ANL488 Final Project Report

**Comparison of SARIMA and LSTM models**

**in forecasting solar irradiance**



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**Abstract**

With the imminent risks posed by global warming, businesses and governments are pushing for climate friendly solutions such as renewable installations. However, renewable generation is more challenging to forecast than traditional fuel sources as it is subjected to highly variable weather conditions. In terms of geographic scope, this study aims to explore renewable generation potential in Singapore, with a focus on solar assets due to Singapore’s tropical climate. As identified in the literature review, there were numerous methodologies to forecast solar irradiance, from numerical weather predictions, linear, to non-linear algorithms. While SARIMA and the novel LSTM consistently outperformed other linear and non-linear models, there has not been a direct comparison for solar irradiance. Therefore, this study aims to compare and identify the champion model based on model performance.

Aligning with the CRISP-DM framework, the data preparation steps included removing outliers, normalization, and filling in missing variables. Using the 2010 to 2020 solar irradiance as the training data, inputs for 2021 were used for the testing data. Besides building the SARIMA model, 2 LSTM models with different hyperparameters were tested. Between the 2 LSTM models, the setting with 100 epochs, 120 steps, as well as a validation split of 0.1 delivered better accuracy. Comparing both linear and non-linear models, we discovered that the LSTM outperformed the SARIMA (1,0,1) × (0,1,1,7) model with a significantly lower error margin. The results indicate that the LSTM model would be the optimal model for solar project developers to maximize irradiance forecasting accuracy and minimize project investment risk.

(252 words)

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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.

**1.1. 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 applications for irradiance forecasts, 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 cost savings 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 elevate grid stability by helping utility-scale operators forecast periods of lower PV yield and plan, calibrating their fuel mix to minimize 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).

**1.2. 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 identify the best model for forecasting annual solar irradiance using historical solar irradiance and other weather parameters as inputs.

**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 implementation, 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 very high error rates with forecasts beyond 3 days (Ihshaish et al., 2012). As this study examines irradiance forecasts for one-year horizons, the NWP will not be excluded from the project scope.

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.

**Chapter 3: CRISP-DM Methodology**

To develop a robust framework for examining the business problem, we will be applying the CRISP-DM guidance (Hotz, 2022). Established in 1999, CRISP-DM is the industry standard process for data science projects. There are 6 phases: namely understanding the business, analyzing the data, performing data treatment, integrating the data science model, evaluation the results, and lastly deploying the findings. As we have identified the business problem and identified the data mining objectives, the first phase has been completed. Based on the objectives and background research identified in phase 1, we will then collect the relevant data, audit the quality of the data, and decipher the characteristics and preliminary insights in phase 2. For the data preparation steps, we will apply the information found from the data quality check and treat the data accordingly, such as filling in for missing information, removing outliers, or performing data normalization. Upon finishing the data preparation, we can then determine the appropriate models based on literature review and relevance to our objectives, then building the model and fitting the data. Phase 5 would consist of evaluating the results we retrieved from the modelling phase, such as comparing across different models using a common metric to identify which model has the better performance.

After identifying the champion model, the last phase would involve deploying the model to support our business objectives, which in this case involves scoping the solar project bankability and reducing the level of risk associated with investment. By equipping solar developers with the best performing model, these developers can use the forecasts of the irradiance and calculate the most accurate generation and revenue potential of their investments, enabling them to make investment decisions.

**Chapter 4: Data** u**nderstanding and preparation**

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 Dec 31st, 2020, amounting to 4,018 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.

**4.2. Data preparation**

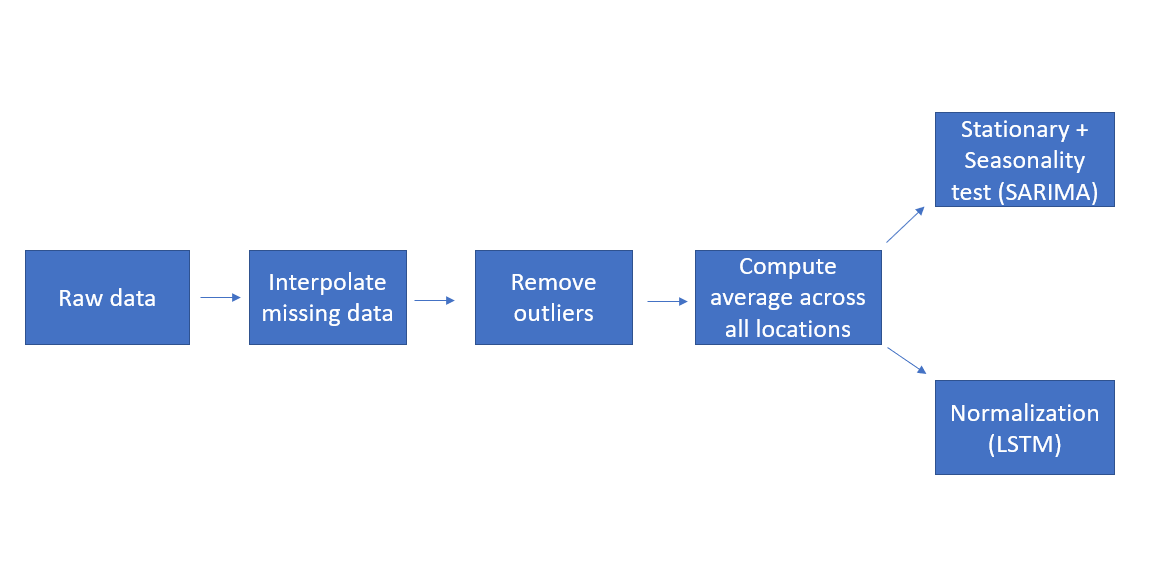
The dataset is first read into Python through the Pandas data frame module. By performing a data quality check, there are 9 missing entries for downward radiation and 170 missing values for insolation clearness index. To impute the missing information, forward linear interpolation is performed using historical data as reference. This method assumes a linear relationship between inputs, and populates missing data based on existing values. 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. As Singapore’s land size is relatively small, the NASA Satellite resolution is not high enough to differentiate parameters across the 5 locations due to the small geographical proximity. Hence, the inputs across the 5 regions are the same as the national 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. 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 with varying scales 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*

**Chapter 5:** **Modelling**

While various models have been explored in the literature review, SARIMA and LSTM models have consistently outperformed out respective linear and non-linear models. Hence these 2 models have been identified to be the linear and non-linear champion models and 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.

**5.1. SARIMA**

As a permutation of the ARIMA algorithm, SARIMA is constituted by the autoregressive (AR) and moving average (MA) terms (Shadab et al., 2020). The AR term represents the dependence of irradiance forecasts based on historical inputs, while MA explains the average changes in irradiance over time. Furthermore, 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 annual daily solar irradiance (Alsharif et al., 2019). Our approach would be to first identify the time series for stationarity and detrend if non-stationary, identifying the AR and MA terms by plotting the autocorrelation function (ACF) and Partial autocorrelation function (PACF), then fitting the model based on the identified parameters and training dataset. The ACF explains both the direct and indirect correlation of the time series with its time-shifted version, while the PACF only explains direct correlation. 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 return to the parameter identification stage to explore better parameters; assuming the model is adequate however, we will then proceed to model deployment.

Diagram

Description automatically generated

*Figure 6: SARIMA modelling process*

As discussed in our literature review, the weakness of past SARIMA studies would be the lack of accountability for exogeneous variables such as temperature and humidity. Hence, we will be applying the SARIMAX approach using the parameter format:

*(p, d, q) × (P, D, Q, M)*

The first parentheses (p, d, q) are orders derived from AR, differencing, and MA respectively. The second parentheses (P, D, Q, M) represent the seasonal order for AR, difference, MA, and the quantity of time steps per seasonal period. To identify whether our time series requires differencing, a Dickey-Fuller (ADF) test was applied to check for stationarity. The ADF indicates whether the dataset’s unit root is contained within the model. Furthermore, the output of an ADF test is binary, as the p-value greater than the significant level implies that the unit root is present, and differencing is needed due to the model’s non-stationarity. As our p-value was less than the significance level of 0.05, we rejected the null hypothesis and concluded that our time series is stationary without the need for differencing. To derive the p and q terms, we then plot the ACF and PACF respectively.

Chart, scatter chart

Description automatically generated

*Figure 7: Plot of ACF*

Chart, scatter chart

Description automatically generated

*Figure 8: Plot of PACF*

As we are forecasting daily irradiance, we used 30 lags to identify for AR and MA processes. In figure 7 and 8, we can observe that while there is significant autocorrelation for the first two lags, the values for ACF and PACF decay for the rest of the lags.

To find the optimal SARIMAX parameters, we included several combinations to determine the best model. Akaike information criterion (AIC) is a common metric for measuring prediction error as it quantifies the model’s information loss upon fitting the training data. Using the maximum likelihood estimation as a basis for scoring, the model with the lowest AIC would provide the best fit. Using python’s statsmodel package to create possible models and AIC criterion for model scoring, the converged model with the lowest AIC and best fit is (1,0,1) × (0,1,1,7)7.

*Θ(L)1θ(L7)1Δ1yt=Φ(L)1ϕ(L7)0Δ1ϵt +βi*

*Equation 1: SARIMAX equation with optimal parameters*

Using the parameters with lowest AIC, our SARIMAX equation should resemble equation 1. Our next step would then be to fit the training data based on the model parameters. For the train: test split, we used data from 2010 to 2020 as training data, followed by 2021 irradiance for testing data.

Table

Description automatically generated

*Table 3: Model performance for (1,0,1) × (0,1,1,7)7*

Using the SARIMAX parameters identified, we fitted the training model and derived the following results as illustrated in Table 3. The coefficients are 0.8320 for AR component,

-0.6218 for the MA, -1.0048 for seasonal MA, followed by 1.1400 for the sigma2, also known as the variance of error terms. After training the model, we would need a scoring metric to evaluate model performance. As we are comparing the SARIMA model against the LSTM approach, we would use RMSE as the common scoring metric. The RMSE and MSE tells us about the error between actual vs forecasted value, hence a lower figure would be ideal. By comparing the model forecasts with observed data as illustrated in figure 9, our model generated an MSE of 1.57 and a RMSE of 1.25.

Chart

Description automatically generated

*Figure 9: Standardized residual plot for daily irradiance*

To examine the goodness of fit, we then plotted the standardized residual for daily irradiance as illustrated in figure 9. The residual plot tells us if our model has captured the information needed from the time series. While there are a few outliers in figure 9, they fall within the 95% confidence interval as majority of irradiance are between ±3.

Chart, line chart

Description automatically generated

*Figure 10: Correlogram of residuals*

Another measure of model goodness would be the correlogram. This visualization tells us the degree of correlation across different lags. As observed from figure 10, the correlation is within ±0.25 for lag 1 onwards. Hence, we can conclude that the residuals are uncorrelated, and that our model has captured sufficient information for forecasting.

**5.2. LSTM**

![Diagram, schematic

Description automatically 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*Figure 11: LSTM Layer*

*Note. By Rainardi, V., 2021, RNN and LSTM. Accessed at* [*https://dwbi1.wordpress.com/2021/08/07/recurrent-neural-network-rnn-and-lstm/*](https://dwbi1.wordpress.com/2021/08/07/recurrent-neural-network-rnn-and-lstm/)

As illustrated in figure 12, our LSTM model has 3 layers: the input gate which assigns weights based on the significance of different variables, forget gate to retain only useful information, and output gate which manages the information flow. 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). As illustrated in Figure 12, the LSTM’s also 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). All things considered, LSTM is positioned as the optimal non-linear algorithm for our dataset, especially with a longer time period spanning from 2010 to 2021. Furthermore, as supported by 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.

While LSTM requires less steps than SARIMA, it requires more weather parameters and a greater emphasis on hyperparameter tuning to avoid model over and underfitting. Hence, we will be developing 2 LSTM models to test performance using different hyperparameters. As compared to parameters which are derived after model training, hyperparameters are instead defined before training. As the value of these hyperparameters significantly affect model performance, we employed Python’s randomizedsearch to test out a range of hyperparameters and determine the model with the best R2 value. While the randomizedsearch is characterized by fixed iterations and specified hyperparameter range, we also employed Python’s gridsearch which attempts all parameters without limits on the number of iterations. The hyperparameters of interest would be the learning rate which refers to the model’s degree of responsiveness to errors, number of neurons which are used to processed inputs, batch size which refers to the quantity of inputs processed before updating the model, and lastly epochs which is the number of iterations across the entire dataset.

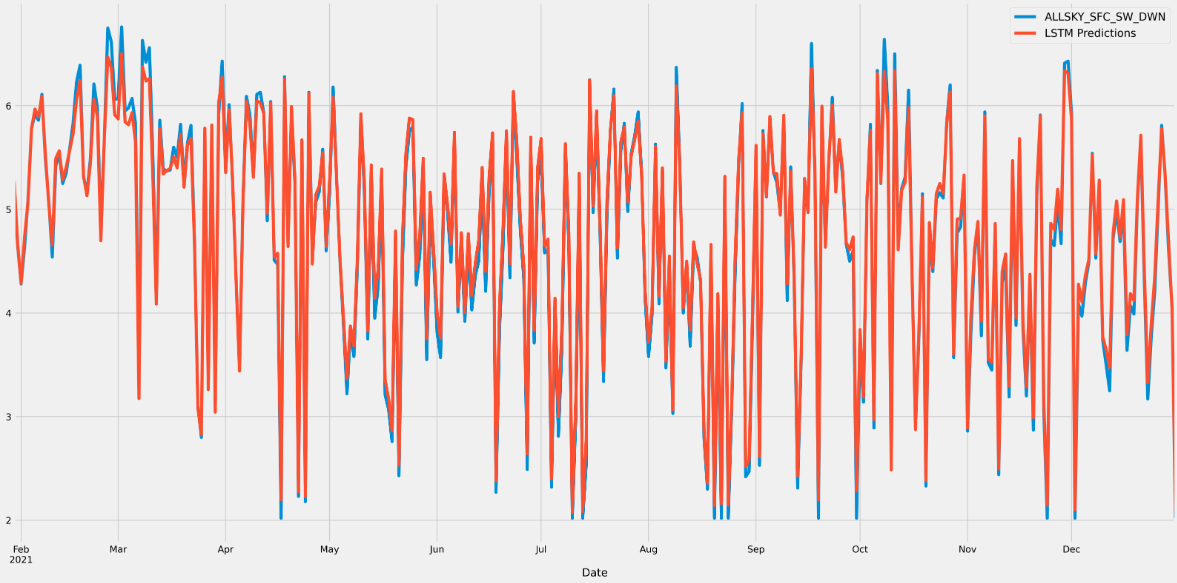
Before building the LSTM model, we split the time series sequence into samples. The reason is due to LSTM’s nature of being a memory-based model, which retrieves information from sequences to create forecasts. After testing several window sizes for lagged values, we discovered that smaller window sizes such as 1 provide more accurate results. To ensure that our model comparison is unbiased, we used the same train: test split as the SARIMA model. Hence for the LSTM model, data from 2010 to 2020 for training and 2021 for testing. While 2 LSTM models with different hyperparameters were generated for comparison and optimization, the model with lower MAE had 100 epochs, 120 steps per epoch, as well as a validation split of 0.1.

Chart, histogram

Description automatically generated

*Figure 12: Model Accuracy from training*

Using MAE as the Y-axis and training-validation for X-axis, we can observe that the model accuracy improves with each epoch, with comparable performance between the training (train) and validation (val) dataset. The model is trained using gradient descent, which aims to identify the best model parameters (also known as the point of convergence) at the point with minimum information loss. As this LSTM model’s loss landscape is large, the number of epochs were limited to 100 to reduce computational expenditure. As illustrated in figure 13, the MAE does not change significantly after the 60th epoch, hence the LSTM model is sufficiently converged.



*Figure 13: LSTM forecast*

After training the model, we then reverse the normalization process to retrieve the original variable scales and perform validation using testing data from 2021. As illustrated from figure 14, we can observe that the LSTM forecasts (in orange) capture the weather variations across the year rather accurately, with small errors in the months of February to March. The MSE and RMSE of this model would be 0.022 and 0.149 respectively.

**Chapter 6: Evaluation**

Chart, line chart

Description automatically generated

*Figure 14: Comparison of models*

By visualizing both forecasts against the testing data, with the yellow, orange, and blue lines being forecasts for LSTM, SARIMA, and testing data respectively, we can observe that the LSTM model is significantly better at capturing the finer variations in irradiance across the year. Furthermore, both the LSTM’s lower MSE and RMSE indicate that LSTM is less prone to errors, and hence the better performing model. On the other hand, the SARIMA forecasts are more concentrated around the median of the testing data and do not seem to capture the changes in irradiance. While the scope of this research focuses on MSE and RMSE as the means of model comparison, some limitations to consider would be the complexity of neural network like LSTM which makes it harder to interpret than SARIMA, as well as the longer computation time as it requires the input of other weather parameters. However, the benefit of including other weather parameters supported by LSTM’s information capture from sequential patterns supports its position as one of the best forecasting algorithms for annual irradiance.

**Chapter 7: Deployment**

This chapter provides an implementation use case to deploy the LSTM model to generate irradiance forecasts in a solar planning project. The process would begin with the solar developer, who intends to expand its business by building new assets. With several location choices to install these assets, the developer would need to assess the project bankability by performing a site survey to collecting data. Using the coordinates of the shortlisted locations, the developer can then collect the 10-year historical weather parameters from the NASA Power database or any similar sources. After collecting the data, the developer can input into the LSTM model designed in this study with the prescribed hyperparameters. Notably, the hyperparameters are subjected to the developer’s discretion as different datasets may require further tuning to provide the lowest RMSE. With the irradiance forecast, the project developer can then generate the project generation potential using the following formula:

*E = A × r × H × PR*

*Equation 2: Calculation methodology for solar generation potential*

Where E refers to the energy generated (kWh2), A is the m2 surface area of the solar panel, r the percentage yield, H the solar irradiation received, and PR the performance ratio which refers to the PV system’s efficiency of converting irradiance to energy. Using the annual H derived from the forecast, the developer can multiply by the other parameters to calculate the annual generation, then multiplied by the contracted energy price (e.g., from power purchase agreements) to estimate the project’s revenue potential. The last step would be to compare the revenue potential with the estimated project cost to determine the return on investment and payback period. Depending on the estimated project returns across various potential sites, the developer would then decide if and which location to develop the project.

**Chapter 8: Conclusion**

With the increasing demand for renewable generation, research on irradiance forecasting methodologies have been a topic of growing interest. The rationale of minimizing forecasting errors is because forecasts with high variation would result in overrepresented estimates of renewable generation, leading to prolonged project payback periods. As a result, project developers need a more accurate model to reduce the risk of project investments. In this study, both linear models such as SARIMA and novelty approaches such as LSTM forecasting networks were presented. The algorithms used to historical daily solar irradiance to forecast daily irradiance within a one-year horizon. Using input data from 2010 to 2020 and 2021 as testing data, the outputs are presented as forecasts for 2021. By calculating the error between forecasted data and the testing data, we derived the RMSE as the common benchmark of model performance. The results of this process have indicated that the LSTM model had an 88.08% improvement in performance as compared to the SARIMA RMSE. Moreover, the simplistic model design of the SARIMA algorithm also resulted in significant underfitting, as supported by its high bias in figure 14. Hence, deploying LSTM models would be more effective in mitigating risks associated with solar projects.

**8.1. Future Research**

While this study examines the performance of various models within the computational environment, future research can involve the examination of model reliability through real-time deployment. Using 2023 as the forecast year with input data from 2022 and prior years, the model can first be applied to forecast irradiance for 2023. After forecasting the irradiance, the developer can apply the irradiance forecast, multiply by the solar panel area, yield and performance ratio to calculate the generation potential. Afterwards, the developer can use IoT sensors to collect real-time generation data and compare the daily forecasts with the actual generation to calculate the variation.

While this study compares different model performance in forecasting irradiance, the dataset collected consists of array inputs including numeric and time inputs. However, irradiance data collected from satellites can also be downloaded in image format, such as the study by Siddiqui et al. (2019). As certain algorithms such as CNN may be more effective based on the format of data source, future studies can explore and compare model performance in the context of image-based irradiance data.

Another opportunity for further research would involve forecasting irradiance on the hourly interval to provide more granular insights. As discussed in the study by Qing & Niu (2018), hourly applications for irradiance can be particularly useful especially in the case of PV-storage systems. As energy prices and solar irradiance fluctuate throughout the day, asset owners can monetize the opportunity by generating solar energy during periods of higher irradiance, storing the excess energy in the storage systems, and then selling the stored energy to the grid when prices are high. This would enable asset owners to maximize their revenue and reduce payback period on solar investments. Assuming asset owners are also using the solar energy generated for self-consumption, a separate forecasting model to forecast energy consumption would need to be built besides forecasting the price of energy for each hour. These models would then be consolidated with the irradiance forecast through an energy management system to identify the optimal timings for selling solar energy to the grid, thus unlocking a lucrative revenue stream for solar investments.

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**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

Hotz, N. (2022). What is CRISP-DM. Retrieved October 2nd, 2022, from: https://www.datascience-pm.com/crisp-dm-2/

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

Rainardi, V. (2021). RNN and LSTMs. Data warehousing and Data science. Retrieved September 25th, 2022, from: https://dwbi1.wordpress.com/2021/08/07/recurrent-neural-network-rnn-and-lstm/

Rana, M., Atef, M., Sarkar, R., Uddin, M., & Shafiullah, G. (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

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