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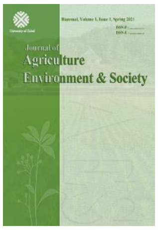

Forecasting air temperature in Zabol city: a comparative study of SARIMA, BP-FFNN, and RNN-LSTM models

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ABSTRACT

This study compares three models, Back -Propagation Feed-Forward Neural Networks (BP-FFNN), Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM), and Seasonal Autoregressive Integrated Moving Average (SARIMA), for temperature prediction using historical air temperature data from Zabol City, Iran. The dataset consists of daily average air temperature observations, and the models were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Median Absolute Percentage Error (MDAPE), and Coefficient of Determination (R^2) metrics. The BP-FFNN model outperformed the RNN-LSTM and SARIMA models, achieving the lowest values for RMSE (0.018), MAE (0.013), and MDAPE (1.59%). It demonstrated accurate temperature predictions with a strong correlation between predicted and actual values (R^2=0.99). The RNN-LSTM model showed comparable results, capturing long-term patterns with RMSE of 0.042, MAE of 0.031, and MDAPE of 3.53%. The SARIMA model provided insights into seasonality and autocorrelation, achieving RMSE of 0.042, MAE of 0.03, and MDAPE of 3.65%.The study's findings have implications for weather forecasting, climate research, and energy management systems. The superior performance of the BP-FFNN model suggests its reliability for accurate temperature prediction, while the RNN-LSTM model offers an alternative approach for capturing long-term patterns. The SARIMA model contributes insights into seasonality and autocorrelation. The study highlights the strengths and limitations of each model and their practical applications in temperature forecasting. In conclusion, the BP-FFNN model effectively predicts temperatures in Zabol City while the RNN-LSTM and SARIMA models provide alternative approaches for capturing long-term patterns and understanding seasonality. The study's results advance temperature prediction techniques and have practical implications for various fields reliant on accurate temperature forecasting.

Highlights

- This study highlights the applications of forecasting air temperature in Zabol City, recognizing its importance in energy generation and agriculture.
- The study demonstrates the use of statistical approach and two deep neural network algorithms for averaged temperature prediction, showcasing advanced techniques.
- A comparative analysis of three approaches is conducted, providing insights into their respective strengths and limitations in averaged temperature forecasting.
- The study identifies the potential for enhancing accuracy through a hybrid deep neural network algorithm, emphasizing the importance of combining different models or techniques to achieve improved predictions.

1. Introduction

Accurately predicting air temperature at a specific location and time is crucial for various applications, including energy generation and agriculture. With climate experts warning about the potential environmental impacts of rising temperatures, the need for reliable temperature

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forecasting becomes even more critical (Abrahams and Carr, 2017). However, The prediction of air temperature presents significant challenges due to its multidimensional and chaotic nature within the broader weather data system (Kirchgässner et al., 2013). Nevertheless, advancements in weather observation data availability have facilitated the development of data-driven forecasting approaches (Cifuentes et al., 2020). The primary challenges in air temperature prediction involve understanding the interrelationships among weather variables and building robust models capable of revealing hidden patterns in the data (Zhang et al., 2020).

Air temperature prediction plays a critical role in various applications, including agriculture, industry, energy, the environment, and tourism (Abdel-Aal, 2004). These applications encompass areas such as short-term load forecasting for power utilities (Li et al., 2016), the development of air conditioning and solar energy systems (García and Balenzategui, 2004; Ruano et al., 2006) adaptive temperature control in greenhouses (Altan Dombaycı and Gölcü, 2009), prediction and assessment of natural hazards (Camia et al., 1999), and the estimation of cooling and energy consumption in residential buildings (Ben-Nakhi and Mahmoud, 2004; Mihalakakou et al., 2002). Accurate temperature forecasting is essential in conjunction with analysing additional relevant factors, as it enables effective planning for infrastructure upgrades, insurance decisions, energy policies, and business growth (Smith et al., 2007). Given the wide-ranging significance of temperature predictions across these domains, there is a growing demand for reliable and precise temperature forecasting methods.

Traditional numerical weather prediction (NWP) models based on physical equations have been widely used for temperature forecasting. However, these models rely on prior knowledge and substantial computational resources (Bauer et al., 2015). In contrast, machine learning techniques, particularly deep learning, offer an alternative by uncovering hidden patterns in the data without the need for prior knowledge. These approaches show promise in weather forecasting and prediction, surpassing the limitations of physics-based models (LeCun et al., 2015).

In recent years, air temperature forecasting has garnered significant attention in domains such as agriculture, energy management, and climate modeling. Various methods have been explored to accurately predict the air temperature. One such method is the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, which effectively captures temporal dependencies and seasonal patterns in time series data (Box et al., 2015; Hyndman and Athanasopoulos, 2018). SARIMA has been successfully applied to forecast air temperature in different regions and time scales, capturing both short-term fluctuations and long-term trends (Al Dhaheri et al., 2017).

In addition to SARIMA, machine learning models have gained prominence in time series forecasting. The Back Propagation Feed-Forward Neural Network (BP-FFNN) is one such model that captures complex patterns and non-linear relationships (Bishop, 2005). Researchers have employed BP-FFNN for air temperature prediction, achieving competitive results by effectively capturing the intricate relationships between temperature and meteorological variables (Kuligowski and Barros, 1998; Roy, 2020; Smadi and Mjalli, 2007).

Shi et al. (2015) introduce ConvLSTM, a convolutional LSTM network, for prediction of the future rainfall intensity. ConvLSTM outperforms other models in capturing spatiotemporal correlations and accurately predicting future rainfall intensity (Shi et al., 2015). Their study demonstrates the successful application of deep learning techniques to address the challenging problem of precipitation forecasting. Another popular approach is the Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) model, which captures long-term dependencies in sequential data, making it suitable for air temperature prediction (Hochreiter and Schmidhuber, 1997). RNN-LSTM has shown improved accuracy compared to traditional methods, particularly in capturing nonlinear patterns and long-term trends in air temperature dynamics (Jingxiao et al., 2021; Tran et al., 2021).

In summary, the forecasting of air temperature has been extensively studied using various methods including SARIMA, BP-FFNN, and RNN-LSTM. These models have demonstrated their effectiveness in capturing the complex patterns and temporal dependencies present in air temperature time series data. Furthermore, hybrid models combining multiple approaches have shown improved forecasting performance. In this study, we aim to compare and evaluate the performance of SARIMA, BP-FFNN, and RNN-LSTM models for forecasting and one-step-ahead prediction of air temperature using a dataset consisting of approximately 4,000 samples and seven features.

The remainder of the paper is organized as follows: Section 2 introduces the dataset from Zabol City, Iran, and the models are implemented. Section 3 presents the results which are obtained. Section 4, concludes the paper by summarizing the key findings and suggesting future research directions.

2. Material and Methods

2.1. Data Collection and Pre-processing:

Zabol City in southeastern Iran presents a compelling case for studying the interplay between topography and weather patterns. To explore the intricate dynamics that shape the environment of Zabol, we compiled an extensive dataset from (TuTiempo.Net, 2010-2021) for each day from 2010 to 2021. This dataset encompasses various features such as average, minimum, and maximum wind speed, humidity, average temperature, maximum temperature, and minimum temperature, providing valuable insights into the City's climatic patterns. With scorching temperatures exceeding 40 degrees Celsius during the summer, Zabol is one of the hottest places on Earth, posing challenges for residents and necessitating effective water management and adaptation strategies.

In this research, we go beyond analysing historical climate data and focus on temperature forecasting in Zabol City. By leveraging advanced statistical and machine learning models, and considering factors like solar radiation, air pressure, and geographical features, we aim to deliver accurate and reliable temperature predictions for the region. The forecasting aspect of our study holds significant implications for key sectors such as agriculture, energy management, and urban planning, as it enhances our understanding of Zabol climate dynamics. By integrating temperature forecasting into our analysis, stakeholders can make informed decisions based on trustworthy projections, enabling effective planning and decision-making processes.

By employing a range of statistical and machine learning models, we seek to advance our comprehension of Zabol weather conditions and provide stakeholders with the tools to make data-driven choices. Figure 1 indicates the flowchart of the pre-processing and post-processing approaches with three models.

To prepare the data for modelling, a preprocessing step was applied using the Min-Max normalization method. This technique rescales the data to a fixed range, typically between 0 and 1, by subtracting the minimum value and dividing by the range of the data. Min-Max normalization was chosen as it preserves the relative relationships between the values and is suitable for neural network models. This step ensures that all features are on a similar scale, preventing any one feature from dominating the model's learning process. The Min-Max normalization technique has been widely used in time series analysis and forecasting (Radhika and Shashi, 2009).

2.2. Proposed Statistical and Neural Network Architectures

In this section, we will present a concise overview of statistical method and two deep neural networks that have been employed in the field of forecasting.

The SARIMA model captures complex dynamics in time series data by incorporating both seasonal and non-seasonal components. It combines autoregressive (AR) dependencies, moving average (MA) components, differencing operations, and seasonality patterns for comprehensive analysis and forecasting (Atasever et al., 2022). Optimal SARIMA parameters were determined using grid search or automated methods such as the Akaike information criterion (AIC) or Bayesian Information Criterion (BIC) (Box et al., 2015; Hyndman and Athanasopoulos, 2018). The dataset was divided into training and testing sets, and the SARIMA model was fitted to the training data. It was then used to make one-step-ahead predictions on the testing set.

The SARIMA model offers flexibility and robustness in time series analysis, allowing the identification of dependencies, trends, and seasonality for accurate forecasting and insights into underlying dynamics. Its performance can be assessed using statistical metrics like root mean squared error (RMSE) and AIC to measure goodness of fit and predictive capabilities.

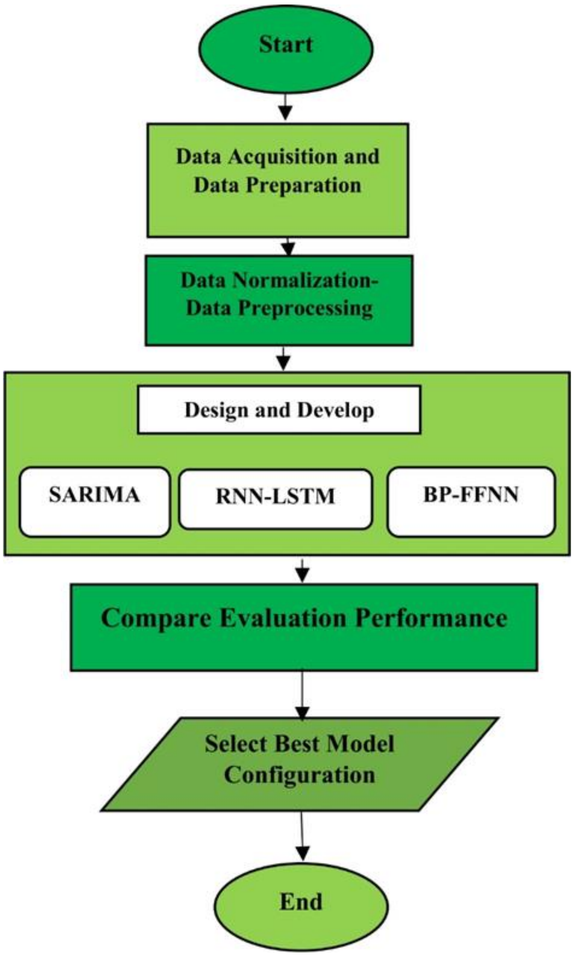

Figure 1. Schematic Flowchart of the study

The BP-FFNN is a powerful machine learning model known for capturing complex patterns and non-linear relationships (Bishop, 2005). Before training, the dataset was split into training and testing sets, and feature normalization techniques such as MinMax normalization were applied. The BP-FFNN model, with multiple hidden layers and appropriate activation functions, was trained iteratively using the Backpropagation algorithm to optimize the network weights based on prediction errors. After training, the BP-FFNN model was evaluated on the testing set, generating one-step-ahead prediction.

The BP-FFNN model belongs to the family of artificial neural networks and features a feed-forward architecture where information flows from input to output layers. The back propagation algorithm plays a crucial role in training, adjusting weights based on the error gradient. This iterative learning process allows the BP-FFNN to optimize performance and capture the underlying dynamics of time series data. Once trained, the model can forecast future values by leveraging past observations. The learned representations within the network enable it to capture intricate patterns and relationships, facilitating accurate forecasts and revealing underlying trends and dynamics in the data (Yang and Wang, 2018).

The RNN-LSTM model is a powerful deep learning model designed to capture long-term dependencies in sequential data (Hochreiter and Schmidhuber, 1997). Similar to the BP-FFNN model, the dataset was split into training, validation and testing sets, and feature normalization techniques such as Min-Max normalization were applied. The RNN-LSTM model, consisting of LSTM units with recurrent connections, was trained using historical data to capture temporal dependencies (Hochreiter and Schmidhuber, 1997). After training, the model was evaluated on the testing set, generating one-step-ahead prediction.

The RNN-LSTM model overcomes the vanishing gradient problem of traditional RNNs by utilizing LSTM units, specialized memory cells that retain and update information over long time spans (Hochreiter and Schmidhuber, 1997). This allows the model to effectively model long-term dependencies in time series data. The architecture of the RNN-LSTM includes an input layer, one or more LSTM layers, and an output layer. The input layer receives the sequential time series data, while the LSTM layers process the data, updating hidden states and cell states at each time step. The output layer produces predictions or classifications based on the learned representations from the LSTM layers. The recurrent connections in the LSTM layers enable the network to learn and leverage temporal dependencies inherent in the time series data (Hochreiter and Schmidhuber, 1997).

The two algorithms, the BP-FFNN and the RNN-LSTM have been implemented using the widely-used deep learning framework, Keras (Chollet, 2021). The BP-FFNN model consists of two hidden layers, each composed of 10 neurons. The RNN-LSTM model utilizes two LSTM layers which first LSTM layer consists of 100 neurons and the second LSTM with 50 neurons, followed by a dense layer.

In terms of activation functions, all models employ the rectified linear unit (ReLU). The RMSE has been chosen as the loss function, and the Adam optimizer is utilized with a recommended learning rate of 0.01 in BP-FFNN model and 0.001 in RNN-LSTM model. Training models involve 150 epochs with a batch size of 512 in the BP-FFNN model and a batch size of 32 in the RNN-LSTM model. The predictions are made for the subsequent day as well as the following last year (from 2020 to 2021). These configurations ensure that the models are optimized and trained effectively for average air temperature prediction. For the SARIMAX model, the seasonal and non-seasonal components of the temperature data are captured using appropriate parameters.

2.3. Evaluation Metrics

To assess the forecasting performance of each model, we employ several evaluation metrics. These metrics include:

- RMSE: It is the square root of the average squared difference between the predicted and actual air temperature values and provides a more interpretable measure of prediction error. Lower RMSE values indicate better accuracy (Liu et al., 2019).

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{predicted}-X_{observed})^2} \tag{1}$$

- Mean Absolute Error (MAE): It calculates the average absolute difference between the predicted and actual air temperature values, providing a measure of the average magnitude of the prediction error (Liu et al., 2019).

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|X_{predicted}-X_{observed}\right| \tag{2}$$

- Mean Directional Absolute Percentage Error (MDAPE): It quantifies the average absolute percentage difference between the predicted and actual air temperature values. MDAPE provides a measure of the average percentage error in capturing the magnitude of temperature changes (Liu et al., 2019).

$$MDAPE = median(\sum_{i=1}^{N}\frac{\left|X_{observe}-X_{predicted}\right|}{X_{observed}})\times 100\% \tag{3}$$

- R^2(R-squared): R-squared is a statistical measure that indicates the proportion of the variance in the dependent variable that can be explained by the independent variable(s) in a regression model. It represents the goodness fit of the model, indicating how well the model's predictions match the actual data (Liu et al., 2019).

$$R^2=1-\frac{\sum_{i=1}^{N}(X_{observe}-X_{predicted})^2}{\sum_{i=1}^{N}(X_{observe}-\bar{X})^2}\ , \tag{4}$$

Where $X_{predicted}$ is the prediction data, $X_{observed}$ is the real data, N is the number of real data and X_{bar} is the mean value of the dataset. These metrics provided measures of accuracy, prediction error magnitude, the proportion of variance explained by the models, and the average absolute percentage difference between predicted and actual values. By calculating these metrics, we compared and evaluated the performance of the SARIMAX, BP-FFNN, and RNN-LSTM models in forecasting air temperature.

2.4. Experimental setup

In this study, the proposed network models were trained and evaluated using specific hardware and software environments. The hardware consisted of an Intel Core i7-8750H processor and Nvidia GeForce GTX 1070 GPU, providing powerful computing ability and memory bandwidth. Deep learning frameworks like Tensor Flow or PyTorch were utilized for model implementation and training. The Nvidia GeForce GTX 1070 GPU accelerated the training process due to its parallel processing capabilities. Python, along with libraries like Pandas and NumPy, was used for data manipulation and pre-processing tasks. This hardware and software setup ensured efficient analysis and reduced computational time.

3. Results and discussions

3.1. Performance Comparison of Forecasting Models

We evaluated the performance of three forecasting models, namely SARIMA, BP-FFNN, and RNN-LSTM, on the task of air temperature prediction in the Zabol City dataset. The models were trained and tested using a dataset consisting of 4000 samples with 7 features and a target variable of average air temperature. In this subsection, we present a comprehensive analysis of the results obtained from each model and discuss their strengths and weaknesses.

Neural network approaches in weather prediction have utilized a range of meteorological and geographical variables as input factors. These variables encompass air temperature, wind speed and direction, air pressure, precipitation, solar radiation, relative humidity, cloudiness, latitude, longitude, and altitude (Bilgili and Sahin, 2009; Hou et al., 2022). Specifically, air temperature, relative humidity, precipitation, and wind speed are commonly used inputs for air temperature predictions. While different types of neural network approaches have incorporated various meteorological variables as inputs, simpler techniques like multi-layer perceptron (MLP) (Jallal et al., 2019) and feed-forward neural network (FFNN) (Kisi and Shiri, 2014) have included geographical inputs such as latitude, longitude, and altitude. However, it is important to acknowledge the challenges in selecting the optimal input variables for a specific neural network approach due to the complexity of the problem and the limited number of studies available on this topic.

Furthermore, it has been observed that neural network techniques are primarily employed for short-term air temperature forecasting. Limited studies have been dedicated to medium- and long-term air temperature prediction, with a focus on utilizing RNN and LSTM models known for their ability to capture temporal trends in air temperature time series (Thi Kieu Tran et al., 2020). RNN and LSTM models have demonstrated their effectiveness in long-term forecasting of hydrologic variables (Liu et al., 2019; Thi Kieu Tran et al., 2020). The accuracy of these models primarily depends on the selection of input variables and the structure of the network. Incorporating additional data, such as rainfall, air pressure, and humidity, in deep learning methods has shown to enhance air temperature predictions.

Error! Reference source not found. summarizes the performance of the forecasting models based on several evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Median Absolute Percentage Error (MDAPE), and Coefficient of Determination (R2). The evaluation results are as follows:

Table 1. Comparison of error evaluation results for One-Step-Ahead prediction of air temperature across different models

Model	RMSE	MAE	MDAPE	R^2
BF-FFNN	0.018	0.013	1.59%	0.99
SARIMAX	0.042	0.03	3.65%	0.96
RNN-LSTM	0.042	0.031	3.53%	0.96

From the results in **Error! Reference source not found.**, it is evident that the BP-FFNN model outperformed the SARIMA and RNN-LSTM models in terms of all evaluation metrics with values of MAE (0.013), RMSE (0.018), MDAPE (1.59%), and R^2 (0.99), which are indicated in bold font. However, the RNN-LSTM model demonstrated a similar level of performance to the SARIMA model, with comparable values of MAE (0.031 vs. 0.03), RMSE (0.0421 vs. 0.0424), MDAPE (3.65% vs. 3.53%), and R^2 (0.964 vs. 0.96).

Figure 2 displays the comparison between the actual air temperature values and the temperature predictions made by the BP-FFNN model. The model exhibits a close fit to the actual values, indicating its effectiveness in capturing the underlying patterns in the temperature time series.

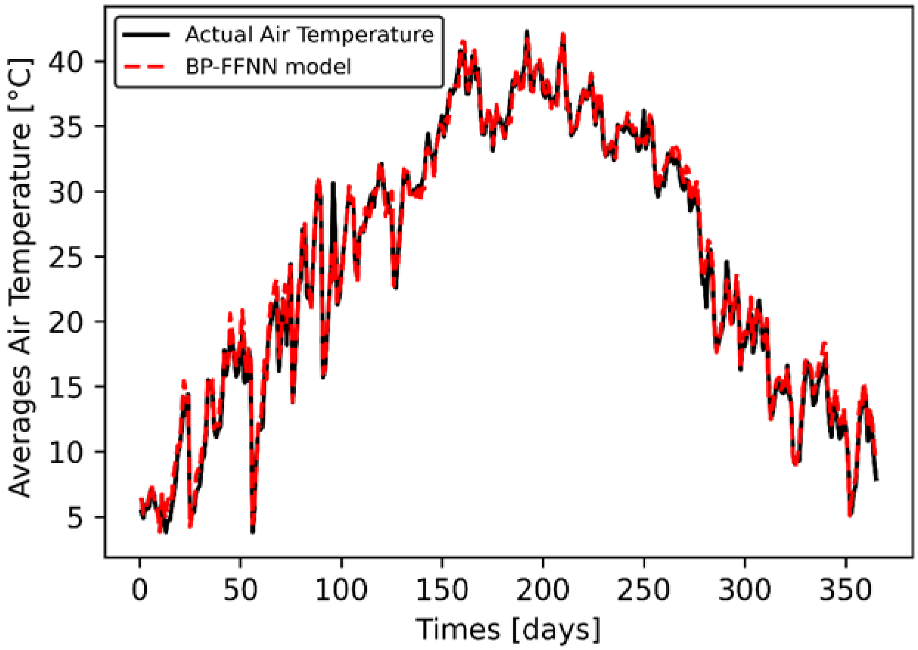

Figure 1. Comparison of BP-FFNN Temperature Predictions and Actual Values

Similarly, in Figure 3, the RNN-LSTM model, and in Figure 4, the SARIMA model, demonstrate good agreement with the actual values, capturing the fluctuations and overall trend in the temperature time series. The performance of this models comparable to that of the BP-FFNN model, indicating its effectiveness in capturing the complex relationships within the data.

The best-performing model obtained using the auto_arima function is a SARIMA model with an autoregressive (AR) component of order 2, a differencing (I) component of order 1 to ensure stationary, and a moving average (MA) component of order 2. The model does not include any seasonal AR, differencing, or MA terms as denoted by the absence of seasonal components. The amount of time taken for model estimation and fitting was determined to be about 30.60 seconds.

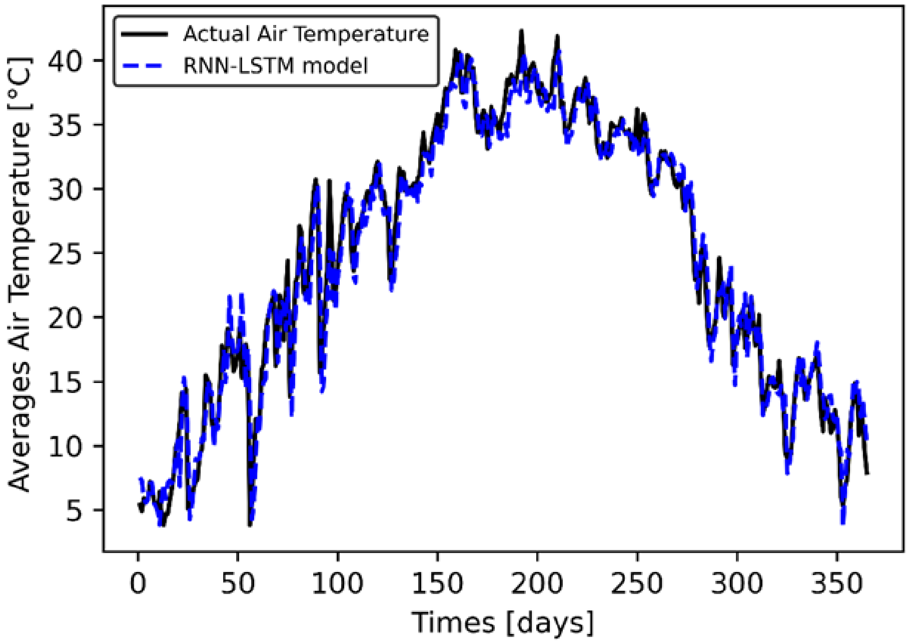

Figure 3. Comparison of RNN-LSTM Temperature Predictions and Actual Values

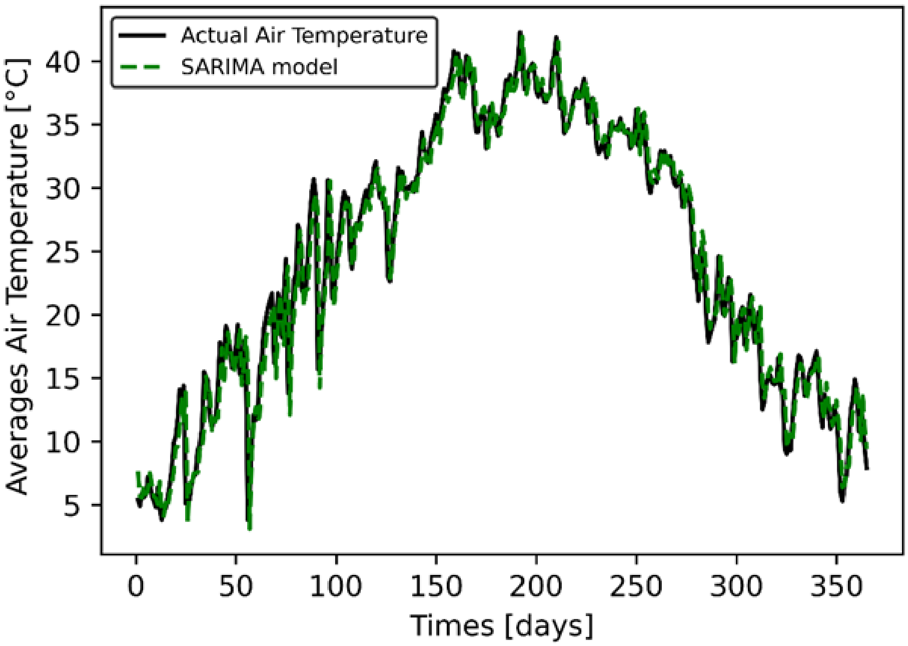

Figure 4. Comparison of SARIMA Temperature Predictions and Actual Values

In contrast, the SARIMA model exhibited higher errors and a lower R^2 value compared to the BP-FFNN model. Although it showed reasonable accuracy, the SARIMA model was outperformed by the more advanced deep learning models.

In summary, The performance of BP-FFNN models is influenced by their network configuration, including the number of hidden neurons and layers (Fahimi Nezhad et al., 2019; Park et al., 2019). The determination of the optimal configuration to avoid under fitting and over fitting often relies on trial and error due to the absence of specific guidelines (Jallal et al., 2019). While increasing the size of hidden layers and neurons can enhance the ability of neural networks to learn complex processes and improve their forecasting capabilities, it has been observed in several studies that adding more layers and neurons does not always lead to increased accuracy (Fahimi Nezhad et al., 2019; Jallal et al., 2019). Therefore, selecting the most suitable methodology for air temperature forecasting remains challenging based on the existing literature. The BP-FFNN model demonstrated superior performance, exhibiting better predictive capabilities compared to the other models. The results of the RNN-LSTM and SARIMA models were found to be relatively similar and closely aligned. Both models yielded comparable forecasting outcomes, suggesting that they possess similar forecasting capabilities for the given dataset. However, it is worth noting that the performance of these models was slightly lower compared to the BP-FFNN model. In this study, the BP-FFNN model proved to be a promising option, demonstrating its potential for accurate and reliable predictions in the context of daily air temperature forecasting.

4. Conclusions

In this study, we conducted a comprehensive analysis of three different models, namely BP-FFNN, RNN-LSTM, and SARIMA, for air temperature prediction. Our results demonstrated that the BP-FFNN model outperformed the other models, exhibiting the lowest Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Median Absolute Percentage Error (MDAPE), and highest Coefficient of Determination (R^2). This highlights the exceptional capability of the BP-FFNN model to capture complex patterns and non-linear relationships in the temperature data.

The RNN-LSTM model also showed promising performance, delivering comparable results to the BP-FFNN model. This finding underscores the effectiveness of RNN-LSTM in capturing long-term dependencies in sequential data. The RNN-LSTM model's ability to retain and update information over extended periods enables it to effectively model the dynamic nature of temperature data. This makes RNN-LSTM a valuable tool for analyzing and forecasting temperature patterns.

Additionally, we explored the application of the SARIMA model using the auto_arima function. The SARIMA model provided valuable insights into the relationship between the current and past values of the temperature series. It offered a deeper understanding of the underlying dynamics and seasonal components present in the data. The SARIMA model's ability to capture temporal patterns can be advantageous for interpreting temperature trends and identifying recurring patterns in the dataset.

While our study demonstrates the effectiveness of deep learning models (BP-FFNN and RNN-LSTM) and the interpretability of the SARIMA model in temperature prediction, it is important to acknowledge certain limitations. One limitation is the reliance on historical data, which assumes that future temperature patterns will follow similar trends. Changes in environmental factors, unforeseen events, or long-term climate variations may introduce uncertainties that could impact the accuracy of predictions. Additionally, the performance of the models may vary depending on the specific geographical location and the availability of high-quality and consistent temperature data.

Despite these limitations, our work provides several key advantages. Firstly, it highlights the potential of deep learning models for accurate temperature prediction, which can benefit various applications in weather forecasting, climate modeling, and environmental analysis. Secondly, our study sheds light on the interpretability of the SARIMA model, facilitating a deeper understanding of temperature dynamics and seasonal variations. Lastly, the comparative analysis of these models contributes to the advancement of temperature prediction methods, guiding researchers and practitioners in selecting appropriate models based on their specific requirements and datasets.

In conclusion, our study demonstrates the superior performance of the BP-FFNN model, the comparable performance of the RNN-LSTM model, and the interpretability of the SARIMA model in temperature prediction. These findings contribute to the growing body of knowledge in the field and have practical implications for various applications. Further research can focus on refining the models, incorporating additional variables, and exploring ensemble approaches to enhance the accuracy and reliability of temperature predictions.

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References

Abdel-Aal, R. E. (2004). Hourly temperature forecasting using abductive networks. *Engineering Applications of Artificial Intelligence, 17*(5), 543-556. **doi: 10.1016/j.engappai.2004.04.002**

Abrahams, D., & Carr, E. (2017). Understanding the connections between climate change and conflict: Contributions from geography and political ecology. *Climate Change Reports, 3*. **doi: 10.1007/s40641-017-0080-z**

Al Dhaheri, K., Woon, W. L., & Aung, Z. (2017). *Wind speed forecasting using statistical and machine learning methods: A case study in the uae*. Paper presented at the Data Analytics for Renewable Energy Integration: Informing the Generation and Distribution of Renewable Energy, DARE 2017. **doi: 10.1007/978-3-319-71643-5_10**

Altan Dombaycı, Ö., & Gölcü, M. (2009). Daily means ambient temperature prediction using artificial neural network method: A case study of turkey. *Renewable Energy, 34*(4), 1158-1161. **doi: 10.1016/j.renene.2008.07.007**

Atasever, S., Öztürk, B., & Bilgiç, G. (2022). A new approach to short-term wind speed prediction: The prophet model. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 44*(4), 8826-8841. **doi: 10.1080/15567036.2022.2126035**

Bauer, P., Thorpe, A., & Brunet, G. (2015). The quiet revolution of numerical weather prediction. *Nature, 525*(7567), 47-55. **doi: 10.1038/nature14956**

Ben-Nakhi, A. E., & Mahmoud, M. A. (2004). Cooling load prediction for buildings using general regression neural networks. *Energy Conversion and Management, 45*, 2127–2141. **doi: 10.1016/j.enconman.2003.10.009**

Bilgili, M., & Sahin, B. (2009). Prediction of long-term monthly temperature and rainfall in turkey. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 32*(1), 60-71. **doi: 10.1080/15567030802467522**

Bishop, C. M. (2005). *Neural networks for pattern recognition*: Oxford University Press.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control* (Fifth Edition ed.): Wiley.

Camia, A., Bovio, G., Aguado, I., & Stach, N. (1999). Meteorological fire danger indices and remote sensing *Remote sensing of large wildfires* (pp. 39–59): Springer, Berlin, Heidelberg. **doi: 10.1007/978-3-642-60164-4_4**

Chollet, F. (2021). *Deep learning with python* (Second Edition ed.): Manning

Cifuentes, J., Marulanda, G., Bello, A., & Reneses, J. (2020). Air temperature forecasting using machine learning techniques: A review. *Energies, 13*(16), 4215. **doi: 10.3390/en13164215**

Fahimi Nezhad, E., Fallah Ghalhari, G., & Bayatani, F. (2019). Forecasting maximum seasonal temperature using artificial neural networks “tehran case study”. *Asia-Pacific J Atmos Sci, 55*, 145-153. **doi: 10.1007/s13143-018-0051-x**

García, M. C. A., & Balenzategui, J. L. (2004). Estimation ofphotovoltaic module yearly temperature and performance based on nominal operation cell temperature calculations. *Renewable Energy, 29*(12), 1997-2010. **doi: 10.1016/j.renene.2004.03.010**

Hochreiter, S., & Schmidhuber, J. u. (1997). Long short-term memory. *Neural Computation 9*(8), 1735-1780.

Hou, J., Wang, Y., Zhou, J., & Tian, Q. (2022). Prediction of hourly air temperature based on cnn–lstm, geomatics. *Natural Hazards and Risk, 13*(1), 1962-1986. **doi: 10.1080/19475705.2022.2102942**

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed. ed.): OTexts.

Jallal, M. A., Chabaa, S., Yassini, A. E., Zeroual, A., & Ibnyaich, S. (2019). *Air temperature forecasting using artificial neural networks with delayed exogenous input*. Paper presented at the 2019 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS), Fez, Morocco, 2019.

Jingxiao, S., Dongyue, Z., Xuda, Z., Yiwen, L., & Yufeng, Z. (2021). *Bridge temperature prediction model based on long-short term memory neural network*. Paper presented at the 2021 International Conference on Artificial Intelligence and Industrial Technology Applications (AIITA 2021), Nanchang, China.

Kirchgässner, G., Wolters, J., & Hassler, U. (2013). *Introduction to modern time series analysis* (Second Edition ed.): Springer Berlin, Heidelberg. **doi: 10.1007/978-3-642-33436-8**

Kisi, O., & Shiri, J. (2014). Prediction of long-term monthly air temperature using geographical inputs. *International Journal of Climatology, 34*(1), 179-186. **doi: 10.1002/joc.3676**

Kuligowski, R. J., & Barros, A. P. (1998). Localized precipitation forecasts from a numerical weather prediction model using artificial neural networks. *Weather and Forecasting, 13*(4), 1194–1204 **doi: 10.1175/1520-0434(1998)013<1194:lpffan>2.0.co;2**

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444. **doi: 10.1038/nature14539**

Li, S., Goel, L., & Wang, P. (2016). An ensemble approach for short-term load forecasting by extreme learning machine. *Applied Energy, 170*, 22-29. **doi: 10.1016/j.apenergy.2016.02.114**

Liu, H., Duan, Z., Wu, H., Li, Y., & Dong, S. (2019). Wind speed forecasting models based on data decomposition, feature selection and group method of data handling network. *Measurement, 148,* 106971. **doi: 10.1016/j.measurement.2019.106971.**

Mihalakakou, G., Santamouris, M., & Tsangrassoulis, A. (2002). On the energy consumption in residential buildings. *Energy and Buildings, 34*(7), 727–736. **doi: 10.1016/s0378-7788(01)00137-2**

Park, I., Kim, H. S., Lee, J., Kim, J. H., Song, C. H., & Kim, H. K. (2019). Temperature prediction using the missing data refinement model based on a long short-term memory neural network. *Atmosphere, 10*(11), 718. **doi: 10.3390/atmos10110718**

Radhika, Y., & Shashi, M. (2009). Atmospheric temperature prediction using support vector machines. *International Journal of Computer Theory and Engineering, 1*(1), 1793-8201. **doi: 10.7763/ijcte.2009.v1.9**

Roy, S. (2020). Forecasting the air temperature at a weather station using deep neural networks. *Procedia Computer Science, 178*, 38-46. **doi: 10.1016/j.procs.2020.11.005**

Ruano, A. E., Crispim, E. M., Conceição, E. Z. E., & Lúcio, M. M. J. R. (2006). Prediction of building's temperature using neural networks models. *Energy and Buildings, 38*(6), 682-694. **doi: 10.1016/j.enbuild.2005.09.007**

Shi, X., Chen, Z., Wang, H., Yeung, D.-Y., Wong, W.-k., & Woo, W.-c. (2015). Convolutional lstm network: A machine learning approach for precipitation nowcasting. *Advances in neural information processing systems*, 802 - 810. **doi: 10.48550/arXiv.1506.04214**

Smadi, M. M., & Mjalli, F. S. (2007). Forecasting air temperatures using time series models and neural-based algorithms. *Journal of Mathematics and Statistics, 3*(2), 44-48. **doi: 10.3844/jmssp.2007.44.48**

Smith, D. M., Cusack, S., Colman, A. W., Folland, C. K., Harris, G. R., & Murphy, J. M. (2007). Improved surface temperature prediction for the coming decade from a global climate model. *SCIENCE, 317*(5839), 796-799. **doi: 10.1126/science.1139540**

Thi Kieu Tran, T., Lee, T., Shin, J. Y., Kim, J. S., & Kamruzzaman, M. (2020). Deep learning-based maximum temperature forecasting assisted with meta-learning for hyperparameter optimization. *Atmosphere, 11*(5), 487. **doi: 10.3390/atmos11050487**

Tran, T. T. K., Bateni, S. M., Ki, S. J., & Vosoughifar, H. (2021). A review of neural networks for air temperature forecasting. *Water, 13*(9), 1294. **doi: 10.3390/w13091294**

TuTiempo.Net. (2010-2021). Global climate data, from https://en.tutiempo.net/climate

Yang, Z., & Wang, J. (2018). A combination forecasting approach applied in multistep wind speed forecasting based on a data processing strategy and an optimized artificial intelligence algorithm. *Applied Energy, 230*, 1108–1125. **doi: 10.1016/j.apenergy.2018.09.037**

Zhang, J., Hu, J., & Liu, J. (2020). Neural network with multiple connection weights. *Pattern Recognition, 107*, 107481. **doi: 10.1016/j.patcog.2020.107481**