ANL488 Project Proposal

Comparison of SARIMA and LSTM models

in forecasting solar irradiance



Submitted by:

Chen Guo Hao, Alvin

School of Business

Singapore University of Social Sciences

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**Chapter 1: Introduction**

Climate change has triggered unprecedented phenomena across the globe, such as rising temperature and sea levels, loss in biodiversity, as well as compromised food security (IPCC, 2022). Left unchecked, these events will cascade into extreme weather events, mass extinctions and population displacements (IPCC, 2022). With more than two-thirds of CO2 production attributed to power generation, authorities such as the Singapore government and businesses worldwide have begun exploring cleaner alternatives such as renewable energy (IEA, 2021).

While Singapore is constrained by limited land resources, insufficient wind speeds and hydropower, it boasts intensive solar resources with 1,580 kWh/m2 of irradiation per annum, hence positioning photovoltaic (PV) systems as an ideal source of clean energy generation (NCCS, 2022). As part of the Green Plan, the Singapore government targets at least 2 GWp of PV generation before 2030, hence fulfilling at least 4% of its current electricity demand (NCCS, 2022). To achieve this, the government provides incentives to promote the financial viability of solar projects for private developers (Oh, 2022). One example would be the SolarNova programme, where private solar developers such as Sunseap are contracted to install PV systems across various government agencies (HDB, 2021). While these private developers finance and maintain ownership of the solar projects, they recuperate costs by selling the solar energy generated to the contracted agencies. As a result, the project payback period and return on investment relies on the quantity of energy generated from PV systems.

**Business** p**roblem**

While solar developers stand to benefit from Singapore’s abundant sunlight, a key issue with solar assets would be intermittent generation (NCCS, 2022). PV generation is strongly dependent on solar irradiation – the quantity of sunlight received per square meter, characterized by high variability due to weather parameters such as cloudy skies or time of day (Alsharif et al., 2019). As solar developers require a feasibility study of the energy potential and economic benefits before investing in PV systems, the need for an accurate irradiance forecast emerges.

To mitigate solar intermittency, data science models can be applied to forecast irradiance across various time intervals. There are 3 main benefits to irradiance forecasting, namely: PV planning for developers, grid stabilization for utility operators, and optimisation of distributed energy assets for residential and commercial owners (Qing & Niu, 2018). Through the application of solar forecasting, the economic benefits of PV system projects can be estimated, whether it be revenue from selling solar energy to the grid, or costs saved from replacing purchased electricity with self-generated solar energy (Kumar & Subathra, 2018). Forecasting irradiance will not only help validate economic prospects of PV projects, but also support grid stability by helping utility-scale operators forecast periods of lower PV yield and plan ahead, calibrating their fuel mix to minimise grid disruptions (IRENA, 2020). Lastly, owners of co-located PV-storage systems can consolidate forecasted solar generation with energy consumption demands to achieve peak shaving (Rana et al., 2022).

**Research** o**bjectives**

The **business objective** is to leverage the forecasted solar irradiance to reduce uncertainty associated with intermittent solar generation, facilitating the calculation of economic benefits for PV systems. The **data mining objective** is to forecast the daily solar irradiance for the next one-year period using historical solar irradiance and other weather parameters as inputs.

**(538 words)**

**Chapter 2: Literature review**

Over the past decades, the evolution of computer processing hardware and advancements in artificial intelligence have led to several forecasting models being proposed. Based on historical sequence, numerical weather predictions (NWP) were the pioneering algorithms, followed by statistical approaches such as the Box-Jenkins (ARIMA) methodology, with non-linear algorithms such as neural networks being the avant-garde approach. To develop a comprehensive view and devise the optimal model, this literature review will examine research from each algorithm type (Maimouna et al., 2013).

Before mainframe computers became commonplace, solar irradiance was predominantly forecasted using NWP (Yang, 2018). NWP operates by modelling atmospheric data with mathematical equations to provide weather forecasts. While machine learning algorithms have replaced NWP as the tool of choice, Verbois et al. (2018) explored a hybrid approach of combining NWP with statistical learning to forecast hourly irradiance in Singapore. Using data collected from 25 meteorological stations, Verbois et al. (2018) applied the WRF – an NWP permutation which offers more flexibility in parameter tuning to suit weather simulations. While the WRF model produced lowest RMSE compared to benchmark models, both the benchmark models (Smart Persistence and Climatological Model) were not statistical nor machine learning algorithms. Hence, it cannot be concluded whether the NWP remains the methodology of choice without benchmarking against modern high-performing algorithms. Furthermore, the mathematical equations used in NWP forecasts tend to produce high error rates (Ihshaish et al., 2012).

To overcome NWP’s limitations, the sphere of statistical methods introduced the ARIMA model, which then became one of the most researched algorithms for irradiance forecasting (Parasyris et a., 2022). Colak et al. (2015) explored the use of ARIMA and ARMA models in forecasting hourly irradiation across multi-year periods. It was discovered that ARIMA was the top performing model with an improvement percentage of over 70% as compared to the Persistence model (Colak et al., 2015). However, while ARIMA produced high forecasting accuracy for hourly irradiance, it was noted that the error rate compounds significantly when the forecasting horizon is extended beyond a day (Parasyris et a., 2022). Furthermore, meteorological data is seasonal in nature and the ARIMA algorithm could not account for seasonal weather variations. To mitigate this challenge, seasonal ARIMA (SARIMA) models were introduced to support prolonged irradiance forecasts.

Alsharif et al. (2019) investigated the application of SARIMA models to forecast solar irradiance in Korea on both day and month basis. Using 37 years of historical hourly irradiation data collected from the Korean Meteorological association, Alsharif et al. (2019) pre-processed the data into two separate types: first the daily average irradiation, followed by monthly average irradiance. Further data treatment steps involved removing outliers, interpolating missing inputs, as well as treating irradiance readings which were zero (e.g., irradiance during the night). A key difference for SARIMA would be the need for stationary tests and differencing, followed by an ACF and PACF test to identify auto-regressive (AR) and moving average (MA) terms. While several combinations were identified for the SARIMA model parameters, each combination was tested for the RMSE, which is used for model scoring. The predicted results were then compared with true values from the testing data, providing the standardised residual to test for goodness of fit. The Jarque-Bera test – a test which checks if the kurtosis and skewness of sampled data align with normal distribution, was performed on the standardised residual. As the ACF and PACF remained within the 95% confidence interval, the residuals were deemed white noise and hence the SARIMA model was capable of forecasting irradiance.

Similar to Alsharif et al. (2019), a study by Shadab et al. (2020) also applied the SARIMA approach to forecasting monthly irradiance. Using 34 years of monthly irradiation data collected from NASA, Shadab et al. (2020) followed the conventional SARIMA process by including tests for stationarity, determining AR and MA parameters, residual checking, and forecasting. In contrast to Alsharif et al. (2019) single point forecast however, Shadab et al. (2020) extended the scope to spatial forecasts by forecasting for several regions concurrently. Through analysing the irradiation of multiple regions, Shadab et al. (2020) could consequently present the optimal location for PV installation.

As compared to NWP and machine learning algorithms such as ANN and LSTM, the advantage of Shadab et al. (2020) and Alsharif et al. (2019) approach would be that SARIMA does not only require less inputs but are also easier to interpret as compared to e.g., neural networks which are modelled like “black-boxes”. While neural networks perform better for high resolution forecasts such as irradiance over 5-minute intervals, SARIMA performs better for lower resolution forecast such as daily intervals (Reikard, 2009). Another issue would be that the model does not consider exogeneous variables. For example, solar irradiance can be influenced by independent variables such as cloud type, precipitation, dew point, temperature, and humidity (Qing & Niu, 2018). As a result, both Shadab et al. (2020) and Alsharif et al. (2019) had to collect a large volume of solar irradiance data to compensate for the lack of deterministic causes, leading to a more computationally expensive data processing.

Moving on to non-linear models, a Singapore-based study by Sharma et al. (2016) examines the application of mixed wavelet neural networks (WNN) to forecast solar irradiance on both 15-minute and hourly intervals. WNNs combine the flexible learning features of artificial neural networks with wavelet analysis’s signal compression to model high dimension and frequency data, in this case solar irradiation (Sharma et al., 2016). For data collection, 12-months of 15-minute interval irradiance was collected from 25 irradiance monitoring stations across Singapore. As compared to benchmark models including ARIMA, Multilayer perceptron (MLP), and Error-Trend-Seasonality (ETS), the WNN model was observed to have lower NRMSE in general. Another observation from the model output was a reduction in accuracy in 15-min irradiance forecasts, as opposed to 1-hour forecasts. While the WNN model required less training time as compared to the ANN approach, linear models such as ARIMA still produce better accuracy and are less computationally expensive (Zhang et al., 2019). Furthermore, Sharma et al. (2016) did not include exogeneous variables such as precipitation, temperature, humidity which could have improved model performance significantly (Siddiqui et al., 2019).

Beyond classic neural networks, the novel deployment of LSTM has gained prominence as an avant-garde methodology for non-linear forecasting (Qing & Niu, 2018). LSTM is a type of RNN which uses useful patterns from sequential data to provide accurate forecasts (Qing & Niu, 2018). While the recurrent network was previously deemed applicable for forecasting time series data, it not only suffered from gradient vanishing but also less adept to processing long data sequences which limited model performance (Yu et al., 2019). To address this challenge, the LSTM model was subsequently developed. In the data collection stage, Qing & Niu (2018) collected hourly irradiance from a solar plant in Cape Verde, Santiago. The time series data spanned for 30 months and was dated from 2011 to 2013. Besides solar irradiation data, the following inputs were gathered: type of weather, temperature, speed of wind, dew point, humidity, and temperature. In the data preparation step, feature extraction was performed on the irradiance date and time, hence creating 3 additional variables: the month of data, day in month, as well as the hour. Linear scaling normalization was then performed on the data to achieve faster convergence. For the modelling stage, 3 models were generated. Compared to other forecasting algorithms such as ANN, linear regression, persistence method, the LSTM had the best performance as it consistently produced the lowest RMSE. In the final model, 11 years of data from 2006 to 2016 was used instead, with data before 2015 used as training and data after 2015 as testing. In this case, LSTM’s RMSE decreased by 42.9% against BPNN, evidencing that the LSTM model performs better with larger datasets.

While majority of past research worked with quantitative irradiance data, Siddiqui et al. (2019) advanced the LSTM algorithm further by modelling satellite-based imagery data. To achieve this, a hybrid model was developed through integration with CNN. Using images collected from sky-cameras in Colorado, Siddiqui et al. (2019) applied CNN to encode the images and extract incident light data. Besides encoding, the data preparation also included normalization which is observed to be a vital LSTM pre-processing step with cross-reference to the Qing & Niu (2018) study. As compared to other LSTM-CNN algorithms however, Siddiqui et al. (2019) collected auxiliary data such as weather parameters in parallel from sensors and integrated with the encoded data to boost model accuracy. After splitting the dataset into an 60%:40% train-test ratio to simulate nowcasting performance, LSTM was applied to each data types, followed by concatenation into a single layer for testing and calculation of nMAP. From comparison against benchmark models, the CNN-LSTM algorithm provided more accurate forecasting.

As compared to linear models such as SARIMA forecasting by Alsharif et al. (2019), the LSTM model deployed by Qing & Niu (2018) and Siddiqui et al. (2019) incorporated exogeneous variables such as other weather conditions. Despite LSTM’s high model accuracy however, it is computationally expensive to train due to the complex layers and high number of inputs required to provide an accurate forecast. Furthermore, the high number of inputs needed also results in LSTM being prone to overfitting.

Across the assortment of literature presented, it would appear that while several studies proposed different methodologies to forecast irradiance, there is no universal approach as the type of algorithm prescribed is dependent on the data mining objective, which is in turn reliant on the research problem. On one hand, machine learning algorithms, namely LSTM tend to be effective for nowcasting applications, such as hourly and daily irradiance to optimize PV-storage synergy (Nuray et al., 2021; Qing & Niu, 2018); On the other hand, statistical methods such as SARIMA tend to be relevant for longer horizons, as in the case of daily to monthly forecasting to calculate the economic benefit of PV projects (Shadab et al., 2020; Alsharif et al., 2019). While SARIMA and LSTM are the top contenders for their linear and non-linear models respectively, a direct comparison has yet to be published in the discipline of irradiance forecasting (Shadab et al., 2020; Alsharif et al., 2019). Hence, we will employ both the approaches taken by Alsharif et al. (2019) for SARIMA, as well as Qing & Niu (2018) for LSTM to forecast daily irradiance.

**(1723 words)**

**Chapter 3: Data** u**nderstanding**

To develop our forecast, we collected 12 years of Singapore’s historical irradiance from a publicly accessible database. Our data source would be a XLSX file downloaded from the NASA Power renewable energy dataset, which provides weather parameters collected from satellites to facilitate the system planning phase for PV and wind powered assets (NASA, n.d.). Not only did Shadab et al. (2020) perform irradiance forecasting using the NASA Power dataset, but a dedicated study by Sayago et al. (2019) confirmed that the data product is reliable for forecasting solar irradiance.

To account for weather variance based on location, we collected data from 5 different locations in Singapore. More details about the locations are provided in Table 1 and Figure 1.

|  |  |  |  |
| --- | --- | --- | --- |
| **Location** | **Region** | **Latitude** | **Longitude** |
| Woodlands | North | 1.4373 | 103.778 |
| Mount Faber | South | 1.2734 | 103.8178 |
| Changi Airport | East | 1.3603 | 103.9918 |
| Nanyang Technological University | West | 1.3505 | 103.6811 |
| Upper Pierce Reservoir | Central | 1.3683 | 103.8022 |

Table 1: Coordinates of location for data collection

Map

Description automatically generated

Figure 1: Visualization of data collection points with markers

The daily irradiance collected spans from January 1st, 2010, to July 24th, 2022, amounting to 4,588 rows of inputs. 15 relevant variables were acquired, mostly comprising of temporal and spatial data. Under the weather variable column on table 2, all sky surface shortwave downward irradiance represents the irradiation which PV assets utilise in generating solar energy (Wang et al., 2021). While only the input time and downward irradiance are needed for SARIMA modelling, the other weather parameters are common input parameters to be used in the LSTM model (Parasyris et al., 2022; Qing & Niu, 2018).

|  |  |  |  |
| --- | --- | --- | --- |
| **Weather variable** | **Dataset label** | **Data Type** | **Value Range**  **(Min – Max)** |
| Year of input (YYYY) | Year | Ordinal | 2010 – 2022 |
| Month of input year (MM) | Month | Ordinal | 1 – 12 |
| Day of the month of input (DD) | Day | Ordinal | 1 – 31 |
| All Sky Surface Shortwave Downward Irradiance  (kWh/m2/day) | ALLSKY\_SFC\_SW\_DWN | Continuous | 0.45 – 7.12 |
| Daily Average Temperature (°C) | T2M | Continuous | 23.87 – 29.99 |
| Daily Average Dew/Frost Point (°C) | T2MDEW | Continuous | 20.5 – 26.26 |
| Daily Average Wet Bulb Temperature (°C) | T2MWET | Continuous | 22.3 – 27.54 |
| Daily Average Humidity (g/kg) | QV2M | Continuous | 15.01 – 21.36 |
| Daily Average Precipitation (mm/day) | PRECTOTCORR | Continuous | 0 – 153.75 |
| Daily Average Surface Pressure (kPa) | PS | Continuous | 100.2 – 101.17 |
| Daily Average Wind Speed at 10 Meters (m/s) | WS10M | Continuous | 0.65 – 6.07 |
| Daily Average Wind Direction at 10 Meters (Degrees) | WD10M | Continuous | 4.38 – 347.81 |
| Daily Average Wind Speed at 50 Meters (m/s) | WS50M | Continuous | 0.88 – 8.33 |
| Daily Average Wind Direction at 50 Meters (Degrees) | WD50M | Continuous | 7 – 348.12 |
| Daily Average All Sky Insolation Clearness Index (Dimensionless) | ALLSKY\_KT | Continuous | 0.05 – 0.68 |

Table 2: Dataset variables with range of values

Text

Description automatically generated with low confidence

Figure 2: Example of one-day input

As Sharma et al. (2011) uncovered, there is a significant correlation between solar intensity with temperature, precipitation, clearness of sky, humidity, dew point, wind speed and direction. Furthermore, surface pressure data is included as past research have indicated that the inclusion of atmospheric pressure as input parameters improves model performance (Ssekulima, 2016). As PV projects in Singapore are not only developed on ground level but also on higher elevation such as HDB rooftops, input parameters for wind direction and wind speed at 50 meters above the earth surface are appended as input parameters (NCCS, 2022). The insolation clearness index refers indicates the degree of clearness in the atmosphere, as high cloud coverage may reduce irradiation received from the sun (Yu et al., 2019). From the NASA Power documentation, it is also indicated that missing data is replaced by the ‘-999’ value. As these missing values are present for downward irradiance and insolation clearness index, further data preparation will be necessary.

Table

Description automatically generated

Figure 3: Correlation between irradiation and other parameters

Using the Panda library’s corrwith() function, we calculate the pairwise correlation between solar irradiation and other parameters in the dataset. From Figure 3, we can conclude that our findings align with Sharma et al. (2011), as the variables with highest correlation include sky insolation index, precipitation, temperature, and wind direction.

**Data preparation**

The dataset is first read into Python through the Pandas data frame module. By performing a data quality check, there are 9 missing entries for downward radiation and 170 missing values for insolation clearness index. To impute the missing information, forward linear interpolation is performed using historical data as reference. After filling in the missing data, removal of outliers was then carried out. Data from the 5 locations is then consolidated by computing the daily average. After obtaining the national average daily irradiance, a stationarity test is performed to check if we need to detrend through differencing. Hence, the monthly (in blue) and annual (in orange) average is computed and visualized onto Figure 4.

Chart, line chart, histogram

Description automatically generated

Figure 4: Monthly and annual average solar irradiance

As indicated in figure 4, the time series is already stationary, hence no further differencing is required. Furthermore, there is also a pattern of seasonality on the monthly basis, with lower irradiance at the beginning and end of each year. Notably, irradiance tends to rise in the 1st and 3rd quarter, then falling again in the 2nd and 4th quarter of each year. While normalization is not necessary for SARIMA due to its univariate inputs, LSTM requires several input parameters from our dataset, hence min-max normalization is conducted. The flow of data preparation is as illustrated in Figure 5.

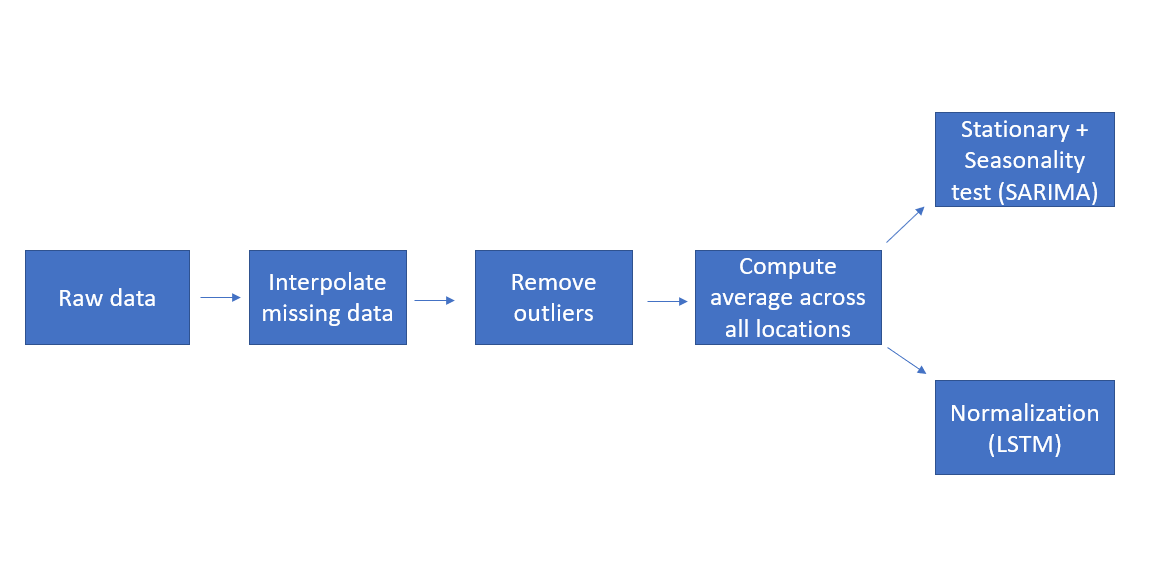


Figure 5: Data preparation process

**(887 words)**

**Chapter 4:** **Proposed modelling**

Based on our literature review, SARIMA and LSTM models have been identified to be the optimal models and hence are chosen as our modelling process. For SARIMA modelling, the “Statsmodel” and “Pmdarima” package will be imported into Python. On the other hand, the “TensorFlow Keras” library will be applied for non-linear forecasting as it is especially effective in developing RNN models such as LSTM (Yu et al., 2019). After generating the models, The MSE, RMSE, and MAE metric will be used as metrics to compare between the model performance and identify the best performing model for forecasting irradiance.

**SARIMA**

The first model will be built using SARIMA’S Box-Jenkins methodology. As a permutation of the ARIMA algorithm, SARIMA is similarly constituted by the autoregressive (AR) and moving average (MA) terms (Shadab et al., 2020). Worth mentioning would be that SARIMA does not only carry over ARIMA’s reliability and simplicity in forecasting solar irradiance but has also been proven to be effective in modelling seasonal data such as daily solar irradiance over the year (Alsharif et al., 2019). Our approach would be to first identify the time series for stationarity and detrend if non-stationary, followed by identifying the AR and MA terms by plotting the ACF and PACF, then fitting the model based on the identified parameters and training dataset. After forecasts are generated using the trained model, the forecasted irradiance will be compared against the testing data to calculate residuals (Alsharif et al., 2019). Should the residuals be autocorrelated, we will reiterate from the parameter identification stage to identify better parameters; assuming the model is adequate however, we will then proceed to model deployment by forecasting daily irradiance for the next one-year period.

Diagram

Description automatically generated

Figure 6: SARIMA modelling process

**LSTM**

Unlike the SARIMA methodology, LSTM requires other input weather parameters as explored in the data understanding phase. By taking in these inputs, the LSTM algorithm applies a recurrent connection within the hidden layer to capture information associated with sequential data (Yu et al., 2019). Furthermore, the LSTM’s holds a memory cell which retains the captured information over longer time periods and preserves useful constituents using its input and forget gates, hence avoiding the vanishing gradient issue associated with traditional RNNs (Qing & Niu, 2018). Hence, positions LSTM as the optimal algorithm for our dataset, considering that our historical irradiance spans from 2010 to 2022. Furthermore, as covered in the literature review, the LSTM is one of the best performing machine learning algorithms to accurately forecast solar irradiance.

After performing min-max normalization in the data preparation stage, we define the LSTM model parameters, such as determining the number of hidden and LSTM layers to use. Besides the number of layers, we will also need to provide the number of features in our irradiance dataset, as well as the number of timesteps. Afterwards, we fit the normalized data into the model for training, using a similar train: test split as the SARIMA algorithm. The trained model is then validated using the testing dataset, allowing us to derive the RMSE, MAE, and MSE. After deriving these figures, we compare the result with our SARIMA performance to identify the better performing model. Assuming LSTM has the better model performance, we will then proceed to deploy the LSTM in forecasting solar irradiance for the next one-year period.

**(554 words)**

**Chapter 5:** **Proposed schedule**

The Gantt chart in figure below illustrates the planned timeline for this research project. The modelling stage (SARIMA) is to begin shortly after the proposal submission, followed by LSTM. As indicated in the September plan, we intend to complete LSTM before the project presentation so that we can evaluate and compare model performance. Last but not least, feedback gathered from the presentation will be remedied and onboarded concurrently with the finalization of report for submission before 7th November.

Timeline

Description automatically generated

Figure 6: Project schedule plan

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**(87 words)**

**References**

Alsharif, M., Younes, M., & Kim, J. (2019). Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation: The Case Study of Seoul, South Korea. Symmetry, 11(2), 240. doi:10.3390/sym11020240

Colak, I., Yesilbudak, M., Genc, N., & Bayindir, R. (2015). Multi-period Prediction of Solar Radiation Using ARMA and ARIMA Models. 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA). doi:10.1109/icmla.2015.33

Diagne, M., David, M., Lauret, P., Boland, J., & Schmutz, N. (2013). Review of solar irradiance forecasting methods and a proposition for small-scale insular grids. Renewable and Sustainable Energy Reviews, 27, 65–76. doi:10.1016/j.rser.2013.06.042

Fathima, T. A., Nedumpozhimana, V., Lee, Y. H., Winkler, S., & Dev, S. (2019). Predicting Solar Irradiance in Singapore. 2019 Photonics & Electromagnetics Research Symposium - Fall (PIERS - Fall). doi:10.1109/piers-fall48861.2019.9021313

HDB (2021). SolarNova Programme. Retrieved July 25th, 2022, from: https://www.hdb.gov.sg/about-us/our-role/smart-and-sustainable-living/solarnova-page

Ihshaish, H., Cort́es, A., & Senar, M. A. (2012). Towards Improving Numerical Weather Predictions by Evolutionary Computing Techniques. Procedia Computer Science, 9, 1056–1063. doi:10.1016/j.procs.2012.04.114

IPCC. (2022). Summary for Policy Makers. Retrieved July 25th, 2022, from: https://www.ipcc.ch/report/ar6/wg2/downloads/report/IPCC\_AR6\_WGII\_SummaryForPolicymakers.pdf

IRENA. (2020). ADVANCED FORECASTING OF VARIABLE RENEWABLE POWER GENERATION. Retrieved July 25th, 2022, from: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Jul/IRENA\_Advanced\_weather\_forecasting\_2020.pdf%20?%20%20la=en&hash=8384431B56569C0D8786C9A4FDD56864443D10AF

Manoj Kumar, N., & Subathra, M. S. P. (2019). Three years ahead solar irradiance forecasting to quantify degradation influenced energy potentials from thin film (a-Si) photovoltaic system. Results in Physics, 12, 701–703. doi:10.1016/j.rinp.2018.12.027

NASA. (2021). The POWER Project. Retrieved July 25th, 2022, from: https://power.larc.nasa.gov/

NCCS. (2022). SINGAPORE’S APPROACH TO ALTERNATIVE ENERGY. Retrieved July 25th, 2022, from: https://www.nccs.gov.sg/singapores-climate-action/singapore-approach-to-alternative-energy/

Oh, T. (2022). Government considering more initiatives to push solar energy adoption in Singapore. The Business Times. Retrieved July 25th, 2022, from: https://www.businesstimes.com.sg/government-economy/government-considering-more-initiatives-to-push-solar-energy-adoption-in

Ouma, Y. O., Cheruyot, R., & Wachera, A. N. (2021). Rainfall and runoff time-series trend analysis using LSTM recurrent neural network and wavelet neural network with satellite-based meteorological data: case study of Nzoia hydrologic basin. Complex & Intelligent Systems. doi:10.1007/s40747-021-00365-2

Parasyris, A., Alexandrakis, G., Kozyrakis, G., & Spanoudaki, K. (2022). Predicting Meteorological Variables on Local Level with SARIMA, LSTM and Hybrid Techniques. Atmosphere, 13(878), doi:10.3390/atmos13060878

Qing, X., & Niu, Y. (2018). Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. Energy, 148, 461–468. doi:10.1016/j.energy.2018.01.177

Rana, M., Atef, M., Sarkar, R., & Uddin, M. (2022). A Review on Peak Load Shaving in Microgrid—Potential Benefits, Challenges, and Future Trend. Energies, 15(6):2278, doi:10.3390/en15062278

Reikard, G. (2009). Predicting solar radiation at high resolutions: A comparison of time series forecasts. Solar Energy, 83(3), 342–349. doi:10.1016/j.solener.2008.08.007

Sayago, S., Ovando, G., Almorox, J., & Bocco, M. (2019). Daily solar radiation from NASA-POWER product: assessing its accuracy considering atmospheric transparency. International Journal of Remote Sensing, 1–14. doi:10.1080/01431161.2019.1650986

Shadab, A., Ahmad, S., & Said, S. (2020). Spatial forecasting of solar radiation using ARIMA model. Remote Sensing Applications: Society and Environment, 20, 100427. doi:10.1016/j.rsase.2020.100427

Shamim, M. A., Remesan, R., Bray, M., & Han, D. (2015). An improved technique for global solar radiation estimation using numerical weather prediction. Journal of Atmospheric and Solar-Terrestrial Physics, 129, 13–22. doi:10.1016/j.jastp.2015.03.011

Sharma, N., Sharma, P., Irwin, D., & Shenoy, P. (2011). Predicting solar generation from weather forecasts using machine learning. 2011 IEEE International Conference on Smart Grid Communications (SmartGridComm). doi:10.1109/smartgridcomm.2011.61

Sharma, V., Yang, D., Walsh, W., & Reindl, T. (2016). Short term solar irradiance forecasting using a mixed wavelet neural network. Renewable Energy, 90, 481–492. doi:10.1016/j.renene.2016.01.020

Siddiqui, T. A., Bharadwaj, S., & Kalyanaraman, S. (2019). A Deep Learning Approach to Solar-Irradiance Forecasting in Sky-Videos. 2019 IEEE Winter Conference on Applications of Computer Vision (WACV). doi:10.1109/wacv.2019.00234

Ssekulima, E. B., El Moursi, M. S., Al Hinai, A., & Anwar, M. B. (2016). Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: a review. IET Renewable Power Generation, 10(7), 885–989. doi:10.1049/iet-rpg.2015.0477

Vakitbilir, N., Direkoglu, C., & Hilal, A. (2021). Prediction of Daily Solar Irradiation Using CNN and LSTM Networks. ICAFS-2020, 230-238, doi:10.1007/978-3-030-64058-3\_28

Verbois, H., Huva, R., Rusydi, A., & Walsh, W. (2018). Solar irradiance forecasting in the tropics using numerical weather prediction and statistical learning. Solar Energy, 162, 265–277. doi:10.1016/j.solener.2018.01.007

Wang, W., Feng, J., & Xu, F. (2021). Estimating Downward Shortwave Solar Radiation on Clear-Sky Days in Heterogeneous Surface Using LM-BP Neural Network. Energies, 14(2), 273. doi:10.3390/en14020273

Yang, D., Kleissl, J., Gueymard, C. A., Pedro, H. T. C., & Coimbra, C. F. M. (2018). History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. Solar Energy, 168, 60–101. doi:10.1016/j.solener.2017.11.023

Yu, Y., Cao, J., & Zhu, J. (2019). An LSTM Short-Term Solar Irradiance Forecasting Under Complicated Weather Conditions. IEEE Access, 7, 145651–145666. doi:10.1109/access.2019.2946057

Zhang, Y., Yang, H., Cui, H., & Chen, Q. (2019). Comparison of the Ability of ARIMA, WNN and SVM Models for Drought Forecasting in the Sanjiang Plain, China. Natural Resources Research. doi:10.1007/s11053-019-09512-6