SOLAR IRRADIANCE FORECASTING USING DEEP LEARNING TECHNIQUES

COMPLEX ENGINEERING PROBLEM
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1. Abstract

Solar irradiance, the power of sunlight received on a given surface area during a specific time, is crucial in determining the efficiency and performance of solar power systems, as it directly influences the electricity units generated by photovoltaic (PV) cells. In recent years, deep learning and machine learning techniques have been leveraged to enhance the accuracy of solar adsorption and wind power forecasting. In this context, this study presents a comparative study of various deep learning models for very short-term solar irradiance forecasting, aiming to find the most effective model for this specific purpose for our local city Karachi. The key findings indicate that the LSTM model outperforms the other architectures, achieving the highest R-squared value and the lowest Root Mean Square Error (RMSE). These results emphasize the importance of accurate forecasting models in optimizing renewable energy generation and grid management and their potential applications in various sectors.

2. Introduction

The increasing awareness of the need to find alternative means of electric power generation without depleting Earth's natural resources has led to the rise of alternative energy [1]. Alternative energy encompasses various fuel sources that do not rely on fossil fuels, some of which may not necessarily be renewable. Renewable energy sources, a subset of alternative energy, exhibit a relatively lower carbon footprint [2]. One such renewable energy source is solar power, which harnesses sunlight to generate electricity, serving as a clean and sustainable alternative to finite fossil fuels [3].

Photovoltaic (PV) cells play a key role in generating solar power by converting sunlight into electricity. Solar irradiance, the power of sunlight received on a given surface area during a specific time, is crucial in determining the efficiency and performance of solar power systems [2][3]. Accurate forecasting of solar irradiance holds great significance in various applications, it aids in optimizing the use of solar energy and managing its integration into power grids [4]. In recent years, deep learning and machine learning techniques have been leveraged to enhance the accuracy of solar irradiance forecasting [5-8]. Advanced models such as deep recurrent neural networks (DRNNs) and multilayer perceptron regression (MLP) have resulted in significant advancements in forecasting accuracy [9][10].

In this context, our research presents a comparative study of various deep learning models—Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Long-short term memory (LSTM), and Temporal Convolution Network (TCN)—for solar irradiance forecasting, aiming to identify the most effective model for this specific purpose. Notably, our work involves conducting a comparative analysis of these models on the Karachi dataset. Enhanced relevance and applicability are held by our findings when a locally specific dataset from the city of Karachi is focused on.

3. Methodology

The methodology section briefly explains the various deep learning models used, the experimental setup, and details about the dataset, model architectures, and parameters. It also describes the experiment setup and training process for each model

3.1. Recurrent Neural Network (RNN)

A recurrent neural network (RNN) is a powerful neural network architecture that incorporates the memory of past data points through recurrence. RNNs are particularly effective for time series forecasting [5]. In summary, an RNN uses its hidden layer to capture and remember information from previous data points, making it effective for tasks involving sequences. Figure 1 shows the basic working of RNN.

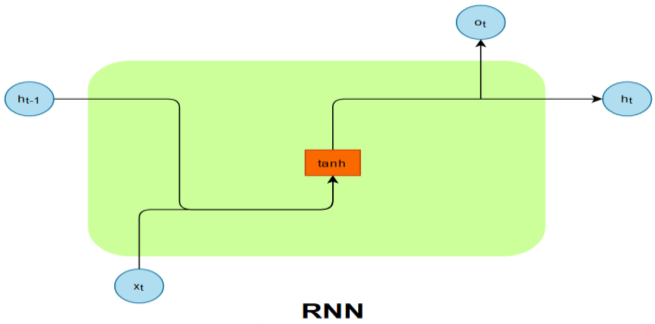

Figure 1*. Recurrent Neural Network (RNN) internal cell structure*

3.2. Gated Recurrent Unit (GRU)

One challenge with recurrent neural networks (RNNs) is that the recurrence of data points can introduce errors in the computation of weights and biases. The (GRU) is a specialized type of RNN designed for sequential data [6]. It tries to solve the issue of exploding and vanishing gradients by incorporating two gate mechanisms: first is the update gate (z_t) and the second is the reset gate (r_t). Using these gates, it remembers relevant information needed and discards the rest.

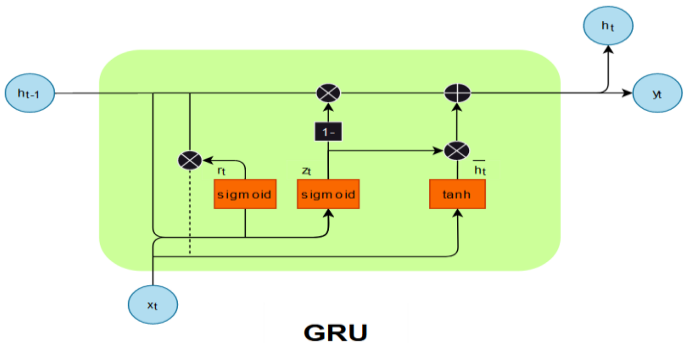

Figure 2*. Gated Recurrent Unit (GRU) internal cell structure*

3.3. Long-Short-Term Memory Networks (LSTMs)

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) architecture that has gained popularity for to their ability to learn long-term dependencies in sequential data, making them particularly well-suited for complex time series forecasting and natural language processing tasks [8] (pp. 5929-5955). The LSTM architecture is a more complex form of RNNs as compared to GRUs and that's why they tend to remember more complex information. They consist of forget gate f_t, candidate layer $\bar{C}_t$, input gate i_t, output gate o_t, hidden state (represented by letter h) and memory state (represented by letter c).

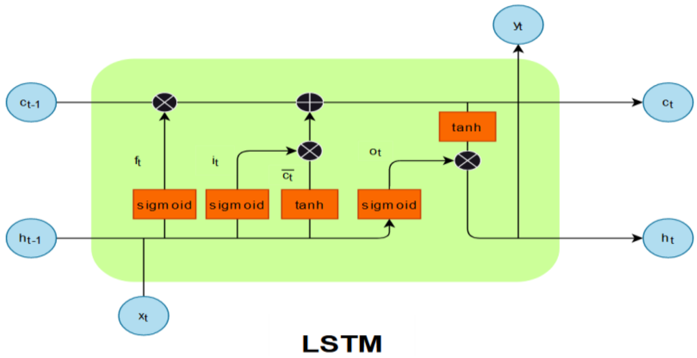

Figure 3. *Long Short-Term Memory (LSTM) internal cell structure*

3.4. Temporal Convolution Network (TCN)

A Temporal Convolutional Network (TCN) is an advanced type of neural architecture that has evolved from a 1-D Convolutional Neural Network (CNN) [11].

This method uses stacked convolutions with causal padding, dilation and residual or skip connections to get a much larger receptive field. This TCN architecture has been shown to outperform traditional RNNs and vanilla CNNs in numerous tasks such as segmentation of some actions and network anomaly detection. TCN has demonstrated superiority over LSTM in several domains such as traffic prediction, audio processing, machine translation, and human motion detection [5, 9-11].

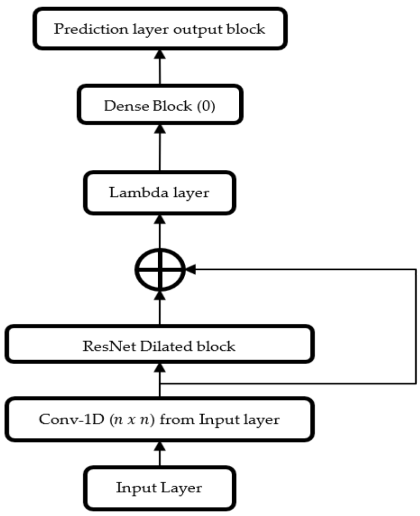

Figure 4. *Overall complete TCN model architecture*

3.5. Dataset

The Karachi dataset of 2019, acquired from the NSRDB, provides solar irradiance readings at a time resolution of 15 minutes. The dataset covers a period of one year, consisting of 35,040 samples. The dataset we used was split into training and testing sets for experimental purposes. And last ten days of data were used exclusively for testing, while the remaining dataset served as the training data. Notably, no portion of the dataset was allocated for validation. The data used to support the findings of this study are available at: *https://nsrdb.nrel.gov/data-viewer*

3.6. Model Architectures and Parameters

The Simple RNN model features a single hidden layer with 64 neurons, a default $tanh$ activation function, a $sigmoid$ activation for the dense layer, and the $AdamW$ optimizer. The GRU model, also utilizing a default $tanh\ activation$ function with a dense layer featuring $sigmoid$ activation and the $AdamW$ optimizer, comprises two hidden layers with a distribution of 2:32 + 32 neurons. Similarly, the LSTM model employs a $sigmoid$ activation function with a dense layer, an $AdamW$ optimizer, and two hidden layers with a distribution of 2:64 + 64 neurons. The TCN model, incorporates a $ReLU$ activation function, with $sigmoid$ activation for the dense layer, the $AdamW$ optimizer, a stack of 2 layers with a kernel size of 15 and 15 no. of filters, causal padding, batch normalization, no skip connection in our selected architecture, and dilation layers with dilation factors of 1, 2, 4, and 8. The Simple RNN, GRU Model, LSTM Model, and TCN models have 4737, 10401, 51777, and 53776 total parameters, respectively, making TCN the largest model among all.

3.7. Experiment Setup:

The experiment was conducted using a window length of 3 days, and all models were trained using a fixed learning rate of 0.001, except for the TCN, which had a learning rate of 0.01 and a weight decay factor equal to 0.001. The loss metric applied consistently across all models was the Mean Absolute Error (MAE), while the metric we used for evaluation was the Root Mean Squared Error (RMSE). The training process involved iteratively optimizing model parameters over a predetermined number of epochs. All models were trained for 500 epochs.

4. Results and Discussion

Figure 5 shows the models' prediction plots, illustrating their performance and differences in the context of very short-term solar irradiance forecasting. These plots demonstrate the superiority of forecasting the LSTM model compared to the other neural network models.

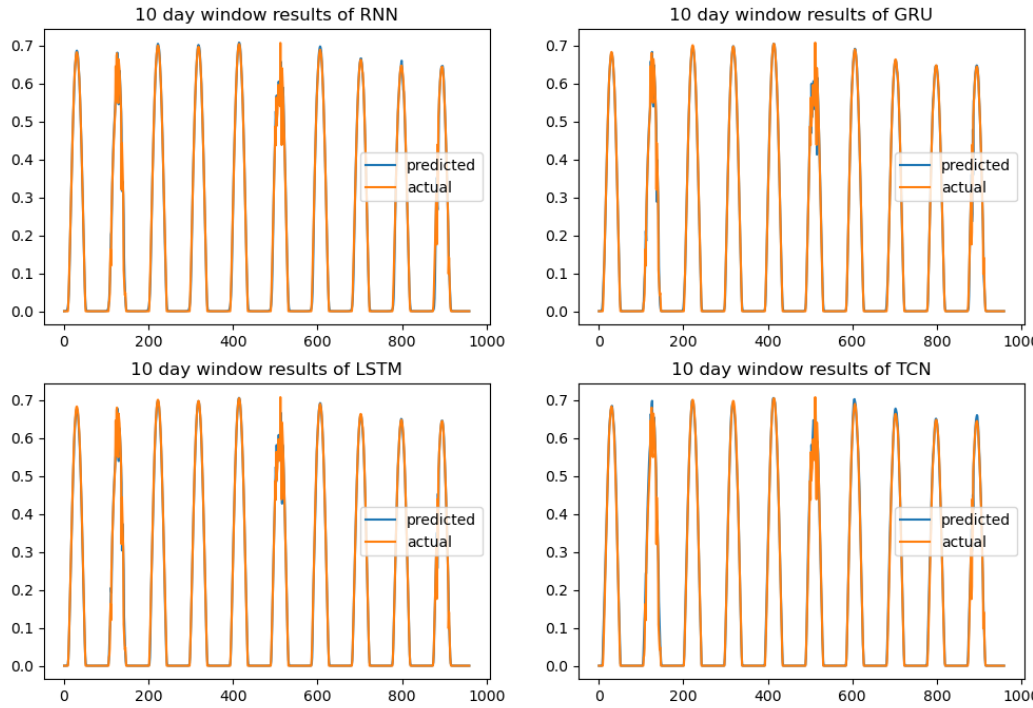

Figure 5. *RNN, GRU, LSTM, and TCN model's prediction plot with ground truth*

The training and inference time taken by each model is shown in Figure 6 respectively which shows that RNNs took the least amount of time to train but also took the most time for inference and for TCN the opposite happens it took the most amount of time to train but during inference they it was the fastest among them all:

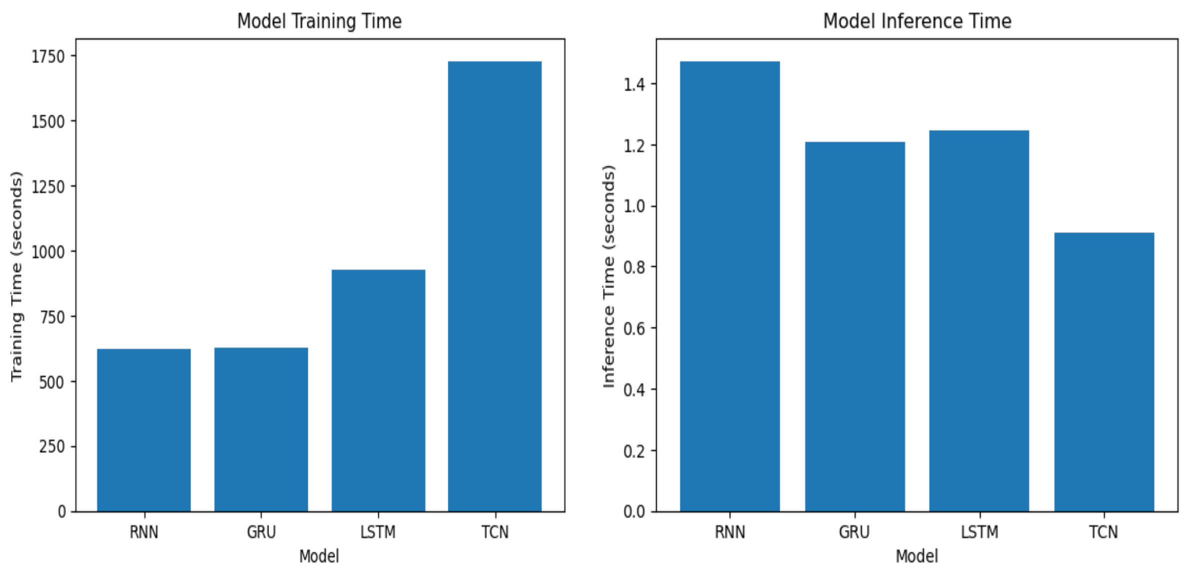

Figure 6. *Bar plots showing the training time taken by models to train for 500 epochs (left) and Inference time taken by models for forecasting the last 10 days (right)*

The model's accuracy was assessed after training the models on the entire year's data, excluding the last 10 days designated as the test set. The LSTM model achieved the highest R-squared value equal to 0.993406, indicating it outperformed the others. The GRU model ranked second with an R-squared value equal to 0.992509, followed by the

TCN model with an R-squared value equal to 0.992405 and the simple RNN model with an R-squared value equal to 0.991935. All model's RMSE values are as follows:

$$LSTM: 0.020051 \qquad GRU: 0.021371 \qquad TCN: 0.021519 \qquad RNN: 0.022175$$

5. Conclusion

This study presents a comparative analysis of various neural network models for very short-term solar irradiance and wind power forecasting using the Karachi dataset.
The key findings indicate that the LSTM model outperforms the other models, achieving the highest and lowest R-squared and RMSE values, respectively. These results emphasize the importance of accurate forecasting models in optimizing renewable energy generation and grid management and their potential applications in various sectors.

5.1. Future Work

Future work could explore feature extraction techniques like time series decomposition to further enhance forecasting model performance. Additionally, the exploration of Liquid Neural Networks, which aim to achieve powerful predictions with fewer neurons and connections inspired by C. Elegans, shows promise. These approaches have the potential to offer more efficient and effective forecasting models. Examining these techniques and alternative architectures can expand and enhance the proposed forecasting models' applicability and generalizability.

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