LSTM network. The model, implemented with TENSORFLOW, leverages past temperature data to forecast future temperature values. The LSTM neural network was tested using temperature data from the city of Vilnius, and subsequently employed to predict future sequences with varying lengths, including both single-step and multi-step predictions.

Materials and methods

LSTM

The LSTM is a type of deep learning network developed specifically for processing data with long-term dependencies, such as time series data. Unlike many traditional artificial neural networks, LSTM has a special structure called memory cells with gate mechanisms that can hold long-term dependencies of data [10, 11].

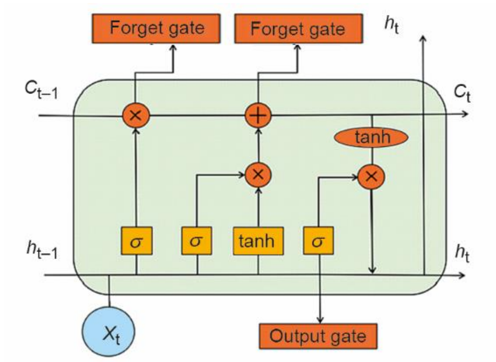

Figure 1. The LSTM cell structure [12]

The structure consists of a series of cell blocks, fig. 1. Each cell block contains a cell state, an input gate, a forget gate, and an output gate. Memory cells store previous entries and previous cell states information. Gate mechanisms, on the other hand, decide how much information the cells store, how much they forget, and how much they update.

$$f_t = \sigma(w_{f,x}x_t + w_{f,h}h_{t-1} + b_f) \tag{1}$$

Equation (1) is used for the forget gate operation of an LSTM cell. The f_t is a sigmoid function output that controls which part of the cell's history at time t is forgotten, x_t – the data entry at time t, h_{t-1} – the cell output from the previous time, $w_{f,x}$ – the weight matrix for input x_t, $w_{f,h}$ – the weight matrix associated with the output of h_{t-1}, b_f – the bias term, and σ – the sigmoid function.

$$i_t = \sigma(w_{i,x}x_t + w_{i,h}h_{t-1} + b_i) \tag{2}$$

Equation (2) is used to calculate the input gate in an LSTM cell. The i_t value decides how much of the input value to keep for the next step.

$$\tilde{C}_t = \tanh(w_{c,x}x_t + w_{c,h}h_{t-1} + b_c) \tag{3}$$

Equation (3) is used to calculate the memory cell component of an LSTM cell. The $\tanh$ is defined as a hyperbolic tangent function. A memory cell candidate $\tilde{C}_t$ is calculated.

$$C_t = C_{t-1}f_t + i_t\tilde{C}_t \tag{4}$$

where C_t is the cell state representing the memory of the LSTM cell, C_{t-1}, this cell state in the previous time step, f_t – the forget weight used to make past information forget, i_t – the input weight used to add new information to memory, and C_t represents a new candidate cell state, which represents the current information and is calculated between the current input and the previous cell state. The C_t updates the cell's memory, f_t determines how much of the previous cell state is forgotten, and i_t determines the new candidate memory state. The C_t determines how much of the new memory state selected by i_t will be added to the actual memory state.

$$o_t = \sigma(w_{o,x}x_t + w_{o,h}h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t \tanh(C_t) \tag{6}$$

With eqs. (5) and (6), the output layer is obtained. The values obtained in the output layer are usually linked to a next layer or output [13].

The LSTM has the advantage of being able to remember information for a long time to forecast temperature. The LSTM is also used in many different application areas besides time series. It is widely used in fields such as natural language processing [14], speech recognition [15] and image recognition [16]. The use of LSTM becomes especially important as data sizes grow. It gives good results.

PROPHET

The PROPHET is an open source automated time series forecasting tool developed by Facebook in 2017. This tool is often used for estimating non-linear time series with seasonal, trend and holiday effects, such as marketing, and financial data. The PROPHET can automatically detect periodic patterns such as holidays, weekly and annual seasonality. The PROPHET takes as input two columns of data called *ds* (date) and *y* (dependent variable). In PROPHET's forecasting phase, the model can make predictions for specified future time periods.

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{7}$$

The PROPHET is actually the sum of three functions of time and an error term as in the equation. Forecasts are calculated as a combination of growth, $g(t)$, seasonality, $s(t)$, holiday, $h(t)$, and error (ε_t). The PROPHET provides prediction intervals, taking into account the uncertainty of the predictions. Various parameters and hyperparameters can be adjusted so that PROPHET gives the best results on a time series dataset [17-19].

AIRMA

Autoregressive integrated moving average (AIRMA) is a statistical model that is often used for short-term forecasting. It works by finding patterns in historical data and using those patterns to predict future values. It also known as Box and Jenkins. It combines a set of parameters to model the disorder and variability in time series. This model is used to predict time-varying and random fluctuation data. It is used in time series that are not stationary but made stationary by taking the difference. There are different models used according to seasonality. It consists of autoregressive (AR) component, integrated (I) component and moving average (MA) component. Its non-seasonal general notation is ARIMA (p, d, q). The AR component models how past observations affect current observations, while the MA component models the effect of past prediction errors on current observations. The integrated component is used to ensure the stationarity of the data. Where p is the degree of the AR model, q is the degree of the moving average model, d is the number of differential operations required to stabilize the time series.

$$y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{8}$$

where C is a constant term, ϕ_i – the autoregressive model parameter, θ_i – the moving average model parameter, y_t – the current time series value, y_{t-1}, y_{t-2}, … historical values, and $\varepsilon_t = y_t - y_{t-1}$, t. represents the error term for the day/time. If $q = 0$, then it becomes an AR model of degree p. When $p = 0$, the model is reduced to an MA model of degree q. In a seasonal time series, d will be 0 [20, 21].

Error metrics

In the study, MSE, MAE, RMSE metrics were used to evaluate the prediction error rates and the performance of the models. The n represents the number of samples in the data set, y_i represents the actual values, and $\hat{y}$ represents the predicted value.

Mean squared error (MSE): Represents the difference between the actual and predicted values extracted by squaring the mean difference in the data set. It calculates how far the predicted values are from the true values and averages the squares of these errors. It handles larger error values more heavily and is therefore a sensitive performance measure.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{9}$$

Mean Absolute Error (MAE): Represents the difference between the original and predicted values extracted by averaging the absolute difference in the data set. It calculates how far the predicted values are from the true values and averages the absolute values of these errors. It is a performance metric that is sensitive to the size of errors. The lower the value of the MAE, the closer the model's predictions are to the true values.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}\right| \tag{10}$$

Root mean squared error (RMSE): Is the square root of the mean squared error, that is, the MSE. It is an evaluation metric that shows how far the predicted values are from the observed values.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{11}$$

Dataset

This study used average daily temperature data from the province of Mus, Turkey, between 2010 and 2022. There were a total of 4748 days of data. The data was obtained from the Mus Provincial Directorate of Meteorology. Our dataset includes the day, month, year, and average temperature for each day.

We first tried to forecast temperature values for less than one year by using a short test dataset. Then, we extended the test dataset and tried to forecast temperature values for more than one and a half years. This allowed us to compare the performance of the models on data of different lengths. First, we used 4523 days of data for training and 225 days (4.74%) for testing. Then, we used 4162 days of data for training and 586 days (12.34%) for testing. This approach was chosen to include examples from different periods and to avoid misleading results. The reason for separating the data in this way was not to consider the whole year. Instead, it was to ensure that the models were not simply memorizing the training data and were able to generalize to new data.

As seen in fig. 2, the average temperature in Mus province varies greatly throughout the year, from –20 ºC in the winter to +30 ºC in the summer. The lowest average temperature in our data set of 4748 days was –21.4 ºC, and the highest was +32.6 ºC. The average temperature is +11.459 ºC, and the standard deviation is +11.436 ºC. The high standard deviation is due to the large difference between the average temperatures in the summer and winter.

Average temperatures in winter may vary from year to year. As can be seen in fig. 2, the average temperature values, especially in the winter seasons of 2012, 2014, 2016, and 2017, have taken values far from the model prediction. The years 2010 and 2018 are the years with the lowest temperature changes on a yearly basis. As can be seen in fig. 3, there has been a gradual increase in summer temperatures in recent years. The average temperature in the winter months varies from year to year. The variation in temperature is greater in the winters than in the summers.

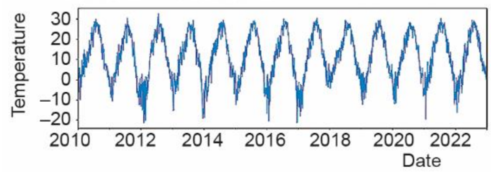

Figure 2. Mus province (2010-2022) average temperature values

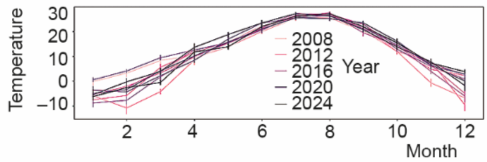

Figure 3. Annual temperature change in Mus province between 2010-2022

Results and discussion

In this section, models and obtained results are evaluated. Time series temperature forecasting was made with LSTM, PROPHET, and ARIMA. The models were compared according to their performance metrics.

The LSTM model used for forecasting was created using the Keras library. The model starts with an LSTM layer as the input layer. It has 128 units and uses the ReLU activation function. It is set to return sequences for further processing. The input shape is defined based on the shape of the training data. A dropout layer is added after the first LSTM layer. Dropout helps prevent overfitting by randomly disabling a fraction (20%) of the neurons during training. Another LSTM layer is added as a hidden layer, also with 128 units and the ReLU activation function. It returns sequences for further processing. Another dropout layer is added after the second LSTM layer, with the same configuration as the previous dropout layer. The final LSTM layer is added as a hidden layer. It has 128 units and uses the ReLU activation function. However, it does not return sequences, as it is the last hidden layer. The output layer is added as a dense layer with 1 unit. This layer is responsible for predicting the next value in the sequence. The model is compiled with the *adam* optimizer and the mean squared error loss function. The model is trained for 20 epochs with a batch size of 32. Additionally, a validation split of 0.1 is used, meaning 10% of the training data is reserved for validation during training. As a result of the experiments, it was seen that the method gave better results with these parameters.

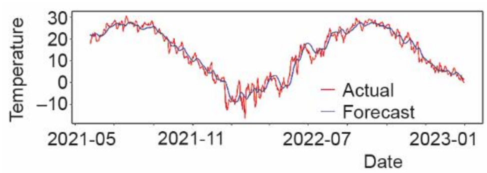

Figure 4. Forecasting with LSTM

When fig. 4 is examined, it can be seen that the actual temperature values are generally higher than the forecasted values of the LSTM model. This suggests that the average temperatures have increased above the forecast. In other words, the temperature has increased over the years.

In fig. 5, the temperature forecasts for the summer months were generally accurate. However, the forecasts for the winter months in the specified years were not completely accurate. This is because the temperature values in the winter months vary greatly, which makes forecasting difficult.

Daily temperature data can be considered seasonal data. The ARIMA model is not always accurate for seasonal data. The accuracy of the model depends on the values of the parameters (p, d, q). In this case, the values (3, 0, 3) were used. The results were acceptable. If you are forecasting seasonal data, it is important to consider the limitations of ARIMA models.

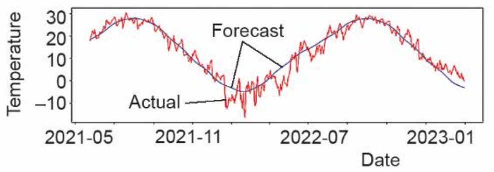

Figure 5. Temperature forecasting with PROPHET

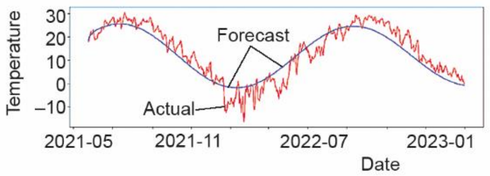

Figure 6. Temperature forecasting with ARIMA

Table 1. Error metric results of models

Metrics	ARIMA		LSTM		PROPHET	
Test data	586 days	225 days	586 days	225 days	586 days	225 days
MSE	19.184	8.958	7.458	3.050	10.182	9.109
MAE	3.577	2.529	2.075	1.356	2.361	2.346
RMSE	4.380	2.993	2.731	1.746	3.191	3.018

As shown in tab. 1, MSE, MAE, RMSE metrics were used to quantitatively evaluate the performance of the models. The LSTM model made more accurate forecasting than the other models because it is a deep learning model that can better capture historical data dependencies and model more complex non-linear relationships. The LSTM model is therefore recommended as a more reliable option for future temperature forecasting. It can be seen that the error rate in the PROPHET model changes less than other when the test data length increases.

Conclusion

This study investigated the changing climate in Mus province. The findings showed that temperatures have been increasing, especially in winter. This is consistent with global warming trends. The study also found that the LSTM model was the most accurate for temperature forecasting in Mus province. This model could be used to make more accurate planning and decision-making processes in agriculture, energy management, transportation, health, meteorology, and other fields. Rising temperatures could impact the environmental balance, so it is important to take precautions to protect the environment. Future studies could develop more specific time series models for temperature forecasting or hybrid models that combine different forecasting methods.

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