Case Studies in Data Science
Work Integrated Learning Project

Forecasting Solar Radiation using Australian Bureau of Meteorology Station Data

Final Report

Group 5

Moretta Song (S3941559)
Alistair Chitty (S3902003)
Yupeng Du (S3698728)
Melani Aluthge Aluthge Dona (S3835610)
Momitha Yepuri (S3856512)

October 2022

1. Introduction

Globally, the rapid emergence and growth of renewable energy sources such as photovoltaic energy (PV) have highlighted the technological and economic issues that need to be resolved to integrate these into the electricity grid. Australia is in a prime position to include large-scale solar power as a significant component of its energy mix since it has one of the highest levels of solar radiation in the world. Forecasting is important to know when it is optimal to start charging up the batteries, because charging takes time and diverts from the overall output. Optimising battery charging at power plants can help prepare for days with less solar exposure while preventing energy loss. Queensland was Australia's leading large-scale solar state in 2020, generating 3.3 GWh of solar power throughout the year. It was followed by New South Wales with 2.4 GWh and Victoria with just over 1 GWh [1]. As of 30 June 2022, there are over 3.19 million PV installations in Australia, with a combined capacity of over 27.2 gigawatts [2]. This increasing number of solar energy plants has created a need for reliable and accurate forecasts.

The irregular nature of the solar resource, seasonal variations in production, increased cost of energy storage and the balance between grid flexibility and reliability impact the development and operation of solar energy plants. During periods of significant fluctuation, solar systems are frequently backed up by backup generators, raising the capital and operational expenses of solar power generation. Ultimately, accurate solar forecasts over various time horizons are required for Independent System Operators (ISOs) or equivalent grid balancing authorities to successfully integrate higher levels of solar energy production while maintaining reliability [3]. Our project focuses on supporting grid operators across Australia to accurately predict solar, allowing the electric grid to adapt to changing circumstances while reducing interruptions and total operating costs.

2. Problem Definition

In Australia, the amount of energy coming from renewable sources is rising. Yet the equilibrium between energy production and consumption must be carefully managed by grid managers, otherwise causing an imbalance in the electricity supply. The aim of this project is to develop a better understanding of historical observations of solar radiation levels, and determine how they can be better forecast using machine learning techniques. With weather station data taken from the Bureau of Meteorology (BOM), we expect to develop a model that predicts localised monthly solar radiation levels within a web-based application, with the ultimate aim of having effective short-term daily forecasting and nowcasting (hourly) in future phases of development. This application we expect to be used by grid managers to understand future electricity output, and therefore form contingencies to handle solar variability. As seen in Figure 1, NSW, QLD and VIC seem to have the greatest number of installations for annual grid-connected capacity since 2016 consistently [4]. This highlights the importance of ensuring a degree of predictability in solar installation output due to their prevalence on the grid.

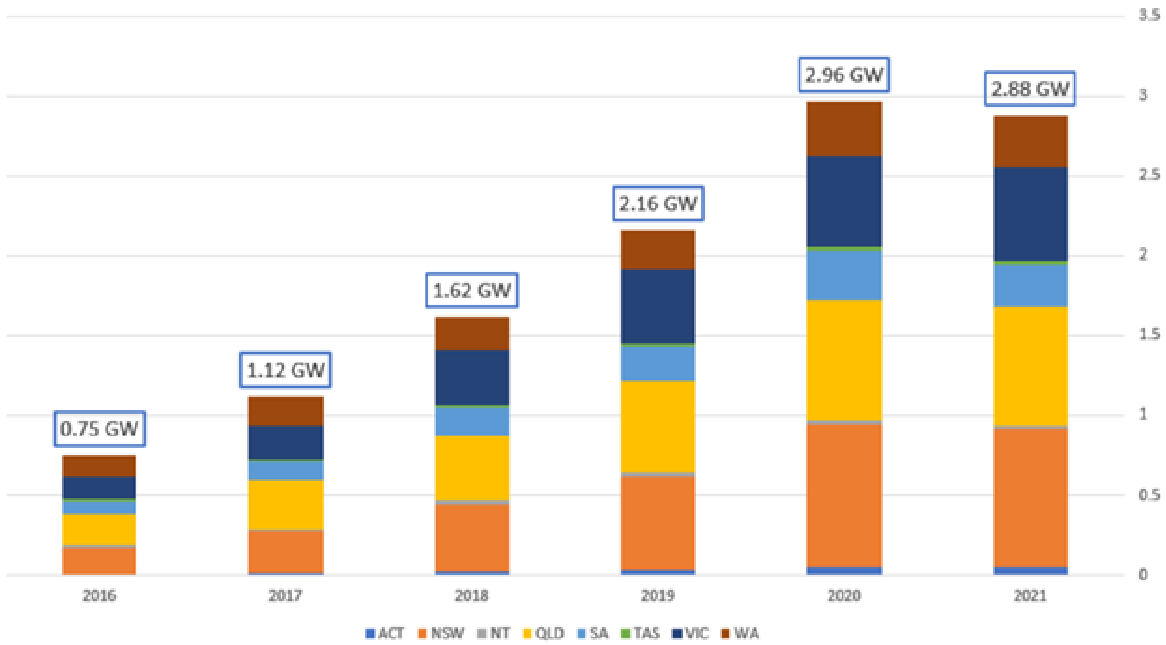

Figure 1: Annual grid-connected capacity of solar installations by states since 2016 in Australia

When it comes to the regulation of its solar output, the availability of reliable and timely information is critical. In Figure 2, the PV monthly usage is trending upwards, and we notice that NSW, QLD and VIC are dominant in producing the highest amount of PV output [2].

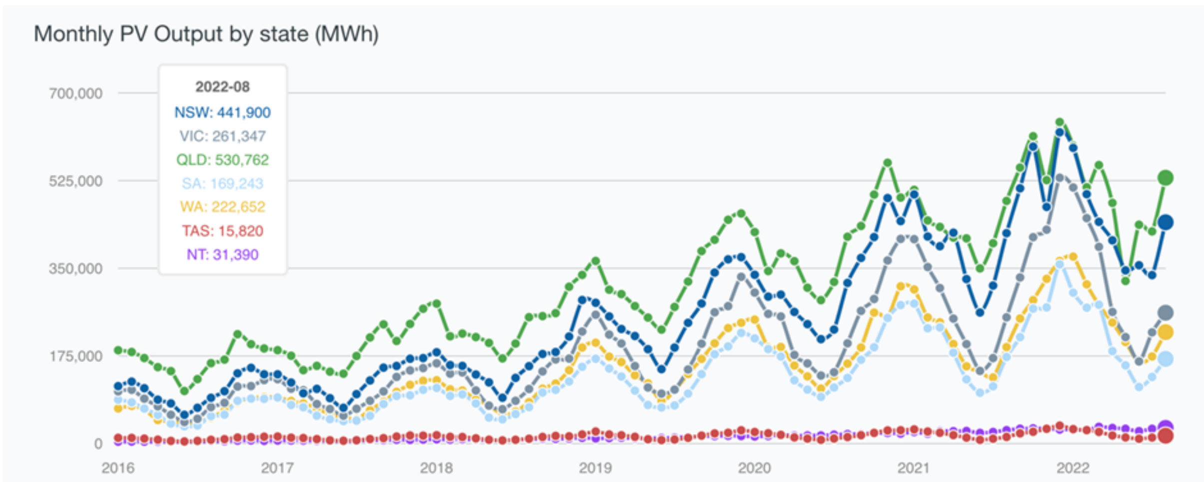

Figure 2: Monthly PV Output by State (MWh) since 2016 in Australia

Several promising approaches have been developed in recent times, for instance, Solcast, a solar forecasting company located in New South Wales, wants to deliver precise weather forecasts to help grid operators better manage the variability of solar energy supply [5]. For the rest of Australia, improved short-term solar energy predictions will mean lower energy costs, fewer emissions, and a more dependable electrical infrastructure. Thus, a reliable forecasting application used at solar power stations can aid in the regulation of photovoltaic systems and the distribution of generated electricity. By making solar energy production more consistent via reliable forecasting, there will be more incentive to integrate this type of renewable energy into the electrical grid. This will improve sustainability and minimise environmental impacts in areas that integrate solar energy.

This report provides an overview of solar resource and solar power forecasting methods, as well as promising methods and a discussion of their effectiveness for operational use.

3. Methodology

Our methodology involved developing a web-based application that grid operators at solar power plants can use to view solar radiation forecasts, which can then help to determine future solar output for the electrical grid.

Data collection was strictly on solar radiation observations recorded across several stations in Greater Melbourne, and was made available through the Bureau of Meteorology. After exploring observations for some stations, we cleaned and concatenated the data into a single file to be used by a SARIMAX model. Using grid search, we tuned the SARIMAX hyperparameters, then trained the model on the concatenated data. In-sample forecasting was used to evaluate the performance of SARIMAX, and used Mean Absolute Percentage Error (MAPE) over MAE or MSE due to MAPE having higher interpretability.

The trained models were used to create forecasts for the web-based application, which was designed in R Shiny. Pre-processing, model development and validation were all performed using Python. The following sections will describe in detail each aspect of our methodology.

3.1 Data Collection

The data we required was the daily solar radiation across the city of Melbourne. We took the data from the Bureau of Meteorology [6] across 22 weather stations in Greater Melbourne focusing on an even spread across the city as shown in Figure 3. This would allow us to map the data to the Greater Melbourne area in our visualisation. All but one of the locations had data starting from 1990. The last station had data beginning from 2007.

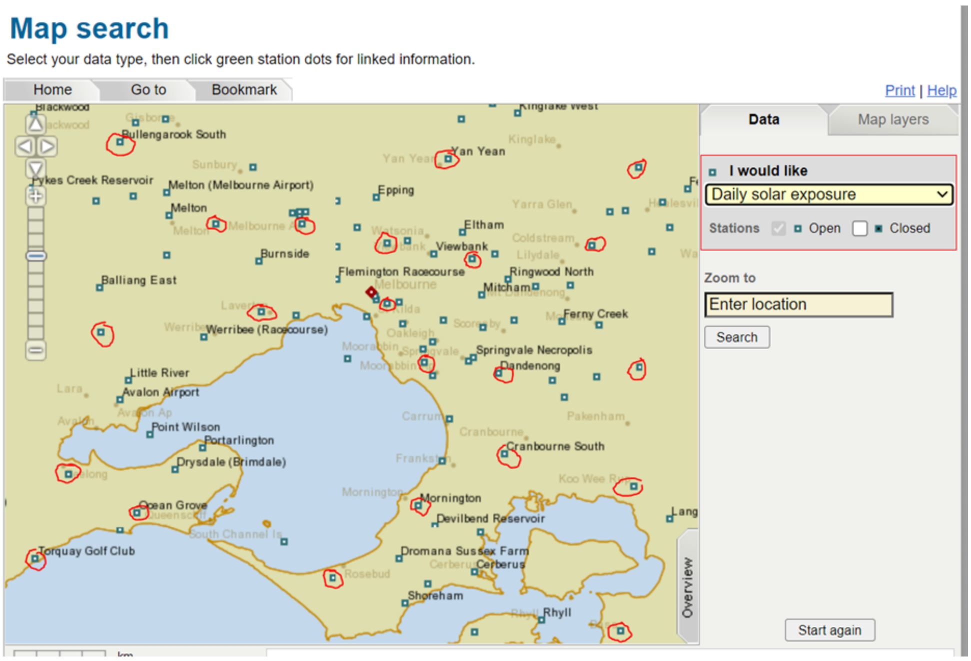

Figure 3: Bureau of Meteorology (2022) Climate Data Online Map Search [digital map], Bureau of Meteorology website, accessed 22 September 2022. http://www.bom.gov.au/climate/data/index.shtml

3.2 Data Preparation

After having selected 22 stations to cover the region of Greater Melbourne, we unzipped each station data file collected, extracted the solar time-series data along with station name, station code, latitude, and longitude. The data pertaining to weather station location and identification will be later used when mapping the data to a visualisation of Greater Melbourne in our web-based application.

Using Python's Pandas module, we stored the extracted features for a given station in a Pandas Dataframe. After creating a dataframe for each station, we concatenated all of the station data into a single dataframe.

Within this concatenated time-series data, we had to merge the year, month, and day columns into a single date column. We observed missing values throughout the stations, which we had to handle before modelling. Grouping by year, we found that earlier historical observations had higher rates of missingness. A method to handle these observations was interpolation. We opted for linear interpolation as it was the default option used by 'pandas.DataFrame.interpolate()'.

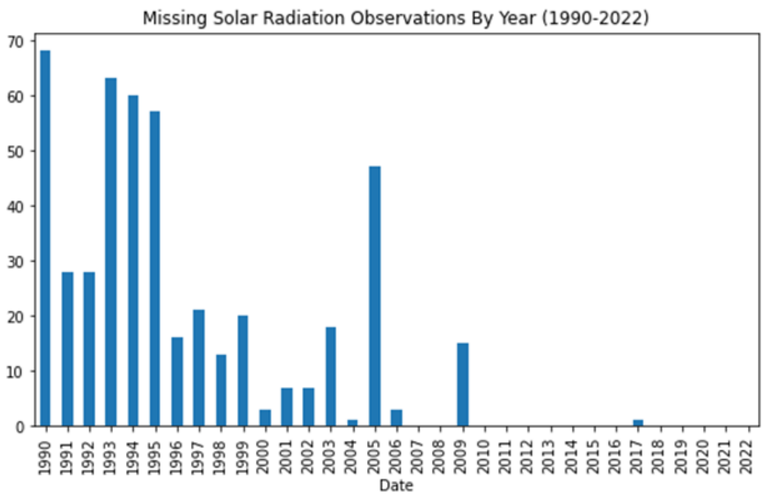

Figure 4. Missing Solar Radiation Observations at East Melbourne Station (1990-2022)

The resultant data after missing value interpolation was saved to a single CSV file, for later use in model development and the web-based application.

3.3 Model Selection

As our aim was to perform solar radiation forecasting on historical weather observations, we decided to select models from a range of time-series based algorithms. Before choosing a model, we perform some exploratory time-series analysis. After sampling observations from a single station in East Melbourne, we plotted them to visually explore for any seasonality or underlying trends in solar radiation levels (see Figure 5).

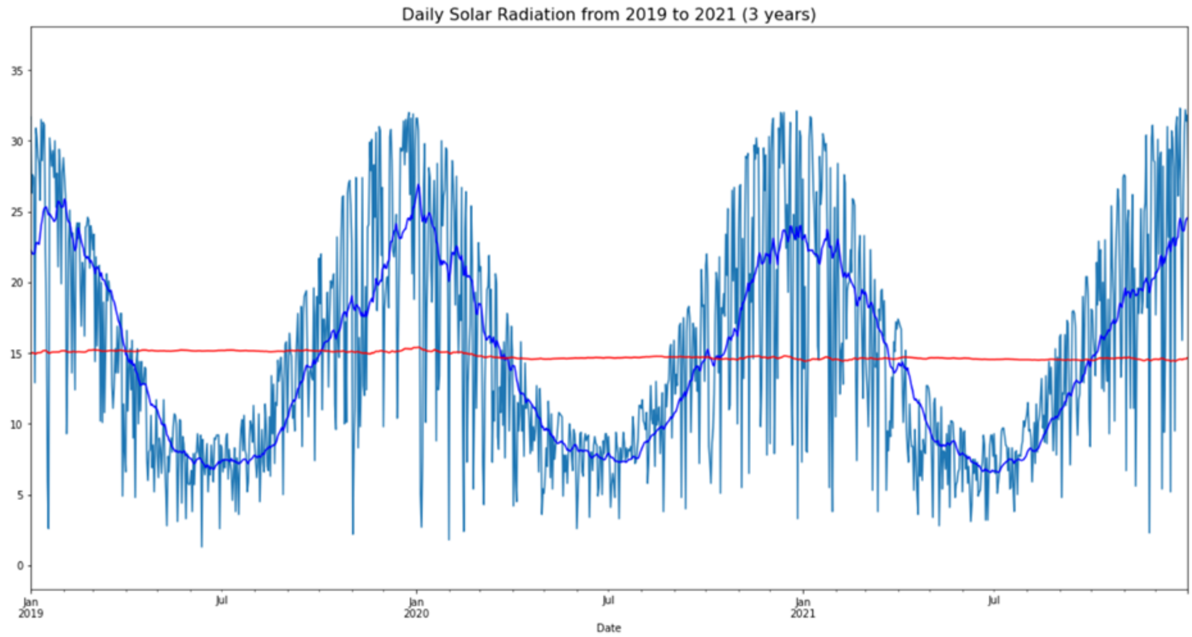

Figure 5. Time Series Plot of Daily Solar Radiation for East Melbourne (2019-2021) with 4-week and 365-day rolling averages.

What we see from the time series plot is that there is a clear yearly seasonality present, and from the 365-day rolling average, we observe stationarity in the data. However, in order to prove that there is no underlying trend across all 32 years of observations, we will perform a statistical test called Augmented Dickey-Fuller (ADF) test using Python's statsmodel library [7].

With a set significance level of 0.05, the ADF test resulted in an extremely low P-value (P = 2e-10), we reject the null hypothesis that the time series data is non-stationary.

Knowing that we have seasonality in our time-series data, we can rule out using ARIMA or ARIMAX for forecasting as they do not take seasonal patterns into account. Models such as SARIMA and SARIMAX can account for a seasonality, so we wanted to decide between the two. We preferred SARIMAX as it allows for exogeneous variables to be incorporated with the forecasting model [8], and while we only collected univariate time series data, in future we may incorporate more variables so our model can account for any confounding factors on solar radiation levels.

Long Short-Term Memory (LSTM) networks were also considered during model selection [9][10]; however, due to time constraints we opted to not initially take a deep learning approach. It was more preferred to take forecasts from SARIMAX which had a simpler implementation, and could be used as a baseline to improve upon in the future.

3.4 Model Validation

For developing the SARIMAX model, we needed to define the following parameters:

$$SARIMAX(p, d, q)(P, D, Q)_m$$

Figure 6: SARIMAX Model Notation

- p = number of autoregressive terms
- d = amount of differencing needed to ensure stationarity in time series
- q = number of moving average terms
- P = number of autoregressive terms for seasonal component
- D = amount of differencing needed for seasonal component
- Q = number of moving average terms for seasonal component
- m = periodicity of seasonal component

Given that we observed stationarity in our time series, we will set d to 1. Since we have annual seasonality, and have transformed the daily solar observations into monthly totals, we can set m to 12. For the other parameters, we will perform a grid search of models with different orders and seasonal orders until we determine an optimal combination. Validation of these models will be done using Akaike's Information Criterion (AIC), which can be used to determine a best-fit model [11]. After grid search, we selected the model with the lowest AIC.

$$SARIMAX(1,1,1)(0,1,1)_{12}$$

Figure 7: Best-fit SARIMAX Model after Grid Search

Using the tuned SARIMAX model, we wanted to validate performance using in-sample forecasts. The below figure shows the predicted solar exposure along with the actual exposure for a selected weather station. The grey area shows the confidence interval for the prediction. The graph shows both the in-sample and out-of-sample forecasts.

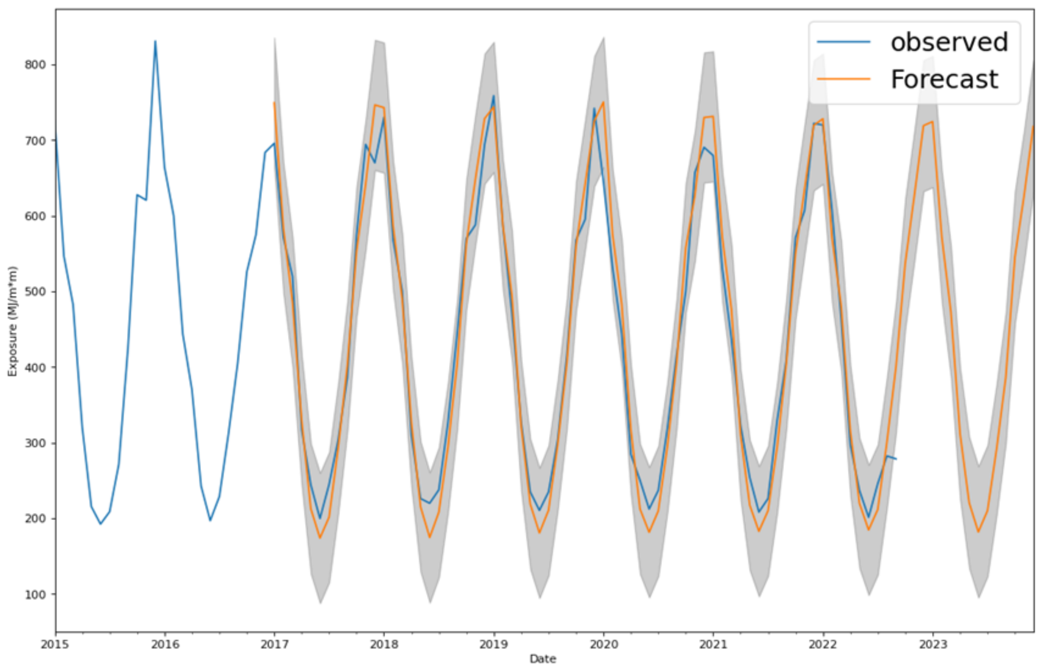

Figure 8: Actual vs. Forecasted Solar Exposure Observations

Mean Absolute Percentage Error (MAPE) was also used to validate the in-sample forecasts made by our model [12].

MAPE was calculated by doing an in-sample prediction. For each data point, the absolute difference between actual and prediction was calculated and divided by the actual. Then the mean was calculated from the resulting series. Mean Absolute Percentage Error for the predictions was 6.80%

Mean Absolute Percentage Error was used as a metric instead of the Mean Absolute Error in this evaluation as the MAPE gives an understanding of the relative size of the error instead of an absolute value – which is harder to evaluate without additional contexts.

3.5 Front-end Application

We developed our web-based application using Python and R. Using pandas, we performed data pre-processing on daily solar radiation observations from multiple weather stations. After retrieving total monthly solar observations and concatenating all the station data into a single CSV file, we used scikit-learn to build the forecasting model. Each observation was also appended with the corresponding station coordinates to help in plotting the stations on a map. When it came to developing the front-end application, we used ggplot2 and Leaflet to build the necessary visualisations, and Shiny to add interactivity to our visualisations.

Initially, we wanted to have the Shiny application receive forecasts from a Python file that loads in a serialised version of our trained model using Pickle, and performs forecasts using the model while the application is running. However, using the reticulate package from CRAN to allow for running Python files within Shiny resulted in many difficulties, so instead we created another CSV file containing model forecasts up until 2050, then loaded them into the Shiny app. That way, the demo would still be able to show how we wanted forecasts to be presented.

When designing the application, the following features were added to ensure accessibility and interpretability for users:

- Use of monochromatic basemap to contrast against the coloured station markers.
- Legend in the bottom-right corner to give context to the colour palette used.
- Red and blue used to distinguish between historical observations and forecasts respectively in the side panel line chart.
- Minimalistic theme used for line charts for better clarity.
- Side panel can be dragged using a cursor to give the user a better view of the map visualisation.

Interactivity was a challenging task when designing the application. Using R packages such as dplyr and tidyr, the loaded solar radiation observations and forecasts could be subset by a given year and month. The user can select a month and year using the side panel inputs, which would then update a reactive subset of the loaded data. On-click and hover events were also included for the map markers, so a user could get a more detailed view of a single station's observations for a given date.

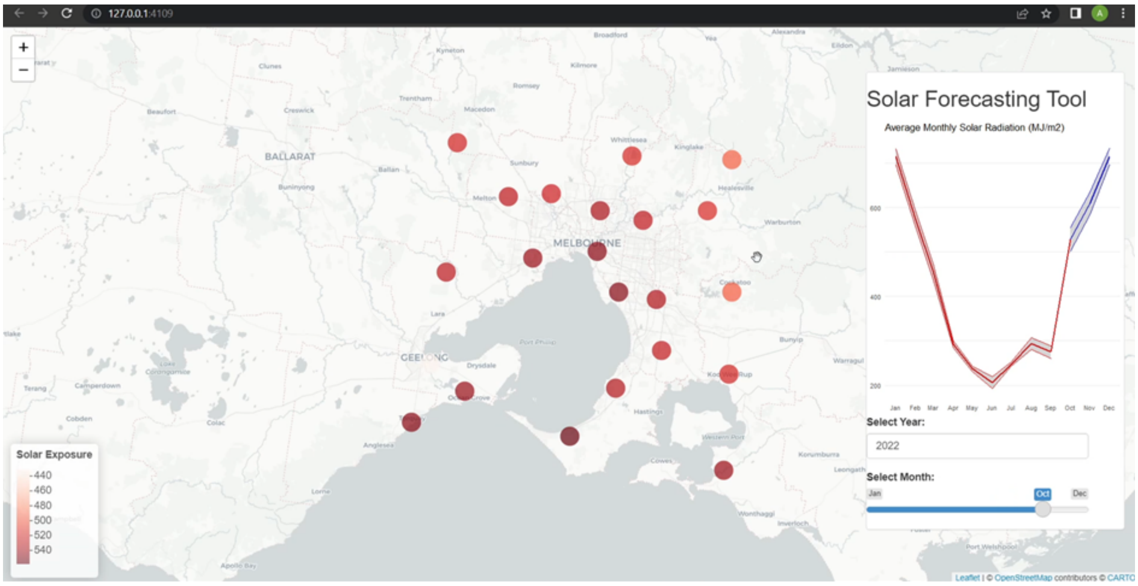

Figure 9. Solar Forecasting Shiny Application prototype

4. Findings

When it came to exploring the data, we discovered that across the Greater Melbourne stations, solar exposure tended to follow the same seasonality (see Figure 10), however there were slight deviations between stations that were likely a result of confounding variables such as localised weather conditions.

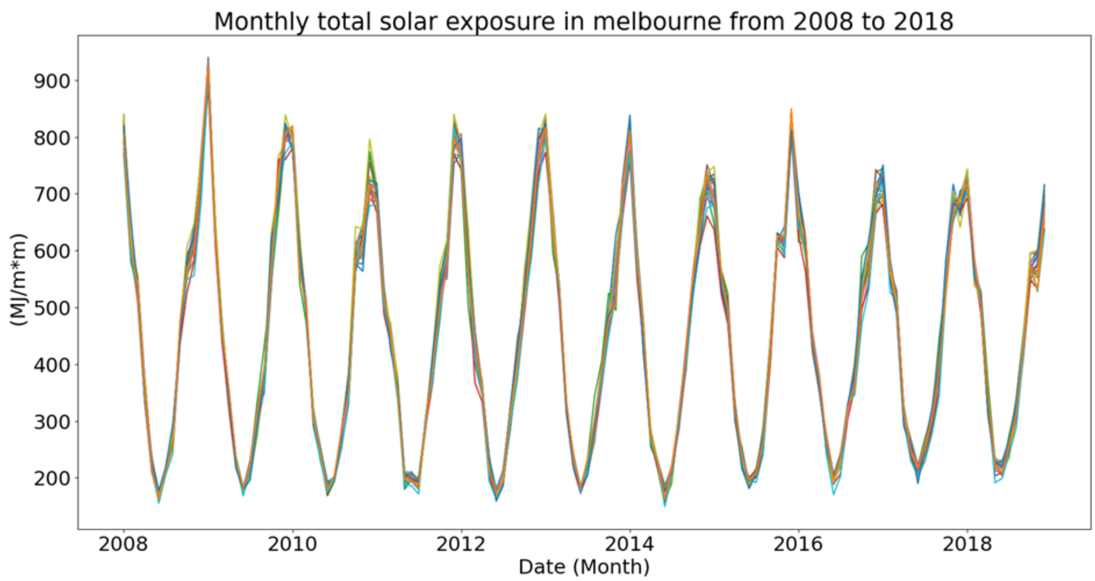

Figure 10. Monthly Total Solar Exposure in select Greater Melbourne stations (2008-2018)

After developing the SARIMAX forecasting model, we wanted to observe the nature of the forecasts generated by the model for a given station. What we observe in the below time-series plot is that SARIMAX was able to learn the seasonal component of monthly solar observations, however we do not see any year-on-year variability in the forecasted solar radiation levels (see Figure 11). This invariability is not representative of the nature of real-world solar radiation levels.

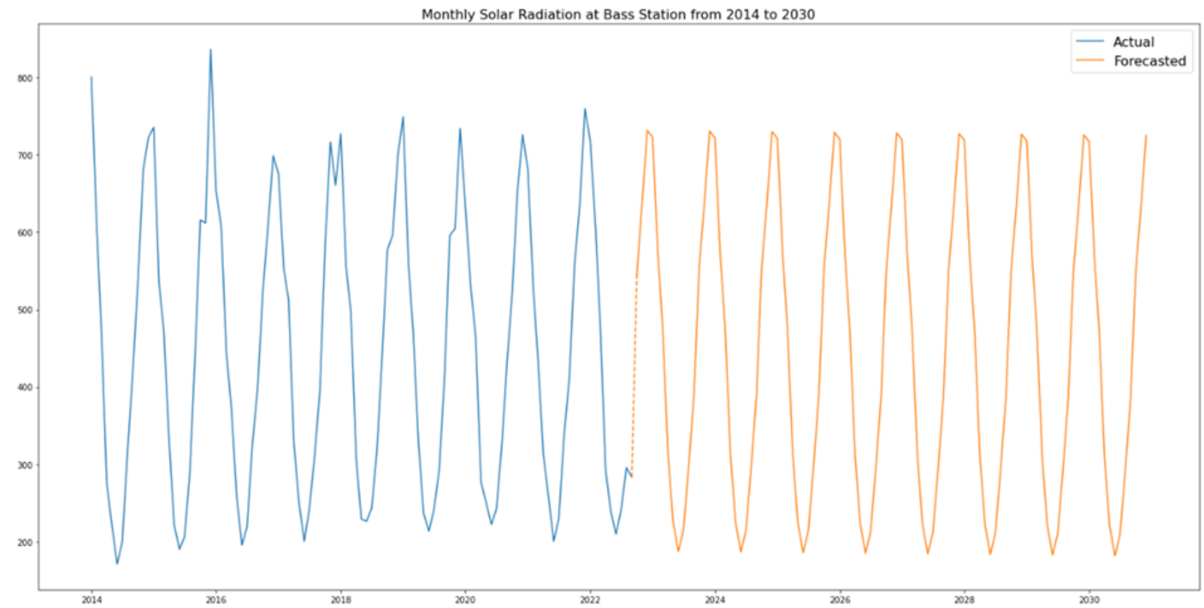

Figure 11. Actual and Forecasted Monthly Solar Radiation at Bass Station (2014-2030)

Therefore, we find that, as a baseline, univariate forecasting on only past solar radiation observations has limitations. We achieved the aim of localised monthly solar forecasting in our model, but for greater effectiveness, we need to consider exogeneous weather variables, which SARIMAX allows for. Retrieving weather variables from BOM in similar quantities to the solar observations requires financial resources and licensing which we could not obtain for this project.

We also found in preliminary experimentation with SARIMAX on daily observations that when setting the periodicity parameter to 365 days, our model was not able to train within a reasonable time. Our ultimate aim of achieving short-term daily forecasting may rely on a different forecasting approach such as LSTM, or having more computing resources.

From time-series analysis taken as part of our methodology, we found that stationarity in the solar observations was common across all Greater Melbourne stations, as well as across multiple decades. However, during exploratory analysis, we found that in January 2019, stations recorded their highest ever solar exposures, whereas minimum exposures at each station varied in year, but always occurred in June.

Table 1: Maximum and Minimum Exposure across Stations

Station	Max Exposure	Month	Min Exposure	Month
BASS	908.1	Jan-2019	149.7	June-1995
BREAKWATER (GEELONG RACECOURSE)	916.1	Jan-2019	151.5	June-1990

BULLENGAROOK SOUTH	939.9	Jan-2019	142.8	June-1991
CHELTENHAM KINGSTON CENTRE	927.8	Jan-2019	154	June-2004
COLDSTREAM	934.7	Jan-2019	144.7	June-1991
CRANBOURNE SOUTH	919.9	Jan-2019	149.25	June-1995
DANDENONG	932.1	Jan-2019	152.3	June-2004
DONCASTER (MANNINGHAM DEPOT)	921.9	Jan-2019	154.45	June-1995
KOO WEE RUP	920.2	Jan-2019	153.2	June-1991
LAVERTON RAAF	930.8	Jan-2019	145	June-1995
LITTLE RIVER (MOUNT ROTHWELL)	935.2	Jan-2019	152.8	June-1995
MELBOURNE AIRPORT	917.5	Jan-2019	152.8	June-1991
MORNINGTON	918.4	Jan-2019	154.5	June-1995
MOUNT BURNETT	888.7	Jan-2019	142	June-1991
OCEAN GROVE	916.9	Jan-2019	144.6	June-1995
PRAHRAN (COMO HOUSE)	921.1	Jan-2019	156.1	June-1995
PRESTON RESERVOIR	931.8	Jan-2019	154.35	June-1991
ROCKBANK (MELTON)	940	Jan-2019	154.1	June-1991
ROSEBUD (COUNTRY CLUB)	918.3	Jan-2019	145.6	June-1995
TOOLANGI (MOUNT ST LEONARD DPI)	906.2	Jan-2019	116.6313	June-2003
TORQUAY GOLF CLUB	919.3	Jan-2019	154.3	June-1991
YAN YEAN	923.8	Jan-2019	133	June-2004

5. Impact and Significance of Results

Our developed web-based application provides forecasted solar radiation levels over a given month using supervised machine learning techniques. The application was developed using Python and R with simplicity and interactivity in mind, ensuring an accessible solution for solar grid operators in Greater Melbourne.

The web application currently predicts monthly solar forecasts. However, if it were to provide daily forecasts (short-term) or perhaps hourly (nowcast):

- With the assistance of Australia's electricity distribution network service providers (DNSPs), it is possible to anticipate the level of demand the grid will need to meet the energy load to prepare for solar-induced voltage fluctuations caused by clouds shading solar systems, particularly in areas with high penetration when several systems are impacted at once.

- The daily/hourly projections attempt to give system operators the knowledge they need regarding how much load can be supplied by solar and what proportion of the heavy work must be done by centrally dispatched generation. This information is relevant to grid operators at large solar farms and dispersed installations such as household rooftops. As the switch to renewable energy sources accelerates and the network becomes more dispersed, this will be essential to maintaining steady energy supplies.

Responding to Climate Change

Toxic gas (CO2, methane, and nitrous oxide) emissions into the atmosphere not only contribute to air pollution, but also to an increase in the greenhouse effect resulting in disastrous weather events in recent years, including flooding, storms, excessive heat, and drought. Solar panels produce no glasshouse emissions and could mitigate the effects of climate change. Sunlight is free. When solar energy is used to power a home or company, no fuel is burned and no emissions from energy generation are produced. If we reduce our carbon footprint and decrease air pollution, solar power can save $259 billion in climate change damages and save more than 25,000 lives [13].

The power grid will be used to promote Australia's decarbonization because the country is transitioning to renewable energy sources and their application in buildings, industries, and road transportation. By 2050, the NEM's energy demand might increase to approximately 100TWh/year, or roughly half of the NEM's current annual demand, if the great majority of Australia's vehicle fleet is electrified, as in Deep decarbonisation [14].

Economic Benefits

A large amount of solar capacity is being installed across the globe, and solar forecasting can create a spectacular surge in job creation in skilled job positions such as manufacturers, engineers, sales representatives, marketers, and installers. In Australia alone, large-scale and rooftop solar have accounted for generating more than 10,000 jobs. The overall renewable energy sector in Australia recorded an enormous 27% growth in employment in the financial year 2018-19 [15]. Solar Forecasting methods could potentially allow users to transition to renewable energy in a way that is financially viable due to the federal and state governments' solar incentive programmes.

The report *Renewable Power Generation Costs in 2019* (IRENA, 2019) [16] estimated the costs for the installation and maintenance of Solar power. Installation costs were estimated to be USD$1,464 per kW. The maintenance cost was also estimated at USD$18.30 per kilowatts per year. From accessing the *Historical accredited power stations and projects* (CER, 2022) [17], we calculated that the average power generation capacity per year for solar plants in Victoria is 3835 kilowatts. This averages to USD $5 million for installation costs and USD$70,000 maintenance costs per year. Our forecasting will help to reduce the risk of initial investment and maximise output in each location to increase the profitability of the site.

One specific way it can help is to reduce clipping losses. In a post about maximising solar project value, they mention how inverter clipping (otherwise known as inverter saturation) occurs when DC power from a PV array exceeds an inverter's maximum input rating. The inverter may adjust the DC voltage to reduce input power, increasing voltage and reducing DC current. Alternatively, the inverter may restrict or throttle the inverter's AC output [18]. This directly affects the efficiency of the Solar power plants. The forecasting will enable companies to decide on DC/AC ratio to ensure optimal output balanced by installation costs.

6. Project Management

Throughout the entire project, the team maintained frequent communication via Microsoft Teams chat and also weekly meetings which were recorded and transcribed for the benefit of members that could not attend in a given week. During a weekly meeting, we would delegate tasks pertaining to an aspect of the solution such as data collection, pre-processing, model development, and front-end application development. During these meetings, we also presented each other with individual progress on tasks allotted in the previous week.

Due to some difficulties with organising the delegated tasks using Microsoft Teams chat, we later opted for a Trello board to organise our tasks. Given the late introduction of using Trello for task management, our board pertains strictly to meetings and tasks that occurred during the report writing phase. The Trello board (as seen in Figure 12) did help to remediate the issues with assigning tasks and documenting progress outside of meetings. It was also used to track recent meetings and the key points covered in them.

On occasion, additional meetings would take place to ensure that a critical task was completed before continuing with the project or if most of the group could not make the usual meeting time.

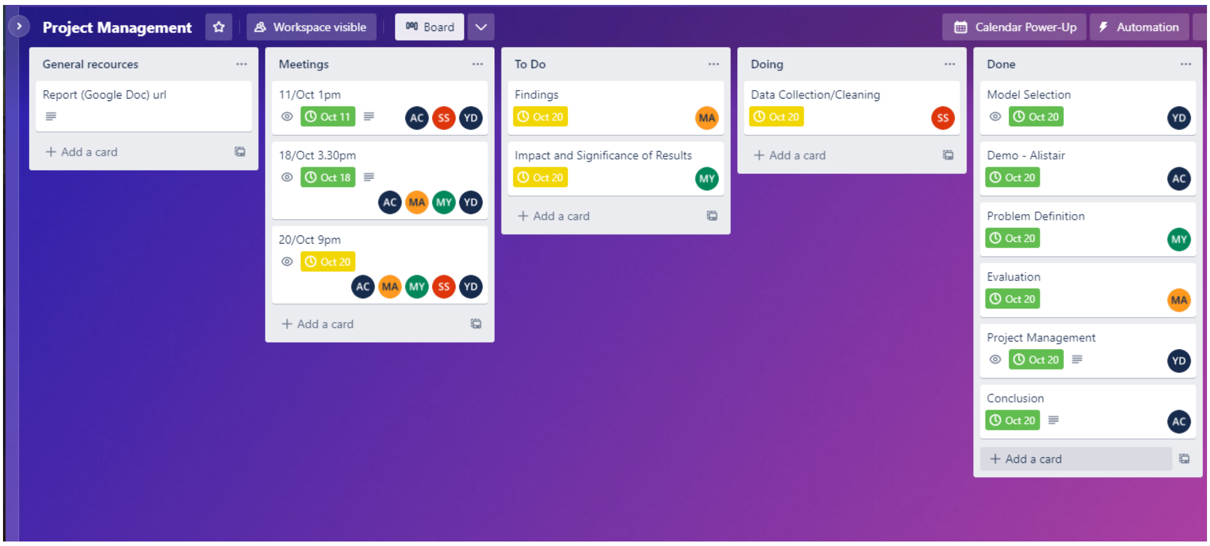

Figure 12: Screenshot of Trello Board used for Group Management (October 20, 2022)

Table 2: Student Contributions

Student ID	Student Name	Contribution (%)	Activities
s3698728	Yuepeng Du	20%	Model Selection, Project Management
s3835610	Melani Aluthge Aluthge Dona	20%	Model Validation, Findings
s3856512	Momitha Yepuri	20%	Problem Definition, Impact and Significance of Results
s3941559	Moretta Song	20%	Data Collection/Cleaning, Impact and Significance of Results, References
s3902003	Alistair Chitty	20%	Model Selection, Front-end Application, Data Collection/Cleaning

7. Conclusion

The project resulted in a successful web-based application prototype that can be used to forecast monthly total solar radiation levels, providing actionable insights to those managing electrical grid output of solar plants. SARIMAX models were an effective and lightweight means of predicting solar exposure. However, our solution did have limitations. We were only able to achieve forecasting on monthly observations rather than daily ones due to SARIMAX runtime issues. Deep learning approaches such as LSTM may prove to be an improvement towards achieving short-term forecasts with our solution. In future, we also want to expand on our data with other weather observations such as rainfall and temperature, and see how they factor into solar exposure using multivariate time-series methods. Through these potential improvements, our application could achieve greater performance and return more frequent forecasts, which grid operators could use to ensure grid reliability as the world transitions to renewable energy.

References

[1] CEC (Clean Energy Council) (2022) *Large-scale solar | Clean Energy Council*. CEC Website, accessed 15 October 2022. https://www.cleanenergycouncil.org.au/resources/technologies/large-scale-solar

[2] APVI (Australian Photovoltaic Institute) (2022) *Australian PV Market since 2011*. APVI Website, accessed 15 October 2022. https://pv-map.apvi.org.au/analyses

[3] Inman R, Pedro H and Coimbra C (2013) 'Solar forecasting methods for renewable energy integration', *Progress in Energy and Combustion Science*, 39(6): 535-576, doi.org/10.1016/j.pecs.2013.06.002.

[4] AEC (Australian Energy Council) (2022) *Solar Report 2022*, AEC Website, accessed 13 October 2022.
https://www.energycouncil.com.au/media/5wkkaxts/australian-energy-council-solar-report_-jan-2022.pdf

[5] Vorrath S (2020) *Australian solar and wind forecasting technology to be live tested on S.A. grid*, RenewEconomy website, accessed 15 October 2022.
https://reneweconomy.com.au/australian-solar-and-wind-forecasting-technology-to-be-live-tested-on-s-a-grid-93539/

[6] Bureau of Meteorology (2022) *Climate Data Online Map Search* [digital map], Bureau of Meteorology website, accessed 22 September 2022.
http://www.bom.gov.au/climate/data/index.shtml

[7] Perktold J, Seabold S and Taylor J. (2022) *statsmodels.tsa.stattools.adfuller*, statsmodel website, accessed 15 October 2022.
https://www.statsmodels.org/dev/generated/statsmodels.tsa.stattools.adfuller.html

[8] Verma Y (30 July 2021) 'Complete Guide To SARIMAX in Python for Time Series Modeling', *Analytics India Magazine*, accessed 16 October 2022.
https://analyticsindiamag.com/complete-guide-to-sarimax-in-python-for-time-series-modeling/

[9] Goswami S (9 April 2021) 'Building LSTM-Based Model for Solar Energy Forecasting', *Towards Data Science*, accessed 16 October 2022.
https://towardsdatascience.com/building-lstm-based-model-for-solar-energy-forecasting-8010052f0f5a

[10] Kutzkov K (13 September 2022) 'ARIMA vs Prophet vs LSTM for Time Series Prediction' *The MLOps Blog*, accessed 16 October 2022.
https://neptune.ai/blog/arima-vs-prophet-vs-lstm

[11] Bevans R (25 May 25 2022) 'Akaike Information Criterion: When & How to Use It (Example)', *Scribbr*, accessed on 17 October 2022.
https://www.scribbr.com/statistics/akaike-information-criterion/

[12] Graves A (8 January 2020) 'Time Series Forecasting with a SARIMA Model: Predicting daily electricity loads for a building on the UC Berkeley campus', *Towards Data Science*, accessed 16 October 2022.
https://towardsdatascience.com/time-series-forecasting-with-a-sarima-model-db051b7ae459

[13] Bank M (3 October 2022) '6 reasons why homes with solar panels sell faster' *E-green electrical*, accessed on 18 October 2022.
https://e-greenelectrical.com.au/6-reasons-why-homes-with-solar-panels-sell-faster/

[14] Transgrid (2021) *Energy Vision - A clean energy future for Australia*, Transgrid website, accessed on 18 October 2022.
https://www.transgrid.com.au/about-us/network/network-planning/energy-vision

[15] Mazengarb M (2020) *Australian renewable energy jobs surged to new record levels in 2018-19*, RenewEconomy website, accessed 20 October 2022.
https://reneweconomy.com.au/australian-renewable-energy-jobs-surged-to-new-record-levels-in-2018-19-62483/

[16] IRENA (International Renewable Energy Agency) (2019) *Renewable Power Generation Costs in 2019*, IRENA website, accessed 28 September 2022.
https://www.irena.org/publications/2020/Jun/Renewable-Power-Costs-in-2019

[17] CER (Clean Energy Regulator) (2022) *Historical accredited power stations and projects*, CER website, accessed 28 September 2022.
https://www.cleanenergyregulator.gov.au/DocumentAssets/Pages/historical-accredited-power-stations-and-projects.aspx

[18] Parker T (9 December 2019) How to maximise solar project value using inverter clipping, Solar Power World, accessed 18 October 2022.
https://www.solarpowerworldonline.com/2019/12/how-to-maximize-solar-installation-value-using-inverter-clipping/