

Solar Radiation Forecasting using Hybrid Convolutional Long Short Term Memory Neural Network

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DOI: <http://doi.org/10.5281/zenodo.3768721>

Abstract

With the quick advancement of solar PV based power invasion in the cutting edge electric power framework, appropriate anticipating of solar irradiance take up a significant role in planning, operation, unit commitment of power system. However, the noteworthy historic solar irradiance data demonstrates uncertain and non-straight patterns, which makes it hard to foresee the radiation precisely. Taking these challenges into account, this paper proposes a deep learning based hybrid model named as Convolutional Long Short Term Memory (CLSTM) neural network to forecast solar radiation in half an hour ahead. The Convolutional part of the model extracts the features (time series patterns) from the data set and the Long Short Term Memory part processes the data to overcome the long term dependency problem and stores the useful information in its memory part. The proposed model has been trained with two years historic data that includes global horizontal radiation (W/m^2), temperature ($^{\circ}C$) and relative humidity (%). The comparative (with recurrent neural network and convolutional neural network) results (Mean Absolute Error, Root Mean Squared Error, Mean Absolute Percentage Error) shows that the proposed model performed better in learning the uncertainties in the dataset and therefore can be useful in predicting the solar irradiance in solar power plants. Along these lines, the proposed model has potential in harvesting power from inexhaustible solar energy resource to contribute in electric power framework.

Keywords: *Convolutional Long Short Term Memory, Convolutional Neural Network, Deep learning, Forecast, Global Horizontal Radiation, Mean Absolute Percentage Error, Recurrent Neural Network, Root Mean Squared Error, Solar PV*

INTRODUCTION

Dependence on fossil fuel like coal, gas, oil etc. is at its all-time high and will keep on growing at an exponential rate, but these resources are depleting [1], [2] at an alarming rate. This concern along with the adverse effects of burning natural resources has prompted the research on more economic and ecofriendly alternatives like solar and wind, which are decreasing global warming, environmental pollution and is overall clean. Among all the available forms of renewable energies, [3][4]solar energy is more popular than others due to its abundance and predictability. As such, solar plants totaling to 1.5 GW PV capacities were installed in the year of 2000 and almost 65 GW PV was installed at the end of the year 2011 across the world [5]. Among them Germany and Italy installed half of that capacity [6]. For the solar power generation the most crucial parameter is solar radiation. Because of the variability of solar radiation, it is necessary to predict the solar irradiance on different location using climatic variables like daily clear

sky, global radiation, total cloud cover, clearness index, maximum ambient temperature, humidity and wind speed to name some of them[1], [7], [8]. The data collected from these variables will have no meaning, if a forecasting model is not designed to use these data efficiently and accurately in predicting the solar radiation.

Throughout the year a lot of work has been done in developing ways to predict the global solar radiation (GSR)[5], [6], [9]–[14] in order to make it readily available for use in optimization in utilization. For example, Elizondo et al. [15]used feed forward neural network (FNN) with meteorological parameters as inputs and forecasted with a root mean square error (RMSE) ranging from 2.92 to 3.64. Qing &Niu[16]used weather forecasting data to predict the hourly solar irradiance a day ahead by implementing long short term memory (LSTM) neural networks, predicting 1 year of GSR from 10 years of historical data, the algorithm decreased the RMSE by 42.9% compared to conventional back propagation neural

network (BPNN). Alzahrani, Shamsi, Dagli, & Ferdowsi [8] proposed a method to predict irradiance using deep recurrent neural network (DRNN) which utilized solar irradiance data collected from localities in Canada for 4 days with conditions of overcast, clear sky, variable and very variable irradiance. Compared to methods like support vector regression (SVR) and FNN the DRNN had a RMSE of 0.086. In the vichy-Rolla National Airport's PV, Station Alzahrani, Kimball, & Dagli [17] implemented a nonlinear autoregressive network with exogenous inputs (NAR) approach. It took inputs like time, day of the year, wind speed, pressure and sky cover. It resulted in a system that outperformed other conventional methods with an MSE of 8.2%. Hontoria [18] et al. took variables of air temperature and relative humidity to use in a recurrent neural network (RNN) method. Upon analysis it was established that the system had a correlation coefficient ranging from 98.6% to 98.8%. H. M. Diagne [19] proposed artificial neural network (ANN) which used gradient decent back propagation with adaptive learning rate. The model used maximum ambient temperature, minimum ambient temperature and minimum relative humidity as input variables and predicted the GSR. The testing was done by

randomly selecting the data and the best results was found when minimum ambient temperature and day of the year as variables outperformed all the other cases; the proposed model yielded a MAPE of 6.65%. Likewise the paper utilizes the radiation, relative humidity, temperature and wind speeds as input variables to train a convolutional long - short term memory (CLSM) neural network to using supervised learning methods to forecast the GSR for seven days. The proposed system will be compared to conventional CNN and RNN algorithms.

DATA COLLECTION AND PROCESSING

The sample data collected from Asian Institute of Technology's meteorological station consists of 24 months of historic data on temperature ($^{\circ}\text{C}$), radiation (W/m^2) and relative humidity (%); the raw data consisted of 5 minutes interval and has been converted to 30 minutes interval as shown in Figures 5 and the statistical parameters of the data is presented in Table 1 respectively. Over the two year period the average half hourly temperature was found to be 29.56°C with an approximate minimum of 14.7°C and maximum of 40.47°C . The GHR for the test data was found to be in a range of 20.84 (W/m^2) to a maximum of 894.17

(W/m²) and the average GHR was found to be 153.48. For the relative humidity the data reflects a range with minimum

humidity of 20.64% and reaches a maximum humidity of 123.05 % as shown in Figure 1.

TABLE 1 STATISTICAL PARAMETER OF COLLECTED DATA

Parameter		Value
Temperature (°C)	Min	14.7
	Max	40.47
	Mean	29.55
Radiation ((W/m ²))	Min	20.64
	Max	123.05
	Mean	81.85
Relative Humidity (%)	Min	-15.24
	Max	894.17
	Mean	153.48

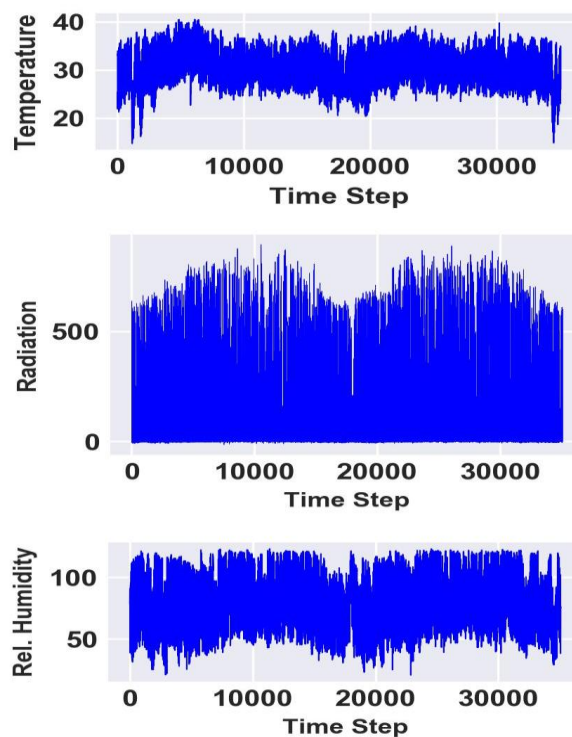


Fig. 1. Half hourly

averaged data

After converting the data from 5 min. interval to half hourly averaged data, the data were normalized

using equation 1. The normalization in this case, was a must as the collected data were of different range.

$$y = \frac{x - \min(x)}{\max(x) - \min(x)}$$

CLSTM MODEL DEVELOPMENT

In this research, we propose a Convolutional Long Short Term Memory neural network to forecast solar radiation at thirty minutes ahead. The proposed model is a hybrid deep learning model. It consists of a 1D convolutional neural network and a Long Short Term Memory neural network. The 1D convolutional part process the input (Solar radiation, Temperature layer in accordance with the pooling layer extract the deep features (sequences) from the training dataset and passes the information as input to the LSTM layer. The LSTM part of model is capable of handling long term dependencies by utilizing its gate control (input, forget and output gate) and memory cells. The mathematical computation of the proposed model are presented in equation 2-7.

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f) \quad (3)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tanh(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \quad (4)$$

$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) \quad (5)$$

$$m_t = o_t \circ \tanh(c_t) \quad (6)$$

$$y_t = W_{ym}m_t + b_y \quad (7)$$

Where, x is input for the LSTM layer (output of CNN part). Input gate in indicated by i_t , forget gate by f_t , memory cell by c_t and the o_t stands for the output vector. W and b represent the weight and bias metrics respectively. ' m_t ' represents the memory block while ' $\circ$ ' stands for the scalar product. ' Y ' is the predicted outputs. The activation functions are symbolized by ' $\tanh$ ' and ' σ ' respectively and their mathematical expression are presented in equation 7 and 8.

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (8)$$

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

The flow chart of working principle of the proposed model is presented in figure 2. It shows the proposed model is consisted of three parts. The data preprocessing part model development part and data post processing part

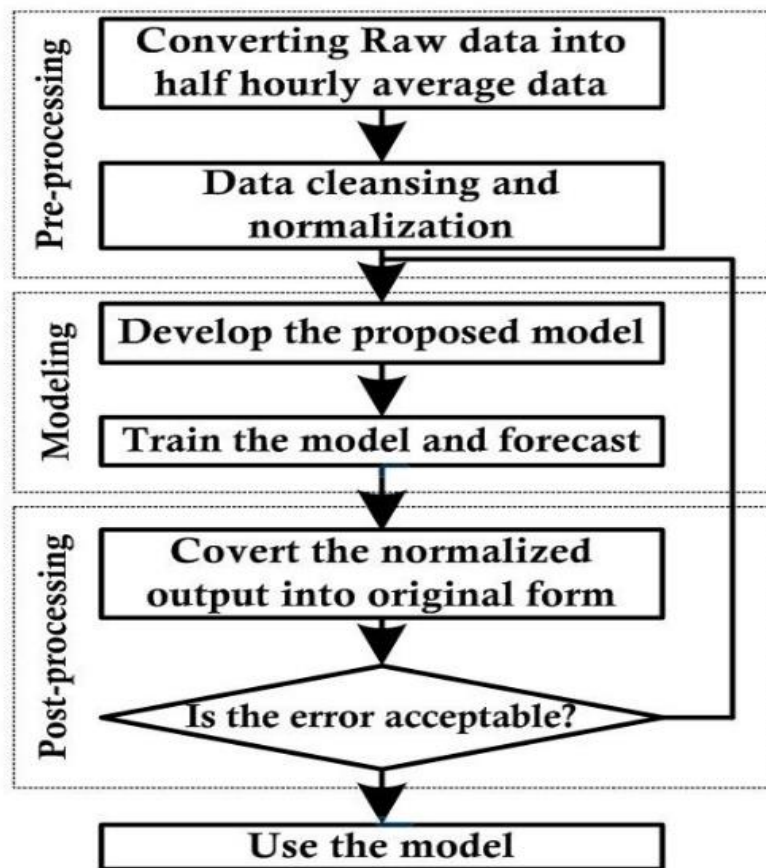


Figure:2 Flow chart of the proposed model

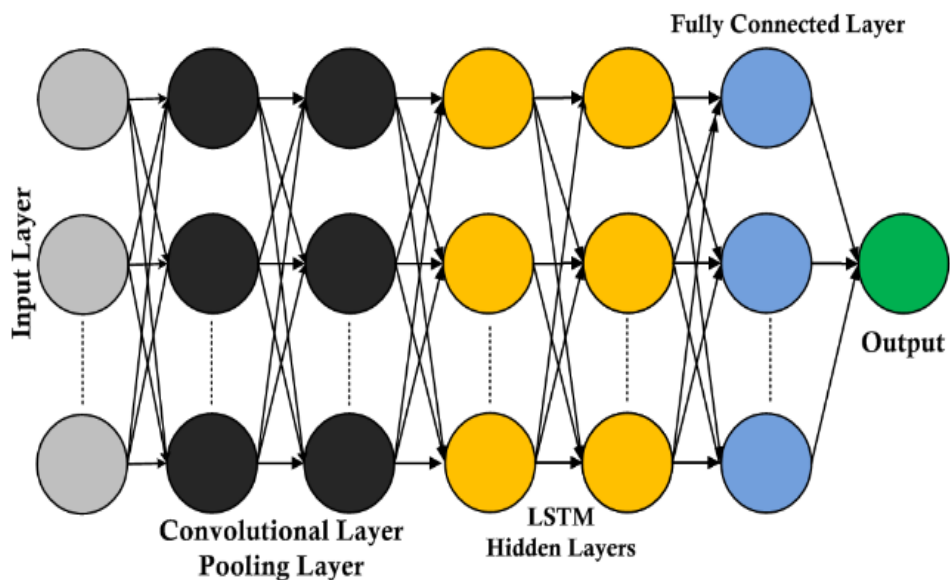


Figure:-3 CLSTM model architecture

The proposed CLSTM neural network model includes seven layers. Input layer followed by convolution layer and max-pooling layer. Then two LSTM hidden layer (having 10 neurons each) with a fully connected layer that passes output to the output layer. The model architecture is shown in figure 3.

ACCURACY MEASUREMENT

The accuracy index of the performance model can be done with several quantifiers, indicated in the literature. In this paper Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are utilized for the evaluation of the model's performance, mathematical illustrations of which are demonstrated below:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - y_i'| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y_i')^2} \quad (9)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - y_i'|}{y_i} * 100\% \quad (10)$$

Where, y_i is actual value and y_i' is the predicted value.

RESULT AND SIMULATION

The research paper is primarily based on the training of the neural networks for

which, approximately 35,000 historical data samples have been acquired. The samples are propagated as 80% (28,000), 15% (5,250) and 5% (1,750) for training, validation and testing. The training of the network has been done with three variables namely, Temperature, GHR and relative humidity along with a lagged series of previous 12 samples. List of which is given in table 2.

The radiation prediction represented in Figure 4 shows the prediction being fairly identical to the actual radiation with a 91% accuracy. From the results it is apparent that the proposed forecasting method is able to predict the magnitude of radiation to a high degree of accuracy. Furthermore, the error distribution and error line curve has been represented in Figure 6 and Figure 5 respectively. From the error distribution curve it can be suggests that the proposed model is apt in successfully predicting the radiation index. From the error line curve, in Figure 5 it is apparent that the majority of error occurs when the radiation is close to zero with some random spikes. These random errors occur due to instantaneous changes in the weather conditions; such as cloud cover, change in wind speed, precipitation etc. All these further validates the viability of the proposed model.

TABLE II LIST OF INPUTS

Input Variable	Description
X_0	Global Horizontal Radiation
X_1	Temperature
X_2	Relative Humidity
X_3-X_{14}	Lagged Series

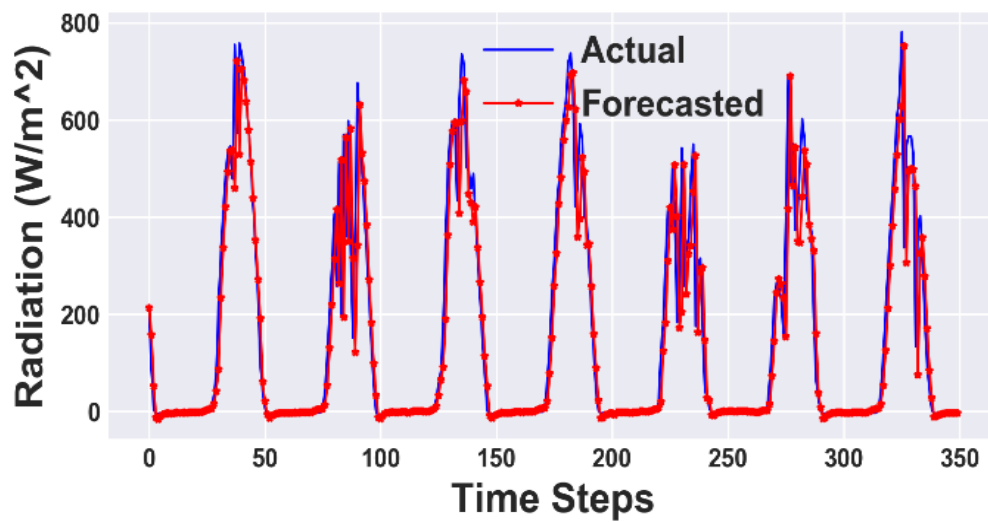


Figure:-4 Actual VS predicted solar radiation

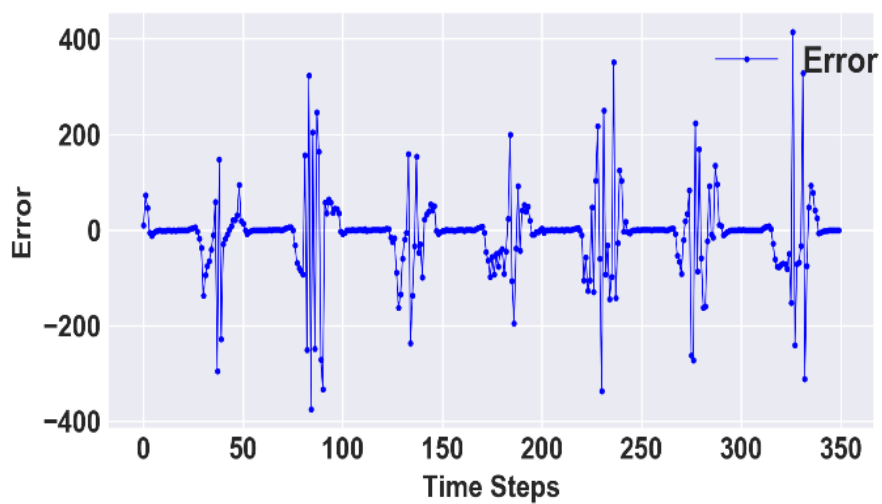


Figure:-5. Error curve for prediction

Upon the affirmation of the viability of the proposed model, the performance of the model is determined by the comparison of MAE, RMSE and MAPE with that of CNN and RNN models. Table 3 represents the performance data and Figure 8 shows the graphical comparisons of the model. Considering the MAE of CLSTM, CNN and RNN model it is found that the proposed model has 18.7% and 12.91%

less error compared to RNN and CNN respectively. Similarly, the CLSTM model has 42.43% and 31.35% less RMSE. From the comparison chart the MAPE of the three models shows the proposed model has about 91% accuracy which is 11.95% more than the conventional CNN models and 13.62% more than conventional RNN models.

TABLE III. COMPARISON OF PERFORMANCE

Model	Performance		
	MAE	RMSE	MAPE
RNN	3.351	9.148	11.025
CNN	3.127	7.71	11.237
CLSTM	2.723	5.293	9.707

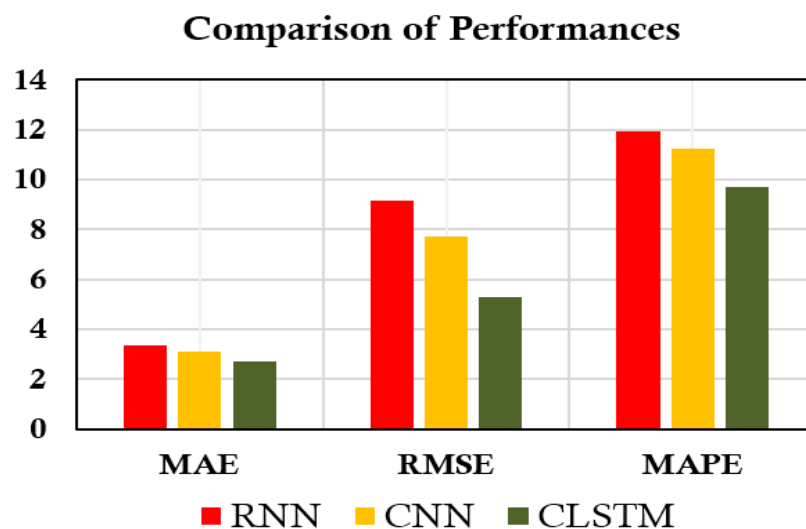


Fig. 6. Error distribution for predicted values

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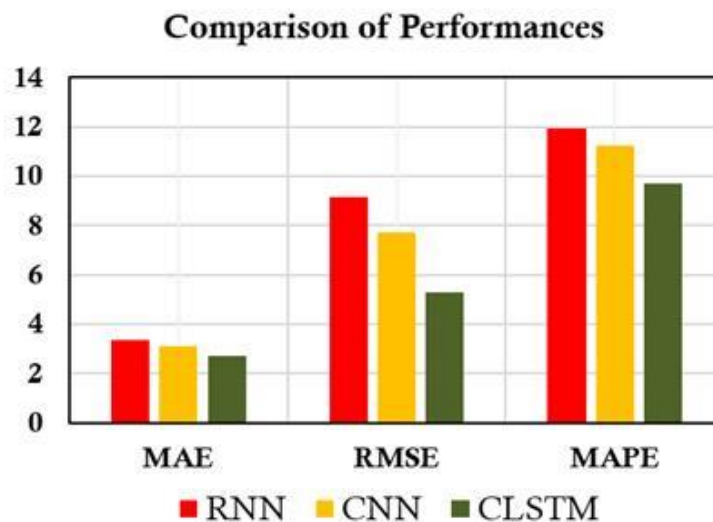


Fig. 7: Comparison of performances

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CONCLUSIONS

Climate change and global warming has made it apparent that the dependence on fossil fuel has to be reduced and alternate ecofriendly sources to be made more efficient and affordable, also stated in the sustainable development goal (SDG) 2030 memorandum. As such, solar energy is at the forefront of alternate generation sources and making it efficient will help in getting a step closer to achieving the SDG 2030. A forecasting model is able to provide useful information about the erratic changes in the variables of solar radiation and help in utilizing the resources to improve solar energy generation. The forecasting approach utilized in this paper, takes recorded historical values of temperature, GHR and relative humidity to predict the global radiation. Data of two years has been used in the process of training, validating and testing a hybrid deep learning ANN using supervised learning methods. The proposed CLSTM model has an accuracy of around 91%, in predicting the solar irradiance. The performance comparison is also demonstrated in figure 8, with significantly low RMSE and MAE it can ascertained that the proposed model is viable in forecasting the solar radiation.

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Cite this Article as

Firuz Ahamed Nahid, Hussain Mahmud Chowdhury, Mohammad Nayeem Jahangir (2019) “Solar Radiation Forecasting Using Hybrid Convolutional Long Short Term Memory Neural Network” *Journal of Research in Physics and Applied Sciences*, 2 (2), 1-13

<http://doi.org/10.5281/zenodo.3768721>