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Data-driven deep learning model for predicting ambient temperature: environment and solar energy

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Abstract

This study proposes and evaluates a hybrid gated recurrent unit–long short-term memory (GRU–LSTM) deep learning (DL) model to forecast ambient temperature, a key factor influencing photovoltaic (PV) module temperature and efficiency. Ambient temperature varies due to a range of environmental and weather conditions and is not consistently predictable during daytime. However, it is often assumed to remain constant in PV module design and solar power production calculations. To address unsolved issue, the study exploits the power of DL by introducing a novel hybrid model to forecast ambient temperature based on historical data, focusing on one month of measurements. The proposed model demonstrates predictive solid performance, with a mean absolute error (MAE) ranging from 0.024 to 0.046, root mean squared error (RMSE) in the range of 0.032 to 0.061, and an R-squared (R^2) value between 0.882 and 0.962. Temperature data from the Icelandic Meteorological Office (IMO) and the Danish Meteorological Institute (DMI) is used to test the model across two locations in two countries, highlighting the model's robustness. The superiority of the model lies in its accurate predictions using limited data and reasonable computational resources. Furthermore, the novelty of the proposed model lies in its applicability across different metrological locations. Model training and inference are run on the high-performance computing (HPC) DEEP-DAM system at the Jülich Supercomputing Centre. Accurate ambient temperature forecasting enhances the precision of solar power production predictions and aids in managing power generation in hybrid wind-solar power plants.

1. Introduction

Solar energy capacity and its environmental benefits make it a highly attractive clean energy source [1, 2]. In recent years, wind and solar energy have been the two most focused on and developed renewable energy resources [3–5]. Additionally, many renewable power plants now combine wind and solar energy to enhance green power production [6, 7].

In photovoltaic (PV) modules, the conversion of solar energy into electricity depends on the module's physical properties and environmental factors [1, 8]. Ambient temperature (T_a) is a key variable that directly affects the temperature and efficiency of the PV module [9]. Studies have shown that PV module efficiency decreases as its temperature rises [10]. Therefore, understanding the heat transfer in PV modules, which is closely related to ambient temperature, is crucial for optimizing their performance [8]. Furthermore, the importance of integrating solar energy into the power grid has been emphasized in recent years [11], and deep learning has demonstrated significant capability in modeling nonlinear and unknown pattern events related to solar energy and environmental factors [12].

Ambient temperature is an environmental factor that does not have a known analytical model [13, 14]. Analytical studies of ambient temperature reveal the randomness of this variable [15, 16]. This variable depends on several factors, including irradiance, cloud cover, weather conditions, wind, humidity and rain. Many

different scenarios can be explored. For example, in a summer midday scenario, when the Sun is at its highest point and irradiance is at its maximum, a high ambient temperature is expected. However, cloud cover can significantly alter this expectation. Furthermore, rainy or windy conditions will also affect the ambient temperature. To the best of the authors knowledge, no analytical model currently exists that can accurately predict or measure ambient temperature hours in advance. Thus, in the numerical solution and engineering design of the PV module, it is assumed to be a constant value. However, it is not.

Based on the available ambient temperature measurements, the temperature fluctuates in a randomness and non-linear pattern. Observing the sunrise, sunset, and solar irradiance throughout the day, one can assume that as the Sun rises and reaches a higher position in the sky, the ambient temperature increases. Conversely, as the Sun descends toward sunset, the temperature decreases. As noted earlier, weather conditions have a direct impact on ambient temperature. While the sunrise and sunset may occur similarly on consecutive days, factors such as wind, clouds, rain, and snow during the day can vary and alter the temperature pattern.

Currently, deep learning (DL) demonstrates a remarkable ability to extract hidden features and predict non-linear events [17]. Data-driven DL models rely on data for training [18, 19]. However, in engineering physics applications [20], it is crucial to use variables that have a correlation in order to effectively train the model [21, 22].

This study proposes a novel hybrid data-driven DL model to predict ambient temperature. A gated recurrent unit–long short-term memory (GRU–LSTM) hybrid model is developed and trained using historical ambient temperature data to make predictions. The strength of the proposed model lies in its optimization to work effectively with just one month of data. While DL models typically require large datasets to achieve accurate predictions [23], this study addresses that limitation by utilizing the GRU–LSTM combination. The present study uses the ambient temperature from two countries, which was collected by the Icelandic Metrological Office (IMO) at Reykjavik station [24] and the Danish Meteorological Institute (DMI) at the Copenhagen Airport station [25] and is available as free open data.

The structure of this paper is as follows: section 2 presents the methodology, section 3 discusses the results, and section 4 provides the conclusions.

2. Methodology

This section explores the effects of ambient temperature on the PV module and its impact on efficiency. Furthermore, the proposed data-driven model is explained. The measurement method for ambient temperature data from IMO and DMI is presented, and the setup for training, testing, and validating the deep learning (DL) model is defined.

2.1. Theory

To assess the impact of ambient temperature on PV module efficiency, it is essential to understand its effects on the PV module temperature and review the available PV operating temperature models. One of the most well-known models for PV module temperature is the Nominal Operating Cell Temperature (NOCT) condition. These conditions assume solar radiation of 800 W m^{-2} , an ambient temperature of 20°C , an average wind speed of 1 m s^{-1} , an open circuit, and a module tilt angle of 45 degrees, with perpendicular irradiance gain assumed [1, 9]. Based on these conditions, the NOCT is defined as follows [1]:

$$\text{NOCT} = (T_C - T_a) + 20^\circ \text{C}, \quad (1)$$

where T_C is the PV module temperature, the NOCT method assumes that the ambient temperature (T_a) remains consistent on both sides of the module. The temperature difference ($T_C - T_a$) is specifically influenced by T_a and exhibits a linear relationship with the solar radiation flux [26, 27].

Moreover, in contrast to the NOCT conditions, the Standard Test Conditions (STC) represent controlled, idealized lab environments where the primary goal is to benchmark the maximum possible performance under consistent and replicable conditions [28]. Manufacturers use STC to establish performance characteristics, which include solar irradiance of 1000 W m^{-2} , an ambient temperature of 25°C , and an air mass of 1.5 (AM1.5), representing the spectral content of sunlight [29].

NOCT, on the other hand, is intended to reflect more practical, real-world outdoor conditions. In practice, PV modules will operate at temperatures higher than the ambient air due to sunlight absorption. Under NOCT conditions, with an ambient temperature of 20°C , the module's cell temperature is typically around 45°C – 50°C . This temperature difference between the module and the ambient air directly influences heat transfer through both free and forced convection, as heat naturally flows from higher to lower temperatures. This relationship highlights the significant role of ambient temperature in the efficiency and operation of PV modules.

Furthermore, the equation that determines the PV module temperature T_C and wind velocity V_f is influenced by the ambient temperature T_a and is defined as follows [10]:

$$T_C = T_a + \left(\frac{0.32}{8.91 + 2V_f} \right) G_T; V_f > 1 \text{ m/s}, \quad (2)$$

where G_T is solar irradiance in W/m^2 and V_f is the wind velocity. Recently, a novel model by Hassanian *et al* [13] determined the ambient temperature effects in the PV module heat transfer model, which is directly relevant to the PV module temperature and its efficiency as follows:

$$\begin{aligned} T_C - T_a = & \frac{0.25(1 - \eta_c) G_T}{\left(\frac{0.017}{L} + 3.8V_f \right) + 1.34L^{-1/4}T_a^{1/4}} \\ & + \frac{\left(\frac{0.017}{L} + 3.8V_f \right) T_a}{\left(\frac{0.017}{L} + 3.8V_f \right) + 1.34L^{-1/4}T_a^{1/4}} \\ & - \frac{1.34L^{-1/4}T_a^{5/4}}{\left(\frac{0.017}{L} + 3.8V_f \right) + 1.34L^{-1/4}T_a^{1/4}} \end{aligned} \quad (3)$$

here η_c is the PV module efficiency, L is the PV module length in m and other variables in equation (3) are described in equations (1) and (2).

It is evident that ambient temperature has a direct correlation with PV module temperature in equations (1), (2) and (3). Moreover, PV module temperature plays a crucial role in determining the module's efficiency, and this relationship clearly shows the importance of accurately and simultaneously measuring ambient temperature to calculate PV module efficiency. As mentioned in the introduction, ambient temperature is currently assumed to be constant in design and calculation processes. For a more thorough analysis, it should be considered essential to account for variations in ambient temperature when calculating a solar farm's daily power production, as it directly influences the output. Assuming ambient temperature as a constant can lead to significant errors, which may affect the ability to meet power grid demand. Additionally, the integration of offshore or onshore solar power plants with wind power could also be impacted by errors resulting from assuming a constant ambient temperature.

This study proposes a data-driven DL model to address this deficiency in solar power calculation and production. Developing a prediction model for ambient temperature, even for short-term forecasts, could enhance the ability of solar power systems to more accurately estimate their production in the short term.

2.2. Hybrid data-driven model

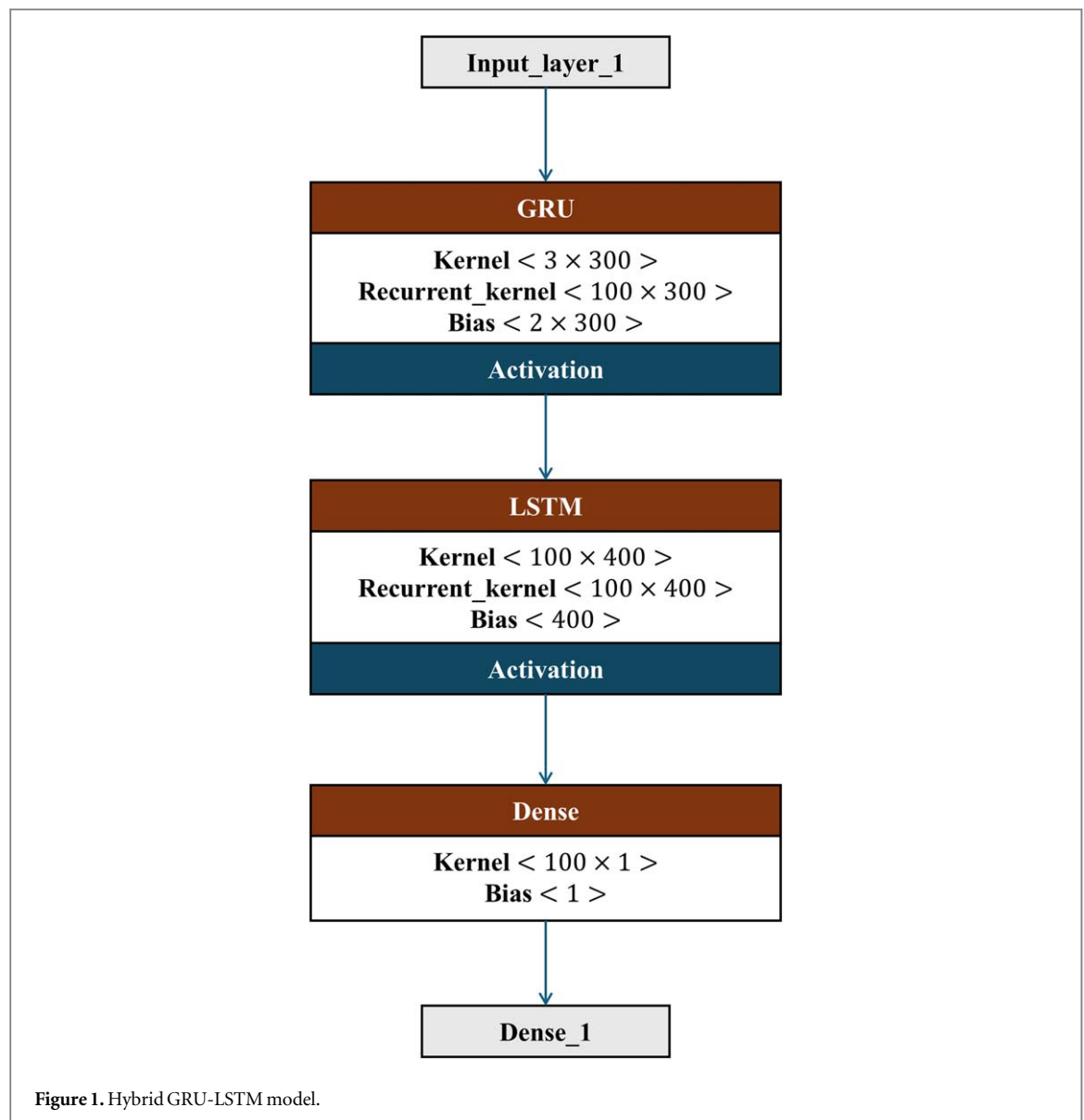
This study proposes a novel model that combines GRU and LSTM, both of which are variants of recurrent neural networks (RNNs). These models are designed to address the issue of long-term data dependencies in RNNs, commonly known as the vanishing gradient problem [30]. While LSTM and GRU share similar architectures, GRU operates with fewer gates and parameters, making it computationally more efficient than LSTM [22, 31].

DL models typically require large datasets to achieve accurate predictions [32]; however, this study introduces a GRU-LSTM hybrid model designed to work effectively with smaller datasets while maintaining accuracy. LSTMs, with their larger number of parameters, are prone to overfitting, especially on small datasets. In contrast, GRUs offer faster training times and a reduced risk of overfitting on smaller datasets [22]. By stacking GRU layers before LSTM layers, the model can be tailored to specific data characteristics. The different gating mechanisms in GRUs and LSTMs complement each other, facilitating better gradient flow during training, which can result in more stable training processes and faster convergence [22].

By leveraging this hybrid form, the model can achieve improved performance, reduce the risk of overfitting, and balance computational efficiency with greater flexibility in modeling sequential data. The GRU-LSTM approach capitalizes on sequential data dependencies by combining the strengths of both models. The second part of the model is trained using the output from the first part, as shown in figure 1, enabling it to capture more information and improve the forecasting of the target variable, which in this case is ambient temperature.

2.3. Temperature data

Utilizing a data-driven DL model requires data for training. In this study, ambient temperature data measured at the Reykjavik station [24] and Copenhagen Airport station [25] is used, both of which are available as open data. Examining the proposed hybrid model in two geographical locations can help generalize its applicability to similar meteorological regions. Reykjavik, Iceland, generally experiences two main seasons—winter and summer. Due to its geographical location, it is often windy and cloudy, with summer temperatures rarely exceeding 20°C [33]. In contrast, Copenhagen, Denmark, has four distinct seasons. Its winters are colder and less windy than those in Reykjavik, while its summers are sunnier, with midday temperatures often exceeding 20°C [34]. Based on historical weather patterns, July tends to have the highest temperatures in both countries,



making it a prime candidate for higher solar power production efficiency. Therefore, this study focuses on the measured temperatures for that month. The Reykjavik station (IMO) is located at a latitude of 64.127 and a longitude of -21.902 , at an elevation of 52 m. Similarly, the Copenhagen Airport station (DMI) is located at a latitude of 55.614 and a longitude of 12.645, with an elevation of 5 m.

The measurement method of the temperature of the air is measured with an electronic thermometer, which is shielded from the Sun's rays. This ensures that the temperature of the air is measured and not the direct solar radiation. It is essential that the thermometer sits in the shade and that there is ventilation around it to measure as representative as possible. The temperature is measured at a height of 1.25–2.0 m. One of the main environmental factors affecting photovoltaic (PV) panels and their efficiency is ambient temperature. Since PV systems are mostly installed in open and flat areas in these regions, the measurement height of 1.25 to 2.0 m provides conditions that closely reflect the real-world environment experienced by PV modules. Additionally, in the troposphere—where weather phenomena occur—it is well known that temperature generally decreases with increasing altitude. Therefore, temperature measurements taken near the Earth's surface (in the range of 1.25 to 2.0 meters) are not only relevant for human perception of weather but also accurately represent the conditions experienced by ground-level installations such as PV systems.

The data consists of three different measured temperatures: average, maximum, and minimum. The average temperature is an average of the temperature measured within the last hour. The maximum temperature is the maximum temperature measured within the last hour. The minimum temperature is the lowest temperature measured within the last hour. The measured data time step is one hour.

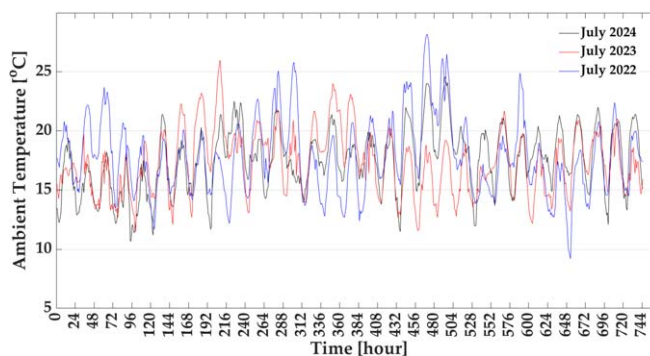


Figure 2. Ambient temperature of July 2022, 2023, and 2024 at copenhagen airport station.

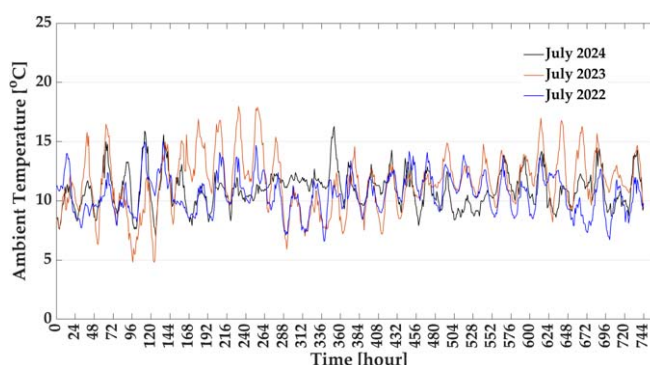


Figure 3. Ambient temperature of July 2022, 2023, and 2024 at Reykjavik station.

Figures 2 and 3 illustrate the average ambient temperature of July 2022, 2023, and 2024 for Copenhagen airport and Reykjavik, respectively.

Figures 2 and 3 show that the temperature follows a randomness pattern; temperature consistently rises during the day and drops at night, and this pattern remains synchronized across three years. While there may not be a straightforward correlation in temperature values, only the general daily cycle is evident. In DL model prediction, the target variable needs to have a value correlation to forecast it. For instance, July 15th has three different ambient temperatures for three years, which shows no correlation for the target variable. It is important to note that, due to global warming, identifying correlations from earlier years presents a challenge. Therefore, this study focuses on utilizing a data-driven model that relies on more recent temperature data.

Figures 4 and 5 display the average, maximum, and minimum ambient temperatures for July 2024 at the Copenhagen Airport and Reykjavik stations, respectively. As shown, there is a clear correlation between the maximum, minimum, and average temperatures.

Since the training data in a DL model must correlate with the input and target variables [21], this study uses the maximum, minimum, and average ambient temperatures to train the model in forecasting the average ambient temperature.

2.4. Model setup

This study employs a hybrid GRU-LSTM model, using three variables for training: maximum temperature, minimum temperature, and average temperature. The target prediction is the average temperature in the unseen future. The data are first fed into the GRU network, with the input shape defined by the batch size, a sequence length of 30, and 3 features per time step. Next, the output of the GRU is passed into the LSTM network, which processes a sequence of 30 time steps, each containing 100 features (as generated by the GRU layer). The LSTM produces a single hidden state for each sequence, represented by a vector of size 100 for each input in the batch.

The output from the LSTM is then passed to the dense (fully connected) layer, which receives a vector of size 100 for each batch element. The dense layer reduces the 100 features from the LSTM to a single value, which is the final prediction for each input in the batch. The model's block diagram is shown in figure 1. The batch size is a hyperparameter that affects both the error rate and training speed. Therefore, batch sizes of 32, 64, 128, 256, and 512 were tested, with the optimal value presented in the results section.

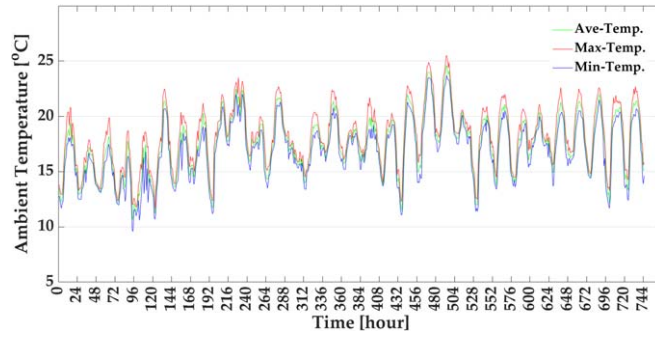


Figure 4. Measured ambient temperature in the type of average, maximum, and minimum of July 2024, Copenhagen Airport station.

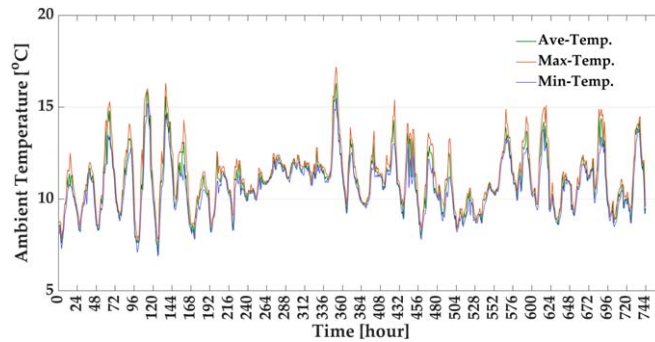


Figure 5. Measured ambient temperature in the type of average, maximum, and minimum of July 2024, Reykjavik station.

The model is implemented in Python using the TensorFlow library [35, 36], with Adam specified as the optimizer [23]. The dataset was normalized using the MinMaxScaler transformation [22, 37], which scales the minimum and maximum values to 0 and 1, respectively. The model was run on the DAM module [38] of a DEEP parallel computing machine, utilizing one GPU on a single node for parallel computing. The DEEP machine features a modular supercomputer architecture [39]. The DAM module is composed of 16 nodes, each equipped with an Intel Xeon 8260M CPU (24 cores @ 2.4 GHz), one NVIDIA V100 GPU [40].

The model was trained and tested using two different data splits: 60% for training and 40% for testing in one scenario, and 80% for training and 20% for testing in the other. Additionally, during the training phase, 20% of the training data was allocated as a train-dev set [22, 23] (a cross-validation technique) to fine-tune the model's parameters. Given the small dataset, determining the appropriate training and testing split is crucial. It is common practice to select 60% to 80% of the data for training [23], ensuring sufficient data for the model to learn from.

Furthermore, to assess the model's performance with a smaller portion, such as the 60% training set, this study incorporates a train-dev set [23], which evaluates the model after each training subtest. The train-dev set refers to training the model on a subset of the data and evaluating it on a separate validation (development) set. This approach ensures the model is not evaluated on the same data it was trained on, providing a more accurate measure of its generalization performance. The development set in cross-validation changes with each fold, helping to assess the model's robustness and reliability across multiple subsets of data.

To evaluate the prediction error of the model, this study applied the mean absolute error (MAE), root mean squared error (RMSE), and the R-squared (R^2) metrics. These three evaluation metrics are defined by the equations below [41]:

$$MAE = \frac{1}{N} \sum_{i=1}^N |s_{i,a} - s_{i,p}|, \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (s_{i,a} - s_{i,p})^2}, \quad (5)$$

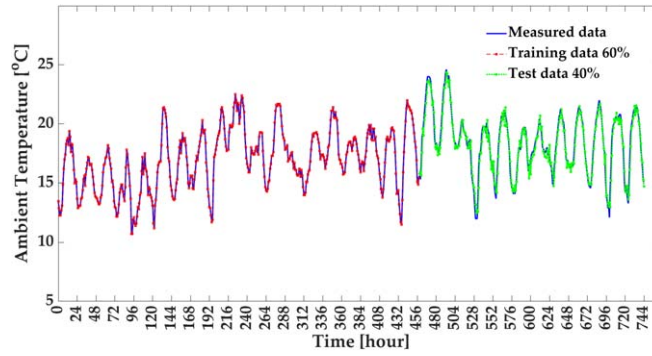


Figure 6. Ambient temperature prediction of the hybrid GRU-LSTM model for Copenhagen airport data, 60% training (red color dashed-square mark line) and 40% test (green color dashed-circle mark line) data. The measured data are in a blue color line curve.

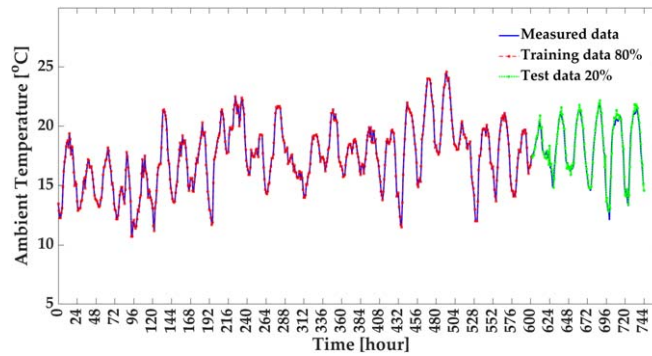


Figure 7. Ambient temperature prediction of the hybrid GRU-LSTM model for Copenhagen airport data, 80% training (red color dashed-square mark line) and 20% test (green color dashed-circle mark line) data. The measured data are in a blue color line curve.

$$R^2 = 1 - \frac{\sum_{i=1}^N (s_{i,a} - s_{i,p})^2}{\sum_{i=1}^N (s_{i,a} - s_m)^2}, \quad (6)$$

where $s_{i,a}$ represents the actual measured data, $s_{i,p}$ is the predicted data, s_m is the mean of the actual data, i refers to the corresponding time (or vector array index), and N is the total number of test data points. MAE treats all errors equally by averaging the absolute differences, making it a more straightforward measure of overall error magnitude. RMSE is more sensitive to large errors because it squares the differences between predicted and actual values before averaging. This means that large outliers or significant deviations have a greater impact on RMSE. R^2 measures how well the model's predictions match the actual observed data.

3. Results and discussions

This section presents the results of the GRU-LSTM model used to predict the average ambient temperature per hour. The model was trained and tested using data from two countries and weather stations to evaluate its performance and its potential for broader, more universal application.

3.1. Ambient temperature prediction

Figures 6 and 7 show the GRU-LSTM model that is forecasting the average ambient temperature per hour, with 60% and 80% training, respectively. The MAE is 0.035 and 0.024 for 60% and 80% training, respectively. The RMSE is 0.045 and 0.032 with training 60% and 80%, respectively. The squared-R was also measured, which is 0.942 for 60% training and 0.962 for 80% training. Increasing the training data from 60% to 80% effectively reduced the MAE and RMSE and increased squared-R.

The model was trained using data from July 2024, with a time step of 1 hour. Therefore, for the 31 days in July, 744 measurements were available. With 60% of the data used for training, the model was able to predict the average ambient temperature per hour for the next 12 days, achieving an MAE of 0.035, RMSE of 0.045, and an

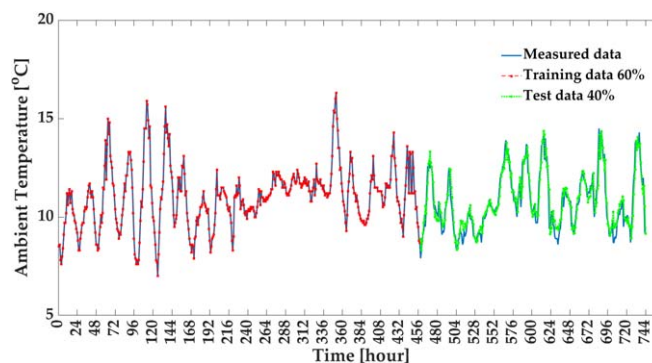


Figure 8. Ambient temperature prediction of the hybrid GRU-LSTM model for Reykjavik station data, 60% training (red color dashed-square mark line) and 40% test (green color dashed-circle mark line) data. The measured data are in a blue color line curve.

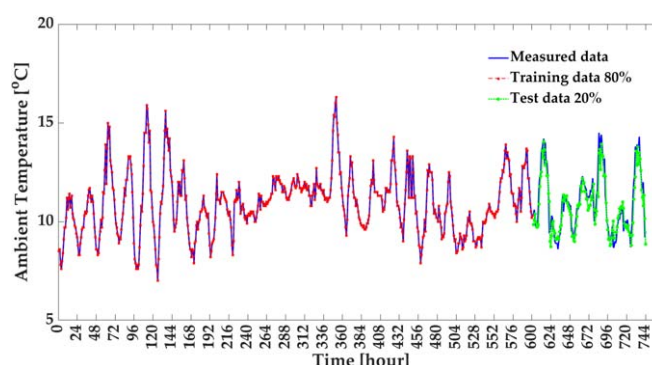


Figure 9. Ambient temperature prediction of the hybrid GRU-LSTM model for Reykjavik station data, 80% training (red color dashed-square mark line) and 20% test (green color dashed-circle mark line) data. The measured data are in a blue color line curve.

R^2 value of 0.942. When the training data was increased to 80%, the model predicted the average temperature per hour for the next six days with an MAE of 0.024, RMSE of 0.032, and an R^2 value of 0.962.

Typically, the design and setup of DL models depend on the data and often require adjustments, making most DL models non-universal and specific to particular datasets. To evaluate the proposed model's universal potential and determine how much modification is necessary, this study further tested the model using the same setup with temperature data from a different location—Reykjavik, Iceland.

Figures 8 and 9 illustrate the performance of the proposed model when trained with Reykjavik's ambient temperature data from July 2024, using 60% and 80% of the data for training, respectively. These figures demonstrate that the model can predict the average ambient temperature per hour for the next 12 days with an MAE of 0.042, RMSE of 0.057, and an R^2 value of 0.881. When the training data is increased to 80%, the model predicts the average temperature per hour for the next six days with an MAE of 0.049, RMSE of 0.064, and an R^2 value of 0.848.

The measured MAE, RMSE, and R-squared values for both models are within acceptable ranges, and the results shown in figures 6–9 indicate that the proposed model can effectively predict ambient temperature using only 60% to 80% of the data for a given month. It is well known that the amount of data in DL is critical, and typically, better predictions are expected with more data. However, the strength of the proposed model in this study lies in its ability to perform well with month-long datasets while delivering substantial metric measurements for two locations with distinct weather conditions.

As mentioned in the introduction, it is important to note that various environmental factors, such as wind, rain, clouds, and irradiation, affect ambient temperature, but these were not included in this model. The strength of the proposed DL model lies in its ability to extract hidden features with a large number of parameters from small data and effectively model the forecasting process.

3.2. Model prediction accuracy and computing power

As explained in the model setup, batch size plays a crucial role in deep DL model training, and it is a smaller subset of the training dataset. The literature mentions that choosing an inappropriate batch size can negatively impact accuracy (by increasing error) while potentially speeding up computation [42]. Batch size is a hyperparameter, along with others such as learning rate, train-test split ratio, and number of epochs. This study

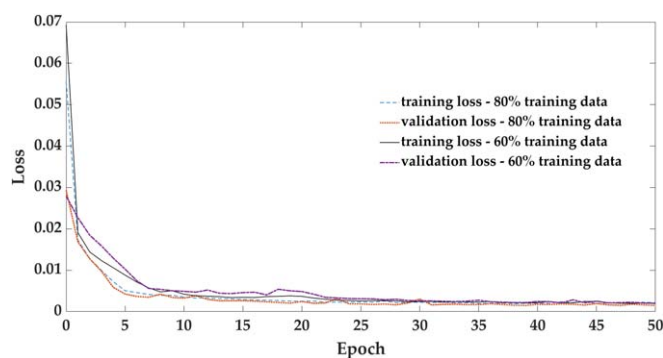


Figure 10. Effect of the train-test split ratio on the training and validation loss of the GRU-LSTM model with batch size = 32.

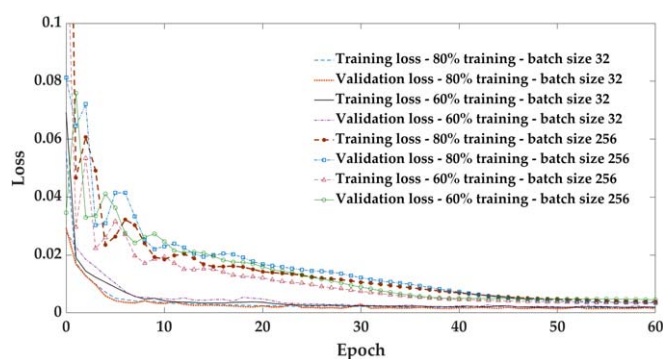


Figure 11. Effect of the batch size and the train-test split ratio on the training and validation loss of the GRU-LSTM model.

focuses specifically on batch size and train-test split ratio to demonstrate their effects on model performance. Furthermore, an epoch refers to one complete pass of the entire training dataset through the model.

Figure 10 shows the training loss and validation loss per epoch for a batch size of 32. It is evident that after epoch 30, the loss rate does not change significantly. Analyzing the train-test split ratio reveals that with a split of 80% for training and 20% for testing, the loss rate exhibits a sharp decline and stabilizes after 20 epochs, in contrast to the 60%–40% train-test split ratio.

Figure 11 illustrates the training loss and validation loss for batch sizes 32 and 256 with different train-test split ratios. It shows that for a batch size of 256, the loss rate stabilizes between epochs 50 and 60, in contrast to the batch size of 32. Additionally, increasing the training ratio from 60% to 80% for a batch size of 256 results in a sharper decrease in the loss rate, which reaches a constant value by epoch 50.

Figures 10 and 11 indicate that smaller batch sizes lead to faster convergence to proper training and validation loss. Additionally, a larger training data ratio improves model performance. Table 1 lists the effects of batch size and train-test split ratio on the MAE, RMSE, R-squared, and computing time. The model was evaluated with 100 epochs in all cases, as shown in table 1 emphasizing the GPU computing power effects on the hybrid GRU-LSTM model.

This study focuses on a small dataset from one month to model ambient temperature forecasting and does not deal with large datasets. GPUs can enhance the model's accuracy when higher precision (double precision) or better model performance is utilized. The current study utilizes the high-performance computing (HPC) DEEP-DAM system at the Jülich Supercomputing Centre, equipped with Nvidia V100 GPUs, and evaluates the model using a single GPU.

Table 1 presents the metrics measured for 80% and 60% training data, with batch sizes ranging from 32 to 512. Since the dataset is limited, the computing speedup for various batch sizes ranges from 0.29% to 2.47%, while model accuracy significantly improved. The MAE increased between 2.3% to 36.8%, and RMSE rose between 3% and 30% across the batch size range. Additionally, the R-squared improved in the range of 0.6% to 4.2%.

Table 1 reveals that a batch size of 32 is the optimal value for the proposed model, yielding the best MAE, RMSE and R^2 values for both training ratios. Additionally, it is observed that increasing the batch size reduces computing time, which is particularly important for large-scale data modeling. However, a larger batch size also results in a decrease in R^2 and an increase in MAE, which is a notable drawback. Based on figures 10, 11 and

Table 1. Comparison of the effects of the batch size and train-test split ratio on the MAE, RMSE, squared-R and computing time for the proposed GRU-LSTM model to forecast the ambient temperature with one month data training.

Training data	Batch size	CPU				1 GPU			
		MAE	RMSE	R^2	Time [s]	MAE	RMSE	R^2	Time [s]
80%	32	0.032	0.042	0.935	41.02	0.024	0.032	0.962	41.14
	64	0.038	0.047	0.922	33.15	0.024	0.033	0.961	29.12
	128	0.033	0.042	0.936	27.14	0.028	0.037	0.951	22.85
	256	0.035	0.047	0.920	19.45	0.035	0.047	0.920	19.93
	512	0.044	0.060	0.872	19.64	0.043	0.057	0.882	20.08
60%	32	0.031	0.040	0.954	32.36	0.035	0.045	0.942	32.52
	64	0.036	0.044	0.943	24.03	0.033	0.042	0.949	24.10
	128	0.036	0.046	0.938	19.06	0.031	0.042	0.949	18.97
	256	0.037	0.049	0.929	18.04	0.039	0.053	0.919	17.31
	512	0.050	0.063	0.883	16.15	0.046	0.061	0.893	16.35

table 1, the optimal tuning for the GRU-LSTM model proposed in this study includes a batch size of 32, a training ratio of 80%, and 20 epochs.

It should be noted that since the RMSE metric is sensitive to large errors and extreme deviations, it can be evaluated using the RMSE-to-MAE ratio, which falls within the range of 1.27–1.35, as shown in table 1. Considering the values of MAE, Squared-R, and the RMSE-to-MAE ratio, the model demonstrates consistent and impressive predictive performance for both average and extreme ambient temperature values.

4. Conclusion

This study proposes a novel hybrid data-driven DL model combining GRU and LSTM to model the ambient temperature. In solar power, the ambient temperature is directly correlated to the PV module temperature and its efficiency and, therefore, affects the solar power plant efficiency. Ambient temperature is an environmental parameter that has no known analytical or model forecasting, and it is affected by weather conditions such as wind, rain, snow, clouds, irradiance, and humidity. In the PV module design and studies, the ambient temperature is assumed to be constant for at least a few hours or categorized as morning, noon, and afternoon. Assuming it as a constant value causes a considerable error in the calculations, and this is known.

The importance of ambient temperature is obvious as the required model to forecast this variable. The current study applies DL capability to predict the ambient temperature. To train the DL model, measured temperature data from weather stations in Iceland and Denmark are used. Additionally, to assess the universal potential application of the proposed model, two weather stations, Reykjavik in Iceland and Copenhagen Airport in Denmark, examined the model. The key findings are:

- The hybrid GRU-LSTM forecasting model demonstrates a strong capability to extract meaningful information from a short dataset, enabling accurate predictions of unseen periods based on historical ambient temperature data. This achievement could enhance the understanding of ambient temperature effects in environmental studies and the performance of photovoltaic modules.
- The proposed GRU-LSTM model performs effectively with data from two distinct geographical locations, and its testing and application can be extended to other regions with similar weather conditions.
- The study proposes a sequential setup that relies solely on data correlated with temperature.
- Hyperparameter optimization effectively enhances the performance of the hybrid model, which also demonstrates good scalability with GPU utilization.

The GRU-LSTM model trained in two set-ups, one time 60% training and the other one is 80% training. The results show the GRU-LSTM has considerable ability to forecast the ambient temperature with MAE, RMSE, and squared-R in the range of 0.024–0.046, 0.032–0.061, and 0.882–0.962, respectively. The model's superiority is that it works with only one month of data and is able to predict ambient temperature per hour between 6 to 12 days, depending on the accuracy. Additionally, using the same model tuning for two different locations of two countries with different weather conditions led to appropriate metrics and results and showed the highlight of the proposed model.

The study investigates the data's batch size and the train-test split ratio to ensure the optimum value for the hyperparameters. The training model was implemented on the DAM module of the DEEP supercomputer machine at the Jülich Supercomputing Centre. The hyperparameter examination dictates that increasing the batch size will reduce the squared and increase the MAE. Furthermore, increasing the training ratio assists the model with respect to MAE and squared-R. Based on the obtained measurements, batch size = 32 and training ratio 80% has an optimum model design. For the proposed model, the RMSE-to-MAE ratio was measured, falling within the range of 1.27 to 1.35. This indicates consistent and strong predictive performance of the model for both average and extreme ambient temperature values.

The results show that GPUs can improve model accuracy by leveraging higher precision (double precision) or optimizing model performance. Outlines the metrics obtained from using 80% and 60% of the data for training, with batch sizes varying from 32 to 512. Due to the small size of the dataset, the computational speedup across different batch sizes was modest, ranging from 0.29% to 2.47%. However, the model's accuracy showed marked improvement. The MAE increased between 2.3% to 36.8%, and the RMSE rose between 3% and 30%. Furthermore, R-squared values improved in the range of 0.6% to 4.2%.

A forecasting model for ambient temperature could assist effectively in the PV module design and its efficiency. For instance, for combined wind-solar power plants, improving the efficiency leads to optimum power supply and power grid management. Furthermore, since weather parameters such as wind, irradiance, and humidity affect the ambient temperature, the authors plan to study the correlation and use this variable to improve the ambient temperature weather forecasting DL model.

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Conflict of interest

The authors declare no conflict of interest.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Author contributions

Reza Hassanian contributed with the conceptualization, method, software, data analysis, and writing—original draft preparation. **Nashmin Yeganeh** contributed with data, and model analysis. **Ásdís Helgadóttir** contributed with review and editing. **Runar Unnthorsson** contributed with review and editing. **Morris Riedel** contributed to writing, review editing, and supervision.

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