CAPSTONE PROJECT BY TEAM 3

A DATA SCIENCE APPROACH TO FORECAST SHORT-TERM ELECTRICITY DEMAND IN NSW

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Acknowledgements

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02/10/2024.

Abstract

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Chapter 1
Introduction

This R Markdown template can be used for the ZZSC9020 course report. You can incorporate R [R Core Team(2017)] chunks and Python chunks that will be run on the fly. You can incorporate LaTeXcommands.

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Chapter 2

Literature Review

2.1 Background

Electricity demand forecasting is crucial for ensuring an efficient, reliable and cost-effective power operation systems. Accurate forecasts enable grid operators to balance supply and demand in real-time, preventing costly overproduction or dangerous shortages that could lead to blackouts. It also helps to optimize the scheduling of power generation for different sectors, reducing operational costs and enhancing system reliability. As renewable energy sources like solar and wind become more integrated, forecasting plays a vital role in managing fluctuations in supply. Additionally, in deregulated markets, precise demand predictions allow energy providers to make informed trading decisions, ultimately benefiting both suppliers and consumers with more stable and affordable electricity.

NSW is largely self-sufficient in relation to electricity supply according to [www.soe.epa.nsw.g meeting most of its local demand through state generation. The remaining electricity is purchased from other states through the National Electricity Market (NEM). Electricity imports enable NSW to manage its supply at the lowest cost to consumers. In 2019–20, renewable energy sources provided around 19% of the state's total electricity generation, which is more than four times that provided in 2008–09. This does not include energy supplied by solar hot water heating, which provided an estimated supply of around 4.4 PJ in 2019–20, equivalent to 1,222 gigawatt-hours (GWh).

According to [NSW EPA(2021)] electricity demand from the NSW grid is projected to experience a slight decline over the next five years before rising once more. The main reason for the decline in energy consumption is the lower consumption by the NSW industrial sector, particularly the manufacturing industry, since 2012–13. There was a noticeable decline in industrial energy consumption following the closure of the Kurnell and Clyde petroleum refineries in October 2014, but few major changes since then (www.soe.epa.nsw.gov.au. (n.d.)). This initial decrease is anticipated to be driven by population growth being counterbalanced by enhancements in the energy efficiency of appliances and machinery. Furthermore, the growing adoption of rooftop solar panels and battery storage systems is expected to further reduce residential demand on the electricity grid. However, beyond the five-year mark, consumption is forecasted to increase as electric vehicle charging and broader electrification begin to significantly impact electricity demand. According to NSW Climate and Energy Action. (n.d.) the share of solar and wind in NSW's energy mix has more than DOUBLED from 5% in 2015 to 12% in 2019. In the Figure 2.1 we can visualize the rapid growth of electricity generation using renewable sources.

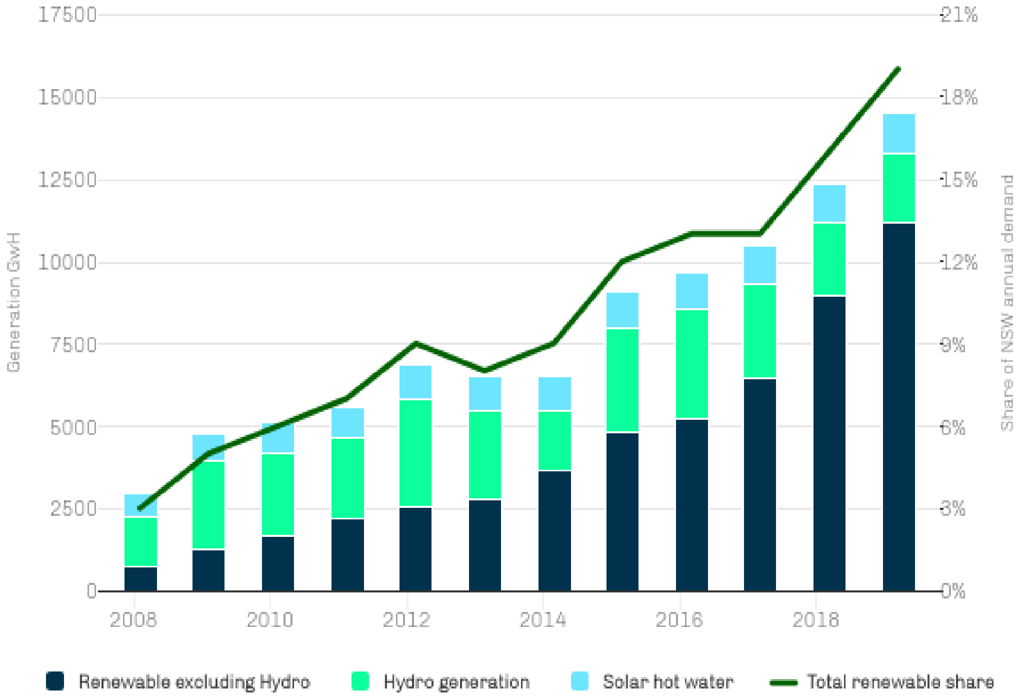

Figure 2.1: Renewable fuel sources [Source: Derived from Department of the Environment and Energy, Australian Energy Statistics, Table O, June 2021]

As stated in [www.soe.epa.nsw.gov.au()] the driving factors of electricity consumption and demand forecasts can be split into two different types: structural drivers and random drivers. Structural drivers such as population, economic growth, electricity price, technology adoption, energy efficiency can be estimated based on past trends and expert judgement. On the other hand, random drivers, such as weather, customer behavior etc, which can be modeled as probability distributions. There are many factors that drive consumers to make similar choices regarding electricity consumption at the same time for example during work and school schedules. And the demand is different during weekdays, public holidays, weekends, due to weather the use of heating and cooling appliances, and many other societal factors, such as whether the beach is pleasant, or the occurrence of retail promotions.

Load forecasting is usually concerned with the prediction of hourly, daily, weekly, and annual values of the system demand and peak demand. Such forecasts are sometimes categorized as short-term, medium-term and long-term forecasts, depending on the time horizon. In terms of forecasting outputs, load forecasts can also be categorized as point forecasts (i.e., forecasts of the mean or median of the future demand distribution), and density forecasts (providing estimates of the full probability distributions of the possible future values of the demand).

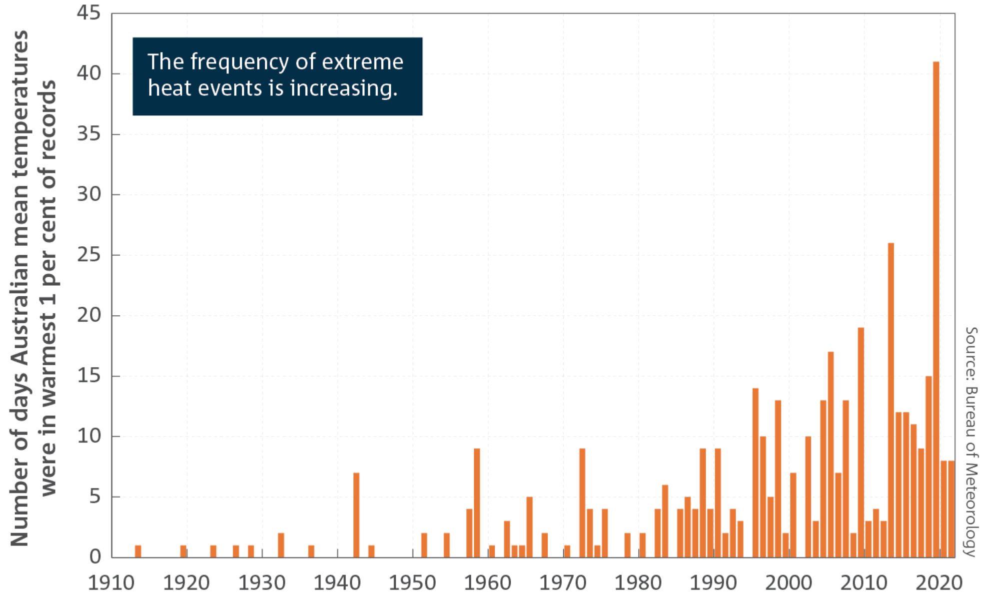

Figure 2.2: A caption1

In addition to the basic components of electricity demand forecasting, several external factors play a significant role in refining predictions and improving accuracy.

Temperature is a crucial factor, as it directly influences electricity consumption patterns. Extreme temperatures, whether very hot or cold, can lead to higher demand for heating or cooling, respectively. Forecasts often need to account for temperature variations to predict demand more accurately, especially during seasonal extremes or unusual weather patterns.

As the graph in Figure 2.2 shows the temperature in Australia is rising and forecast show that it will continue to rise. According to [Adapt NSW(2024)] the climate of NSW is changing, with 6 of the 10 warmest years on record occurring in the past 10 years. The warmest year on record for both average temperature and maximum temperature in NSW was 2019, when average temperature was 1.2°C above the 1990–2009 average. Across NSW, average temperatures will continue to increase throughout this century. By 2090, average temperature is projected to rise by around 1.3°C under a low emissions scenario and around 4.0°C under a high emissions scenario. So temperature is key factor while determining the electricity demand. The usage of heating in colder nights and cooling system during the hot days directly impacts the demand of electricity.

Holidays and weekdays also affect electricity usage. On holidays, electricity consumption patterns can differ significantly from regular weekdays due to changes in work routines and social activities. For instance, public holidays might see a decrease in commercial and industrial electricity use, while residential usage could increase due to family gatherings and home activities. Understanding these variations helps in adjusting forecasts to better reflect the actual demand patterns during such periods.

Overall, incorporating temperature data and considering holiday effects are essential for creating more accurate and reliable electricity demand forecasts, which in turn support better decision-making for power system management and operational planning.

2.2 Electricity Demand Forecast Methodologies

Electricity demand or load forecasting is a well-known problem to predict the future load based on historic information. Researchers used both statistical and probabilistic methods to achieve high accuracy with low errors to find the best model. They also considered this problem as both deterministic and stochastic to include the influence of the external factors that sways the models behaviour at different time horizons. At high-level the problem can be classified into four forecasting groups – very short-term (mins to hrs), short-term (days), medium-term (months), and long-term (years). Based on the required time horizons we can further classify the problem into three broad solution domains – heuristic, statistical or econometric, and probabilistic models. Typically, electricity consumption is influenced by two factors—1) structural like population growth, economic condition, electricity price, etc; and 2) non-structural or random like weather condition e.g., air temperature, extreme heat or cold, bushfire, flood, etc., building type e.g., multi-storey or free-standing house, and adoption of electric vehicles and contributions of renewable energy in the power grid, etc. Time series datasets have the unique property of dependence on what happened on the past. Therefore, we cannot randomly shuffle the order of the data without affecting the trends. With such dependency simple regression technique for forecasting can randomly show statistical significance even if there is no true correlation, and thus suitable for real-world usage. In the following sections, we will discuss the popular forecasting models used in the electricity demand forecasting domain.

2.3 Statistical Models/ Regression Methods

The simplest form of forecasting is Moving Average (MA) which predicts the future values as the average of n previous values. With a larger window we can smooth out the noise to find the actual tend but the forecasts will start to lag as we were to go back further and further to calculate the average. Exponential Smoothing (ETS) eliminates this problem by exponentially decrease the weights of the averages over time. This prioritises more recent values over the older values, however, as the averaging window size increases the overall trend starts to lag again. Additionally, most real-world time series are not stationary i.e., the change in mean or variance over time are not the same at different observation points. Autoregressive Integrated Moving Average (ARIMA) [Box and Jenkins(1970)] extends this idea further by modelling the dependent relationship between an observation and a set of previously lagged observations by taking the difference of successive values many times to make the time series stationary. This is like saying that it will be hot tomorrow since it has been hot so far this week as the high air temperature had not varied much. In short, the $ARIMA(p, q, d)$ model applies a dth order differencing on a time series and takes the last p terms in autoregressive way and the include the last q moving average terms to generate the forecast over a specified time horizon. However, the ARIMA model does not consider the repeating patterns within the time series like temperature increases in the daytime while decreases in night or hotter summer and colder winter. Seasonal ARIMA (SARIMA) [Box and Jenkins(1970)] deals with this challenge by taking the values of p, q, and d over a season period m instead of the immediate past. Auto ARIMA [Hyndman and Khandakar(2008)] scales this process by finding the best combination of $< p, q, d >$ automatic way. Typically, ARIMA models and its other variants forecast very well but it's hard to scale for large datasets and often too complex to fine tune without significant domain expertise. The Theta Forecast [Assimakopoulos and Nikolopoulos(2000)] is another well performed model that uses a parameter θ to smooths the local curvature of a time series. In the original implementation two theta lines are used and the final forecast is the average of them. Later, [Hyndman et al.(2002)Hyndman, Allan and Koehler] showed that an ETS with a drift term can perform equally to the original Theta Forecast and since then adopted to most of its later implementations. [Wang et al.(2021)Wang, Sun, Chen, Zeng, Kong highlights that although these traditional techniques such as fuzzy linear regression, exponential smoothing, Automatic Regressive Moving Average (ARMA) have the advantages of algorithmic simplicity but they are not scalable to handle large dataset and model complicated relationships.

2.4 Machine Learning Methods

Another approach is to first apply Fourier Transformation (FT) to decompose a stationary time series (i.e., removing trends and seasonality) from time domain to frequency domain as temporal frequencies. Once decomposed we can then apply Fast Fourier Transform (FFT) [Shannon(1948)] to filter out the noise and only select the few promising frequencies to perform an Inverse Fast Fourier Transform (IFFT) to reconstruct the time series and add back the trend and seasonality. Due to its unique properties FFT is a versatile and fast generic tool to identify trends and noise filtering in time series and therefore often used as to establish a baseline forecast. A more recent and very popular Generalised Additive Model (GAM) for regression technique is *Prophet* [Taylor and Letham(2017)]. It is designed to optimally handle business forecasting tasks featuring time series captures at the hourly, daily, or weekly level with ideally at least a full year of historical data. It can also handle missing data and outliers, strong seasonality effects occurring daily, weekly, yearly, holidays and other special one-time events that do not necessarily follow the seasonality patterns. These unique properties make it very suitable for both short-term and mid-term electricity forecasting as we will discuss the *Prophet* model in greater details in following subsection. Instead of finding a single point forecast from a time series using statistical methods discussed in the previous subsection, we can also apply probabilistic methods like probabilistic regression or other machine learning models. In the simplest form to cast a time series forecasting as regression we need to first convert the observations i.e., samples as independent and identically distributed. We can treat the set of time lags over a fixed length sliding window as independent feature variables and their succeeding time lag as the corresponding target variable to convert the time series into a dataset for interpolation using regression. We can also use rolling and seasonal rolling time window or Exponentially Weighted Moving Averages (EWMA) instead of sliding window [Roberts(1959)]. This kind of transformation using time lags is called time-delay embedding. Another approach is to embed time into features so that we can train ML models. For instance, timestamps associated with time series can be treated as calendar features i.e., time periodicity like year, month, quarter, day, hour, minutes, seconds, etc. We can also use the timestamps as monotonically increasing integers and treat them collectively as time elapsed feature. tsfeatures (??) and tsfresh (??) are two popular open-source libraries to extract time series features for ML models. One straightforward way is to use Linear regression and estimate using least squares to minimise the Mean Squared Errors (MSE) [Lai et al.(2005)Lai, Yu and Wei]. But multi-collinearity in time series can lead to unstable and unreliable regression models due to the high correlation between variables caused by trends, seasonality, or lagged values. Thus, it's difficult to accurately estimate the coefficients and interpret the relationships between variables. Regularization techniques like applying L1 and L2 norms e.g., lasso and ridge regressions can help address multicollinearity in linear regression by penalising large coefficients. However, we cannot capture the non-linear relationships within the independent features using a linear model. For example, sudden increase in air-conditioning usage after temperature reaches a certain threshold.

A common way to capture such non-linear relationship is to use a Decision Tree (DT) [Spiliotis(2022)] and split branches based on feature importance such as important time lag moment or seasonal rolling. But a DT can easily overfit as it often relies on specific feature importances. We can overcome this by using ensemble learning. Bagging and Radom Forest are two popular ensemble techniques that use a set of DTs as weak learners. Furthermore, we can use Gradient Boosted DT (GBDT) technique for sequential learning and its ability to handle complex relationships for many time series applications. Popular boosting implementations like XGBoost [Chen et al.(2020)Chen, Huang and Zheng] and Light Gradient Boosting Machine (LightGBM) [Salinas et al.(2017)Salinas, Flunkert, Gasthaus, Januschowski and Van den Oord employ techniques like row and column sampling, and optimised tree growth algorithms to reduce training time for large time series dataset and improve prediction accuracy.

Now, we shift our focus into forecasting from time series using supervised learning models like neural network and deep learning. Transforming time series data for supervised learning models requires considerations of temporal dependencies and trends. Encoder-Decoder and Feed Forward Networks (FNNs) are suitable for fixed-length sequences while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks can better handle variable-length sequences and long-term dependencies. RNNs address the sequential nature of time series data by incorporating a recurrent connection allowing information from previous observations to be passed to subsequent ones [Hochreiter and Schmidhuber(1997a)]. While RNNs are capable of modelling long-term dependencies they suffer from the vanishing gradient problem. LSTMs, a variant of RNNs, introduces gates that selectively control the flow of information, mitigating the vanishing gradient problem. LSTMs have been successfully applied to a wide range of time series tasks including forecasting, anomaly detection, and classification [Hochreiter and Schmidhuber(1997b)]. Convolutional Neural Networks (CNNs) originally designed for image processing but later have been adapted for time series analysis too. CNNs can effectively capture local patterns and dependencies making them suitable for time series classification and anomaly detection [?]. Lastly, Attention mechanisms and Transformers can capture global dependencies and the importance of different time steps for complex time series tasks. Attention mechanisms can model long-range dependencies in sequence-to-sequence tasks. Attention allows the model to focus on relevant parts of the input sequence when making predictions [?]. Transformers leverage self-attention mechanisms to capture dependencies between different time steps in the input sequence. Transformers have been shown to outperform RNNs and LSTMs in many sequence modelling tasks [?].

2.5 Challenges to Find the Ideal Electricity Load Forecasting Method

In this study we focus on short-term demand forecasting which is an essential instrument in power system planning, operations, and control. Many operating decisions are based on load forecasts such as dispatch scheduling of generating capacity, reliability analysis, and maintenance planning for the generators. Overestimation of electricity demand will cause a conservative operation which may lead to overproduction or excessive energy purchase. For instance, in [AEMO(2022)] AEMO uses a monthly regression model based on five years (60 months) of historical data. The choice of five years data strikes a balance between ensuring that the model considers only relatively recent univariate consumption trends and behaviours while being long enough to capture seasonality and contain enough multivariate observations to be statistically meaningful. Univariate models, while simpler, often struggle to capture complex relationships and seasonal patterns in load data. Multivariate models, incorporating additional factors like temperature, humidity, and economic indicators, can improve accuracy but introduce challenges in data collection, preprocessing, and model complexity, thus require careful feature engineering. Univariate models use only historical demand data to make future predictions, while multivariate models consider other variables such as atmospheric variations and calendars along with historical demand data in the study of STLF [Chapagain et al.(2023)Chapagain, Gurung, Kulthanavit and Kittipiyakul]. [Wang et al.(2016 Chen et al.(2015)Chen, Wang, Liu, Wang and Liu] both highlight the limitations of traditional methods and the growing interest in advanced hybrid techniques. Therefore, the selection of an ideal forecasting method depends on factors such as data availability, computational resources, and the desired level of accuracy, making it a complex and ongoing research area.

[Taylor and McSharry(2009)] develops both univariate and multivariate models and stated that the univariate models had good prediction capability. In univariate time series models, the historical electricity demand data are arranged with correlated past lags to capture the demand patterns even when the data are limited. [McCulloch et al.(2001)McCulloch, Tsay and Wu] obtains improved accuracy by including the temperature as a variable, recognising that weather conditions play a crucial role in forecasting performance. [Fan and Hyndman(2012)] proposes a semi-parametric additive models are proposed to estimate the relationships between demand and the driver variables. Specifically, the inputs for these models are calendar variables, lagged actual demand observations and historical and forecast temperature traces for one or more sites in the target power system. The proposed methodology has been used to forecast the half-hourly electricity demand for up to seven days ahead for power systems in the Australian National Electricity Market (NEM). To achieve more efficient and accurate load forecasting [Suo et al.(2019)Suo, Song, Dou and Cui] establishes a multi-dimensional short-term load forecasting model based on XGBoost.The decision forest composed of many decision trees is the final learning model of XGBoost. It tries to correct the residual of all the previous weak learners by adding new weak learners. When these learners are combined for final prediction the accuracy will be higher than that of a single learner. The selection of appropriate hyper parameters of XGBoost is directly related to the performance of the model but there is no universal and scientific method to determine the hyper parameters. In order to reduce the randomness and blindness, based on the second search of multi-dimensional grids, a method of hyper parameters optimisation is proposed. Each hyper parameters combination is attempted in a grid traversal manner in turn.

Chapter 3

Material and Methods

3.1 Software

R and Python of course are great software for Data Science. Sometimes, you might want to use `bash` utilities such as `awk` or `sed`.

Of course, to ensure reproducibility, you should use something like `Git` and RMarkdown (or a Jupyter Notebook). Do **not** use Word!

3.2 Description of the Data

How are the data stored? What are the sizes of the data files? How many files? etc.

3.3 Pre-processing Steps

What did you have to do to transform the data so that they become useable?

3.4 Data Cleaning

How did you deal with missing data? etc.

3.5 Assumptions

What assumptions are you making on the data?

3.6 Modelling Methods

Based on the literature review we in this study we explore the two popular model - additive model Prophet by Facebook and another one is the machine learning model XGBoost for short term demand forecasting. According to our EDA, the demand has high variability during peak/off-peak, weekdays, hours of the day and most importantly temperature change.

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Chapter 4

Exploratory Data Analysis

This is where you explore your data using histograms, scatterplots, boxplots, numerical summaries, etc.

```
import numpy as np
np.random.seed(1)
np.random.normal(0.0, 1.0, size=10)
```

```
## array([ 1.62434536, -0.61175641, -0.52817175, -1.07296862,  0.86540763,
##        -2.3015387 ,  1.74481176, -0.7612069 ,  0.3190391 , -0.24937038])
```

Chapter 5

Analysis and Results

5.1 XGBoost

Having a very simple model is always good so that you can benchmark any result you would obtain with a more elaborate model.

For example, one can use the linear regression model

$$Y_i = \beta_0 + \beta_1 x_{1i} + \cdots \beta_p x_{pi} + \epsilon_i, \qquad i = 1, \ldots, n.$$

where it is assumed that the ϵ_i's are i.i.d. $N(0, 1)$.

5.2 Facebook Prophet

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Chapter 6

Discussion

Put the results you got in the previous chapter in perspective with respect to the problem studied.

Chapter 7

Conclusion and Further Issues

What are the main conclusions? What are your recommendations for the "client"? What further analysis could be done in the future?

A figure:

Figure 7.1: A caption

In the text, see Figure 7.1.

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Appendix

Codes

Add you codes here.

Tables

If you have tables, you can add them here.

Use https://www.tablesgenerator.com/markdown_tables to create very simple markdown tables, otherwise use LaTeX.

Tables	Are	Cool
col 1 is	left-aligned	$1200
col 2 is	centered	$12
col 3 is	right-aligned	$1