SOLAR IRRADIANCE FORECASTING USING DEEP LEARNING APPROACHES

W.L.M.Fernando[1], W.M.W.S.Jayalath[1*], A. Kanagasundaram[1], R.Valluvan[1], A.Kaneswaran[2]

[1]*Department of Electrical and Electronic Engineering, University of Jaffna,*

[2]*Department of Computer Engineering, University of Jaffna*

[*]*Corresponding author (email: wathminishari@gmail.com)*

Abstract

The purpose of this study is to come up with a most accurate model for predicting the Solar photovoltaic (PV) power generation and Solar irradiance. For this study, the data is collected from Faculty of Engineering, University of Jaffa solar measuring station. In this paper, deep learning based univariate long short-term memory (LSTM) approach is introduced to predict the Solar irradiance. A univariate LSTM and auto-regressive integrated moving average (ARIMA) based time series approaches are compared. Both models are evaluated using root-mean-square error (RMSE). This study suggests that univariate LSTM approach performs well over ARIMA approach.

Key words - Solar photovoltaic, Solar irradiance, prediction model, time series, ARIMA, deep learning, LSTM.

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Introduction

Energy is an essential source for human's lives and a key factor for development of a country. Due to the changing of the world like industrialization, modernization, population growth and living standard of people, demand for energy, especially electrical energy demand has increased over the years. In recent times, renewable energy installation has become a significant solution for this problem since it has minimal environmental issues. Solar photovoltaic (PV) energy has experienced enormous growth in electricity generation. In the last few years, installation of PV systems increased rapidly in on-grid and off-grid systems. Solar PV power is the outcome of the solar irradiance which is absorbed by the PV panels. There are several parameters, including weather parameters that affect the solar irradiance. The past values of solar irradiance and weather data is very important to model an accurate solar forecasting model and build a profitable power plant.

For this study, we have chosen Killinochchi district, Faculty of Engineering, University of Jaffna as it has a lot of potential for solar PV compared to other districts. Faculty of Engineering, University of Jaffna owns Solar measuring station which was donated by Sri Lanka Sustainable Energy Authority (SLSEA) with the support of Asian Development Bank (ADB).

Previously, Wang et al investigated weather classification based modeling as an effective way to increase the accuracy of day-ahead short-term (DAST) Solar PV power forecasting because PV output power is strongly dependent on the specific weather conditions in a given time period [1]. Jordi et al derived a probabilistic forecast of the solar irradiance during a day at a given location, using a stochastic differential equation model [3]. Lauret et.al used machine learning techniques along with an AR model to predict solar radiation using historical data from three French islands [4]. They observed that at 4-Hour ahead horizon, machine learning models slightly outperform the Linear AR model but the gap becomes more significant in the case of unstable sky conditions [4]. Previously, Kanagasundaram et al studied the ARIMA based time series approach to predict the Solar irradiance [6].

In this paper, deep learning based univariate long short-term memory (LSTM) approach is studied for long-term time horizon prediction. Further a univariate LSTM approach is also compared with ARIMA based time series approach for long-term time horizon prediction. Both models are evaluated using root-mean-square error (RMSE).

Materials and Methods

Database

Our database contains two years of solar irradiance from 2014.01.01 to 2016.01.01 with 10 minute intervals. The

Figure 1 shows the variation of 105120 solar irradiance tuples with the time for two years. For our study, data is split into train dataset and test dataset. 75 % of tuples are used to train our deep learning model and remaining 25% tuples are used to test the model.

Forecasting can be done for four different time horizons as follows [5];

1) Very short-term forecasting (from a few seconds to minutes)
2) Short-term (up to 48–72 hours ahead)
3) Medium-term (up to one week ahead)
4) Long-term (up to months to years)

In this paper, we focus on long-term forecasting.

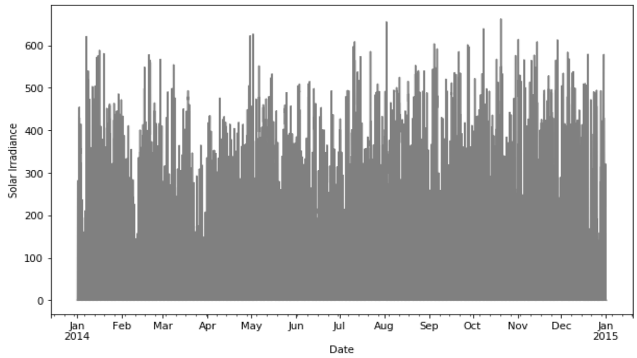

Figure 1 : Diffused Solar Irradiance variations with time

Deep learning based long short-term memory (LSTM) approach

LSTM model is deep learning based forecasting approach which is used to accurately predict the Solar irradiance. A LSTM network is an artificial neural network that includes LSTM units instead of, or in addition to, other network units. A LSTM unit is a recurrent network unit that is remembering values for either long or short durations of time and it uses no activation function within its recurrent components. Therefore, the stored value is not iteratively squashed over time, and the gradient or blame term does not tend to vanish when Back propagation through time is applied to train it. These are implemented in "Blocks" containing several LSTM units. This design is typical with "deep" multi-layered neural networks, and facilitates implementations with parallel hardware. The LSTM block determines how to maintain its memory as a function of those values, and training its weights causes the LSTM block to learn the function that minimizes loss. LSTM blocks are usually trained with Back propagation through time.

LSTM approach is compared with auto-regressive integrated moving average (ARIMA) approach for same data set. The ARIMA models are the most general class of models for time series forecasting. ARIMA (p,d,q) is developed for nonstationary random processes. In here, p the order of AR, d is the number of non-seasonal differences, and q is the MA order. The values of p, d, q can be calculated using autocorrelation function, stationary and partial autocorrelation function. In the case of $d=0$, ARIMA(p,d,q) is transformed to be ARMA(p,q) model [5].

For LSTM approach, first the data is normalized into range between 0 to 1. Then data is split into train and test data. The LSTM network is trained using training data for 100 epochs with Adam optimizer and categorical cross entropy loss function. Changing of epochs in the LSTM model can result in varying RMSE value and the LSTM network that giving minimum RMSE value is selected as the most accurate model for research solution. The root-mean-square-error (RMSE) value is calculated after de-normalizing the data into original data range. The RMSE is calculated as follows,

$$RMSE = \sqrt{\frac{1}{N} . \sum_{n=1}^{N} (Y - X)^2} \quad (1)$$

Results and Discussion

Depending on the number of epochs, the LSTM network provides different RMSE values at different number of epochs which is tabulated in Table 1.

Table 1: RMSE values according to the number of epochs in LSTM network

Number of epochs	RMSE
10	29.54
100	29.09
200	29.28
300	29.30

From Table 1, the minimum RMSE value is selected as accurate model for Solar irradiance forecasting. The Figure 2 shows the difference between predicted data and the test data. The train dataset also predicted again used LSTM network as an advanced step and training data RMSE value is resulted as 29.80.

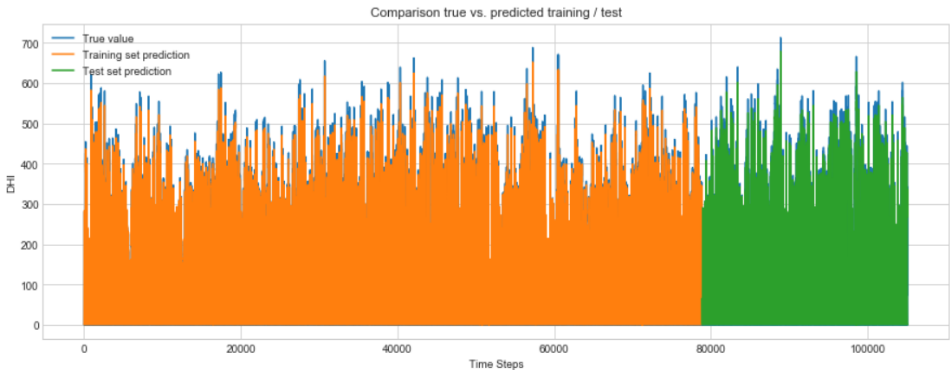

Figure 2: Actual and predicted data for LSTM network

The LSTM approach is also compared with ARIMA (2,1,0) model. The Table 2 shows the performance of LSTM and ARIMA models. It clearly shows that LSTM network performs well over ARIMA models.

Table 2 : RMSE value of the models

Forecasting Model	RMSE value
ARIMA (2,1,0)	29.64
LSTM network	29.09

Conclusions and Recommendations

In this paper, deep learning based LSTM approach was introduced and it was also compared with time series based ARIMA model. It was also found that LSTM approach performs well over ARIMA model. In future, hybrid model will be investigated for solar irradiance forecasting.

References

[1] F. Wang, Z. Zhen, B. Wang, and Z. Mi, "Comparative Study on KNN and SVM Based Weather Classification Models for Day Ahead Short Term Solar PV Power Forecasting," *Appl. Sci.*, vol. 8, no. 1, p. 28, 2017.

[2] P. Poudel and B. Jang, "Solar Power Prediction Using Deep Learning Technique," vol. 146, no. Fgcn, pp. 148–151, 2017.

[3] J. Badosa *et al.*, "Day-ahead probabilistic forecast of solar irradiance : a Stochastic Differential Equation approach To cite this version : HAL Id : hal-01625651 Day-ahead probabilistic forecast of solar irradiance : a Stochastic Differential Equation approach," 2017.

[4] P. Lauret, C. Voyant, T. Soubdhan, M. David, and P. Poggi, "A benchmarking of machine learning techniques for solar radiation forecastingin an insular context," *Sol. Energy*, p. 0, 2015.

[5] C. Wan, J. Zhao, S. Member, and Y. Song, "Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management," *J. Power Energy Syst.*, vol. 1, no. 4, pp. 38–46, 2015.

[6] A. Kanagasundaram, R. Valluvan and A. Atputharajah, "A Study on Solar PV Power Generation Influencing Parameters Using Captured Data From Faculty Of Engineering, University Of Jaffna Solar Measuring Station", International Conference On. Solar Energy Materials, Solar Cells & Solar Energy Applications, Jan 2018.