Predicting Monthly Electricity Demand whilst acknowledging Rooftop Solar data

Alan Nguyen (z5386192),

Darryn Marjoram (z5484676),

Janany Nishatharan (z5390604).

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Abstract

Accurate electricity demand forecasting is essential for the efficient operation and planning of power systems. This report investigates the impact of integrating rooftop solar data on the accuracy of monthly and seasonal electricity demand forecasts in New South Wales, Australia. By employing advanced forecasting models, including Seasonal Autoregressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM) neural networks, we analyse the influence of rooftop solar adoption capacity on demand predictions. Our findings (that utilise monthly data) indicate that while traditional models provide a baseline for demand forecasting, incorporating rooftop solar data **initially did not** statistically enhance monthly forecast accuracy. Which is at odds with some other studies that show an improved forecast accuracy (when utilising daily data) particularly in accounting for seasonal variations and weather conditions.

After tuning our models to achieve higher RMSE and R^2 we found **evidence of improvement in forecasting accuracy in both SARIMA and LSTM models** when solar capacity data is included as a separate input.

For both SARIMA and **LSTM the RMSE and R^2 statistics were higher** for the predictions that incorporated solar capacity as a separate input to total demand.

Then when analysing the statistical significance of the prediction each model made with and without solar capacity data we found that:

- Paired t-test and Wilcoxon signed-rank test p-value for SARIMA where both statistically significant
- Paired t-test was p-value demonstrated statistically significant difference for LSTM
- Wilcoxon signed-rank test p-value was not statistically significant for LSTM

Introduction

Electricity demand forecasting is crucial for the efficient operation and planning of power systems. The integration of rooftop solar energy with the Australia electricity grid has been growing strongly in Australia for more than 12 years contributing to 11.2% or 20MW of Australia's electricity generation by 2023 (Clean Energy Council, 2024 p5). This growing adoption presents unique challenges and opportunities in electricity demand forecasting, particularly as it relates to managing fluctuations throughout the year and across different weather conditions. Our research question "**How does the integration of solar panel adoption data influence predictions for seasonal electricity demand?**" seeks to determine how incorporating data on rooftop solar energy can enhance the accuracy of electricity demand forecasts, both seasonally and monthly.

We aim to explore how demand varies with temperature based on seasonality. Additionally, we will investigate if there is any material impact of rooftop solar data on demand forecasting. Particularly if the incorporation of rooftop solar data as a separate input to forecasting models can improve the accuracy of the forecast. This analysis is crucial for effective grid and power allocation, facilitating more informed planning for when to ramp up generators and how to adapt infrastructure in regions impacted by sunlight or overcast conditions

Literature Review

This literature review explores recent advancements in integrating rooftop solar data into electricity demand forecasting models.

Advances in Solar Power Forecasting

Recent studies have highlighted the importance of accurate solar power forecasting to enhance grid stability and reliability. Machine learning techniques, such as regression models, ensemble models, and neural networks, have shown promise in predicting solar power output based on weather and environmental parameters (Pham, V.H.S., Tran, H.D. 2023 pp3413-3423). These models can improve the accuracy of solar power forecasts, which is essential for integrating rooftop solar into demand forecasting.

For example, one study aligns with our research by exploring how rooftop solar energy data can enhance energy forecast accuracy. It focuses on optimising short-term energy consumption and generation models using advanced deep learning techniques like Long Short-Term Memory (LSTM). By analysing high-resolution smart meter data, including rooftop PV generation, household consumption, and weather conditions, the study shows that integrating granular data improves forecast accuracy, directly addressing the variability of solar energy. (Abu-Salih, A.M., Mostafa, S.A., Ahmad, M.O., Pathan, A.S.K. and Ramachandran, M. 2022)

The study demonstrates that LSTM models outperform traditional forecasting methods in scenarios involving renewable energy. This supports our research by showing that accounting for rooftop Solar's dynamic nature leads to more accurate electricity demand forecasts. By highlighting the effectiveness of these models in managing energy flows and supporting Peer-to-Peer energy trading, the study underscores the value of using solar data to enhance grid stability and energy management, enabling improved seasonal or daily electricity demand forecasts.

Integration of Rooftop Solar Data

The integration of rooftop solar data into electricity demand forecasting involves several approaches. One method is to use historical solar generation data to adjust demand forecasts. Another approach is to develop hybrid models that combine traditional demand forecasting techniques with solar power predictions. Studies have shown that these hybrid models can reduce forecasting errors and improve the overall accuracy of demand predictions, [Refer 2] [refer 3].

Challenges and Solutions

One of the main challenges in integrating rooftop solar data is the high variability of solar power generation. Factors such as cloud cover, temperature, and panel orientation can significantly impact solar output. To address this, advanced forecasting models incorporate real-time weather data and use machine learning algorithms to adapt to changing conditions, (Kelachukwu J. I 2024). Additionally, the use of high-resolution spatial and temporal data can enhance the precision of solar power forecasts.

Case Studies and Applications incorporating solar data

Several case studies have demonstrated the benefits of incorporating rooftop solar data into electricity demand forecasting. For example, a study conducted in Australia showed that integrating solar power forecasts reduced the mean absolute percentage erro r (MAPE) of demand predictions by up to 15% [refer 2]. Another study from India found that using machine learning models to predict solar output improved the accuracy of demand forecasts during peak solar generation periods (Kelachukwu J. I 2024).

Additional Insights from Recent Related Research

Gross electricity consumption forecasting using LSTM and SARIMA approaches: A case study of Türkiye Bilgili M. and Pinar E. (2023). This research evaluated two approaches to effectively forecast Gross Electricity Consumption (GEC) using historical time series data and appropriate estimation strategies. The study explored, assessed, and compared two methods to forecast GEC in Türkiye:

A) A machine-learning model employing a deep-learning technique based on a long short-term memory (LSTM) neural network.

B) A seasonal autoregressive integrated moving average (SARIMA) model.

The report found that: *"Although the results were close to each other, the LSTM model outperformed the SARIMA model in general, with the lowest MAPE (2.42%), MAE (215.35 GWh), and RMSE (329.9 GWh) values and the greatest R-value (0.9992).*"

From Load to Net Energy Forecasting: Short-Term Residential Forecasting for the Blend of Load and PV Behind the Meter: This study explores transitioning from load forecasting to net energy forecasting due to increased residential solar PV adoption. Utilising a multi-input single-output (MISO) LSTM neural network model, the study enhances forecasting accuracy by considering household energy profiles and PV generation's spatial dependencies. It emphasizes the importance of high-resolution smart meter data for accurate predictions and highlights the benefits of integrating rooftop solar data in improving seasonal and daily electricity demand forecasts, directly aligning with our research question.

Forecasting Approach: Electricity Demand Forecasting Methodology by Australian Energy Market Operator (AEMO): This document outlines methods for projecting electricity demand in Australia's National Electricity Market (NEM) and Western Australia's Wholesale Electricity Market (WEM). It covers forecasting customer connections, technology adoption, and electricity consumption, with projections extending up to 30 years for NEM and 10 years for WEM. This methodology supports tools like the Electricity Statement of Opportunities (ESOO) and the Integrated System Plan (ISP). Our research aligns with AEMO's approach by exploring how demand varies with insolation and temperature, accounting for seasonal differences between temperature, hot, and chilly days. We will investigate the correlation between insolation and temperature to refine demand forecasts for better grid management. AEMO uses a half-hourly model and Generalized Extreme Value (GEV) models, incorporating machine learning algorithms such as LASSO, Gradient Boosting Regression (GBR), and Random Forests. These models are rigorously tested through cross-validation and residual analysis to ensure forecast accuracy.

Impacts of Electric Heat Pumps and Rooftop Solar Panels: Van Someren et al. (2021) examined the impacts of electric heat pumps and rooftop solar panels on residential electricity distribution grids. Their findings indicate that the increased electrification due to heat pumps and solar panels alters peak load and load simultaneity, necessitating adjustments in grid capacity planning.

Citywide Impacts of Cool Roof and Rooftop Solar Photovoltaic Deployment: Salamanca et al. (2016) studied the effects of cool roofs and rooftop solar PV on urban heat islands and energy demand in Phoenix and Tucson. They found that both technologies reduce near-surface air temperature and cooling energy demand, with solar panels providing additional benefits by reducing dependence on fossil fuels.

Predictive Modelling for Rooftop Solar Energy Throughput: Houchati et al. (2021) developed a machine learning-based optimization model for building energy demand scheduling. Their model, which uses support vector regression, demonstrated high accuracy in predicting solar PV output and optimizing energy management in buildings.

Impact of Rooftop Solar on Wholesale Electricity Demand: Guan and Han (2023) analysed the impact of rooftop solar on electricity demand in Australia's National Electricity Market. Their study highlighted the significant changes in power demand patterns due to solar PV adoption, particularly the reduction in daytime grid consumption.

Demand Forecast of PV Integrated Bioclimatic Buildings: Raza et al. (2017) proposed a hybrid ensemble framework for forecasting the demand of PV-integrated buildings. Their approach, which combines multiple predictors, showed improved accuracy in load demand forecasts for smart buildings with rooftop PV.

Short-Term Residential Forecasting for Load and PV: Razavi et al. (2020) introduced a multi-input single-output model using long short-term memory (LSTM) neural networks for short-term net energy forecasting. Their study demonstrated the challenges and solutions in forecasting the blend of load and PV generation.

Estimating the Spatial Distribution of Solar PV Power Generation: Sun et al. (2022) developed a deep learning network to estimate the spatial distribution of solar PV power generation potential on rural rooftops. Their method achieved high accuracy and provided valuable insights into the potential of rural rooftop PV systems.

Material and Methods

Software

To address the research questions, multiple software tools were utilised. For data storage and documentation, GitHub and Microsoft Teams were essential, allowing seamless collaboration and version control.

The analysis presented in this report was conducted using Python in a Jupyter Notebook environment. Various libraries were imported for the analysis. For general exploratory data analysis, the main libraries used were numpy and pandas for data manipulation, while seaborn and matplotlib were employed for data visualisation. The SARIMA/SARIMAX models were implemented using sklearn.metrics, statsmodels.tsa, and pmdarima.

LSTM models were implemented via various python libraries and functions.

All coding files and project documentation are stored in GitHub, ensuring reproducibility and collaboration and version control.

The github link for this research paper is listed below:

https://github.com/AlanNgu/Group7_ZZSC9020

Description of the Data

Total Electricity Demand Dataset (NSW): This dataset provides electricity consumption in New South Wales. It includes variables such as 'DATETIME','TotalDemand',"RegionID" with 196513 rows. The data is essential for developing forecasting models, as historical demand data is a key predictor of future electricity needs. The file size is 5,661KB

Air Temperature Dataset (NSW): This dataset includes air temperature reading from the Bankstown airport weather station in NSW. It contains 'DATETIME', 'TEMPERATURE' and 'LOCATION'. It has 220326 rows. This data helps explore the relationship between temperature and electricity demand, potentially improving forecast accuracy.

Forecasted Demand Dataset (NSW): This dataset provides half-hourly electricity demand forecasts for NSW. Variables are 'DATETIME', 'FORECASTDEMAND', 'REGIONID', 'PREDISPATCHSEQID', 'PERIODID' and 'LASTCHANGE' and 10906019 rows. This dataset is valuable for validating predictive models by comparing forecasted and actual demand, which helps refine forecasting accuracy.

Solar Installation and Capacity (NSW): This dataset provides monthly solar capacity at megawatts and rooftop installations. Variables are each month from 2011 to July 2024 and 'Small Unit Installation Postcode'. There are 2810 rows and 164 columns both in Solar Installations and Capacity.

Pre-processing Steps

Filtering Data: State codes not related to NSW were removed, and data from 2021 onwards was excluded, as 2021 was an incomplete year.

Cleaning Solar Data: Unwanted strings were removed from the solar installation and capacity data, and the data was transposed so that months became columns, with total installations and capacity presented as aggregated amounts. Unnecessary columns were removed.

Time series columns added back: year and month columns back in in case it would help LSTM identify month and longer-term yearly trends

Scaling input columns: scaling each input of the LSTM model data via MinMaxScaler,

Indexing: a datetime index using the year and month columns

Aggregating Data: After filtering the NSW data, total demand was aggregated by month and year to align with the solar installation and capacity data. The dates were also resampled to daily for exploratory purposes.

Data Cleaning

To address missing data, the isnull() function in Python was used to identify any potential gaps. Fortunately, the raw data was relatively clean, and no missing data was found. Had there been any missing values, the approach would have been to either remove the row or replace the missing value with the average, depending on the extent of the missing data.

Assumptions

Overall mean increase year-on-year in total demand driven by population growth. As population increases so does households and businesses. More household and business infrastructures are driving up energy consumption.

Demand should fluctuate based on months and weeks. Expectations that the demand should be high during temperatures that are extremely hot and extreme cold.

It is assumed that there should be a linear relationship between rooftop installations and overall capacity generated. More installations mean more energy capacity.

Rooftop installations are expected to increase due to the socioeconomic push for more renewable energy and the rising cost of fossil fuels. Other factors, such as government policies, can also drive rooftop installations through incentives like rebates.

Hypothesis:

Null Hypothesis (H0): Solar panel adoption does not significantly influence the accuracy of seasonal electricity demand predictions.

Alternative Hypothesis (H1): Solar panel adoption improves the accuracy of seasonal electricity demand predictions

Exploratory Data Analysis

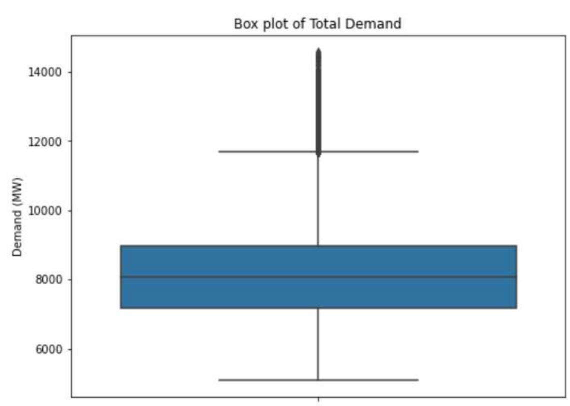

Figure 1: Boxplot of total demand

The core focus of this project is understanding electricity demand patterns, especially as they relate to rooftop solar energy production. This necessitates a thorough exploratory analysis of the NSW electricity demand data, spanning from 2010 to March 2021 which records half-hourly electricity demand in megawatts (MW).

To gain insights into the distribution and characteristics of the electricity demand data, we began by reviewing the descriptive statistics using Python's .describe() method and visualizing the distribution with a seaborn boxplot. Figure1 shows boxplot of total demand which visualizes the distribution of electricity demand over the decade. The median electricity demand was approximately 8053 MW, representing the typical demand during a 30-minute interval. However, the boxplot reveals a wide range of demand values, with the minimum demand around 5074 MW and a maximum as high as 14,579 MW. The interquartile range (IQR) lies between 7150 MW and 8958 MW showing that the middle of 50% of demand values are concentrated within this range.

A key aspect of this analysis is the identification of numerous outliers at the upper end of the distribution. These outliers correspond to instances of elevated demand which may occur during periods of low solar energy production or when there is a heightened dependence on conventional electricity sources. The pronounced variability in electricity demand illustrated by the extended whiskers in the boxplot. It suggests that fluctuations influenced by seasonal variation and the availability of solar energy. Understanding these dynamics is essential for accurately forecasting demand and optimizing the integration of renewable energy sources into the grid.

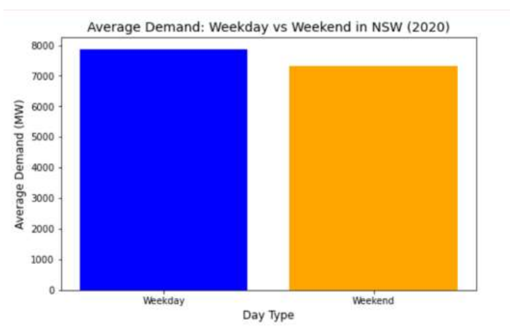

Figure 2: Average electricity demand: Weekday vs Weekend in NSW (2020)

Figure 2 shows electricity patterns for NSW in 2020. We found the average total demand during weekdays was about 7868MW while on weekends it decreased to around 7311MW. This distinction suggests that weekdays typically see higher electricity consumption driven by increased commercial and industrial activities.

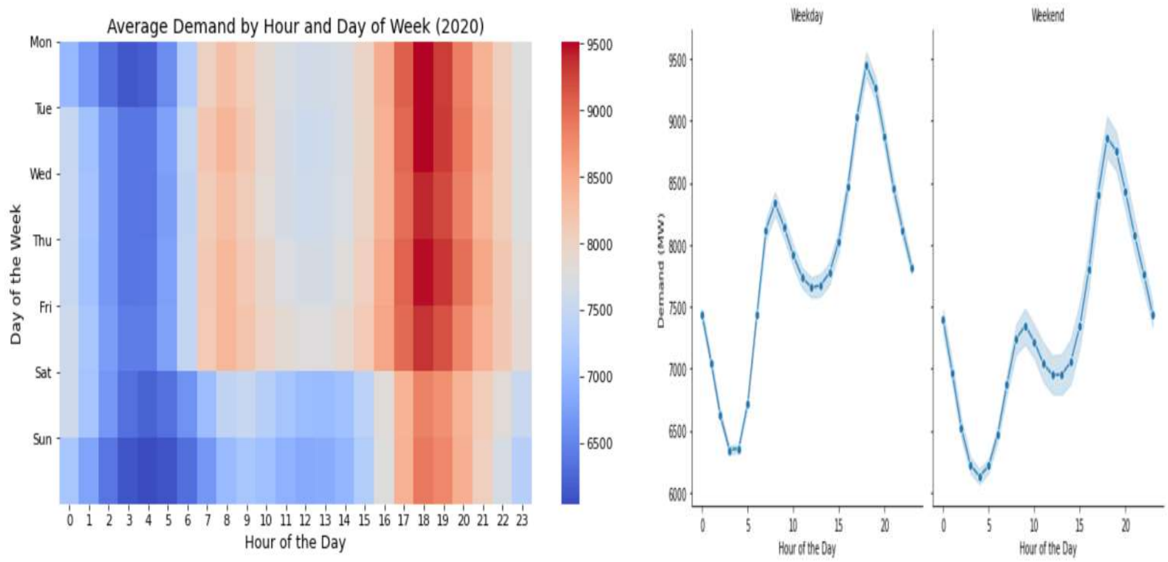

Figure 3 & 4: Average electricity demand: Hours & Days

The heatmap of average electricity demand by hour and day of the week for 2020 shows that electricity demand tends to peak during the evening hours, particularly between 17:00 and 20:00 on weekdays. This surge in demand aligns with typical post-work hours when residential consumption rises as people return home and engage in energy intensive activities.

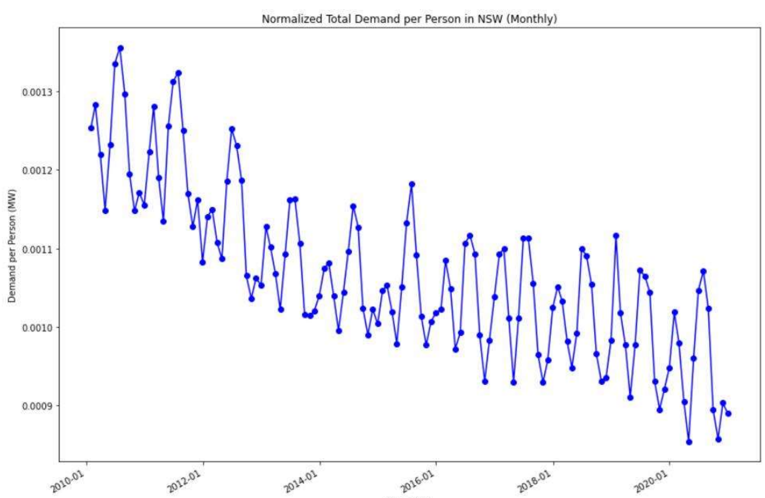

Figure 5: Normalized electricity demand per person

The line chart shows normalized electricity demand per person in New South Wales (NSW) over time, illustrating how the demand has fluctuated across different months. As the chart progresses, a noticeable decrease in demand per person is observed, indicating a downward trend in electricity consumption relative to the population. This could be influenced by a range of factors such as improved energy efficiency, the adoption of renewable energy sources like rooftop solar. The chart effectively highlights this trend, providing valuable insights for policymakers and energy planners.

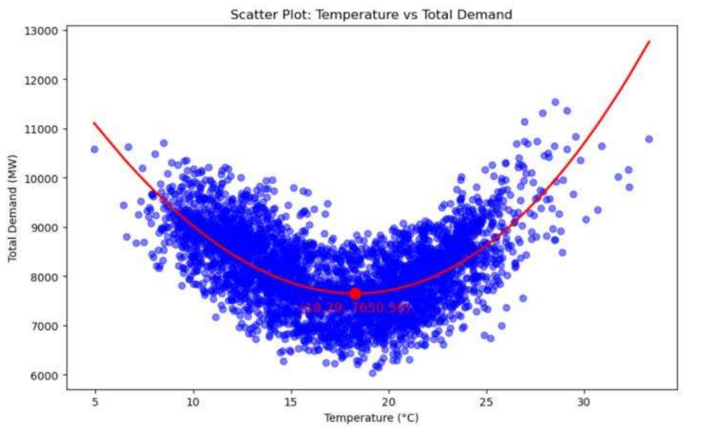

Figure 6: Scatterplot of Total demand vs Temperature

The scatter plot illustrates the relationship between temperature and total electricity demand in NSW, with a cubic polynomial trend line fitted to the data. This trend line reveals how demand fluctuates with changes in temperature. Notably, a distinct minimum point and subsequently rises as temperatures exceed it. The trend suggests that electricity demand is lower during milder temperatures, due to reduced heating and cooling needs, while extreme temperatures result in increased energy consumption for climate control systems.

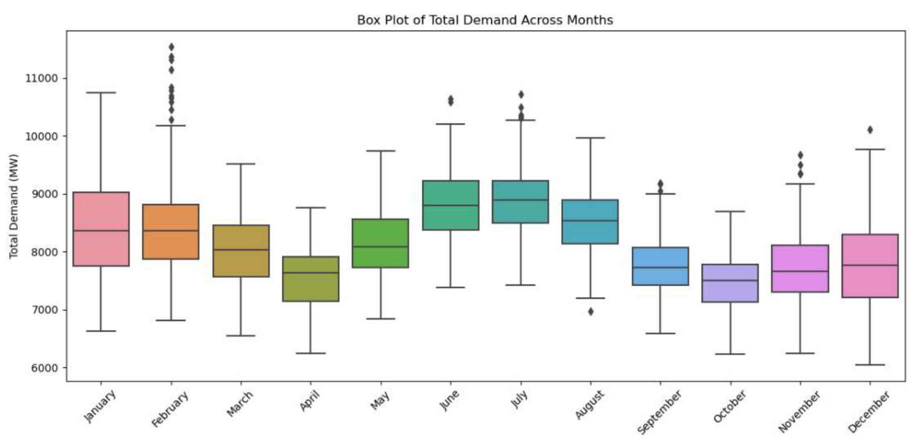

Figure 7: Monthly Total demand

The box plot illustrates the distribution of total electricity demand across the months in New south Wales. By extracting the month from the datetime index and mapping month numbers to their respective names, the data provides a clear view of demand patterns throughout the year. Particularly, February shows many upper outliers in total electricity demand. These outliers indicate instances of exceptionally high demand during this month, suggesting unusual spikes in energy usage. Understanding these demand fluctuations is essential for effective energy management and forecasting.

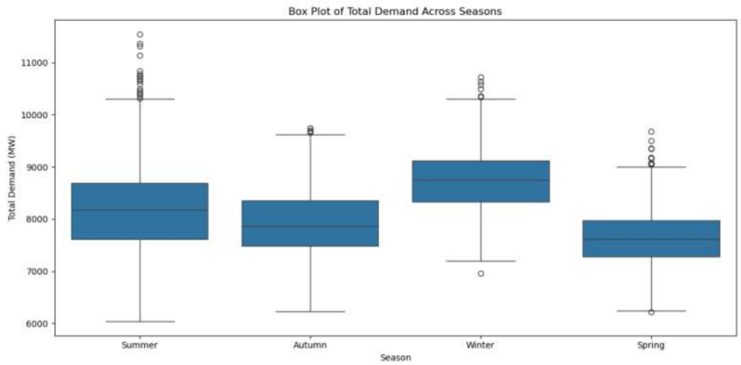

Figure 8: Seasonality Total demand

The box plot illustrates total electricity demand across the four Sessons in NSW: Winter, summer, Autumn, and spring. Winter exhibits the highest demand, driven by heating needs while summer shows lower demand, with occasional spikes from cooling requirements. Autumn and spring display moderate levels of demand, with autumn slightly higher than spring.

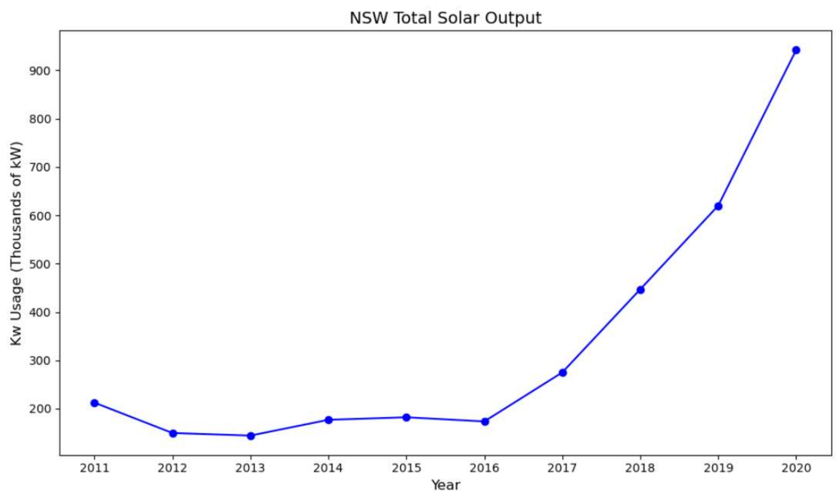

Figure 9: Solar capacity

The graph above shows the total solar capacity (Kw usage in thousands) in NSW from 2011 to 2021. From 2011 to 2016, the growth in solar output remained stable, fluctuating slightly between 200,000 and 250,000 Kw, with minimal overall change. From 2017, there was a sharp increase in solar output. This rapid growth accelerated further after 2018, peaking in 2020 at over 1,000,000 Kw. This steep rise reflects increased adoption of solar power, likely driven by advancements in technology, more government incentives, and a greater public push toward renewable energy source. This data highlights a major shift in solar energy adoption, with a sharp incline from 2017 onward illustrating the accelerating expansion of solar power in NSW.

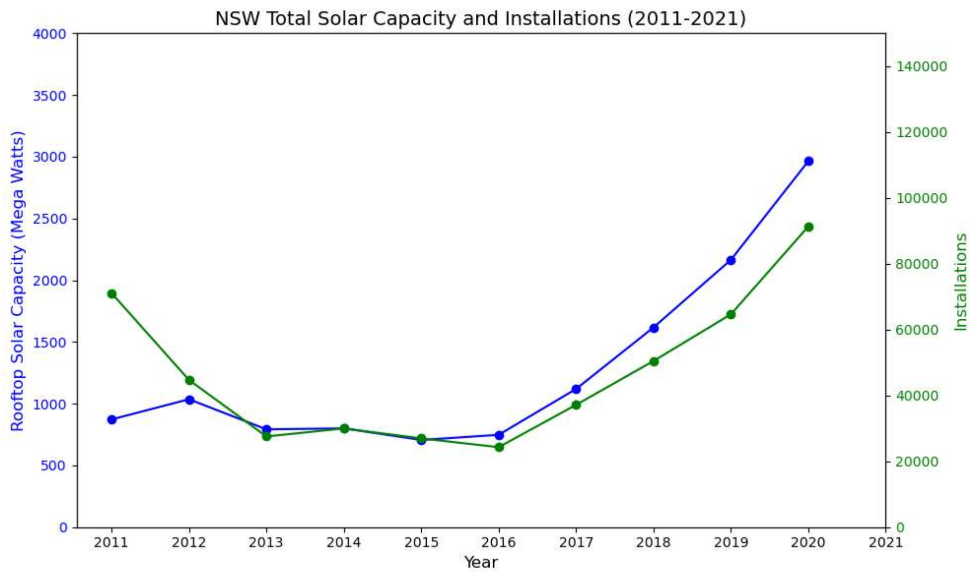

Figure 10: Solar capacity & rooftop installation

declined after 2011 and remained stable between 2013 and 2016, rooftop capacity remained steady during this period. However, both installations and capacity underwent a significant surge from 2017 onwards, with installations peaking in 2020 and solar output exceeding 1,000,000 Kw by 2021.

A First Model: SARIMAX

Seasonal Autoregressive integrated moving-average (SARIMAX)

SARIMAX is a variant of the ARIMA model. ARIMA model is a classical statistic model that uses historical time series data to predict/forecast. There are 3 main components in an ARIMA, Autoregressor(AR), Integrated(I) and Moving Average (MA).

Autoregressor(AR) looks at how things change overtime and uses the history to make future predictions, in our research could look at the demand of last month and predict how much demand will show next week.

Integrated(I) makes the time series stationary by applying differencing. Differencing measures the change between an observation and its previous value (lag) to remove trends or patterns over time, making the data more stable for analysis.

Moving Average (MA) focuses on the relationship between errors in past forecasts to make better future prediction.

Seasonal(S) making it SARIMA is the variant that accounts for cyclical or repeating patterns in the data. For example, energy demand is high on extremely hot and cold days as people are turning on their AC/heater.

Exogenous Variables (X) allows variables to influence the time series. X is critical to the research question as it allows incorporation of the rooftop capacity data into the Sarima model.

A standard Sarima model follows the below formula, the first half (p,d,q) are the ARIMA model, and seasonal elements are denoted in capital (P,D,Q,s)

SARIMA(p, d, q)(P, D, Q, s)

- p: Trend autoregression order.
- d: Trend difference order.
- q: Trend moving average order.
- P: Seasonal autoregressive order
- D: Seasonal difference order
- Q: Seasonal moving average order
- s: number of steps for a single seasonal period

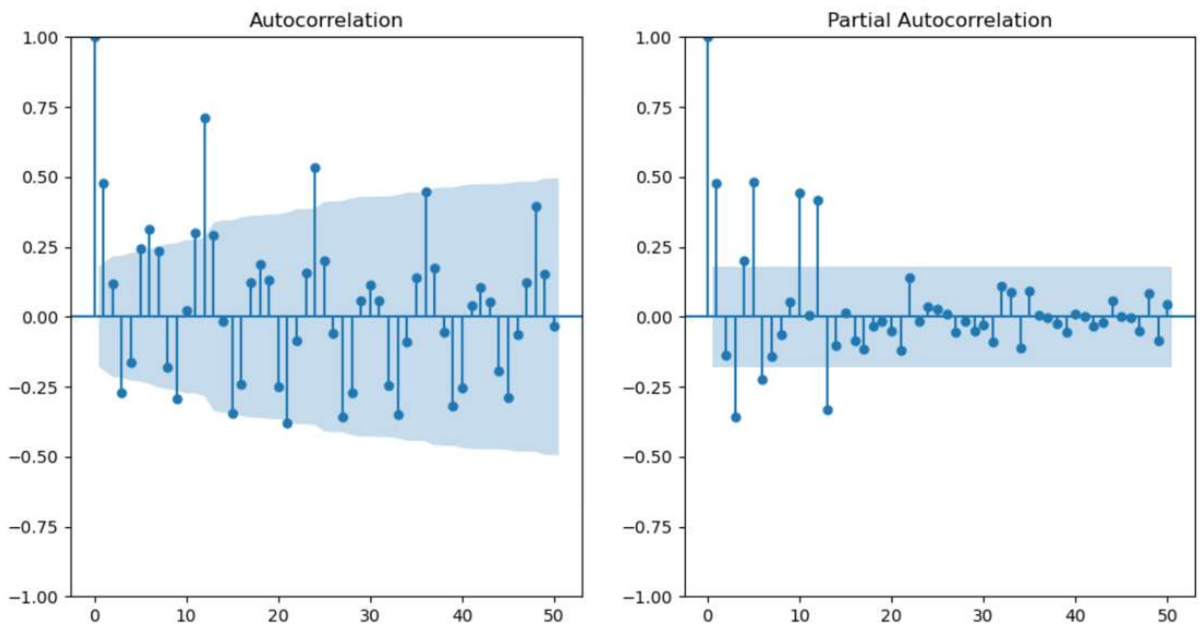

Figure 11: Autocorrelation (ACF) and Partial Autocorrelation (PACF)

The autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs, where each lag represents one month, show strong cyclical patterns, suggesting seasonality in the data. Spikes occur approximately every 6 and 12 lags, indicating both half-yearly and yearly cycles, which align with seasonal fluctuations.

The Partial Autocorrelation graph shows the relationship between a time series and its lagged values after removing the effects of the intervening data points. This reflects that the time series can be explained by its immediate past values after controlling for the effects of intermediate lag.

Modelling and testing

The baseline model will be a standard Sarima model with exogenous variables. To prepare the data, 90% will be split for training and 10% for testing. This is done so the testing data is a period of 12-month. Evaluation of model accuracy done using by calculating MAE, RMSE and R-squared and comparing test and forecast results of the baseline model and model that includes solar data.

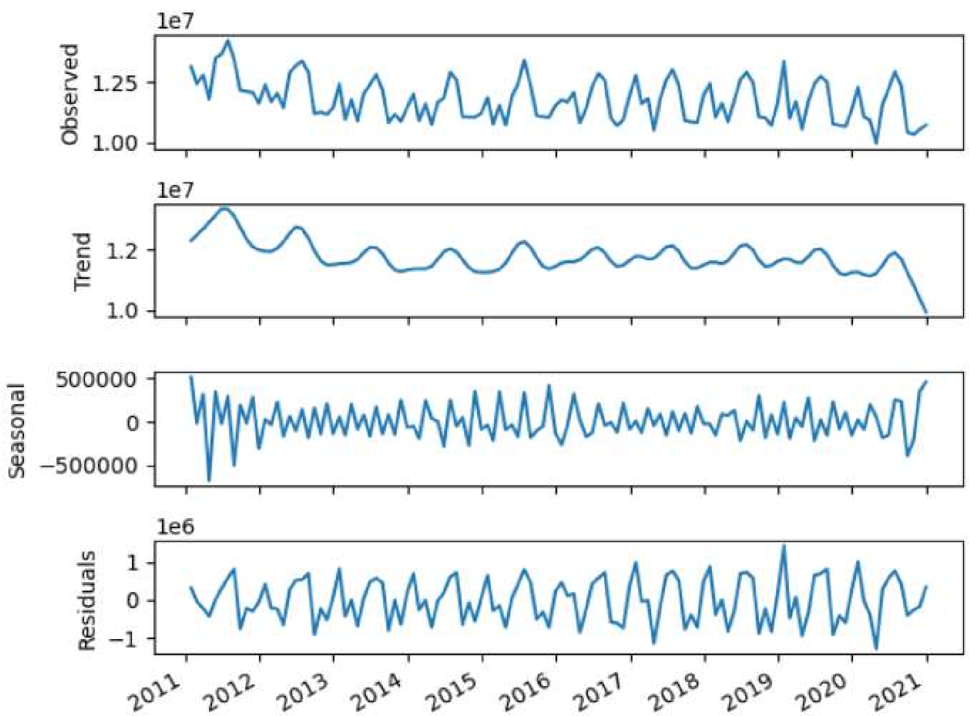

Figure 12: Time series decomposition

The above decomposition sums up the graphs and more clearly shows the seasonality and downward trend. The residuals indicate that while the model has captured the general structure, there may still be unexplained variability. Therefore, potential adjustments or external factors, such as solar data, could further improve accuracy.

Stationarity: Requirement for a SARIMA model is that data is stationary, meaning the time series has a constant mean and variance over time. To identify if the model is stationary, an Augmented Dickey-Fuller(ADF) test was applied using the adfuller().

The ADF on the training data provided a result of p-value of 0.00065. Is less than the 0.05 therefore the data is stationary and no additional transformation such as differencing is required.

Model fitting is required to determine the best optimal parameter combinations for non-seasonal (p,d,q) and seasonal(P,D,Q,s) of the model. The best model combination

ARIMA(0,1,0)(1,1,0)[12] generated by using the pmarima library's auto function. [Refer appendix 1 for results]

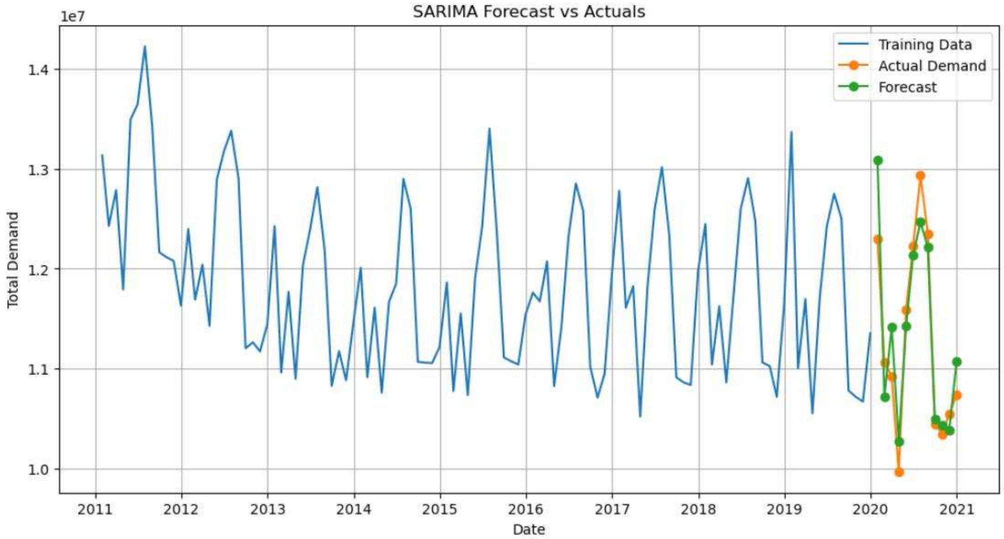

Figure 13: Base model forecast vs actuals

figure13 shows the forecasted results with the actual results. The forecast measured quite closely to the actual demand showing the model is performing ideally capturing the seasonality of the time series.

To measure the accuracy of the model the calculations below were completed in python.

MAE (Mean Absolute Error): 283,404 kW
RMSE (Root Mean Squared Error): 351,507 kW
R-squared: 0.8541 (85.4%)

The MAE score of 283,404 means that on average the model predictions deviate from the actual total demand values by 283,404. RMSE of 351,507kW reflects the magnitude of errors in the prediction. Ideally with MAE and RMSE the lower the better. The R-squared scored 85.4% meaning that 85.4% of the variances is explained, which is an excellent result.

To further improve and the crux of the research question a Sarimax model was developed following the same steps as the Sarima model but included exogenous variable of solar capacity.

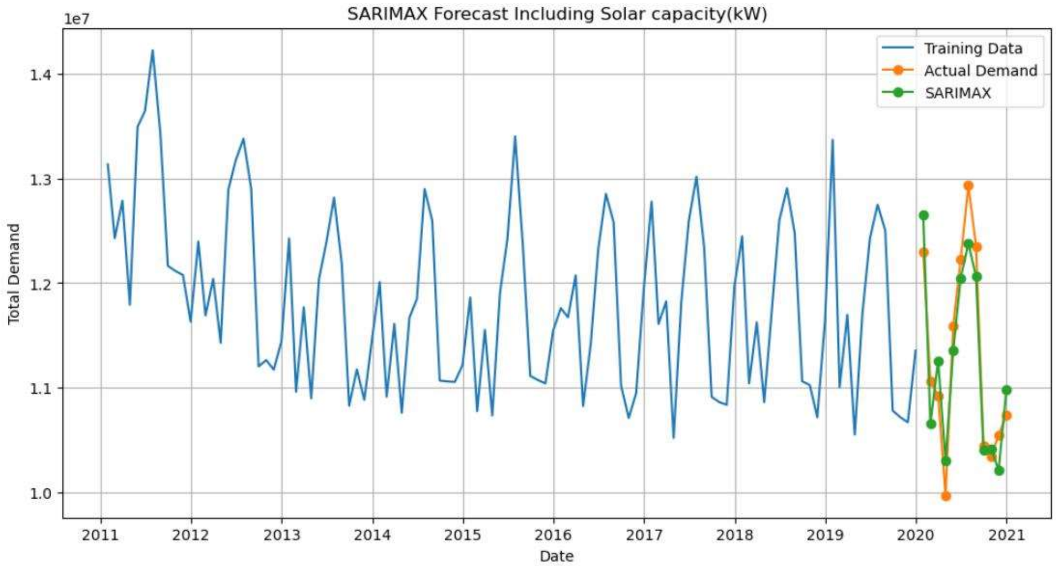

Figure 14: Sarimax model forecast vs actuals

The graph above shows the SARIMAX model, which incorporates the exogenous variable (solar capacity). The results of the SARIMAX model and the base SARIMA model appear remarkably similar visually. Calculating the accuracy metrics showed the SARIMAX model demonstrated improvements over the base SARIMA model.

MAE (Mean Absolute Error): 280,128 kW
RMSE (Root Mean Squared Error): 311,100 kW
R-squared: 0.8857 (88.6%)

The results are favorable towards Sarimax model with MAE decreased from 283,404kW to 280,128kW and RMSE decreased from 351,507kW to 311,100kW. R-squared showed favorable results with an increase from 85.4% to 88.6%.

These results reflect an overall improvement in model accuracy with the inclusion of the exogenous variable (solar capacity), suggesting that incorporating external factors like solar capacity can enhance the performance of demand forecasting models.

A paired t-test was conducted to determine if there is a statistically significant difference between the two models (SARIMA and SARIMAX). The test yielded a p-value of 0.005, which is below the significance threshold of 0.05. This result leads to the rejection of the null hypothesis and accepting the alternative hypothesis. Therefore, the inclusion of exogenous variables (solar capacity) in the SARIMAX model significantly improves the accuracy of seasonal electricity demand predictions.

Second model: LSTM

Long Short-Term Memory is a Recurrent Neural Network and one of the most advanced models to forecast time series, Korstanje J (2021)

Two different approaches were taken for LSTM to predict the total monthly demand:

1. Rooftop solar capacity is subtracted from Actual Demand data and fed into the LSTM model
2. LSTM models with different inputs to predict forecast demand:
    - One that takes BOTH TOTALDEMAND and Solar Capacity
    - Another takes only TOTALDEMAND

The LSTM models were then tuned by modifying architecture and adjusting hyper-parameters after observing several summary statistics:

- RSME; R^2; training loss; validation loss; and the spread of residuals.

The 2 Layer LSTM model architecture was enhanced to improve forecasting accuracy, by:

1. Incorporating a learning rate scheduler to adjust the learning rate after 20 steps
2. Incorporating 5-fold cross validation which provided several benefits such as:

    Improved Model Evaluation: It provides a more reliable estimate of the model's performance by training and testing the model on different subsets of the data. This helps in understanding how the model generalizes to unseen data.

    Reduced Overfitting: By using multiple folds, cross-validation helps detect overfitting. It ensures that the model's performance is not just good on a specific subset of data but consistent across different subsets.

    Hyperparameter Tuning: Cross-validation is useful for tuning hyperparameters. It allows evaluation of the impact of different hyperparameter values on the model's performance and select the best combination.

    Model Selection: It aids in comparing different models or architectures. By evaluating each model's performance across multiple folds, you can choose the one that performs best on average.

    Robustness: It makes the model evaluation process more robust by reducing the variance associated with a single train-test split. This leads to more stable and reliable performance metrics.

The ideal ranges for training loss and validation loss (val_loss) vary depending on each specific problem and dataset. However, the following general guidelines were followed:

Training Loss (loss):

- Low training loss indicates the model fits the training data well. However, if the training loss is too low, it might suggest overfitting, where the model learns the noise in the training data rather than the underlying pattern.
- For many problems, a training loss value between 0.01 and 0.1 is considered good, but this can vary widely.

Validation Loss (val_loss):

- Ideally, the **validation loss should be close to the training loss**. If the validation loss is significantly higher than the training loss, it might indicate overfitting.
- The validation loss should decrease and stabilise over epochs. If it starts increasing while the training loss continues to decrease, it might be a sign of overfitting.

Good Fit:

- A good fit is indicated when both training and validation losses decrease and stabilize at a low value. This suggests that the model is learning the underlying patterns in the data without overfitting Baeldung (2024).

The training loss and validation loss values were observed, and the model adjusted accordingly. Cross-validation was introduced to help achieve a good balance between training and validation loss.

Initial 2 Layer LSTM model before tuning, with Hyper-parameters:

Units: 50, Dropout 0.2; split 60%; epoch: 50; batch with_solar: 6; batch without_sole:6; time_steps: 12

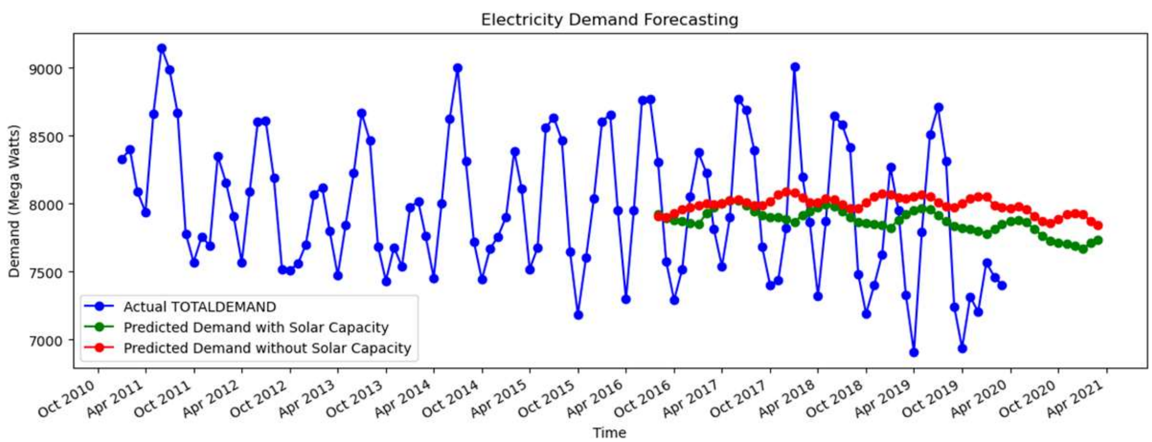

Figure 15: Monthly Electricity Demand actual (blue) vs LSTM Predicted (green with solar, red without): NSW (2020)

Residual plot for initial model

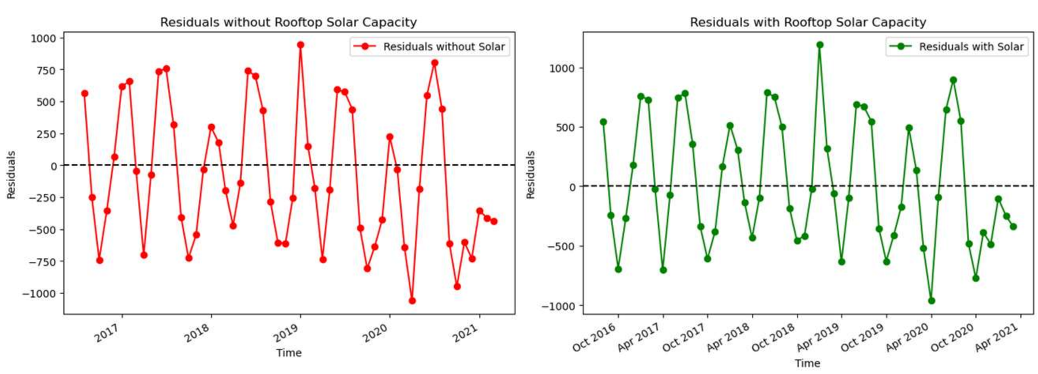

Figure 16: LSTM Monthly Residuals: red without solar capacity; green with solar capacity: NSW (2011-2020)

Initial 2 Layer LSTM model performance

	RMSE	R^2	Mean of 5-fold cross validation RSME	Training loss and validation loss
With solar	520.899	0.093	0.1682	Refer loss plots below
Without solar	441.121	0.021	0.1708	Refer loss plots below

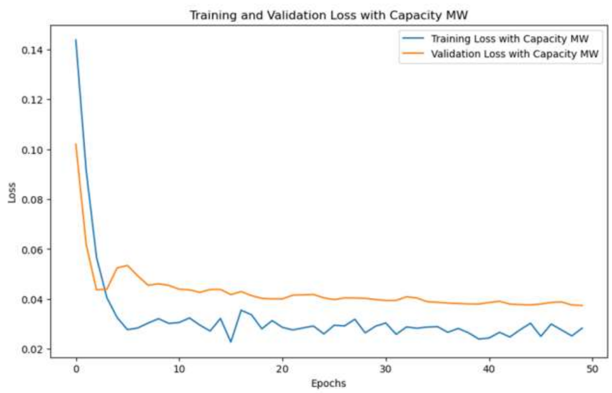

Figure 17: LSTM Training and Validation loss ***without*** *solar capacity: NSW 2020*

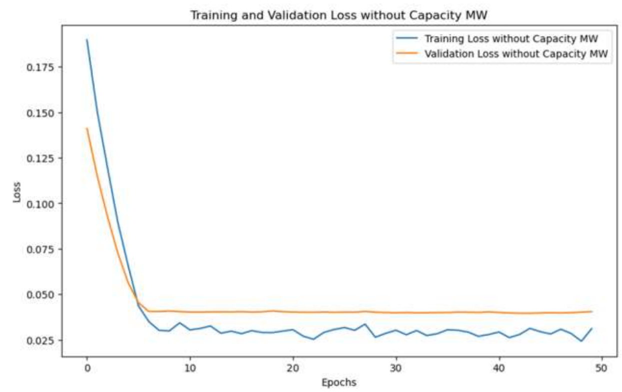

Figure 18: LSTM Training and Validation loss ***with*** *solar capacity: NSW 2020*

2 Layer LSTM model comparison after tuning and modifying LSTM architecture to incorporate cross-validation:

Units: 80, Dropout 0.2; split 50%; epocs 75; batch with_solar: 3; batch without solar: 3 time_steps: 12

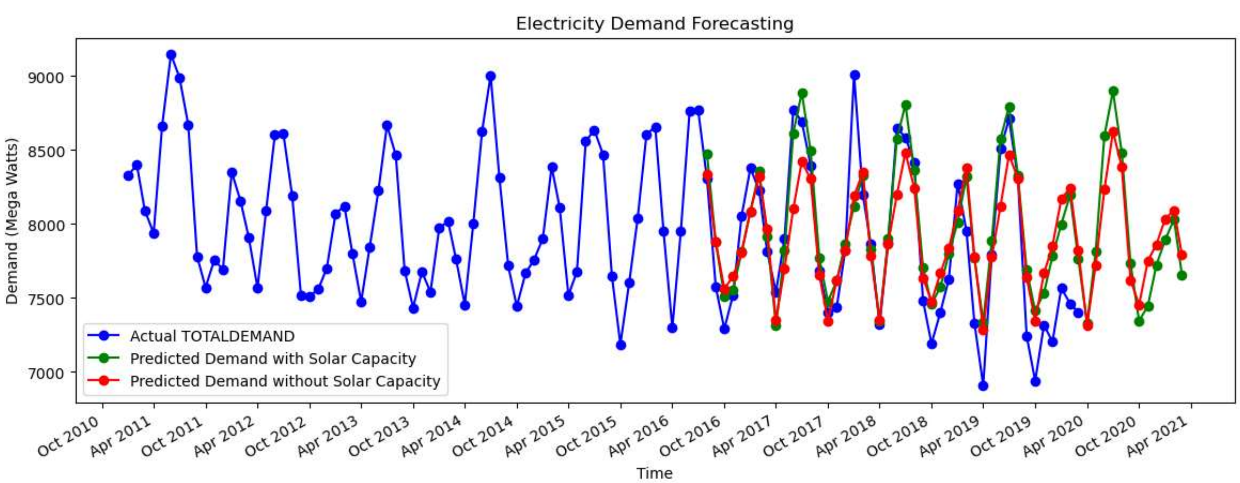

Figure 19: Monthly Electricity Demand: actual (blue) vs Tuned-LSTM Predicted (green with solar, red without): NSW (2020)

Residual plot for tuned LSTM with cross validation

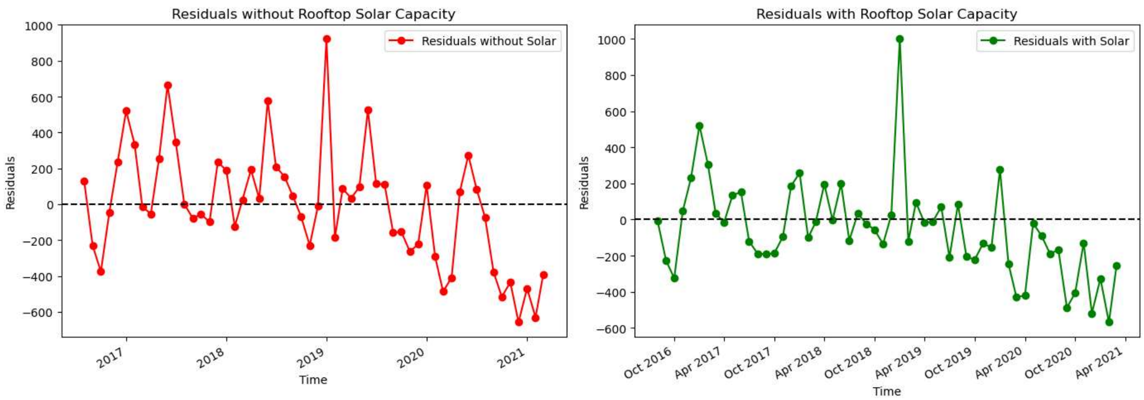

Figure 20: Tuned-LSTM Monthly Residuals: red without solar capacity; green with solar capacity: NSW (2011-2020)

Tuned LSTM model performance. Hyper-parameters were iteratively adjusted to produce an optimal model (Refer to appendix [2] for configuration and results.)

	RMSE	**R^2**	**Mean of 5-fold cross validation RSME**	**Training loss and validation loss**
With solar	265.274	0.765	0.0826	Refer loss plots below
Without solar	318.16	0.662	0.0975	Refer loss plots below

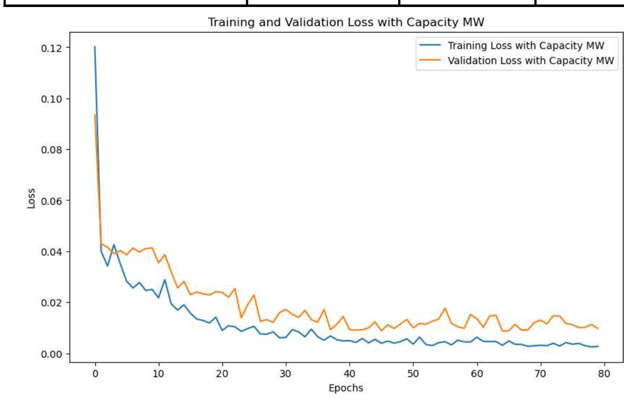

Figure 21: Tuned-LSTM Training and Validation loss without solar capacity: NSW 2020

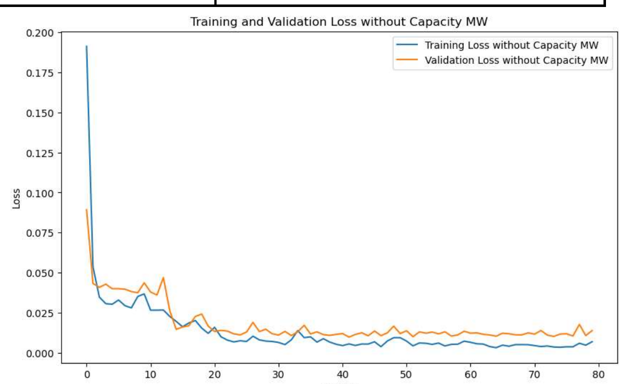

Figure 22: Tuned-LSTM Training and Validation loss with solar capacity: NSW 2020

The p-values from the paired t-test and the Wilcoxon signed-rank test were evaluated to determine if there is a statistically significant difference in the prediction accuracy of the LSTM model with solar capacity, compared with the LSTM model that does not have solar capacity as a separate input

Paired t-test: This test compares the means of two related groups to determine if there is a statistically significant difference between them. **p-value**: If the p-value is less than 0.05 (commonly used threshold), it indicates that there is a statistically significant difference between the two models' predictions.

Wilcoxon signed-rank test: This is a non-parametric test used to compare two related samples. It is used when the data does not necessarily follow a normal distribution.

- Like the paired t-test**, a p-value less than 0.05 indicates a statistically significant difference** between the prediction of two models**.** Conversely, **a p-value ≥ 0.05** indicates that there is **no statistically significant difference**.

These tests helped determine if the inclusion of "Solar Capacity" in our model significantly improves the prediction accuracy compared to the model without it.

Statistical comparison of prediction accuracy

RMSE with Solar Capacity: 265.2737274220416
RMSE without Solar Capacity: 318.15964979311156

R-squared value with Solar Capacity as input: 0.7647040862159433
R-squared value without Solar Capacity as input: 0.6615331766201199

MAE with Solar Capacity: 195.98200366945088
MAPE with Solar Capacity: 2.5025077811733616

MAE without Solar Capacity: 244.1500151067093
MAPE without Solar Capacity: 3.095144442662891

Paired t-test: t-statistic = 2.193425, p-value = 0.03252 **Statistical differenc**e
Wilcoxon signed-rank test: statistic = 631.0, p-value = 0.17312 **No statistical difference**

Discussion

The results of this study indicate that incorporating rooftop solar capacity data into electricity demand forecasting models produced mixed outcomes. For the SARIMAX model, the inclusion of solar capacity resulted in a statistically significant improvement in forecasting accuracy. However, for the LSTM model, there were mixed results in the prediction accuracy measures. Possible due to a 50% training split on the data (to avoid over-fitting). LSTM had statistically significant difference in prediction accuracy for the paired t-test but waws not statistically significant for the Wilcoxon (although approaching the p-value threshold).This difference in results may be partly due to the training and testing split of the data, as the SARIMAX model used a 90% training and 10% testing split, while the LSTM model adopted a 50% training and 50% testing split. Despite these differing outcomes for SARIMAX and LSTM, both models showed favorable improvements in R-squared and RMSE values when solar capacity was included in the model.

Despite expectations that both models integrating solar data would enhance prediction performance, the outcomes of this analysis did not reflect these anticipated improvements. This divergence may arise from various factors including differences in methodology, the granularity of the data used or the unique characteristics of the region and the levels of the solar adoption present in the dataset. Understanding this variation is crucial for interpreting the results and guiding future research efforts in electricity demand forecasting.

While the initial LSTM model produced low prediction accuracy, adjustments to the architecture and cross-validation method resulted in improved performance. However, the comparison of models with and without solar capacity using paired t-test showed statistical significance while the Wilcoxon signed-rank test showed no statistically significant difference in prediction accuracy. This suggests that rooftop solar data has the potential to influence electricity demand. But it may not have been a strong enough factor in specific datasets and model configurations used to drive substantial forecast improvements.

It is also important to consider the complexity of forecasting electricity demand which depends on numerous factors beyond solar generation. Temperature, clo ud cover, consumer behavior and grid dynamics all play significant roles in electricity consumption patterns. As such, the limited improvement observed in this study may be due to absence of other critical variables or the need for more sophisticated models that can better capture the interaction between these factors.

The minor improvement in forecasting accuracy when using monthly data further underscores the potential limitations of temporal aggregation. Finer time solutions such as daily or even hourly data may better capture the fluctuations in solar generation and its impact on electricity demand, allowing for more accurate and responsive forecasts.

While the inclusion of solar capacity data did not yield a significant improvement in the LSTM model in this specific case, it does not negate the importance of considering solar generation in future forecasting models. Continuous development in both solar technology and data science provides opportunities for advanced modeling approaches that could lead to better forecasting outcomes.

Incorporation of rooftop solar capacity data into the SARIMAX model did result in a statistically significant improvement in forecasting accuracy. However, the same integration into the LSTM models did not statistically significantly improve forecasting ac curacy. This was shown via the p-values from both the paired t-test and Wilcoxon signed-rank test, which compared the forecast accuracy of the two LSTM models.

Conclusion and Recommendations

The integration of rooftop solar data into electricity demand forecasting is essential for modern power systems. Advances in machine learning and data analytics have enabled more accurate and reliable forecasts, which can enhance grid stability and support the transition to renewable energy sources.

Whilst there is evidence of research Razavi et al. (2020); Guan and Han (2023); Razavi et al. (2020) where electricity demand forecasting, improved by incorporating rooftop solar data, our research and modelling support this research.

Future research should focus on improving the granularity and accuracy of rooftop solar power forecasts and developing robust models that can adapt to the dynamic nature of solar generation.

Interestingly, the physical effect of solar panels on a roof contributes an 8% reduction in near-surface air temperature in hot days due to the panel proving shade to the roof, which in turn reduces demand for electricity for cooling purposes (Salamanca et al. (2016)

Recommendations for the client,

1. Forecast accuracy with Monthly data is not significantly different. It is worth evaluating prediction accuracy utilising daily (or weekly) data which will provide the models more opportunity to learn and potentially provide an improvement
2. Look to run the analysis through a third model such as Random Forrest to further substantiate the results
3. Account for regional variability: Solar generation's impact on demand may vary regionally due to differences in solar adoption, energy consumption patterns and grid infrastructure. Consider region-specific models.

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Alphabetical order by surname Titles in italics; Hanging indent

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Appendix

Appendix 1 - Pmarima – Auto

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(1,1,1)[12]             : AIC=inf, Time=0.44 sec
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=2718.915, Time=0.01 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=2718.795, Time=0.06 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=2719.736, Time=0.08 sec
 ARIMA(1,1,0)(0,1,0)[12]             : AIC=2719.715, Time=0.02 sec
 ARIMA(1,1,0)(2,1,0)[12]             : AIC=2720.581, Time=0.22 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=inf, Time=0.35 sec
 ARIMA(1,1,0)(0,1,1)[12]             : AIC=2718.867, Time=0.07 sec
 ARIMA(1,1,0)(2,1,1)[12]             : AIC=inf, Time=0.66 sec
 ARIMA(0,1,0)(1,1,0)[12]             : AIC=2717.678, Time=0.03 sec
 ARIMA(0,1,0)(2,1,0)[12]             : AIC=2719.485, Time=0.08 sec
 ARIMA(0,1,0)(1,1,1)[12]             : AIC=inf, Time=0.24 sec
 ARIMA(0,1,0)(0,1,1)[12]             : AIC=2718.639, Time=0.05 sec
 ARIMA(0,1,0)(2,1,1)[12]             : AIC=inf, Time=0.49 sec
 ARIMA(0,1,1)(1,1,0)[12]             : AIC=2719.659, Time=0.05 sec
 ARIMA(1,1,1)(1,1,0)[12]             : AIC=2721.646, Time=0.15 sec
 ARIMA(0,1,0)(1,1,0)[12] intercept   : AIC=2719.386, Time=0.04 sec

Best model:  ARIMA(0,1,0)(1,1,0)[12]
Total fit time: 3.062 seconds
```

Appendix 2 - LSTM Hyper parameter tuning, iterations

		Hyper-Parameters									Results				5-fold X validation		
		Layer1		Layer 2		learning				time	accuracy		loss				
		Units	Dropout	Units	Dropout	rate	Split	Epocs	batch	steps	RMSE	R^2	Training	validation	mean RMSE	Residual plot	Forecast Plot
Plot1	with solar	50	0.2	50	0.2	0.001	60%	50	6	12	520.899	0.093	decreasing to 0.02	decreasing & > train	0.1682	random about zero	poor
	without	50	0.2	50	0.2	0.001	60%	50	6	12	541.121	0.021		decreasing & > train	0.1708	random about zero	poor
Plot2	with solar	50	0.2	50	0.2	0.01	60%	100	6	6	271.148	0.5511	decreasing to 0.006	decreasing & > train		slightly below zero	close for 36 months
	without	50	0.2	50	0.2	0.01	60%	100	6	6	383.536	0.5206				slightly below zero	close for 36 months
Plot3	with solar	50	0.2	50	0.2	0.01 LRS 0.1decay	60%	50	6	12	398.521	0.4912	decreasing to 0.022	decreasing & > train		above zero	under amplitude
	without	50	0.2	50	0.2	0.01 LRS 0.1decay	60%	50	6	12	436.247	0.3903				slightly below zero	under amplitude
Plot4	with solar	50	0.2	50	0.2	0.01 LRS 0.1decay	60%	50	2	12	367.883	0.5665	decreasing to 0.01	hit 0.0133 for last 15 steps		random about zero	close for 36 months
	without	50	0.2	50	0.2	0.01 LRS 0.1decay	60%	50	2	12	310.161	0.6918				random about zero	close for 36 months
Plot5	with solar	50	0.2	50	0.2	0.01 LRS 0.2decay	60%	50	2	12	303.166	0.6937	decreasing to 0.01	hit 0.0125 for last 10 steps		random about zero	close for 36 months
	without	50	0.2	50	0.2	0.01 LRS 0.2decay	60%	50	2	12	300.965	0.6982				slightly below zero	close for 36 months
Plot6	with solar	60	0.2	60	0.2	0.005 LRS 0.8decay	60%	50	4	12	405.837	0.4512	decreasing to 0.005	decreasing & > train		random about zero, then falls away	close for 36 months
	without	60	0.2	60	0.2	0.005 LRS 0.8decay	60%	50	4	12	283.561	0.732				random about zero, then falls away	close for 36 months
Plot7	with solar	60	0.2	60	0.2	0.005 LRS 0.8decay	60%	50	1	12	377.149	0.6937	decreasing to 0.005	decreasing & > train	0.092	random about zero, then falls away	close for 36 months
	without	60	0.2	60	0.2	0.005 LRS 0.8decay	60%	50	1	12	300.734	0.6982			0.094	random about zero, then falls away	close for 36 months
Plot8	with solar	80	0.2	80	0.2	0.005 LRS 0.8decay	75%	75	1	12	336.715	0.6501	decreasing to 0.003	decreasing & < train	0.081	slightly below zero most recent	close for 18 months
	without	80	0.2	80	0.2	0.005 LRS 0.8decay	75%	75	1	12	397.476	0.5124			0.095	slightly below zero most recent	close for 18 months
Plot9	with solar	80	0.2	80	0.2	0.005 LRS 0.8decay	75%	75	6	12	313.504	0.6702	decreasing to 0.005	decreasing & < train	0.0818	randomly scatter about zero	close for 48 months
	without	80	0.2	80	0.2	0.005 LRS 0.8decay	75%	75	3	12	295.69	0.7077			0.091	randomly scatter about zero	close for 48 months
Plot10	with solar	80	0.2	80	0.2	0.005 LRS 0.8decay	50%	75	6	12	303.636	0.6917	decreasing to 0.01	decreasing & > train	0.0804	randomly scatter about zero	close for 48 months
	without	80	0.2	80	0.2	0.005 LRS 0.8decay	50%	75	3	12	296.944	0.7052			0.0958	randomly scatter about zero	close for 48 months
Plot11	with solar	80	0.2	80	0.2	0.005 LRS 0.8decay	50%	80	8	12	262.299	0.77	refer plots	refer plots	0.0832	random about zero, then falls away	close for 48 months
	without	80	0.2	80	0.2	0.005 LRS 0.8decay	50%	80	4	12	296.445	0.706	refer plots	refer plots	0.0922	random about zero, then falls away	close for 48 months
Plot12	with solar	140	0.2	140	0.2	0.005 LRS 0.8decay	50%	80	8	12	265.274	0.765	refer plots	refer plots	0.0826	random about zero, then falls away	close for 54 months
	without	140	0.2	140	0.2	0.005 LRS 0.8decay	50%	80	4	12	318.16	0.662	refer plots	refer plots	0.0975	random about zero, then falls away	close for 54 months

Appendix 3 – Github link

https://github.com/AlanNgu/Group7_ZZSC9020