Team J - A data science approach to Predicting Energy Demand In New South Wales

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2 Abstract

Enter Abstract here

3 Introduction

With the advent of climate change, rapid adoption of technology, growth in population and life expectancy, and continued industrialisation and globalisation in the twentieth century, energy demand has increased exponentially during the last century, and the trend is continuing. Global energy consumption is expected to increase by 50% within this decade if the current consumption pattern continues (Smith et al., 2007). Disruptions in power can have serious economic impacts, both for industries, and individual companies. In December of 2023, the Australian Energy Market Commission (AEMC) introduced new rules for National Electricity Market to ensure energy reliability as the country transitions to increased reliance on renewable energy sources (Latief, 2023). These rules include incremental raises to the Market Price Cap, Cumulative Price Threshold and Administrative Price Cap with the aim to provide greater flexibility for investors to contribute to new generation and storage infrastructure for periods of high demand.

Energy demand management is an important issue for energy suppliers and policy makers in Australia. While energy consumption is expected to increase overall, the introduction of renewable energy sources has seen demand on traditional energy sources stabilise and even reduce. By 2030, the Australian Energy Market Operator (AEMO) expects 50% of consumers to be driving demand to the National Electricity Market to meet their energy needs (Energy Security Board, 2021). Two of the factors that will significantly impact energy demand in the next decade is Climate change which will impact average and extreme Temperatures across Australia (Ahmed, Muttaqi and Agalgaonkar, 2012), and dedicated investment in Electric Vehicle (EV) infrastructure (Zhang et al., 2017) and the subsequent growth of EVs.

However, Australia's national approach to energy management and in particular renewables as response to climate change is fragmented and ineffective (Nelson, 2015). As a result, this paper will focus on a specific state, New South Wales (NSW). NSW has seen a 2% decrease in energy consumption from the grid, driven by a 19% increase in renewable energy sources, primarily in the residential sector which only accounts for 11% of overall energy demand in the state (NSW Environment Protection Authority, n.d.). While this is exciting, the NSW Government is planning to invest $209m in an EV charging network, when coupled with additional policies and incentives is intended to make EVs represent 52% of new car sales in NSW by 2031 (NSW Climate and Energy Action, 2022), which may offset some of this demand stabilisation.

With competing pressures to tackle climate change, it is not a viable option to meet this demand through traditional energy sources. This presents a significant challenge for NSW, as current strategies and lack of political momentum has resulted in limited success in finding other sources of energy through large scale renewable energy assets. The objective of this paper is to identify the short and long term influencers of energy demand in NSW, and build models to support policy makers and organisations to effectively predict the energy demand so that they can plan for the right solutions. This paper will use a Linear Regression model to predict long term changes in energy demand, and an ARIMA model to show the short term prediction.

4 Literature Review

International Energy Agency (IEA) publishes reports and statistics on energy usage for various countries, covering about 80% of global energy usage (International Energy Agency, n.d.). As per statistics published by IEA (IEA, 2019), total electricity consumption in Australia was about 253 TWh in 2022. The following chart shows that there has been slight decline in industrial electricity consumption since 2010 but residential electricity consumption has continued to increase following a slump in 2013-14. The decline in industrial electricity consumption can be attributed to reduced growth of larger industrial energy users, closures of industrial facilities, energy efficient programs and embedded generation. The reduction in residential electricity consumption during 2013-14 may be attributed to energy efficiency programs, widespread deployment of rooftop solar PV, water heating fuel-switch program and consumer response to increasing retail electricity price (Sandiford et al., 2015).

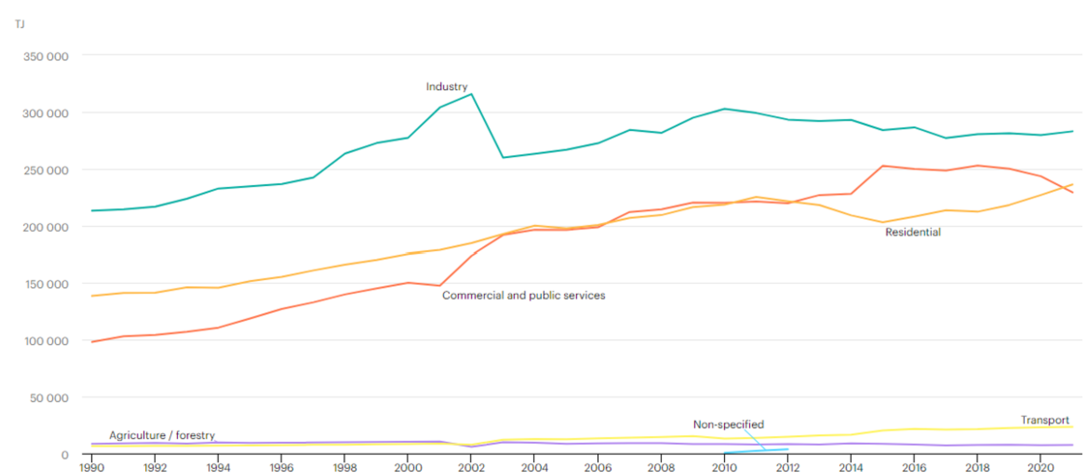


Figure 1: Energy consumption by sector, Australia, 1990-2021 (IEA, 2019)

It is noticeable that per capita electricity usage has reduced during the last decade, following the peak of 11 MWh per capita consumption during early 21st century.

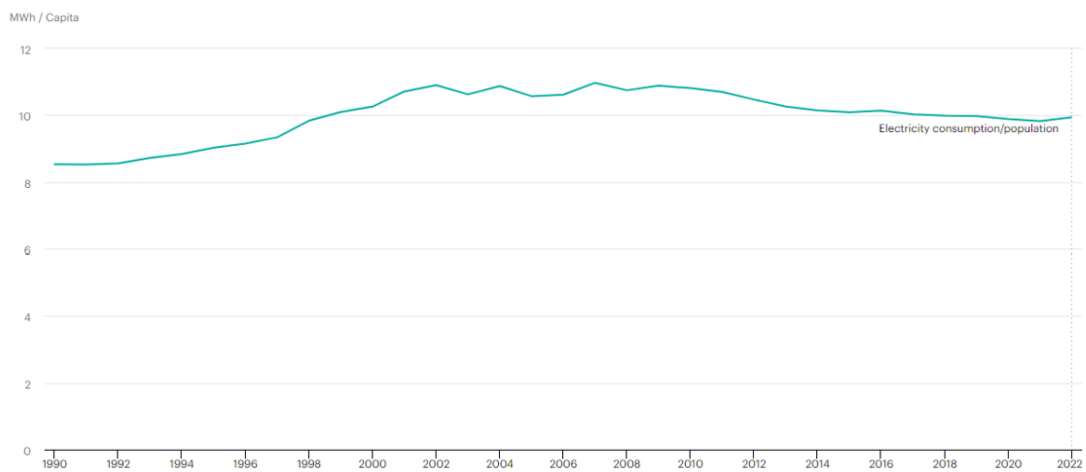


Figure 2: Energy consumption per capita, Australia, 1990-2022 (IEA, 2019)

While in Australia more than 50% of electricity is generated still being generated by traditional sources, it is noticeable that wind and solar PV account for more than 20% of the total electricity generated in 2022.

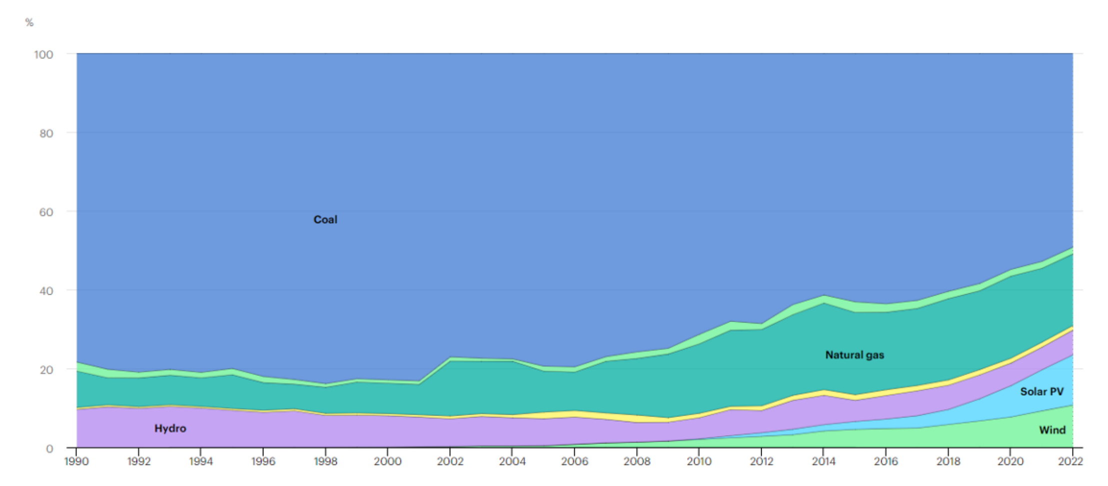


Figure 3: Distribution of energy generated by source, Australia, 1990-2022 (IEA, 2019)

A look into Australia's energy strategies and frameworks is fundamental to understand the shift in energy source, and how the shift may evolve in the future. The Australian Government's Powering Australia plan (Department of Climate Change, Energy, the Environment and Water, 2023b) is focused on lowering emissions by boosting renewable energy and reducing pressure on energy bills. Of particular note is the National Energy Transformation Partnership (Energy.gov.au, 2022) established in 2022. It is a framework for Commonwealth, state and territory governments to work together on reforms to help transform Australia's energy systems to achieve net zero target by 2050. Some of the key themes of this partnership are:

- Planning for adequate energy generation and storage
- Understanding demand evolution
- Coordinating gas and electricity planning
- Enhancing energy security management and
- Accelerating nationally significant transmission projects

In addition to above, the Australian Government's Department of Climate Change, Energy, the Environment and Water (DCCEEW) recently published the National Energy Performance Strategy (Department of Climate Change, Energy, the Environment and Water, 2023a) which provides a long-term framework to manage energy demand. There are 5 focus areas in this strategy:

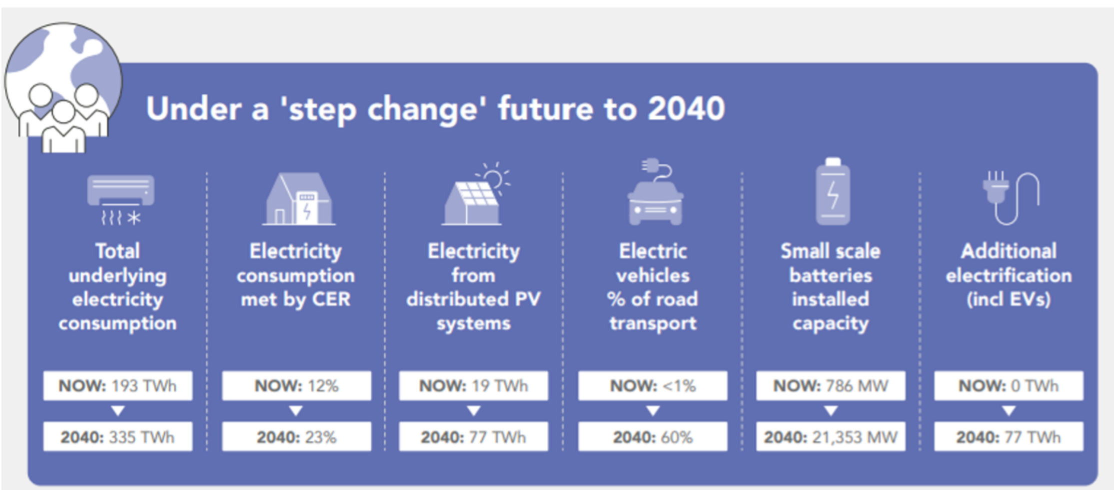
- Economy wide momentum
- Households
- Communities, businesses and industries
- Energy system
- Technology and Innovation

The focus of energy system, in the National Energy Performance Strategy, is to drive Australia's energy transformation. The government is strengthening the role of demand side in energy system planning and governance frameworks to support ongoing energy performance measures.

The Australian Energy Market Operator (AEMO) develops energy planning scenarios used in forecasting and planning analysis and publications for the National Electricity Market (NEM). (Australian Energy Market Operator, 2023a). The 2023 Electricity Statement of Opportunities (OSOO) assumes three scenarios to forecast energy demand in Australia. (Australian Energy Market Operator, 2023b):

1. Green energy exports: A scenario where rapid transformation happens in the energy sector, including strong use of electrification, green hydrogen and biomethane.
2. Step change (ESOO central scenario): A central scenario where the scale of energy transformation supports Australia's contribution to limiting global temperature rise to below 2degree C compared to pre-industrial levels. It relies on a strong contribution from orchestrated consumer energy resources (CER), strong transport electrification, and opportunities for Australia's larger industries to electrify to reduce emissions, or to use developing hydrogen production opportunities or other low emissions alternatives to support domestic industrial loads. This is considered to be the most likely scenario.
3. Progressive change: A scenario where transformation is sufficient to meet Australia's commitment to 43% emissions reduction by 2030 and net zero emissions by 2050, but under challenging economic conditions and higher relative technology cost

Under the step change scenario, total underlying electricity consumption is expected to increase further by 2040. However, electricity consumption met by consumer energy resources is forecasted to be almost double during this period, from 12% to 23%, and electricity generated from distributed PV systems is forecasted to increase by 300%, from 19 TWh to 77 TWh.



Source: (Australian Energy Market Operator, 2023a)

The central forecast scenario shows that underlying electricity consumption will continue to increase, driven by population growth, economic activity, and emerging opportunities to electrify new customer. At the same time, CER and energy efficiency is expected to slow operational consumption growth. The figure below with actual and forecast under the central scenario show that while underlying residential and business electricity consumption is expected to grow, reductions from rooftop PV and energy efficiency will meet significant part of the increased demand.

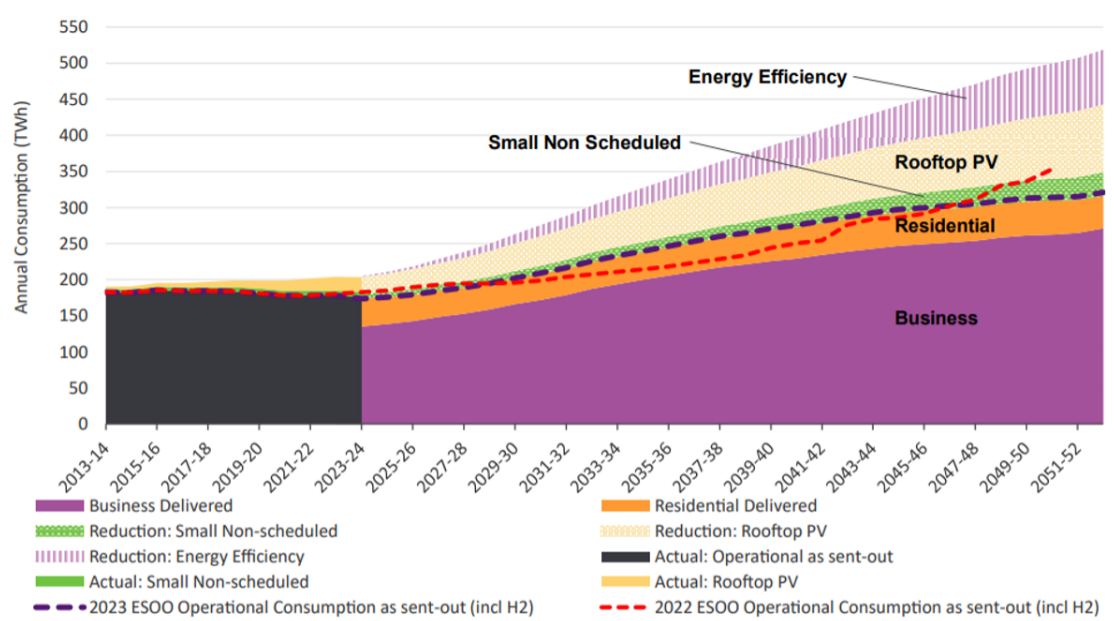


Figure 4: Actual and forecast NEM electricity consumption, ESOO central scenario

The underlying residential electricity demand is expected to increase significantly. Under the 2023 ESOO Central scenario, underlying residential consumption is forecast to increase 31% over the next decade, from approximately 57 TWh in 2022-23 to 75 TWh in 2032-33. This is primarily due to transition from traditional vehicles to electric vehicles (EVs) and growth in residential dwellings (driven by population growth). The model assumes that by 2032-33, approximately 30% of residential passenger vehicles or more than 4 million residential passenger vehicles will be EVs, consuming 11 TWh per annum. Construction of around 1.7 million new dwellings is forecast to increase consumption by 12 TWh per annum, along with electrification of space heating, hot water heating and switch from gas cooking appliances to electricity. However, distributed PV generation is also increasing simultaneously. It is expected that within the next decade, roughly half of residential sectors underlying consumption will be fulfilled by distributed PVs in the NEM, which is forecasted to grow to 60% in the long term and thereby keeping the underlying residential consumption stable over the longer term.

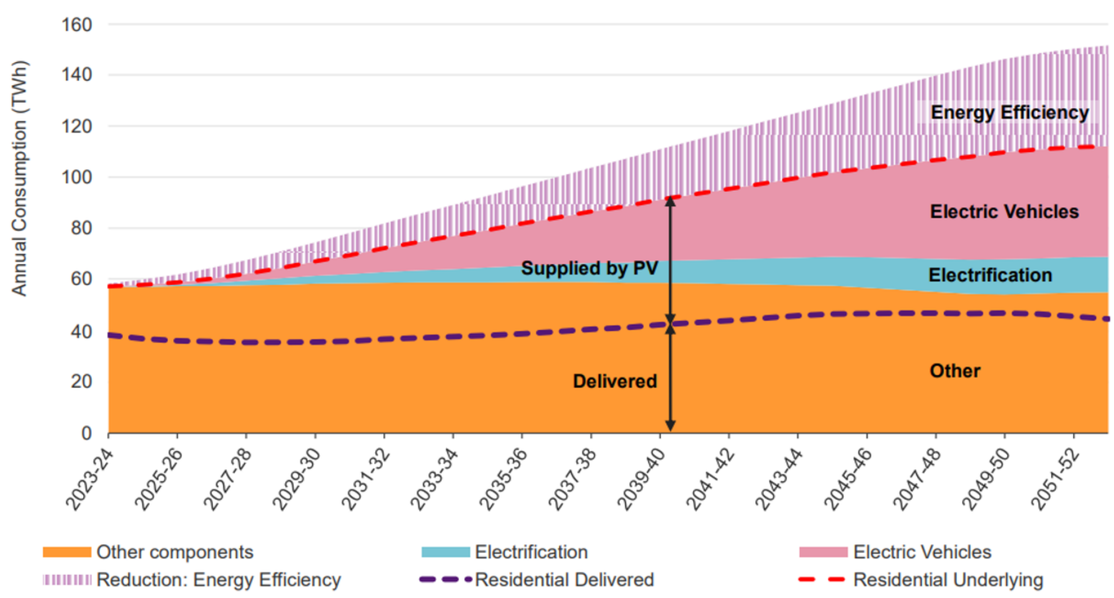


Figure 5: Forecast of residential consumption, ESOO central scenario

Industrial consumption is driven by economic conditions, global commodities market, and emerging hydrogen production. In contrast with residential consumption, operational consumption is expected to grow for industrial sector. While energy efficiency gains are anticipated to increase in future, it is not sufficient to meet the increasing demand for business. Therefore, both underlying and operational electricity consumption for businesses are expected to continue to rise.

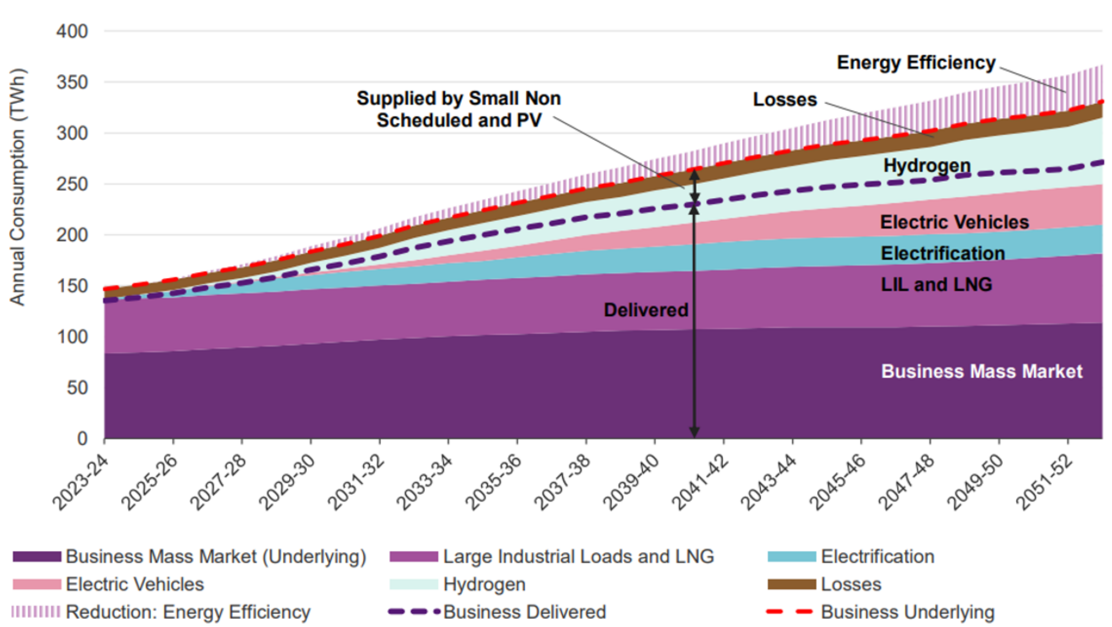


Figure 6: Forecast of industrial consumption, ESOO central scenarios.

4.1 Significance and challenges of forecasting

Energy demand forecasting is essential to ensure sustainable economic growth and environmental security. It plays a critical role in energy supply-demand management by private suppliers as well as government agencies (Islam et al., 2020). While a private supplier may be interested in accurate forecast to meet customer demand, set appropriate price and meet investors' expectations, government agencies are interested in ensuring suitable allocation of energy resources, deciding upon construction of infrastructure, framing policies to meet and/or influence future demand and drafting strategies for reduced emission. Energy demand management considers a series of technical, organisational, and behavioural solutions to decrease consumer demand. A range of cost effective and environmentally friendly yet commercially viable solutions are being explored. Accurate forecast of demand is expected to promote change in consumer usage pattern, cost effectiveness and ultimately achieve self-sufficiency.

Energy demand models have been studies by many researchers, in many countries across the world and with varying perspectives. The models are usually developed specific to a nation or utility, depending on economic and market conditions prevailing at the time of prediction and expected evolution in those conditions (Islam et al., 2020). The models can be classified in several ways – static versus dynamic, univariate versus multivariate and techniques like conventional time series, engineering models and hybrid models.

Due to availability of real measurements of historical demand data, statistical parametric models are often used to describe and forecast energy demand, in particular for residential consumption. A study (Verdejo et al., 2017) summarised a comparison of such techniques for residential energy demand forecast models as below.

Category	Advantage	Disadvantage
Linear	Easy implementation and interpretation. Estimation techniques well established. Scientific acceptance and a wide range of applicability	In real world a few phenomena correspond with models assumptions, this leads sometimes, does not really provide useful results.
Non-linear	More general than linear methods, which gives a major flexibility at the moment to fit a data series.	The function that gives the optimum fit should be determined, this hinders the preparation analysis. Less amount of validations tools: for example, there is not exist a explicit calculus for the R2 coefficient.
Discrete	Uses and gives more simplified information	Analysis and result too robust for short time intervals studies.
Continuous	Wide application field in the description of any phenomenon	Estimation, simulation and validation techniques more complex and sophisticated For good parametric estimation, a lot data and/or small time intervals between observation are required. Explicit analytic solutions do not always be able and numeric approximations must to be used exist

Category	Advantage	Disadvantage
Parametric	Greater provision of information, due to certain probability distribution is assumed for the data.	To assume that the data come from of a specific probabilistic model, biased conclusions could be obtained if a wrong model is used.
Non-parametric	Less condition about the data should be assumed. Which is better in situations when the truly distribution is unknown or can not be approximated easily.	Limited software implementation. Oriented to hypothesis test, instead of effect estimations. Non-parametric estimations and confidence intervals extraction does not

Table 1: Modelling techniques comparison for residential energy demand (Verdejo et al., 2017)

In another study (McLoughlin, Duffy and Conlon, 2013) time series approaches to forecast demand at individual dwelling level were evaluated. The study used individual and aggregate demand data from the Irish Transmission System Operator, Eigrid. Analysis of aggregated data demonstrate that typically there are consistent peaks in the morning, lunch, and evening times. The shape varies marginally over the course of the year due to seasonality. However, for a single consumer, the profile shape can change significantly from one day to the next. Similarly, the demand profile can vary significantly from one consumer to another, on the same day. Such variations pose a challenge for accurate forecasting in the short term.

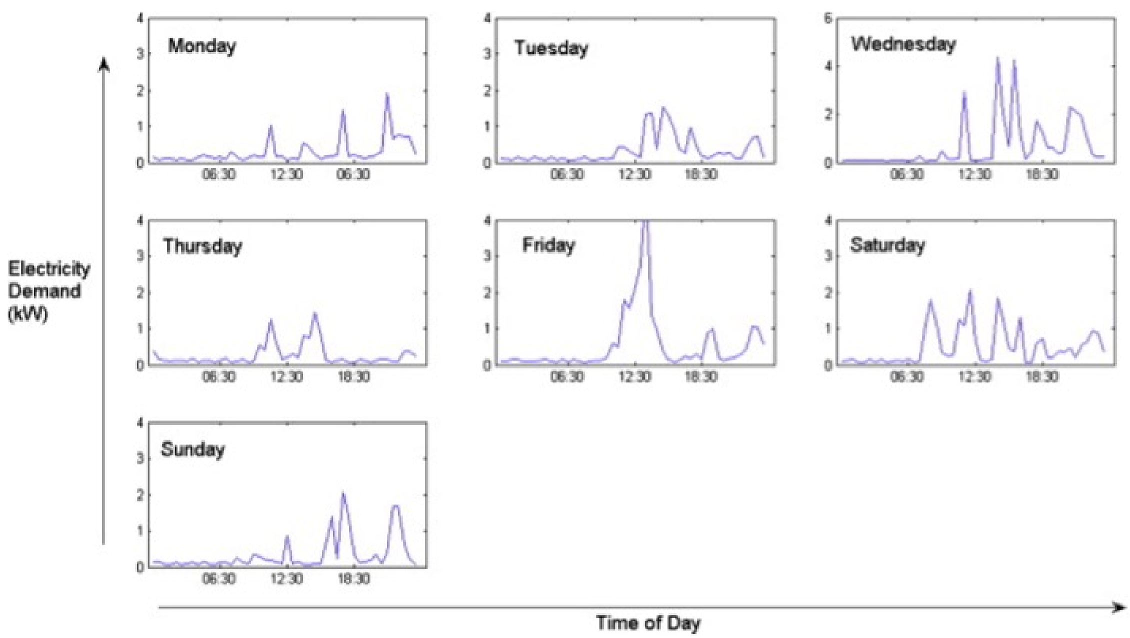


Figure 7: Daily electricity load profiles for a single randomly chosen customer over a weekly period showing intra-daily variations (McLoughlin, Duffy and Conlon, 2013)

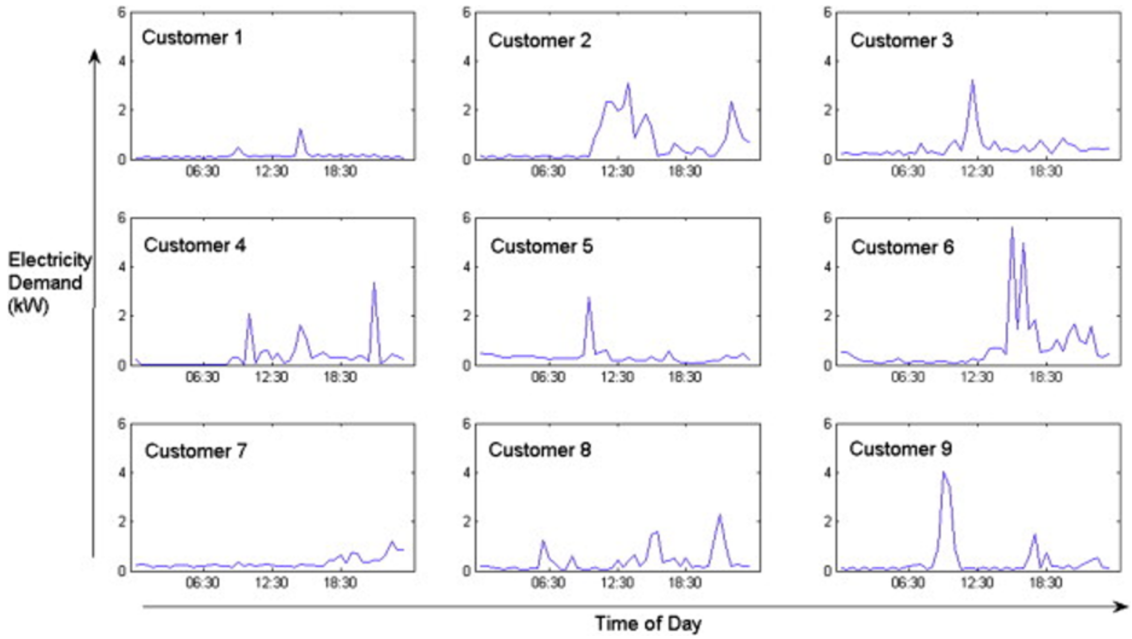


Figure 8: Daily electricity load profiles for a nine randomly chosen customers over a weekly period showing intra-daily variations (McLoughlin, Duffy and Conlon, 2013)

It was found that neural networks are good at characterising highly non-linear nature of residential electricity demand profile, which can have many sharp changes in demand within a small interval. The model can perform particularly well in shorter time intervals. A Gaussian process is good at approximating small intervals of sharp electricity demand, but it was found to be less good at approximating smoother average demand. A multiple regression model is widely used for standard forecasting. In order to replicate the variability of electricity load profile, the model needs to characterise each half-hour period separately. It is the method of choice for the UK grid operator, National Grid, to develop standard load profiles for the purposes of electricity settlement. Autoregressive models are also widely used to profile aggregate electricity demand (as opposed to individual demand profile). Finally, the study found that Fourier transformation had the ability to characterise temporal and magnitude components of demand profile. Scalability is additional benefit of this transformation, although the model had difficulty characterising small intervals of high demand. Fourier transforms and Gaussian processes showed the greatest potential for characterising domestic electricity demand load profiles.

While short-term (an hour to a week) or medium-term (a month to 5 months) forecasting is used for planning energy production, tariffs etc., long-term forecasting (5-20 years) is applied for resource management, strategic planning and investment in infrastructure (Ghalehkhondabi et al., 2016). Majority of forecasting horizons are shorter in duration – hourly, daily, weekly, or monthly. It is assumed that the time series formed by energy consumption data can be accumulated accurately, and previous values can be used to forecast over shorter time horizons. In such forecasting, input variables capture short term variabilities, such as temperature and humidity which vary hourly or half-hourly and are recorded accurately. On the other hand, energy demand changes with time, climatic variables, socioeconomic and demographic parameters which poses difficulties for accurate long-term forecasting. Socioeconomic and demographic parameters, such as Gross Domestic Product (GDP), population of an area considering long-term forecasting, increase in number of dwellings and changes in types of dwellings etc. are measured annually and can be used for long-term forecasting.

4.1.1 Short term forecasting

For short term forecasting purpose, factors such as temperature, humidity, population density along with past consumption trend is more For short term forecasting purpose, factors such as temperature, humidity, population density along with past consumption trend is more suitable (Hagan and Behr, 1987) (Nogales et al., 2002). ARIMA or SARIMA models are widely used to model non-stationary time series which contains trend or seasonality. Kareem and Majeed (Kareem and Majeed, 2006) used the SARIMA model to forecast the monthly peak load demand for the Sulaimany Governorate in Iraq. They proposed a SARIMA model and evaluated it based on measuring the MAPE from data created during the year 2005. The ARIMA and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models were used by Hor et al. (Hor, Watson and Majithia, 2006) to forecast the daily electricity consumption. Sigauke and Chikobvu (Sigauke and Chikobvu, 2011) used the different combinations of regression, SARIMA and GARCH models to forecast the daily peak electricity demand in South Africa. Results of developed models are compared with a piecewise linear regression model and approved that the developed model including all regression, SARIMA and GARCH models has the best accuracy among all other individual and combined methods.

A study to forecast peak daily electricity demand in NSW, Australia used half hourly demand data and an ARIMA (autoregressive moving average) model (As'ad, 2012). The analysis demonstrated that ARIMA model based on past 3 months data is likely to perform best (compared to six-, nine- or twelve-months data) to forecast short-term demand, based on RMSE (root mean squared error) and MAPE mean absolute percentage error) measures of accuracy.

4.1.2 Long-term forecasting

A multiple linear regression model for annual electricity consumption in New Zealand used GDP, average price of electricity and population and found strong correlation between the predictors and electricity consumption (Mohamed and Bodger, 2005).

Energy supply and demand for the Asia-Pacific region is analyzed using econometric factors (GDP, foreign trade) with oil prices, domestic oil prices, and substitution (Intarapravich et al., 1996). An econometric model is defined by the following steps: developing economic hypothesis; a mathematical model of the hypothesis; an econometric model of the hypothesis; an estimation of the econometric model; testing the hypothesis; and forecasting (Kayacan et al., 2012).

System Dynamic model, a computer-oriented mathematical modelling approach that uses interrelation of variables in a complex setting including time-to-time variation in system behaviour and a feedback loop to consider new system conditions, has been used to forecast urban energy consumption trends under different growth scenarios. The model was divided into sub-models for residential, commercial, industrial and transportation (Fong et al., 2007). In various other such implementations, following predictors were considered: - Regional services, population, regional attractiveness etc. (Vaudreuil, M.P.,2011) - Per capita consumption of electricity and population (Akhwanzada and Tahar, 2012)

5 Methods, Tools and Data

5.1 Methods

There are multiple methods to be used for this problem, all of which have pros and cons. We used the following ones in our modeling:

- Linear Regression
  Pros: Simple and easy to explain; computationally efficient and can handle large datasets. Cons: It assumes that the relationship between variables is linear; it may oversimplify the problem and the outcome may not be satisfying.
- ARIMA (Autoregressive Integrated Moving Average) Pros: Suitable for Time Series problems; it can capture the dynamics of time series data, such as seasonality and trend; it is a simple and interpretable algorithm. Cons: It assumes that the time series data is stationary, which may not always be the case in real-world data.

5.2 Tools

1. GitHub - for team collaboration.
2. Monday.com - for Project Plan
3. MS Office 365 - for data storage, and collaboration tools (Word, Excel, etc.).
4. Python - utilizing Pandas & NumPy for data analysis
5. Statsmodel - ARIMA/SARIMA modeling
6. Scikit-learn - machine learning development;
7. Jupyter Notebook – for report building

5.3 Data

We use 6 data sources:

temperature_nsw.csv (provided by the course),

totaldemand_nsw.csv (provided by the course),

population_nsw.csv (collected from the website of Austraian Bureau of Statistics),

GDP.csv (collected from the website of Austraian Bureau of Statistics),

electricity_price_nsw.csv (collected from CEIC's website) and

home_solar_nsw.csv (collected from Clean Energy Regulator, Australian Government).

These datasets encompass crucial variables for our analysis, namely temperature, population, GDP, and energy demand. However, the GDP data reflects the national figure rather than being specific to New South Wales (NSW), as such detailed state-level data was not accessible. To adjust for this, we proceed under the assumption that GDP trends in NSW are representative of the national average, thereby applying the Australia-wide GDP statistics to our NSW-centric forecasting model.

[152]:
```
# Import necessary libaraies
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error,␣
 ↪mean_absolute_percentage_error, mean_squared_error
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
```

[153]:
```
# Read Temperature file
df_temp = pd.read_csv('../data/NSW/temperature_nsw.csv')
df_temp.columns = df_temp.columns.str.lower()
```

[154]:
```
# Read totaldemand file
df_demand = pd.read_csv('../data/NSW/totaldemand_nsw.csv')
df_demand.columns = df_demand.columns.str.lower()
```

[155]:
```
# Read population file
df_population = pd.read_csv('../data/NSW/population_nsw.csv')
df_population.columns = df_population.columns.str.lower()
```

[156]:
```
# Read GDP file
df_gdp = pd.read_csv('../data/NSW/GDP.csv')
df_gdp.columns = df_gdp.columns.str.lower()
```

[157]:
```
# Read Eelectricity price file
df_electricity_price = pd.read_csv('../data/NSW/electricity_price_nsw.csv')
df_electricity_price.columns = df_electricity_price.columns.str.lower()
```

[158]:
```
# Read Small Scale Solar Install file
df_solar_install = pd.read_csv('../data/NSW/home_solar_nsw.csv')
df_solar_install.columns = df_solar_install.columns.str.lower()
```

5.3.1 First Glance at Data

[159]:
```
df_temp.head()
```

[159]:

	location	datetime	temperature
0	Bankstown	1/1/2010 0:00	23.1
1	Bankstown	1/1/2010 0:01	23.1
2	Bankstown	1/1/2010 0:30	22.9
3	Bankstown	1/1/2010 0:50	22.7
4	Bankstown	1/1/2010 1:00	22.6

[160]:
```
df_temp['location'].nunique()
```

[160]: 1

[161]:
```
df_demand.head()
```

[161]:

	datetime	totaldemand	regionid
0	1/1/2010 0:00	8038.00	NSW1
1	1/1/2010 0:30	7809.31	NSW1
2	1/1/2010 1:00	7483.69	NSW1
3	1/1/2010 1:30	7117.23	NSW1
4	1/1/2010 2:00	6812.03	NSW1

[162]:
```
df_demand['regionid'].nunique()
```

[162]: 1

[163]:
```
df_population.head()
```

[163]:

	time	population
0	Dec-2009	7101504
1	Mar-2010	7128356
2	Jun-2010	7144292
3	Sep-2010	7162726
4	Dec-2010	7179891

[164]:
```
df_gdp.head()
```

[164]:

	time	gdp
0	Dec-2009	334934
1	Mar-2010	314838
2	Jun-2010	340575
3	Sep-2010	345512
4	Dec-2010	365403

[165]:
```
df_electricity_price.head()
```

[165]:

	year	region	avgrrp
0	2010	NSW	44.19
1	2011	NSW	36.74
2	2012	NSW	29.67
3	2013	NSW	55.10
4	2014	NSW	52.26

[166]:
```
df_solar_install.head()
```

[166]:

	year	nsw	solar_install
0	2009	14,008	14,008
1	2010	69,988	83,996
2	2011	80,272	164,268
3	2012	53,961	218,229
4	2013	33,998	252,227

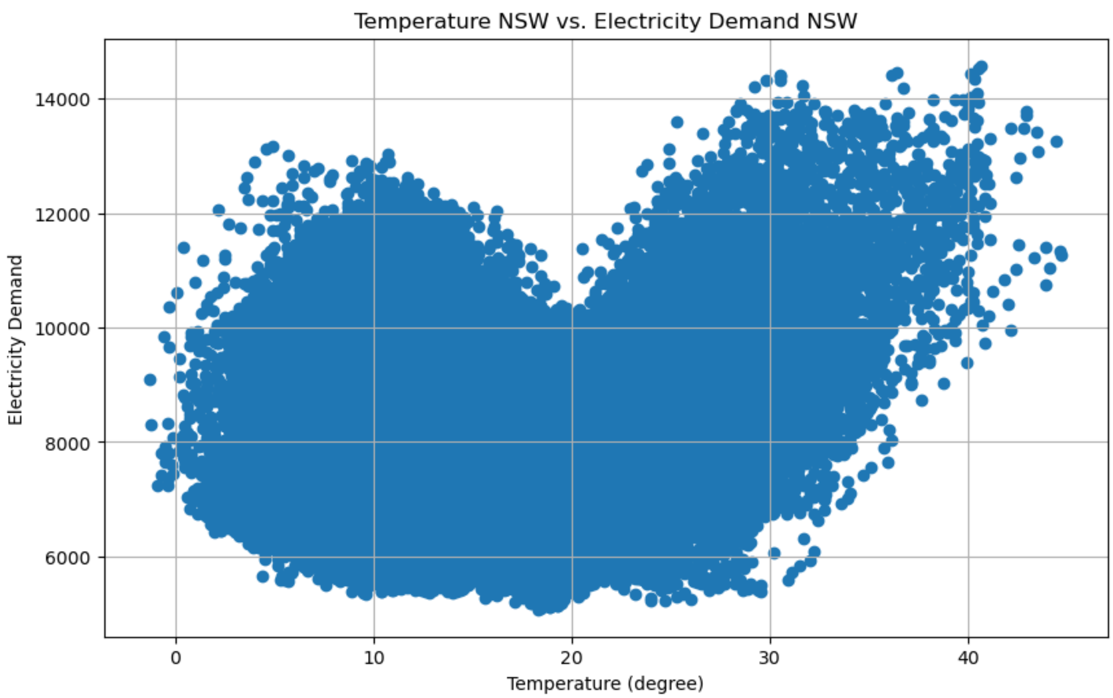
6 Exploratory Data Analysis (EDA)

To begin our analysis we begin by checking the correlation between energy demand and each of our variables:

6.1 Temperature and Demand

[167]:
```
df_temp_demand = pd.merge(df_temp, df_demand, on='datetime')
```

[168]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df_temp_demand['temperature'], df_temp_demand['totaldemand'])
plt.title('Temperature NSW vs. Electricity Demand NSW')
plt.xlabel('Temperature (degree)')
plt.ylabel('Electricity Demand')
plt.grid(True)
plt.show()
```



As depicted in the graph, it resembles a V shape. Below approximately 20 degrees, the demand increases as the temperature decreases; above 20 degrees, the demand rises with increasing temperature. This pattern aligns with our everyday experience. Temperature is useful in our modeling.

6.2 Population and Demand

The demand is recorded every 30 mins while GDP quarterly. We shall aggregate the electricity demand to a quarterly frequency. We can calculate the average demand for each quarter.

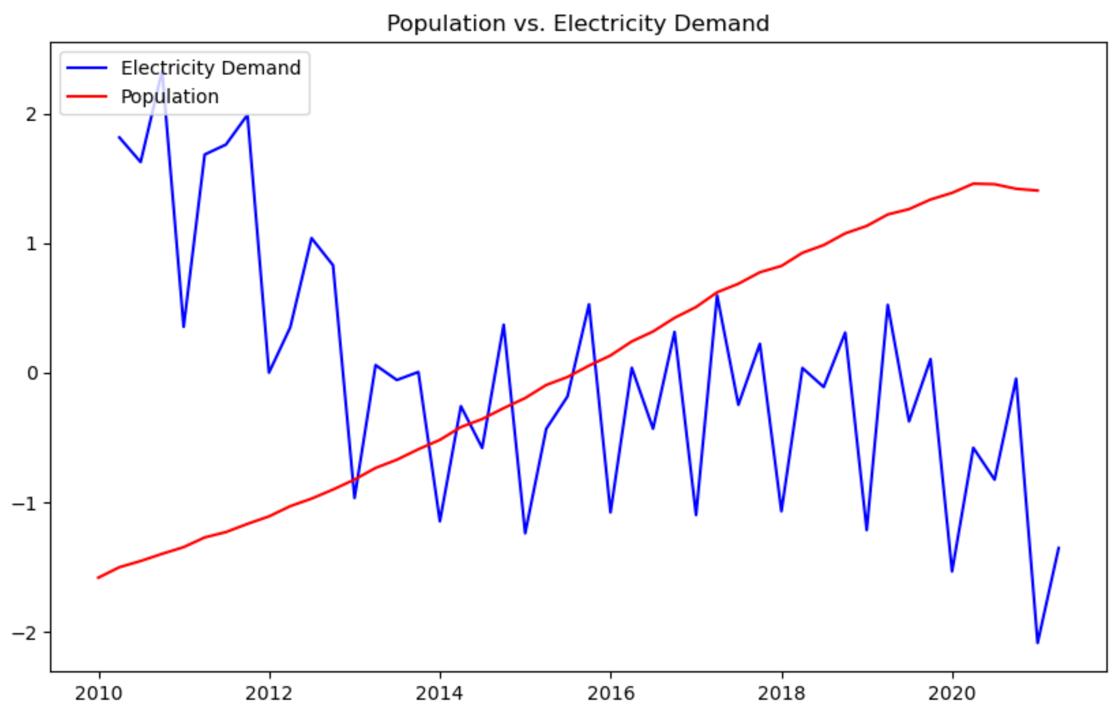
[169]:
```
df_demand['time'] = pd.to_datetime(df_demand['datetime'], format='%d/%m/%Y %H:
↪%M')
```

[170]:
```
df_demand.set_index('time', inplace=True)
total_demand_quarterly = df_demand['totaldemand'].resample('Q').mean()
df_total_demand_quarterly = total_demand_quarterly.reset_index()
```

[171]:
```
df_total_demand_quarterly['normalized_demand'] =␣
↪(df_total_demand_quarterly['totaldemand'] -␣
↪df_total_demand_quarterly['totaldemand'].mean()) /␣
↪df_total_demand_quarterly['totaldemand'].std()
```

[172]:
```
df_population['time'] = pd.to_datetime(df_population['time'], format='%b-%Y')
df_population['time'] = df_population['time'] + pd.offsets.MonthEnd(1)
df_population['normalized_population'] = (df_population['population'] -␣
↪df_population['population'].mean()) / df_population['population'].std()
```

[173]:
```
plt.figure(figsize=(10, 6))
plt.plot(df_total_demand_quarterly['time'],␣
↪df_total_demand_quarterly['normalized_demand'], label='Electricity Demand',␣
↪color='blue')
plt.plot(df_population['time'], df_population['normalized_population'],␣
↪label='Population', color='red')
plt.legend(loc='upper left')
plt.title('Population vs. Electricity Demand')
plt.show()
```



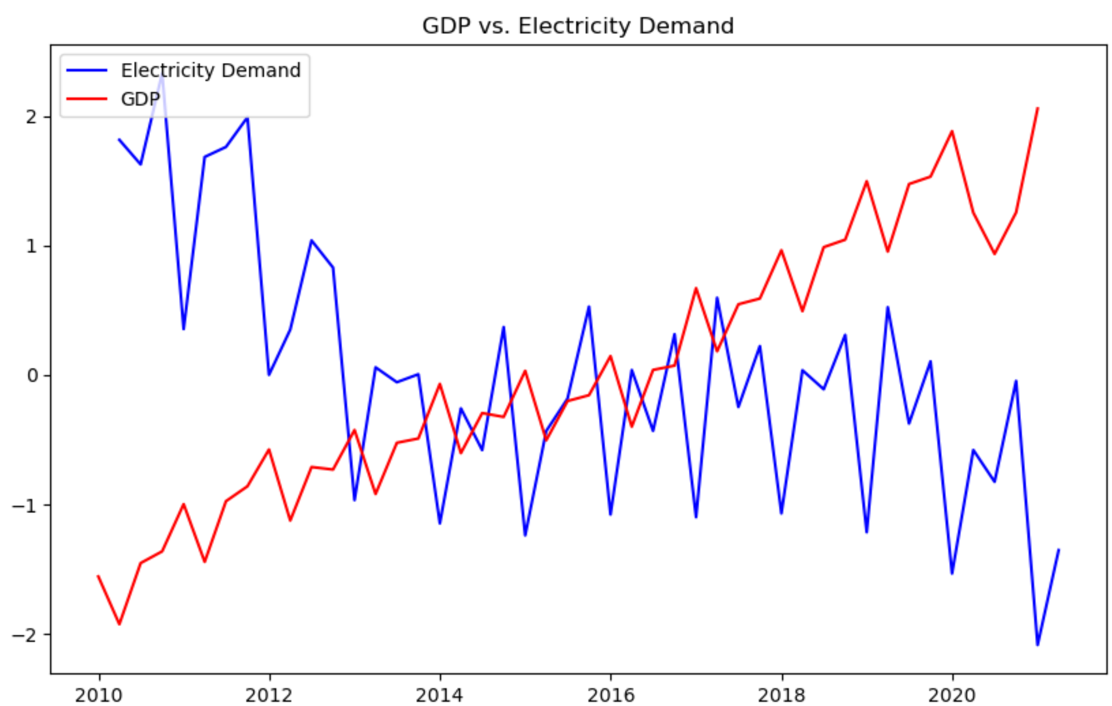
This is very interesting. As the population grows, we would typically expect electricity demand to rise, assuming individual consumption remains steady. Contrary to this expectation, we observe a decline in electricity demand. This suggests that the per capita electricity demand is decreasing. Possible explanations for this trend might include a relative decrease in personal income against the cost of electricity, prompting individuals to limit usage, or the adoption of alternative energy sources, like residential solar panels, reducing reliance on traditional electricity supplies.

GDP can rougly (if not totally) represent the income of citizens. Let's check GDP trend first.

6.3 GDP and Demand

[174]:
```
df_gdp['time'] = pd.to_datetime(df_gdp['time'], format='%b-%Y') + pd.offsets.
    ↪MonthEnd(1)
df_gdp['normalized_gdp'] = (df_gdp['gdp'] - df_gdp['gdp'].mean()) /␣
    ↪df_gdp['gdp'].std()
```

[175]:
```
plt.figure(figsize=(10, 6))
plt.plot(df_total_demand_quarterly['time'],␣
    ↪df_total_demand_quarterly['normalized_demand'], label='Electricity Demand',␣
    ↪color='blue')
plt.plot(df_gdp['time'], df_gdp['normalized_gdp'], label='GDP', color='red')
plt.legend(loc='upper left')
plt.title('GDP vs. Electricity Demand')
plt.show()
```



GDP kept increasing from 2010 to 2020. So could it be that the electricity price increased a lot during that period? So let's check the price over the last decade. We got the dataset from CEIC's website.

6.4 Electricity Price over the last decade

[176]:
```
df_electricity_price
```

[176]:

	year	region	avgrrp
0	2010	NSW	44.19
1	2011	NSW	36.74
2	2012	NSW	29.67
3	2013	NSW	55.10
4	2014	NSW	52.26
5	2015	NSW	35.17
6	2016	NSW	51.60
7	2017	NSW	81.22
8	2018	NSW	82.27
9	2019	NSW	88.56
10	2020	NSW	71.95
11	2021	NSW	64.81

[177]:
```
plt.figure(figsize=(10, 6))
plt.plot(df_electricity_price['year'], df_electricity_price['avgrrp'])
plt.title('Year vs. Average Recommended Retail Price ')
plt.xlabel('Year')
plt.ylabel('Average RRP')
plt.grid(True)
plt.show()
```

We do see the price increased over the last decade. So in our modeling, it is better to include the factor of pricing.

The increased adoption of residential solar panels might be another factor to consider, as this can lead to a reduction in dependency on conventional electricity grids. As more households install solar panels, the aggregate demand on traditional energy providers is likely to diminish.

6.5 Home Solar Installation over the last decade

We got Small-scale installation postcode data from Clean Energy Regulator, Australian Government. Let's see how many small-scall solar installation was done in the past a decade.

[178]:
```
df_solar_install
```

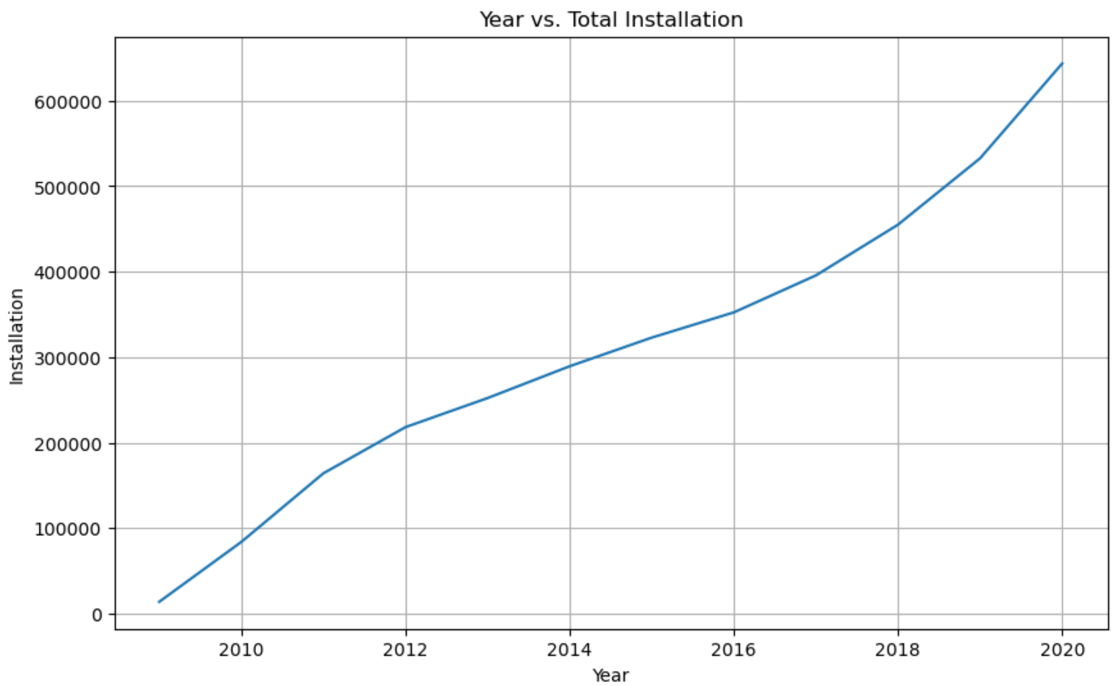
[178]:

	year	nsw	solar_install
0	2009	14,008	14,008
1	2010	69,988	83,996
2	2011	80,272	164,268
3	2012	53,961	218,229
4	2013	33,998	252,227
5	2014	37,210	289,437
6	2015	33,478	322,915
7	2016	29,498	352,413
8	2017	43,253	395,666
9	2018	59,329	454,995

```
10  2019   77,630       532,625
11  2020  110,788       643,413
```

[179]:
```
df_solar_install['solar_install'] = df_solar_install['solar_install'].str.
 ↪replace(',', '')
df_solar_install['solar_install'] = df_solar_install['solar_install'].
 ↪astype(int)
```

[180]:
```
plt.figure(figsize=(10, 6))
plt.plot(df_solar_install['year'], df_solar_install['solar_install'])
plt.title('Year vs. Total Installation')
plt.xlabel('Year')
plt.ylabel('Installation')
plt.grid(True)
plt.show()
```



We can see the installation increased over the last decase. It is reasonable to include the total installation in NSW into our model too.

7 Modelling

We will look at two types of energy prediction models:

- Long Term: We can predict the average demand for a quarter. As discussed above, such a prediction should consider factors including time, quarterly average temperature, population, GDP, price, and solar installations.

- Short Term: We can predict short-term demand every 30 minutes. For such predictions, long-term factors such as population, GDP, price, or solar installations will not play a significant role. Therefore, we will exclude them from our modeling.

7.1 Long Term Model

When predicting quarterly demand, we should use population, average temperate, and GDP. In reality we can not get the data of these features before the end of the quarter we want to predict. So to compose the data for training and testing, we need to modify our dataset a bit.

We will build a linear regression model.

7.1.1 Data Preparation

Population

[181]:
```
df_population.head()
```

[181]:

	time	population	normalized_population
0	2009-12-31	7101504	-1.582523
1	2010-03-31	7128356	-1.501659
2	2010-06-30	7144292	-1.453668
3	2010-09-30	7162726	-1.398155
4	2010-12-31	7179891	-1.346464

[182]:
```
df_population_quarterly = df_population.copy(deep=True)
```

[183]:
```
# offset the time by 3 months
df_population_quarterly['time'] = df_population['time'] + pd.
 ↪DateOffset(months=3)
df_population_quarterly['time'] = df_population_quarterly['time'] + pd.offsets.
 ↪MonthEnd(0)
```

GDP

[184]:
```
df_gdp.head()
```

[184]:

	time	gdp	normalized_gdp
0	2009-12-31	334934	-1.557029
1	2010-03-31	314838	-1.925885
2	2010-06-30	340575	-1.453491
3	2010-09-30	345512	-1.362874
4	2010-12-31	365403	-0.997781

[185]:
```
df_gdp_quarterly = df_gdp.copy(deep=True)
```

[186]:
```
df_gdp_quarterly['time'] = df_gdp['time'] + pd.DateOffset(months=3)
df_gdp_quarterly['time'] = df_gdp_quarterly['time'] + pd.offsets.MonthEnd(0)
```

Solar Installation

[187]:
```
df_solar_install.head()
```

[187]:

	year	nsw	solar_install
0	2009	14,008	14008
1	2010	69,988	83996
2	2011	80,272	164268
3	2012	53,961	218229
4	2013	33,998	252227

We only have annual data for Solar Installations. To make the data usable for our model we can convert yearly solar installation data to quarterly data using linear interpolation within each year.

[188]:
```
quarterly_solar_install = {'year_quarter': [], 'solar_install': []}

for i in range(len(df_solar_install)):
    if i == 0:
        growth = (df_solar_install.loc[i + 1, 'solar_install'] -␣
 ↪df_solar_install.loc[i, 'solar_install']) / 4
        for q in range(1, 5):
            quarterly_solar_install['year_quarter'].append(f"{df_solar_install.
 ↪loc[i, 'year']}-Q{q}")
            quarterly_solar_install['solar_install'].
 ↪append(int(df_solar_install.loc[i, 'solar_install'] + growth * (q - 1)))
    else:
        growth = (df_solar_install.loc[i, 'solar_install'] - df_solar_install.
 ↪loc[i - 1, 'solar_install']) / 4
        for q in range(1, 5):
            quarterly_solar_install['year_quarter'].append(f"{df_solar_install.
 ↪loc[i, 'year']}-Q{q}")
            quarterly_solar_install['solar_install'].
 ↪append(int(df_solar_install.loc[i, 'solar_install'] + growth * (q - 1)))

df_quarterly_solar_install = pd.DataFrame(quarterly_solar_install)
```

[189]:
```
df_quarterly_solar_install.head()
```

[189]:

	year_quarter	solar_install
0	2009-Q1	14008
1	2009-Q2	31505
2	2009-Q3	49002
3	2009-Q4	66499
4	2010-Q1	83996

[190]:
```
def quarter_to_date(quarter_str):
    year, q = quarter_str.split('-')
    if q == 'Q1':
        return f'{year}-03-31'
```

```
    elif q == 'Q2':
        return f'{year}-06-30'
    elif q == 'Q3':
        return f'{year}-09-30'
    elif q == 'Q4':
        return f'{year}-12-31'
```

[191]:
```
df_quarterly_solar_install['time'] = df_quarterly_solar_install['year_quarter'].
 ↪apply(quarter_to_date)

# Convert the 'end_of_quarter' column to datetime
df_quarterly_solar_install['time'] = pd.
 ↪to_datetime(df_quarterly_solar_install['time'])
# Offset the time by 1 year
df_quarterly_solar_install['time'] = df_quarterly_solar_install['time'] + pd.
 ↪DateOffset(months=12)
```

[192]:
```
df_quarterly_solar_install.head()
```

[192]:
```
  year_quarter  solar_install       time
0      2009-Q1          14008 2010-03-31
1      2009-Q2          31505 2010-06-30
2      2009-Q3          49002 2010-09-30
3      2009-Q4          66499 2010-12-31
4      2010-Q1          83996 2011-03-31
```

Price

[193]:
```
# Same as what we did to solar install, convert price to quartely data
quarterly_price = {'year_quarter': [], 'avgrrp': []}

for i in range(len(df_electricity_price)):
    if i == 0:
        growth = (df_electricity_price.loc[i + 1, 'avgrrp'] -␣
 ↪df_electricity_price.loc[i, 'avgrrp']) / 4
        for q in range(1, 5):
            quarterly_price['year_quarter'].append(f"{df_electricity_price.
 ↪loc[i, 'year']}-Q{q}")
            quarterly_price['avgrrp'].append(df_electricity_price.loc[i,␣
 ↪'avgrrp'] + growth * (q - 1))
    else:
        growth = (df_electricity_price.loc[i, 'avgrrp'] - df_electricity_price.
 ↪loc[i - 1, 'avgrrp']) / 4
        for q in range(1, 5):
            quarterly_price['year_quarter'].append(f"{df_electricity_price.
 ↪loc[i, 'year']}-Q{q}")
            quarterly_price['avgrrp'].append(df_electricity_price.loc[i,␣
 ↪'avgrrp'] + growth * (q - 1))
```

```
df_quarterly_electricity_price = pd.DataFrame(quarterly_price)
```

[194]:
```
df_quarterly_electricity_price['time'] =␣
 ↪df_quarterly_electricity_price['year_quarter'].apply(quarter_to_date)

# Convert the 'end_of_quarter' column to datetime
df_quarterly_electricity_price['time'] = pd.
 ↪to_datetime(df_quarterly_electricity_price['time'])
# Offset the time by 1 year
df_quarterly_electricity_price['time'] = df_quarterly_electricity_price['time']␣
 ↪+ pd.DateOffset(months=12)
```

[195]:
```
df_electricity_price.head()
```

[195]:

	year	region	avgrrp
0	2010	NSW	44.19
1	2011	NSW	36.74
2	2012	NSW	29.67
3	2013	NSW	55.10
4	2014	NSW	52.26

Temperature

[196]:
```
df_temp['time'] = pd.to_datetime(df_temp['datetime'], format='%d/%m/%Y %H:%M')
df_temp.set_index('time', inplace=True)
temp_quarterly = df_temp['temperature'].resample('Q').mean()
df_temp_quarterly = temp_quarterly.reset_index()
df_temp_quarterly['time'] = df_temp_quarterly['time'] + pd.DateOffset(months=3)
df_temp_quarterly['time'] = df_temp_quarterly['time'] + pd.offsets.MonthEnd(0)
```

Create the long term quarterly dataset for training and testing

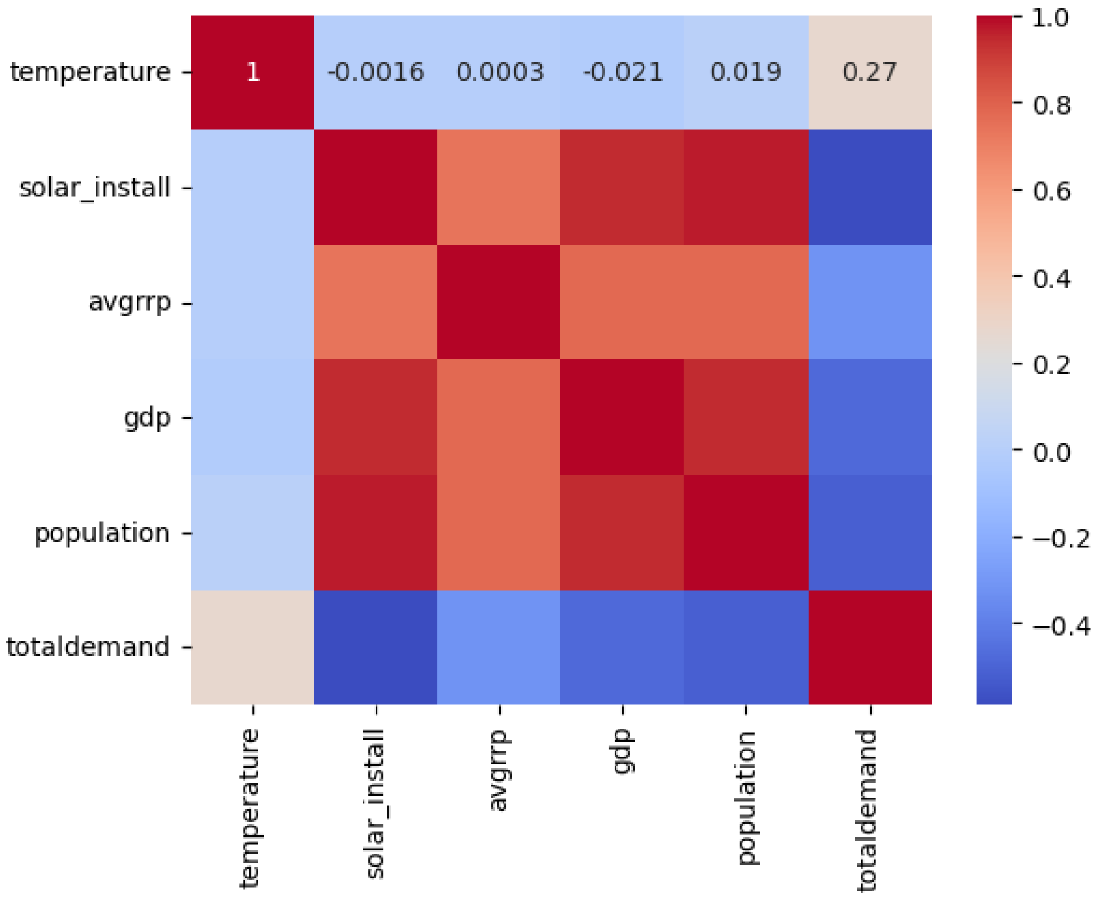
[197]:
```
df_temp_install = pd.merge(df_temp_quarterly, df_quarterly_solar_install,␣
 ↪on='time', how='inner')
df_temp_install_price = pd.merge(df_temp_install,␣
 ↪df_quarterly_electricity_price, on='time', how='inner')
df_temp_install_price_gdp = pd.merge(df_temp_install_price, df_gdp_quarterly,␣
 ↪on='time', how='inner')
df_temp_install_price_gdp_population = pd.merge(df_temp_install_price_gdp,␣
 ↪df_population_quarterly, on='time', how='inner')
df_temp_install_price_gdp_population_demand = pd.
 ↪merge(df_temp_install_price_gdp_population, df_total_demand_quarterly,␣
 ↪on='time', how='inner')
```

NOTE: Depending on which model to use, ‘time’ may not be used in some models.

7.1.2 Correlation Analysis

[198]:
```
df_long_term = df_temp_install_price_gdp_population_demand[['temperature',␣
↪'solar_install', 'avgrrp', 'gdp', 'population', 'totaldemand']]
```

[199]:
```
sns.heatmap(df_long_term.corr(), annot=True, cmap='coolwarm')
plt.show()
```



[200]:
```
y_long_term = df_long_term['totaldemand']
X_long_term = df_long_term.drop('totaldemand', axis = 1)
```

[201]:
```
X_long_term_train, X_long_term_test, y_long_term_train, y_long_term_test =␣
↪train_test_split(X_long_term, y_long_term, test_size=0.2, random_state=42)
```

From the Heat Map we can see that both Solar Installs and Population are strong influencers of total demand. It is important to distinguish at this point that the total demand is the demand on the traditional sources of energy, and does not account for demand that is supplied by personal Solar PV installations. Hence the population is negatively correlated with total demand. As per the literature review, and the Data Analysis this is algined to the downward trend on the energy demand vs population. This is explained by the energy efficiencies that are created by the use of renewable energy sources.

7.1.3 Linear Regression Model

For the long term data set, it is not very big. We can start from a simple Linear Regression model. It is easy to understand and interpret, works well with small datasets.

“time” is not a suitable variable in a linear regression. We can exclude it from out modeling.

[202]:
```
X_long_term_train_lr = X_long_term_train[['temperature', 'solar_install',␣
↪'avgrrp', 'gdp', 'population']]
X_long_term_test_lr = X_long_term_test[['temperature', 'solar_install',␣
↪'avgrrp', 'gdp', 'population']]
y_long_term_train_lr = y_long_term_train
y_long_term_test_lr = y_long_term_test
```

[203]:
```
model = LinearRegression()

model.fit(X_long_term_train_lr, y_long_term_train_lr)

y_long_term_pred_lr = model.predict(X_long_term_test_lr)
```

[204]:
```
mse = mean_squared_error(y_long_term_test_lr, y_long_term_pred_lr)
```

[205]:
```
mse
```

[205]:
```
67635.3984478119
```

[ ]:
```
# Retrieve the coefficients
coefficients = model_lr.coef_

# Print the coefficients
print("Coefficients of the linear model:", coefficients)
```

The Linear Regression expression therefore is:

$$y = a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5$$

$$where:$$

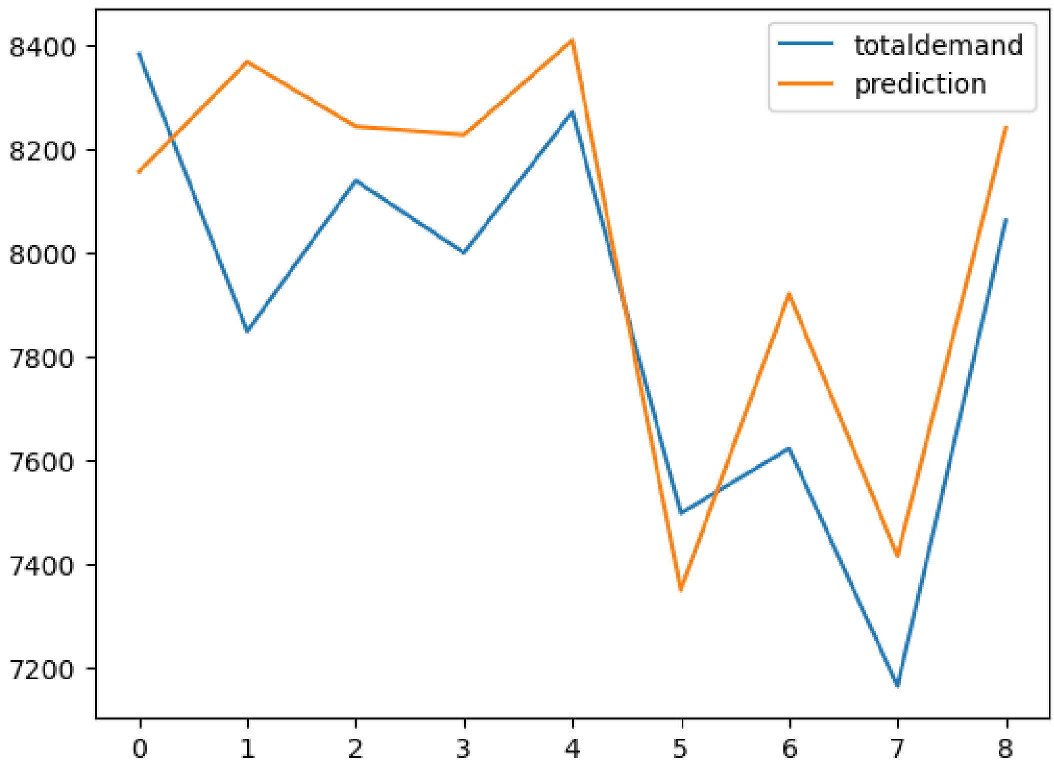
$$x_1 = Temperature$$
$$x_2 = SolarInstallations$$
$$x_3 = Price$$
$$x_4 = GDP$$

$$x_5 = Population$$

[206]:
```
# Visualization
df_lr = pd.DataFrame()
df_lr['totaldemand'] = list(y_long_term_test_lr)
df_lr['prediction'] = list(y_long_term_pred_lr)
```

[207]:
```
df_lr.plot()
```

[207]: <Axes: >



Linear Regression is a pretty simple model but from the graph we can see the result is pretty good. We can try some other models.

7.2 Short Term Model

7.2.1 Data preparation

[208]:
```
df_temp = df_temp.reset_index()
```

[209]:
```
df_demand = df_demand.reset_index()
```

[210]:
```
df_temp_demand_short_term = pd.merge(df_temp, df_demand, on='time', how='inner')
```

NOTE: Depending on which model to use, 'time' may not be used in some models.

[211]:
```
df_short_term = df_temp_demand_short_term[['time', 'temperature',␣
↪'totaldemand']]
```

[212]:
```
y_short_term = df_short_term['totaldemand']
X_short_term = df_short_term.drop('totaldemand', axis = 1)
```

[213]:
```
X_short_term_train, X_short_term_test, y_short_term_train, y_short_term_test =␣
↪train_test_split(X_short_term, y_short_term, test_size=0.2, random_state=42)
```

7.2.2 ARIMA Model

For the short term data set, it is a big one. We can start with ARIMA.

[214]:
```
df_temp_demand_short_term_arima = df_temp_demand_short_term.copy(deep=True)
```

[215]:
```
y_arima = df_temp_demand_short_term['totaldemand']
```

[216]:
```
msk = (y_arima.index < len(y_arima) - 336) # 48 * 7 = 336, corresponding to 7␣
↪days prediction with 30mins granuality.
df_arima_train = y_arima[msk].copy()
df_arima_test = y_arima[~msk].copy()
```

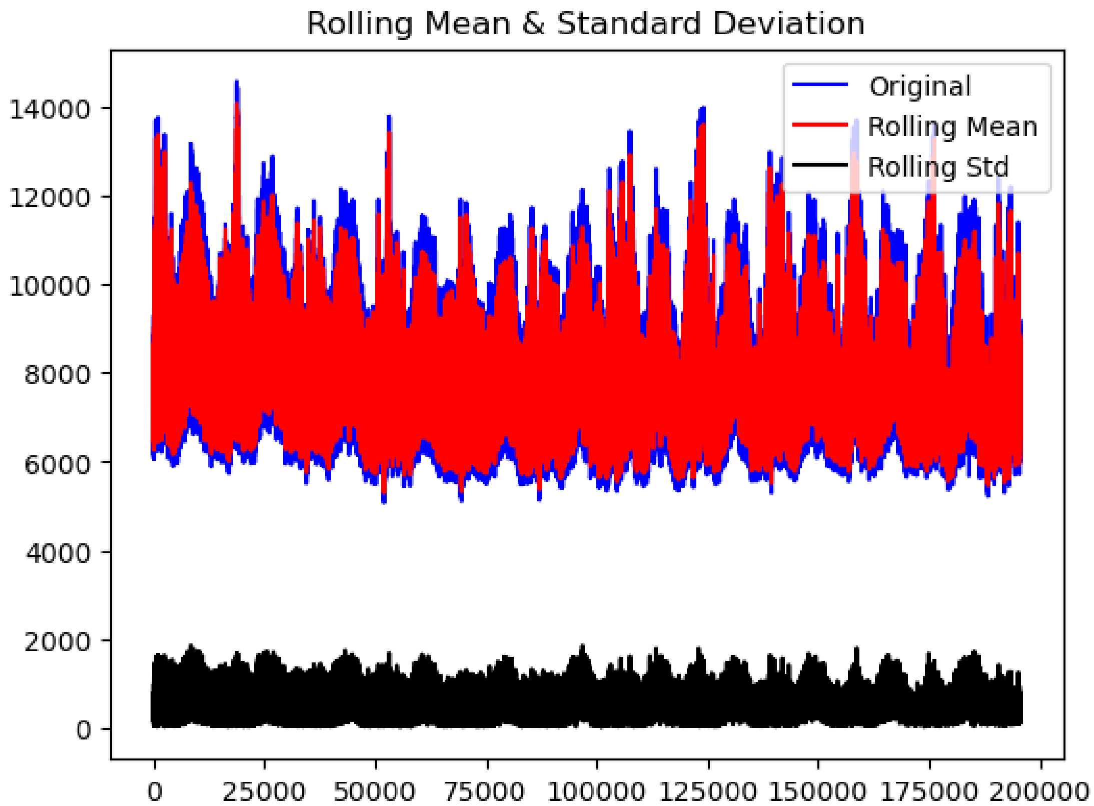
ARIMA requires the time series to be stationary.

[217]:
```
def check_stationarity(timeseries):
    # Determing rolling statistics
    rolling_mean = timeseries.rolling(window=12).mean()
    rolling_std = timeseries.rolling(window=12).std()

    # Plot rolling statistics:
    plt.plot(timeseries, color='blue',label='Original')
    plt.plot(rolling_mean, color='red', label='Rolling Mean')
    plt.plot(rolling_std, color='black', label='Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    # Perform Dickey-Fuller test:
    print('Results of Dickey-Fuller Test:')
    adf_test = adfuller(timeseries, autolag='AIC')
    df_results = pd.Series(adf_test[0:4], index=['Test␣
↪Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in adf_test[4].items():
        df_results['Critical Value (%s)'%key] = value
    print(df_results)
```

[218]:
```
check_stationarity(df_arima_train)
```




```
Results of Dickey-Fuller Test:
Test Statistic                     -25.483385
p-value                              0.000000
#Lags Used                          80.000000
Number of Observations Used     195530.000000
Critical Value (1%)                 -3.430383
Critical Value (5%)                 -2.861555
Critical Value (10%)                -2.566778
dtype: float64
```

The p-value is low (<0.05) and the Test Statistic is lower than the Critical values, so this dataset has passed the stationarity check. We could apply the ARIMA model. The next step in preparing an ARIMA model is to determine the appropriate parameters:

p (autoregressive term), d (differencing order), q (moving average term). Since it is a stationary dataset, we can easily see that d = 0. Let's try to find p and q using ACF and PACF plots.

We can use Grid Search to find the best values of p and q:

```
[ ]: for p in (1, 2, 3, 4, 6):
         for q in (1, 2, 4, 6, 12):
             model = ARIMA(df_arima_train, order=(p, 0, q))
             pred = model.fit().forecast(len(df_arima_test))
             mae = mean_absolute_error(pred, df_arima_test)
             mape = mean_absolute_percentage_error(pred, df_arima_test)
             mse = mean_squared_error(pred, df_arima_test)

             print(f'p: {p}, q: {q}')
             print(f'mae: {mae}')
             print(f'mape: {mape}')
             print(f'mse: {mse}')
             print('--------------')
```

Result: We can see select p = 3 and q = 4.

```
[ ]: model = ARIMA(df_arima_train, order=(3, 0, 4))
     pred = model.fit().forecast(len(df_arima_test))
```

Let's visualize the prediction and see whether it matches the test.

```
[ ]: df_temp_demand_short_term_arima['prediction'] = [None] * len(df_arima_train) +␣
      ↪list(pred)
```

```
[ ]: df_temp_demand_short_term_arima[['totaldemand', 'prediction']].
      ↪tail(len(df_arima_test) * 3).plot()
```

We can see the prediction is almost a straight line which does not match the actual demand very well. We should try using a short period of data to see if the prediction improves.

```
[ ]: # Choose 3 months of data for training and 1 week of data for testing
     msk_train_3_months = ((y_arima.index >= (len(y_arima) - (48 * 30 * 3  + 48 *␣
      ↪7))) & (y_arima.index < (len(y_arima) - 48 * 7)))
     df_arima_train_3_months = y_arima[msk_train_3_months].copy()
     msk_test_1_week = (y_arima.index >= len(y_arima) - 48 * 7)
     df_arima_test_1_week = y_arima[msk_test_1_week].copy()
```

```
[ ]: # Grid search to find the best p and q
     for p in (1, 2, 3, 4, 6):
         for q in (1, 2, 4, 6, 12, 24, 48):
             model = ARIMA(df_arima_train_3_months, order=(p, 0, q))
             pred = model.fit().forecast(len(df_arima_test_1_week))
             mae = mean_absolute_error(pred, df_arima_test_1_week)
             mape = mean_absolute_percentage_error(pred, df_arima_test_1_week)
             mse = mean_squared_error(pred, df_arima_test_1_week)

             print(f'p: {p}, q: {q}')
             print(f'mae: {mae}')
             print(f'mape: {mape}')
```

```
        print(f'mse: {mse}')
        print('--------------')
```

Result: We can choose q = 4 and p = 24.

```
[ ]: model_armia_v2 = ARIMA(df_arima_train_3_months, order=(4, 0, 24))
     pred_v2 = model_armia_v2.fit().forecast(len(df_arima_test_1_week))
```

Let's visualize the prediction and see whether it matches the test.

```
[ ]: df_temp_demand_short_term_arima['prediction_v2'] = [None] *␣
      ↪(len(df_temp_demand_short_term_arima) - len(pred_v2)) + list(pred_v2)
     df_temp_demand_short_term_arima[['totaldemand', 'prediction_v2']].
      ↪tail(len(df_arima_test_1_week) * 3).plot()
```

From the graph we can see the result is actually a bit better than the model trained with longer data. This may be due to the fact that it is easier to find the optimized parameters for the shorter dataset.

8 Discussion, Conclusion and Further Issues

8.1 Conclusions

The results in this paper will be useful for both long term and short term decision making.

From a long term perspective, two key factors which this paper determined to strongly influence energy demand was Solar PV installations, and Population.

First, policy makers can use the linear regression model to understand at a basic level the impact Solar PV Installations has on the reduction in energy demand from traditional sources (Coal and Natural Gas). By doing scenario based planning to determine the optimal amount of Solar PVs that will be required to meet our future energy needs, the NSW Government can develop policies and incentive schemes targeted at increasing grass-roots Solar PV installations to achieve the required Solar PV installation needs. This analysis, in particular the findings from the Literature Review in regards to the energy efficiencies generated through Solar PVs and other renewable energies and Exploratory Data Analysis will be useful for driving support for climate change policy discsussions and analysis more holistically.

Second, the UNSW Government can use the linear regression model to understand the impact population has on the energy demand. By using their own population projections they will be able to see what the long term energy demand is going to look like, also taking into consideration GDP, and Price as other factors that would drive changes to the energy demand along with the population.

From a short term perspective, Temperature is the key element in influencing energy demand. Energy Distributors and organisations in the electricty industry can use this model to predict energy demand over particularly hot periods of time. By doing so, they can incentivise their customers through a variey of means, including but not limited to, schemes to reduce load during hot hours of the day, or pre-purchasing energy blocks so smooth out demand over a period time. The ARIMA model shows…

8.2 Limitations and Further Research

Given more time, we would have liked to explore more deeply are few areas:

1. The impact of Solar PVs on the overall energy demand, to better inform policy making. By looking at data that distinguished residential Solar PV installations versus industrial scale Solar PV installations, and how more large scale implementations of Solar PVs could impact energy demand would be more useful for policy makers to make informed decisions.

2. More investigation on Pricing. Given the macroeconomic climate in 2023 and 2024, and inflation rates in Australia, there has been a lot of discussion about affordability of basic bills (i.e. rent, utilities, etc.). Our model showed that Price does influence energy demand over the long term, and given more time, we should look into this more deeply with other models to see how to better ensure that prices are affordable for all NSW residents.

3. More robust ML models for predicting the short term energy demand. If such a model can be built, it can be used to drive flexible pricing for energy organisations, by increasing prices during peak periods, and lowering prices for off-peak prices, to smooth out demand and ensure overall stability of the grid.

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