Solar Irradiance forecasting using Recurrent Neural Networks

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***Abstract*—Solar irradiance being the chief constituent of the solar power extraction is dominated by the atmospheric conditions. Prediction of irradiance data is highly sought after in the field of forecasting and predictive maintenance. For this purpose various machine learning methods are being used to improve the accuracy of the forecasted value. This paper aims at prediction of solar irradiance using Recurrent Neural Networks (RNN) using Long Short Term Memory (LSTM) architecture. Using different combinations of input in the supervised learning method the accuracy for single as well as multiple time steps are determined. The results are shown in the form of evaluation metric as well as the forecasted values and actual value comparison. It is seen that for single time step prediction the LSTM RNN puts out highly accurate values but error for higher time steps prediction accumulates in a compounded manner. It is also observed that using time based models along with the inputs increases the accuracy of the forecasted values.**

***Index Terms*—Irradiance forecasting, RNN, LSTM, DNI, min-max**

I. Introduction

Solar Irradiance is the power per unit area received from the sun in the form of electromagnetic radiation and measured in the measuring instrument's wavelength range. Forecasting solar irradiance is now an emerging topic in the renewable energy section as this improves the planning and strategic operation of photovoltaic systems across the globe. This yields many economic advantages for electric utilities along with environmental protection and energy security. It further helps increase the amount of renewable energy contribution to the generated power.

The amount of solar radiation received per unit area by a surface that is always held perpendicular (or normal) to the rays that come in a straight line from the direction of the sun at its current position in the sky is referred to as Direct Normal Irradiance (DNI). Keeping a surface normal to incoming radiation allows you to optimize the quantity of irradiance it receives annually. This amount is particularly interesting for concentrating solar thermal systems and systems that track the sun's position. The total radiation received on a horizontal surface on the earth is known as Global Horizontal Irradiance (GHI). GHI factors in both Direct Normal Irradiance and Diffuse Horizontal Irradiance (DHI), while also accounting for the angle of the sun. Irradiance received at a tilted surface on the earth Global Tilted Irradiance (GTI), receives a part of ground reflected radiation and is used as an approximate for the energy yield.

M. S. Hossain et al [1] have compared different Neural Network's performance in forecasting PV power generation. A LSTM based neural network results is compared with that of Generalized Regression Neural Networks (GRNN), Extreme Learning Machine (ELM) based Neural Network, simple Recurrent Neural Network and their performance is evaluated. Using synthetic weather forecast the RMSE metrics is determined to be 0.94, 1.28 and 1.68 MW for 6, 12 and 24 hour forecast respectively.

G. Capizzi et al [2] explains a 2-day ahead forecast model using Wavelet Recurrent Neural Network (WRNN). Time based models of temperature, wind speed and humidity are used as inputs to the network. Wavelet pre-processing of the data is carried out on the dataset and perform inverse transformation to give the predicted output. From the data available in the site of University of Catania, Italy, the performance of the WRNN is evaluated in terms of RMSE which is determined to be less than 1% for 9000 epochs.

A. Aliberti et al [3] attempts to predict Global Horizontal Irradiance (GHI) in terms of deterministic and stochastic factors using four methodologies. Formatting the data on the basis of Tikhonov regularisation, raw GHI data and clear sky index, the performance of the four methodologies i.e. Nonlinear Autoregressive Neural Network (NAR), LSTM Neural network, Feed Forward Neural Network (FFN) and Echo State Network (ESN) are compared. Root Mean Square Deviation and R^2 score is obtained as 3.28, 6.21, 4.99 and 2.76 for NAR, FFN, LSTM and ESN respectively for a 15-minute interval prediction.

C. H. Liu et al in [4] compares a simplified LSTM network with that of a Multi-Layer Perceptron (MLP) in terms of prediction efficiency. Correlation between multiple variables and PV power is determined from the dataset and is used as inputs to the LSTM as well as MLP network. RMSE value of 0.828 is obtained by the LSTM network for a particular dataset compared to that of 1.653 for MLP considering 5 minute sample forecast for a day with 30 days data sample.

There are many methods to forecast time series data using past values. Traditional methods include autoregressive integrated moving average (ARIMA), seasonal ARIMA, Vector Auto Regression (VAR). Modern methods utilize Artificial Neural Networks (ANNs) [5], [6] and [8]-[11], Recurrent Neural Networks (RNNs) [12]-[21], and its variants such as GRU and LSTM. There are time series models such as Prophet and NeuralProphet, which can also be used for this task.

Considering the previous works usage of simple LSTM networks are dominant, but the accuracy of the prediction is point of concern based on the time interval of prediction. Improvements on the forecast accuracy is a main criteria and is been given importance in this paper. Sections mentioned below explain the work carried out on the reductions in the prediction errors and the network architecture used for the same.

II. Recurrent Neural Network And LSTM In Forecasting

A. *Recurrent Neural Networks (RNN)*

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Recurrent neural network is a form of artificial neural network that works with time series or sequential data. 'Memory' is the feature, which allows them to impact current input and output by using knowledge from previous inputs. While typical deep neural network presume that inputs and outputs are independent of one another, recurrent neural networks' output is reliant on the sequence's prior elements. While future occurrences may be useful in determining a sequence's output, unidirectional recurrent neural networks cannot account for them in their predictions.

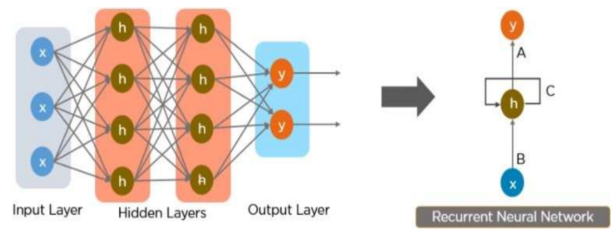

Fig. 1. Analogy between ANN and RNN

Recurrent networks are distinguished by the fact that their parameters are shared across all layers of the network. The similarity between ANN and RNN is shown in Fig. 1 where the neuron is updated using the current input and output and iterated. While each node in a feed forward network has a variable weight, each layer of a recurrent neural network has the same weight parameter. Features of Recurrent Neural Networks include but not limited;

i) To assist reinforcement learning, the weights are modified using back propagation and gradient descent.

ii) To estimate the gradients, recurrent neural networks use the back propagation through time (BPTT) technique, which is significantly different from regular back propagation because it is specialized to sequence data.

iii) Short-term memory is a problem for recurrent neural networks.

The vanishing gradient problem affects recurrent neural networks during back propagation. Gradients are values that are used to update the weights of a neural network. When a gradient reduces as it back propagates through time, this is known as the vanishing gradient problem. When a gradient value falls below a certain threshold, it no longer contributes much to learning.

B. *LSTM*

The acronym LSTM stands for Long Short-Term Memory networks. It's a collection of RNNs that are capable of learning long-term situations, especially when aggregating forecast uncertainties.

The LSTM model is made up of three major components, forget gate which removes information that is not really required for the task to be completed at a particular time and is arranged as shown in Fig. 2. This evolution is essential for streamlining the network's layout. Output gate which selects and delivers critical data and Input gate which is responsible for adding information to the cells.

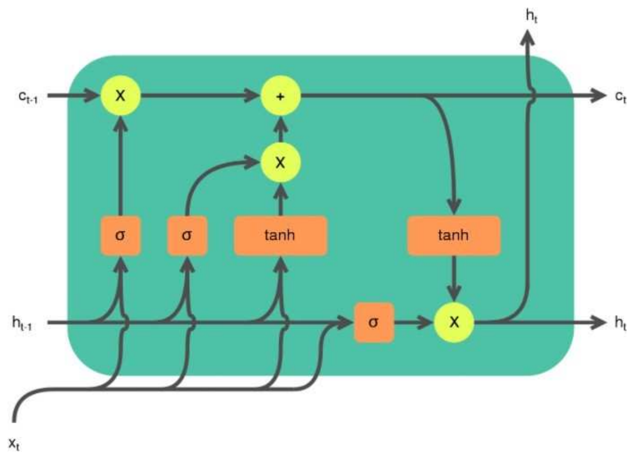

Fig. 2. LSTM architecture showing the input gate, reset gate and forget gate

A LSTM model is centered on a memory cell called a *cell state* which maintains its state throughout time. It's often pictured as a transmission line through which data flows unchanged. Long short-term memory can be used for a variety of deep learning tasks that, for the most part, involve forecasting based on historical data.

III. Application of RNN for irradiance forecasting

A. Proposed Methodologies

Four different approaches are implemented for training the LSTM model for irradiance forecasting and testing it on the dataset. These four methodologies essentially are different combinations of input data fed to the LSTM model. In some cases where the input features themselves are time-variant, a parallel architecture of two LSTM models were considered where in the output of one of the models was used for predicting and updating the other one. Forecasting of individual variables is done whose results help in updating and tuning the network for forecasting the required variable. Given below are the different methodologies implemented and tested:

1) *Irradiation data as input and output*

In this approach a simple LSTM model was created which would take the irradiation data itself as the input and forecast the irradiation data as output. The model is essentially trained by feeding in the input data to the LSTM model and enabling the model to predict the output data which is one time step ahead.

$$Input = Irr(t-1)$$
$$Output = Irr(t) \tag{1}$$

2) *Forecasting using irradiance and temperature as input*

To determine if temperature variable has an impact on the irradiance forecasting a dual LSTM architecture is considered where one standalone LSTM model is used to forecast temperature alone for the future time steps. The forecasted value is used by a parallel dual input LSTM which takes two input features namely the irradiation data and the forecasted temperature outputs. The performance of the stand-alone temperature forecasting model and the dual model obtained on training and testing datasets can be observed in Table 1.

$$Input = [Irr(t-1), Temp(t-1)]$$
$$Output = Irr(t) \tag{2}$$

3) *Using irradiation data and time*

In this case a single LSTM model with two input features consisting of the Irradiation Data and linearly modeled time vector is developed. The input essentially lags the output by one-time step and consists of the time converted to a real number using and the corresponding irradiation data at that instant.

$$time = HH{:}MM$$
$$time = HH + MM/60 \tag{3}$$

Time seems to exert a significant boost in the model performance. The reason for that would be how irradiation data is a periodic function in time over a particular season as seen in Fig. 3.

$$Input = [Irr(t-1), time]$$
$$Output = Irr(t) \tag{4}$$

4) *Forecasting using irradiance, temperature and time*

Finally a dual LSTM architecture is implemented where a standalone LSTM model is used for temperature forecasting. This stand-alone model uses time and temperature as input and gives the forecasted temperature

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values which is simultaneously fed to a parallel connected LSTM model. Three inputs namely Irradiation data, forecasted temperature data and time in real number are used for the overall prediction model. Using all the three features as a whole, essentially seems to give a better result as all the elements that determine solar irradiation are factored in for forecasting.

$$Input = [Irr(t-1), Temp(t-1), time]$$

$$Output = Irr(t) \quad (5)$$

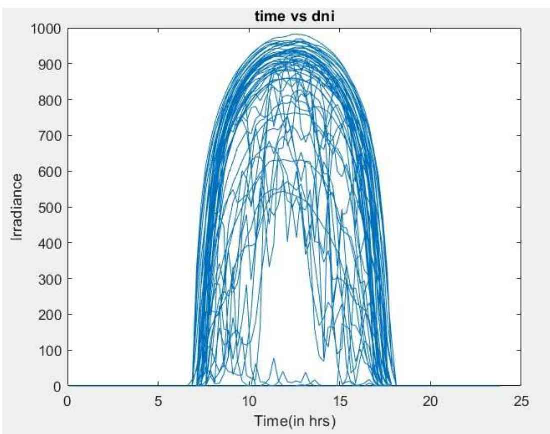

Fig. 3. Plot showing the relation between DNI and Time

B. Dataset

Dataset considered consists of irradiance data of two months data samples in a 15-minute interval of 5568 samples. Along with irradiance data, temperature data was also a part of the dataset. Data normalization is carried out using min-max normalization. To smoothen sharp changes in data, a moving average filter is used with a window size of 10.

Division of the dataset is in the given order,

1. Training set : 80% of dataset = 4454 samples
2. Validation set : 10% of dataset = 557 samples
3. Testing set : 10% of dataset = 557 samples

Training was carried out for various methods proposed ahead by optimizing the network for best output.

C. Evaluation Indices

Metrics are parameters and measurements gathered during evaluating model performance. The following metrics have been used to evaluate all the different methodologies used in the paper.

i. ROOT MEAN SQUARE ERROR (RMSE)

RMSE is the standard deviation of the residuals or prediction errors. Residuals are a measure of the error

$$e_t = |y_{foreacsted} - y_{true\ value}| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} {e_t}^2} \quad (7)$$

ii. MEAN ABSOLUTE ERROR (MAE)

MAE is a statistic that assesses the average magnitude of errors in a group of forecasts without taking into account their direction. It assesses the precision of continuous variables.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \quad (8)$$

iii. MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

A forecast system's accuracy is also measured by the mean absolute percentage error (MAPE). It is determined as the ratio of difference between average absolute percent error for each time period and actual values to the real values expressed as a percentage.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \times 100\% \quad (9)$$

D. Testing Methodologies

After training the model, it is first made to update its state on the training and the validation set. Once the model state is updated the last element in the validation set is used as the input to get the first prediction of the test set. Further the predicted value is once again used as an input for the LSTM to make further predictions. The testing methods are further categorized into three methods:

i. One time-step Forecasting

In this case the assumption is such that a prediction is needed for one time step in future. Hence while testing, the model updates are made with the real time available test values and the corresponding one-time step ahead predictions are recorded.

ii. One day forecasting

For this approach, it is considered that the model is supposed to make predictions for exactly one day in future while it is updated with the real time test values one day before, i.e. the model is supposed to predict for 95 time steps from the present state.

iii. Multi-time step forecasting

Here the model is expected to predict continuously based on the need. The model is updated at every time step by the model's own predicted values from the

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previous time step. In our study this multi-time step forecasting is done for 557 samples [approximately six days].

IV. Simulation Results

The network is trained for the amount of data samples as mentioned in the section above. For the given LSTM model hidden units of 90 is been used. The initial learning rate is set as 0.01 and run for 200 epochs. The dataset combinations are classified into categories with different models being used. MATLAB version 2020b is used to run all the simulations. The Test Numbers mentioned in the table signify the following methods:

1) Irradiation data as Input and Output
2) Forecasting using Irradiance and temperature as inputs
3) Using Irradiation Data and time
4) Forecasting using Irradiance, temperature and time

Test Number	Error		
	RMSE	MAE	MAPE
1	0.016	0.01	0.754
2	0.015	0.01	0.64
3	0.016	0.009	0.1139
4	0.014	0.0095	0.1286

Table 1. Prediction for 15-minute ahead interval

Test Number	Error		
	RMSE	MAE	MAPE
1	0.85	0.62	40.64
2	0.5	0.38	28.96
3	0.3	0.2124	24.02
4	0.11	0.074	5.46

Table 2. Prediction for one day ahead samples

Test Number	Error		
	RMSE	MAE	MAPE
1	0.86	0.69	50
2	0.69	0.57	31.42
3	0.48	0.35	42.98
4	0.23	0.1304	3.82

Table 3. Prediction for variable time interval forecast

Table 1-3 details the evaluation metrics for the predictor results for the combination of the input datasets in different time-scales. The results of the predictor for the best dataset combination model and the least accurate models are depicted in Fig 4. and Fig.5.

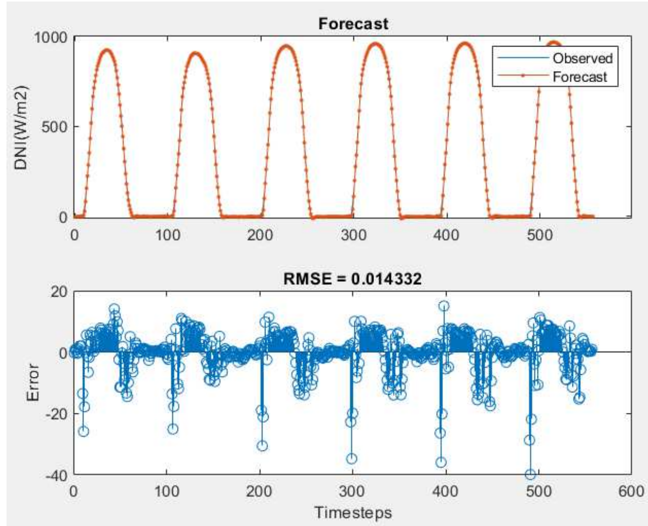

Fig. 5. Forecast of DNI over a single time-step forecasting using DNI, temperature and time as inputs

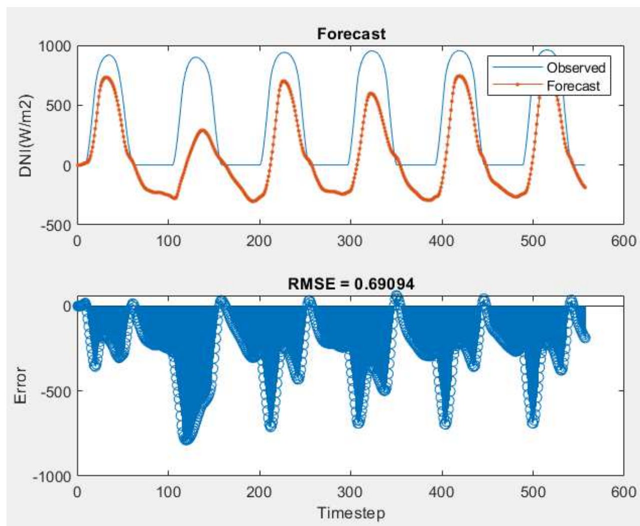

Fig. 4. Forecast of DNI when temperature and DNI were used as input for multi time-step forecasting

V. Conclusion

The performance metrics of the RNN in forecasting of the irradiance listed in the table indicates that the RNN is more efficient when the input is a mix of temperature, irradiance and time models. The forecasting interval also holds key to the accuracy of the network wherein, the bigger time step prediction with the fixed time step input deviates the forecasting error widely. Out of the four combinations of the inputs tried, the more input variable inputs are present, the lower is the error metric which indicates that the weights decided in the input is highly defined by the correlation of the input and output data.

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Since the RNN network uses features in the data to predict the forecast values, the accuracy of the RNN-LSTM is not at par with its counterparts. Hence use of a suitable different network can overcome the feature selection drawback and can improve the accuracy of prediction based on the number of samples which in turn can be a continuation of the foresaid work

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