Research Article

AJOERR (2018) x:xx

American Journal of Engineering Research and Reviews
(ISSN:2637-3785)

Comparison of Solar Irradiance between WRF simulation and Deep Learning: Case study in Nishi Akisawa, Japan

Jose Manuel Soares de Araujo

Gifu University Faculty Of Engineering and Graduate School Of Engineering 1-1 Yanagido, Gifu City 501-1193, Japan

ABSTRACT

A This paper presents a study of evaluation for the reliability of seven-days direct normal irradiance (DNI) and diffuse irradiance (DIF) forecasts which provided by Weather Research and Forecasting (WRF) mesoscale model using six-hourly interval 0.5°x0.5° input dataset obtained from National Oceanic and Atmospheric Administration - National Operational Model Archive and Distribution System (NOMADS) website. 3 km spatial resolution was used to estimate seven-days simulation starting from 1st to 7th January 2017 for comparison purpose. Long short-term memory (LSTM) algorithm has been applied to make future prediction. The one-hourly values input dataset of LSTM obtained from Nishi Akisawa mega solar website is consist of one-year data of solar irradiance starting from 1st January to 31st December 2016. This dataset divided into training datasets (89%) and testing datasets(11%) where the testing datasets values was used to make future prediction of solar irradiance. The result shows the error of root mean square of LSTM algorithm is 129 W/m2 higher compare to 101 W/m2 from the WRF model for seven-days prediction but the result of this study proposed using LSTM algorithm for future prediction of solar irradiance or others parameter of weather.

Highlights

• Comparison of future prediction of solar irradiance has done in Nishi Akisawa-Japan; • This study applied NOAA-NOMADS dataset as input dataset of WRF; • Input data of LSTM algorithm obtained from Nishi Akisawa mega solar weather station; • LSTM algorithm shows error of RMSE is higher compared to WRF model.

Keywords:
Deep Learning, LSTM, Nishi Akisawa, solar irradiance, WRF

***Correspondence to Author:**
Jose Manuel Soares de Araujo
Gifu University Faculty Of Engineering and Graduate School Of Engineering 1-1 Yanagido, Gifu City 501-1193, Japan

How to cite this article:
Jose Manuel Soares de Araujo. Comparison of Solar Irradiance between WRF simulation and Deep Learning: Case study in Nishi Akisawa, Japan. American Journal of Engineering Research and Reviews, 2018, x:xx

eSciPub LLC, Houston, TX USA.
Website: http://escipub.com/

1. Introduction

During the past decade, a forecasting technology of solar irradiance, probabilistic models and ranging of statistical data approaches to physical has been paid attention in order to know the solar energy. The power generation of photo voltaic (PV) system is strongly dependent on solar irradiance and the accuracy forecasting of solar irradiance can help to understanding the PV power generation and reduce the impact of uncertainty of PV generation itself. Therefore, the forecasting of solar irradiance has been studied extensively in the literature for the benefit of PV generation. The forecasting of solar irradiance is divided into three categories: physical, statistical and machine learning. Physical method is mostly implemented by using numerical weather methods which suitable for long period forecasting such Weather Research and Forecasting (WRF), Regional Atmospheric Meteorologic System (RAMS) and Meteorologic Mesoscale (MM5). Solar forecasting using statistical method is commonly based on historical time data series which is simpler then physical method. Lastly is machine learning method as a part of artifcial neural network (ANN) such as Long Short Term Memory (LSTM), Linear Regression (LR), and BPNN can be used to construct a nonlinear mapping from datasets between input and output data without being programmed [1] [2].

The forecasting of PV power generation are always performed using meteorological forecast datasets to obtain good accuracy. Variation of meteorological elements such as cloud cover and aerosol may cause PV power forecasting become unstable. Furthermore, other parameters such as Global Horizontal irradiance (GHI), Direct Normal Irradiance (DNI), Diffuse irradiance (DIF), temperature, pressure, relative humidity, rainfall, wind speed, wind direction, date and month of the year are also important for solar PV power generation forecasting. The artificial neural network (ANN) model is commonly used to estimate solar irradiance can be determined also as multi variable parameters such as coordinate (latitude and longitude), altitude, temperature, relative humidity, rainfall, and duration of of hour and month of the year [5]. Many researchers have conducted many method of study by using the solar irradiance parameters such as GlobalHorizontal irradiance (GHI), Direct Normal Irradiance (DNI) and Diffuse irradiance (DIF) to analyze the PV power generation.

Xiangyun Qing et al., (2018) [1] conducted study of solar irradiance prediction using long shortterm memory (LSTM) compare to persistence algorithm, linear regression (LR) and BPNN for hourly day-ahead in island of Santiango, Cape Verde, for one day of rain season at August 20, 2013. This study concluded that the error RMSE of LSTM algorithm is smallest compare to other three algorithms.

Richard et al., (2010) [3] have conducted forecasting for short term that extend up to 6-h and medium term extend up to 6-d for hourly global horizontal irradiance (GHI) using numerical weather prediction (NWP) based upon cloud motion derived from consecutive geostationary satellite image for seven climatically distinct locations in United State.

V. Lara-Fanego et al., 2012) [4] conducted three-days evaluation of Global Horizontal irradiance (GHI) and Direct Normal Irradiance [DNI] using WRF mesoscale atmospheric model for Andalusia (Southern Spain). This work presents study of different seasons of the year and three different sky conditions : clear, cloudy and overcast.

The aim of this study is to know the comparison of solar irradiance between Weather Research and Forecast (WRF) model and Deep Learning method for location in Nishi Akisawa, Japan. Parametersettings and model configurations have been evaluated in this study order to presented modeling results for a final optimized configuration. Therefore, This study propose a results of comparison between physical method (WRF) and deep learning method (Long Short-

Term Memory) for hourly solar irradiance can be used to analysis for future prediction.

2. Study area and data sources

2.1. Study area

Nishi Akisawa [6] (latitude: 35°33'31.20"S, longitude: 136°39'27.70"E) is one district located in South of Gifu prefecture. Nishi Akisawa is location of croplands area mix with forests where the average annual temperature is 15.5 C and average annual rainfall is 1799 mm with September as the wettest month. Meanwhile, the temperatures are highest on average in August and lowest in January. Gifu recorded a record high of 38.8 °C on August and record low of minus 14.3 °C on January. This area was chosen in this study for it has mega solar PV system installed with free available data downloaded such as solar irradiance, temperature, wind speed, wind direction and power generation. Fig.1 shows land cover of Nishi Akisawa as study area.

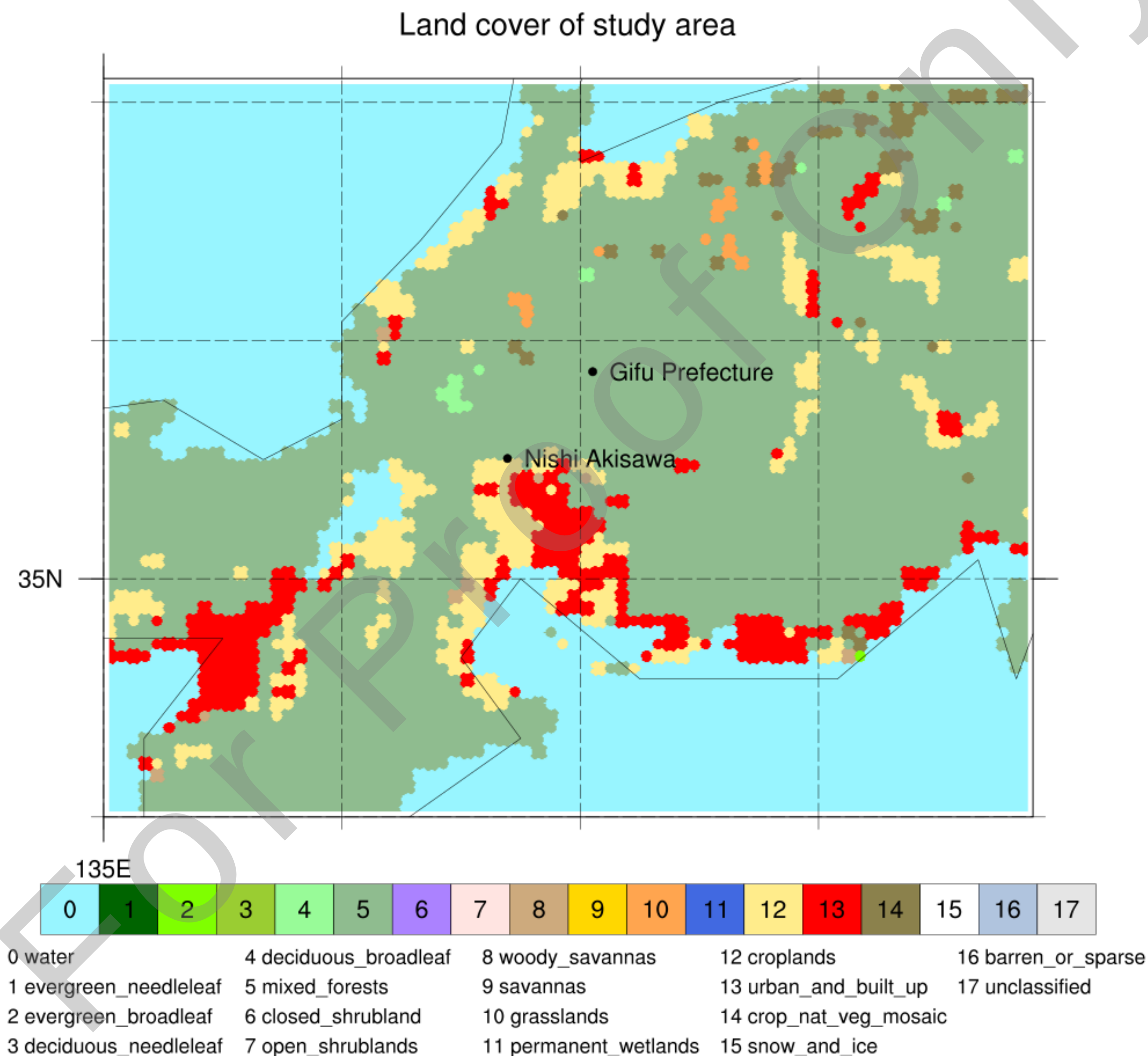


Fig. 1. Land cover of study area

2.2. Data source

2.2.1. WRF data source

Six-hourly interval 0.5°x0.5° of Climate Forecast System version 2 (CFSv2) spatial resolution of analysis data obtained from National Oceanic and Atmospheric Administration – National Operational Model Archive and Distribution System (NOMADS) website (https://nomads.ncdc.noaa.gov/modeldata) were used as Global Forecast System (GFS) for initial and lateral boundary conditions data for the meteorological fields with 03 as 00 UTC, 09 as 06 UTC, 15 as 12 UTC, and 21 as 18 UTC where the Japan Standard Time (JST) is UTC+9. These datasets composed of various variables of weathers such solar irradiance, temperature, u-wind, vwind, relative humidity, pressure, water vapor and others. The boundary condition of these data include landuse based on the U.S. Geological Survey (USGS) 24 category. The simulation model was run starting from 31st December 2016 at 15:00 UTC corresponding to 00:00 JST on 1st January 2017. This numerical simulation using history interval settings to 60 minutes and vertical layer is 38 levels with the first 15 h used as spin-up time for the model. The simulation was carried out for seven days starting from January 1st to 07th January 2017.

2.2.2. Deep Learning data source

For Deep Learning input data case, this study obtained dataset from Nishi Akisawa mega solar weather station through homepage http://services46.energymntr.com/megasolar/SEQ0132636/login/ for solar irradiance. Nishi Akisawa mega solar weather station provides 1 hour time values. Thedata collected for 12 months (January to December 2016), where the data from January to December 2016 were set to training dataset (89%) and testing dataset (11%). The hourly data of solar irradiance with 1 hour is starting from 00:00 AM to 23:00 PM cover 366 days. Respectively, these training dataset and testing dataset are composed for 7823 hours 961 hours, where the 961 hours testing dataset were used to predict future solar irradiance.

3. Methodology

3.1. Numerical configuration

The WRF model [7] is a mesoscale numerical weather prediction platform with advances in dynamics, physics and data assimilation developed by the National Center for Atmospheric Research (NCAR), the National Oceanic and Atmospheric Administration (NOAA) represented by the National Centers for Environmental Prediction (NCEP) and the Forecast System Laboratory (FSL), the Air Force Weather Agency (AFWA), the Naval Research Laboratory, the University of Oklahoma, and the Federal Aviation Administration (FAA). This model can simulate atmospheric data using observed data or/and idealized conditions and it is divided into two dynamical cores: Nonhydrostatic Mesoscale Model (NMM) and Advances Research WRF(ARW).

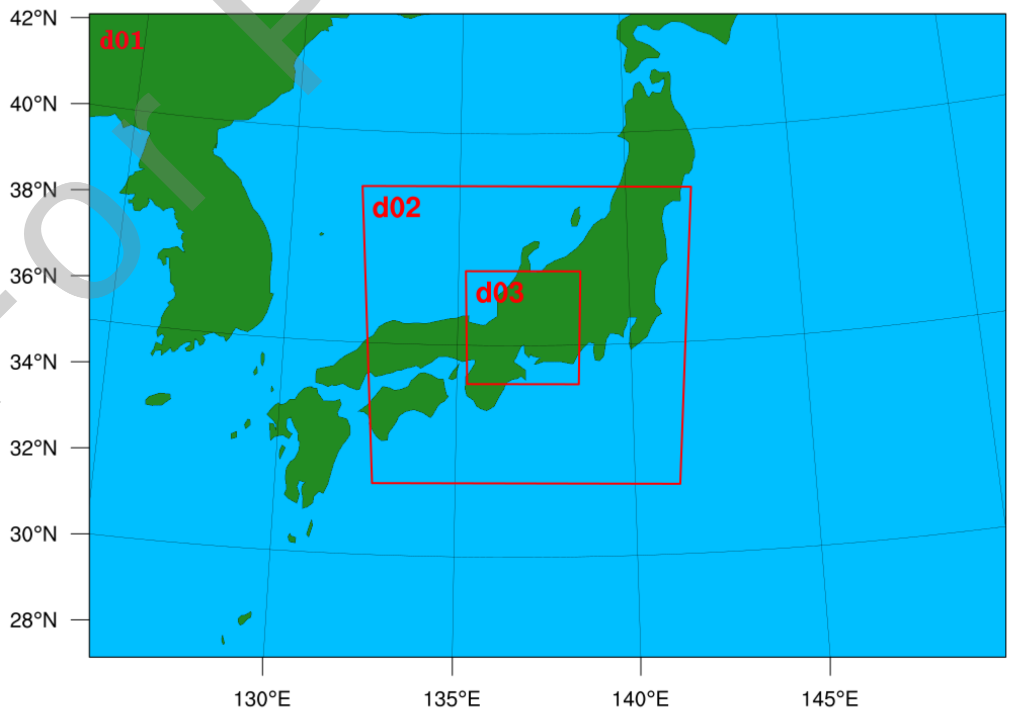
The WRF-ARW [7] version 3.9.1 model with three two-way nested domain were used in this simulation from west to east and south to north for horizontal grid resolution 27000 m, 9000 m and 3000 m (Fig.2a) with grid size 90x64 as parent domain (d01), 94x88 as 1st nested domain (d02) and 100x100 as most innnermost domain (d03)(Fig.2b). This study applied Thompson and Eidhammer (2014) scheme for microphysics with user_aero_icbc is set to true in order to use auxiliary aerosol climatology file placed into WRF through WPS program [20]. Rapid Radiative Transfer Model for Global (RRTMG) scheme is used for longwave and shortwave radiation [8][9], Monin-Obukhov MM5 for surface layer [10], Noah land surface for land surface, Yonsei university for planetary boundary layer [11] and Kain-Fritsch for cumulus parameterization with configuration of time step of 20s applied for all configuration. Plotting for its grid points and its variable is using NCL (NCAR Command Language) programming language version 6.5.0 [12]. Table 1 shows details configuration of WRF parameters. In this study, the data from domain d03 were used as result to analysis for prediction purpose.

3.2. Deep Learning – LSTM algorithm

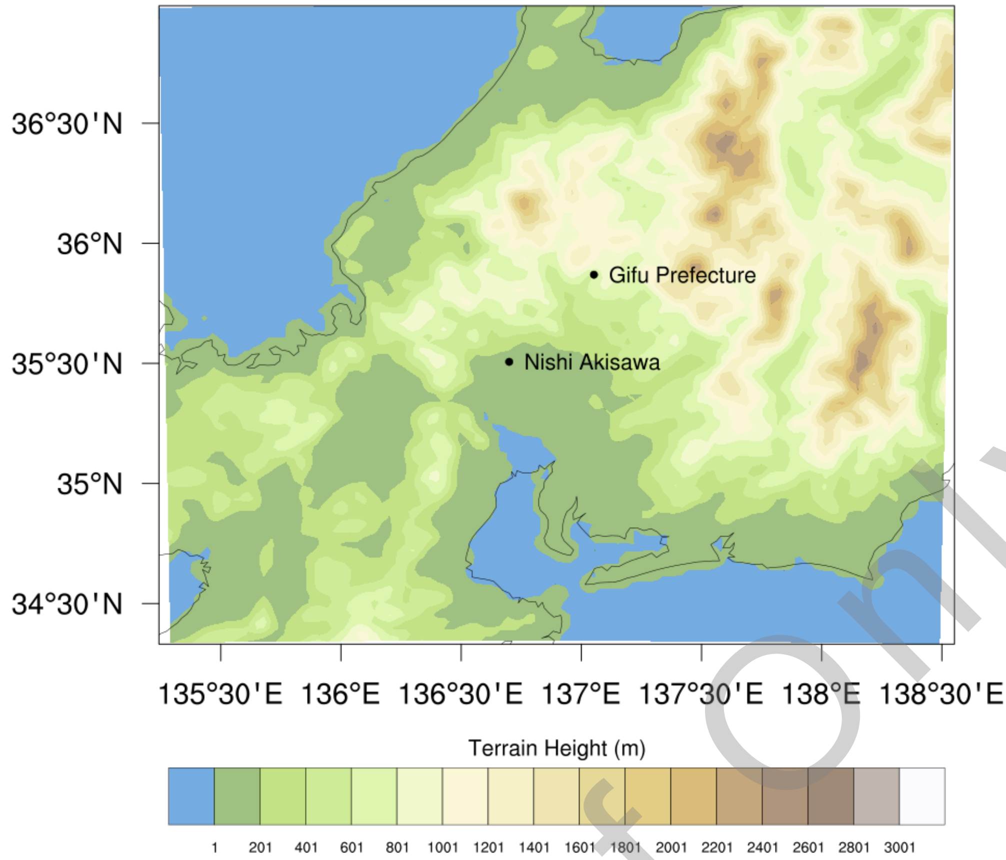
Deep Learning or deep structure learning has been applied to forecasting and it is successfully applied in numerous learning problems for solar irradiance forecasting. The concept of time from recurrent neural network (RNN) as one such machine has been introduced to LSTM algorithm. The structure of LSTM as part of Deep Learning composed of input date, forget date, output date and candidate value [13]. The LSTM algorithm is mostly implemented using Keras package for training and testing datasets [14]. The capable of LSTM in how to remember information for long time with good accuracy make it becomes powerful for forecasting. This study applying moving-forward window technique to make prediction at the next time step [15 - 17]. In this case, window of size 50 was used for moving-forward to make one-step prediction, which mean that, the first 50 data points was used as out input X to predict y1-51st data point, next is data point of window between 1 to 51 used as X to predict y2 and so on. The data were normalized to [-1,1] using minmax scaler technique before applying the algorithm. Table 2 shows more configuration about LSTM network using two layered LSTM architecture of 50 hidden neurons and 256 hidden neurons couple with two layered Dropout of 0.5 with a dense output layer to make prediction with number of time steps 50 and number of features is 1. Maximum epoch were set to 200 with batch size 300 and validation split is 0.09.

Table 1 Model settings use in WRF.

Domain settings	Domain 1	Domain 2	Domain 3
Horizontal and vertical grid size	27 km	9 km	3 km
Horizontal and vertical grid cells	90 x 64	94 x 88	100 x 100
Map projection	Lambert	Lambert	Lambert
Geographic data resolution	10m	5m	2m
Microphysics	Thompson	Thompson	Thompson
Longwave radiation	RRTMG	RRTMG	RRTMG
Shortwave radiation	RRTMG	RRTMG	RRTMG
Surface layer	MM5	MM5	MM5
Land surface	Noah land surface	Noah land surface	Noah land surface
Planetary boundary layer	Yonsei University	Yonsei University	Yonsei University
Cumulus parameterization	Kain-Fritsch	Kain-Fritsch	Kain-Fritsch
FDDA	None	None	None



a



b

Fig. 2. a). View of configuration three two-way-nested domain, b). View of terrain height of domain d03

Table 2 LSTM architecture based on Keras package.

```
Model = Sequential
model.add(LSTM(return_sequences=True, units=2, input_shape=(50,1)))
model.add(Dropout(0.5))
model.add(LSTM(256))
model.add(Dropout(0.5))
model.add(Dense(1,activation='linear'))
model.compile(loss='mse', optimizer = 'adam')
history = model.fit(train_X, train_y, epochs=200, batch_size = 300, validation_split=0.09)
```

3.3. Error evaluation

Evaluation of accuracy between actual data from Nishi Akisawa WS with simulated data from WRF and LSTM algorithm is using one of the three widely from David et al. [18] root mean square error (RMSE) which defined as below ;

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}.\sum_{i=1}^{n}\left(\mathrm{pred}_i-\mathrm{obs}_i\right)^2}$$

Where *pred* represented WRF simulated data from domain d03 and LSTM algorithm and *obs* represented Nishi Akisawa WS actual data.

4. Results

The comparison between WRF model and Deep Learning performances shows some interesting features. Fig.3 shows the comparison of solar irradiance actual data from Nishi akisawa and the result from both WRF model and LSTM algorithm in seven-days prediction. Respectively, the blue, red and green curves represent actual data from Nishi Akisawa PV system, LSTM algorithm and WRF model. This result shows that the WRF model and LSTM algorithm solar irradiance was quite good because both model and algorithm precisely predicted values are almost closed to the actual data from Nishi akisawa although the weather type at seven-days prediction was composed of rain day, sunny day and cloud day. However, it is highlight that the prediction of solar irradiance values of these seven-days can change rapidly based on hourly weathers values.

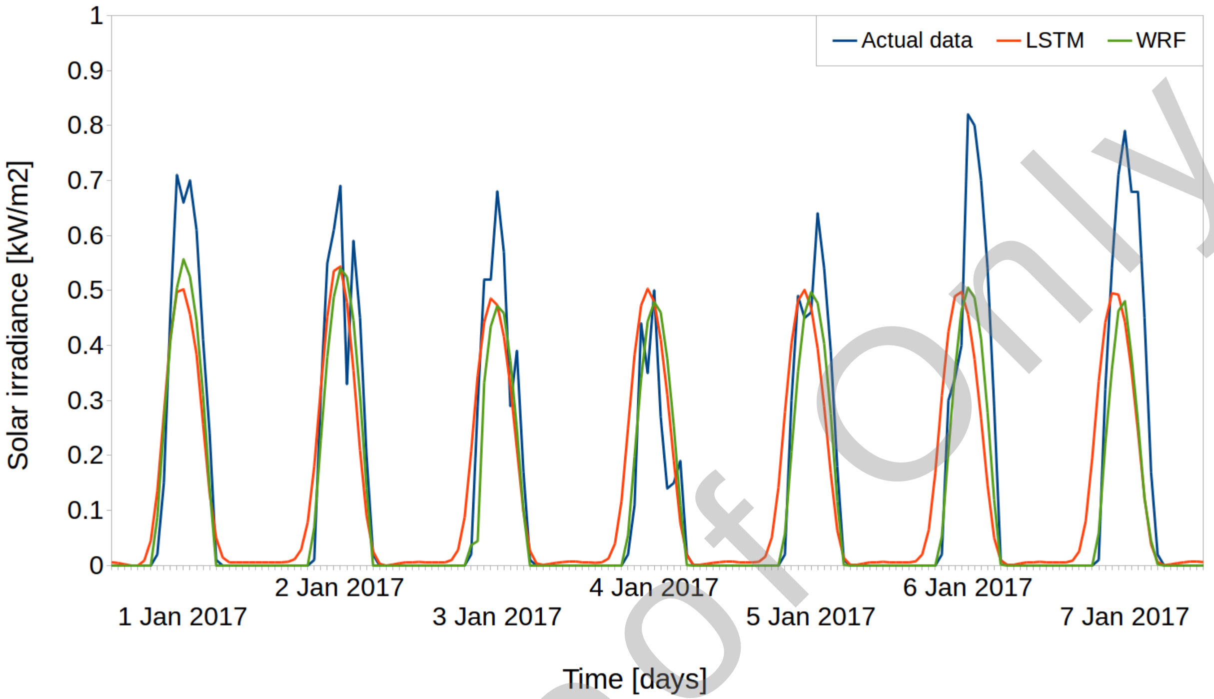


Fig.3 Comparison of Actual data, LSTM and WRF

The RMSE between WRF simulated data from domain d03 and LSTM algorithm are represented in Table 3. As we can see that RMSE of the WRF model is lower compare to LSTM algorithm in seven-days prediction, obviously the more accurate prediction is obtained when the RMSE is lower. Meanwhile, this study also compared the RMSE of one day solar irradiance with other researcher LSTM algorithm from paper reference [1]. Table 4 shows comparison of RMSE one day solar irradiance from this study and other researcher LSTM algorithm with paper in ref. [1]. Here we can see that the one day RMSE of LSTM in this study is higher dependent to the hourly weather forecasting values. Table 5 shows also comparison of RMSE one day solar irradiance from this study and other researcher WRF model with paper in ref. [19] using WRF-RRTMG model. In this comparison, WRF-RRTMG from this study performances lower RMSE compare to other researcher model.

Table 3 RMSE of the WRF model and LSTM algorithm.

	WRF (W/m^2)	LSTM (W/m^2)
RMSE	101	129

Table 4 RMSE of the one day solar irradiance with other research LSTM algorithm.

	LSTM (W/m^2)	Other researcher LSTM (W/m^2)
RMSE	98	76

Table 5 RMSE of the one day solar irradiance with other research WRF model.

	WRF (W/m^2)	Other researcher WRF – rrtmg (W/m^2)
RMSE	75	258

5. Conclusion

In this study, Deep Learning using LSTM network based on algorithm has been applied to compare with WRF model for prediction purpose was conducted. The LSTM algorithm used hourly weatherof solar irradiance to predict the output future data of solar irradiance. For WRF case, the 6-hourly input datasets of weather forecast were used to predict the output at the same days. Obviously, these two methods applied good results at output of prediction but this study proposed to apply LSTM algorithm for future prediction of any weather forecast. For future research, this study will focus to apply WRF simulation results as input data to LSTM algorithm to make a prediction and evaluate the error of solar irradiance predicition.

Acknowledgment

The author would like thank to Mega Solar of Nishi Akisawa for the free download solar irradiance dataset for one year and National Oceanic and Atmospheric Administration - National Operational Model Archive and Distribution System (NOMADS) for the dataset obtained free from website. Author also would like thank to Professor Hiroki Yoshida as the supervisor and Assistant Dr.Nobukazu Kameyama for the discussions and advice.

Conflict of interest statement: None

Nomenclature

ARW : Advanced Research WRF

DIF : Diffuse irradiance

DNI : Direct Normal Irradiance

FDDA : Four Dimensional Data Assimilation

LSTM : Long Short-Term Memory

RMSE : Root Mean Square Error

SAM : System Advisor Model

WRF : Weather Research and Forecasting

References

1. Xiangyun Qing, Yugang Niu. Hourly day-ahead solar irradiance prediction using weather forecast. Volume 148, 1 April 2018, Pages 461-468 https://doi.org/10.1016/j.energy.2018.01.177

2. Solar energy prediction using linear and non-liner regularization models: A study on AMS (American Meteorological Society) 2013-2014 Solar Prediction Contests. Volume 78, 15 December 2014, Pages 247-256 DOI: 10.1016/j.energy.2014.10.012

3. Richard Perez, Sergey Kivalov, James Schlemmer, Karl Hemker Jr., David Renné, Thomas E.Hoff. Volume 84, Issue 12, December 2010, Pages 2161-2172 Validation of short and medium term operational solar radiation forecasts in the US http://dx.doi.org/10.1016/j.solener.2010.08.014

4. V.Lara-Fanego, J.A.Ruiz-Arias, D.Pozo-Vázquez, F.J.Santos-Alamillos, J.Tovar-Pescador Evaluation of the WRF model solar irradiance in Andalusia (Southern Spain). Volume 86, Issue 8, August 2012, Pages 2200-2217. https://doi.org/10.1016/j.solener.2011.02.014

5. Yashwant Kashyap Ankit Bansal Anil K.SaoSolar radiation forecasting with multiple parameters neural networks Volume 49, September 2015, Pages 825-835 https://doi.org/10.1016/j.rser.2015.04.077

6. Nishi Akisawa-Gifu. https://www.japanpostalcode.net/cp27707/zip-code-501-1184 nishiakisawa-gifu-shi-gifu.

7. W. Skamarock, J. Klemp, J. Dudhia, D. Gill, D. Barker, M. Duda, et al. A Description of the Advanced Research WRF Version 3. Technical Report NCAR/TN– 475+STR, NCAR 2008. (2008) Available: http://www2.mmm.ucar.edu/wrf/users/docs/arw_v3.pdf (accessed 24.09.15).

8. Mlawer, E. J., Taubman, J., Brown, P. D., Iacono, M. J., & Clough, S. A. (1997). Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated model for the longwave. Journal of Geophysical Research, 102(D14), 16663–16682. http://dx.doi.org/10.1029/97JD00237.

9. Iacono, M.J., Mlawer, E.J., Clough, S.A., Morcrette, J.-J., 2000. Impact of an improved longwave radiation

model, RRTM, on the energy budget and thermodynamic properties of the NCAR community climate mode, CCM3. J. Geophys. Res. 105,14873–14890.

10. Laura Bianco, ATOC 7500: Mesoscale Meteorological Modeling Spring 2008 http://cires1.colorado.edu/.

11. S.Y. Hong, Y. Noh, J. Dudhia. Mon Weather Rev, 134 (2006), pp. 2318–2341 A new vertical diffusion package with an explicit treatment of entrainment processes.

12. NCL, 2017. The NCAR Command Language (version 6.4.0). http://dx.doi.org/10.5065/D6WD3XH5.

13. Fischer T, Krauss C. Deep learning with long-term memory networks for financial market

predictions. Eur J Oper Res 2018. FAU Discussion Papers in Economics, No.11/2017.

14. https://keras.io/.

15. Jitendra Kumar, Rimsha Goomer, Ashutosh Kumar Singh. Long Short Term Memory Recurrent Neural Network (LSTM-RNN) Based Workload Forecasting Model For Cloud Datacenters.Volume 125, 2018, Pages 676-682 https://doi.org/10.1016/j.procs.2017.12.087

16. https://machinelearningmastery.com

17. https://towardsdatascience.com/using-lstms-to-forecast-time-series-4ab688386b1f

18. David, M., Diagne, M., Lauret, P., 2012. Outputs and error indicators for solar forecasting

models. In: Proceedings of the World Renewable Energy Forum 2012 (WREF 2012), Denver,

USA.

19. Hadrien Verbois, Robert Huva, Andrivo Rusydi, Wilfred Walsh Solar irradiance forecasting in the tropics using numerical weather prediction and statistical learning. Volume 162, 1 March 2018, Pages 265-277
https://doi.org/10.1016/j.solener.2018.01.007

20. Notes for running WRF with the Aerosol-aware Thompson Scheme (mp_physics = 28)

http://www2.mmm.ucar.edu/wrf/users/wrfv3.9/mp28_updated.html