Chapter 1 Introduction

The volatility of energy supply and demand poses a challenge for suppliers to enter and remain profitable in the market. Accurately predicting and efficiently supplying energy to the grid is critical for profitability. A key determinant of energy demand is weather; heating is necessary when temperatures drop, and air conditioning becomes essential as temperatures rise. Therefore, this analysis aims to examine the influence of weather on energy demand, considering the significant effects of global warming and erratic weather patterns.

However, other variables also come into play. As the International Atomic Energy Agency suggests, "The analysis should be conducted with relevant and consistent macroeconomic and microeconomic data, so that electricity demand projections can be more reliable and consistent with demographic, economic and industrial development projections"[1]. This sentiment is further echoed by Emami Javanmard and Ghaderi who state, "The increase in population and economic growth of countries has led to a rise in energy consumption, which has created several challenges and problems for governments and nations"[2].

Considering these challenges, the project will explore daily and seasonal variations, as well as the impact of holidays on energy demand. By incorporating these factors, we intend to highlight the benefits of using machine learning models for more efficient demand prediction, a point also emphasized by a report stating, "The demand for energy continues to grow as the world's population increases. And to ensure we meet these demands, utility and energy companies need reliable energy demand forecasting"[4].

Specifically, we will uncover hidden temporal trends in demand, including daily and seasonal fluctuations, through the identification of energy consumption patterns. “According to the Global Energy Statistical website, energy consumption worldwide has increased by approximately 70% from 1990 to 2020”[3]. We will try to understand how variables like temperature impact energy demand. Furthermore, we will analyze the effect of holidays and special events on demand, aiding better planning efforts.

In New South Wales, the government anticipates exponential population growth, but this prediction may not sufficiently account for the intertwined relationship between energy resources and population capacity.

As populations grow, the demand for energy escalates, putting strain on existing resources. This can make energy sources scarcer and more difficult to extract, exemplified by the need to mine deeper for coal or explore complex environments for oil. The scarcity leads to declining marginal returns in energy extraction, pushing the quest for new energy sources. These new sources, in turn, can expand the Earth's carrying capacity, enabling further population growth.

Therefore, the correlation between energy availability and population size could imply that if energy resources are nearing their peak production rates, New South Wales might also be approaching its maximum sustainable population. Hence, planning for the future should factor in these variables to create more accurate and sustainable growth forecasts. "In economies experiencing rapid residential electricity consumption and burgeoning energy-intensive activities, there is a notable link between economic growth and electricity use. Specifically, in less developed non-OECD countries, per capita electricity growth more than doubled from 2000 to 2017. This is in stark contrast to the nearly flat trend observed in more developed OECD countries”[5].

We hypothesize that growing population correlates with increasing energy demand. To confirm or refute this, we will perform an analysis that may also reveal other influential factors. Consequent to our analysis, policy recommendations will be provided to aid in energy policy formulation, including diversification of energy sources to meet demand. We aim to develop a machine learning model capable of predicting future energy demand with high accuracy, incorporating all the identified variables.

Electricity demand forecasting is an indispensable tool for managing the power grid and ensuring a reliable supply. It is a complex task, influenced by a multitude of factors. While traditional forecasting methods have their merits, there is growing interest in employing machine learning algorithms such as Linear Regression, Random Forest, and XG Boost for more accurate predictions.

For model performance evaluation, metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) will be used, given the time-dependent nature of the data. These metrics will serve as complementary tools for a comprehensive evaluation of our forecasting models.

Two common approaches to forecasting energy demand are top-down and bottom-up. The top-down approach focuses on macro factors like the economy, population growth, and weather, while the bottom-up approach examines energy consumption at the individual or company level. Both methods contribute to understanding future energy needs.

The subsequent sections of this report are organized as follows: Chapter 2 presents a literature review, establishing the relevance and importance of our study for policymakers in New South Wales and the energy sector. Chapter 3 elaborates on the methods, machine learning algorithms, and evaluation benchmarks. Chapter 4 delves into the data, exploring descriptive statistics and outlier analysis. Chapter 5 prepares the data for the main model and explores various visual plots. Chapter 6 examines the relationship between total demand and the estimated population of New South Wales. Chapter 7 analyzes and compares the results to other metrics, while Chapter 8 discusses these results. Finally, Chapter 9 concludes the report, offering recommendations and addressing further issues.

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1- Energy projections 2016, www.iaea.org.

2, 3 - Emami Javanmard, M. and Ghaderi, S.F. (2023). Energy demand forecasting in seven sectors by an optimization model based on machine learning algorithms. Sustainable Cities and Society, [online] 95, p.104623. doi:https://doi.org/10.1016/j.scs.2023.104623.

4 Predicting power: How machine learning is enhancing energy demand forecasting n.d., www.perle.com.

5 Global electricity consumption continues to rise faster than population - Today in Energy - U.S. Energy Information Administration (EIA) n.d., [www.eia.gov](http://www.eia.gov).

Chapter 2 Literary review

Previous studies and approaches for electricity demand forecasting have surveyed the use of different manual and automated techniques for forecasting energy demand. Some of them have covered other machine learning (ML) techniques. Other surveys have examined general uses of ML in energy systems, not only for demand and load but also for generation, and not restricted to electricity but considering all sources of energy. Our exclusive focus on demand in NSW electricity demand forecasting allows for providing deeper insight, to the point of questioning aspects traditionally taken for granted, such as the relationship between price, temperature, and also the correlation between population growth and the forecasting problem. It's worth noting, though, that we cover not only pure uses of some benchmark metrics to examine the performance of our main model but also deeper approaches where grid search is employed to look for the best model.

1- In a recent papers titled “Analysis and Forecasting of Monthly Electricity Demand Time Series Using Pattern-Based Statistical Methods” by Paweł Pełka uses the monthly forecast of electricity demand. This paper discusses the importance of accurately forecasting loads on power systems, emphasizing that electricity cannot be stored in large quantities and must be produced in real-time to meet demand. The accuracy of these forecasts directly impacts production costs, transmission efficiency, and the reliability of the electricity supply. Inaccurate forecasts can lead to either an excess or a shortage of generating units, which can result in additional operating costs or potential supply issues. The paper focuses on medium-term forecasting of monthly electricity load (MEL), which involves analyzing time series data containing non-linear trends, annual seasonality, and random disturbances. The MEL is influenced by various factors, including economic, climatic, and weather variables. The paper reviews different forecasting models, including classical/statistical methods, neural networks, deep learning, and similarity-based methods. It also discusses the application of pattern representation in statistical methods, which simplifies the relationship between input and output variables. Additionally, the paper introduces the concept of stationary time series and highlights its significance in constructing accurate forecasting models. The provided figures illustrate the variability and non-stationarity of MEL time series data for both Poland and 35 European countries.

2- Graham Zabel's paper examines the sum-of-energies model as it relates to population growth, noting that it measures a macro phenomenon. The paper acknowledges that there are multiple complex factors affecting population growth, including energy resource availability. Zabel posits that while issues like mandated population control, disease epidemics, and natural disasters do play a role, energy resources have an indirect demographic effect on all these phenomena. The paper does not discuss specific types of energy resources like nuclear, hydroelectricity, or renewables, as their contributions to global energy are minor but still essential for population growth. The model's primary focus is on the global impact of fossil fuels on the human population, as they influence nearly every aspect of society. Zabel suggests that when considering our planet's carrying capacity against a growing human population, it's crucial to recognize the positively and negatively reinforcing relationship between population growth and energy resources.

3- Ari Kahan, writing for the U.S. Energy Information Administration, notes that global electricity consumption is outpacing population growth. This trend is most prominent in developing, non-OECD countries where per capita electricity consumption more than doubled between 2000 and 2017. In contrast, developed OECD countries have seen a nearly flat trajectory in electricity consumption. Efficiency measures, such as improved lighting technology, have partially offset this rise in consumption. Kahan emphasizes that while growth in electricity use is closely tied to economic activities in developing countries, large, developed economies can experience economic growth without proportional increases in per capita electricity use. He also observes significant within-country variances, using the United States as an example, where per capita electricity consumption varies widely from state to state.

4- In their article titled "Energy demand forecasting in seven sectors by an optimization model based on machine learning algorithms," Majid Emami Javanmard and S.F. Ghaderi offer an advanced approach to predicting energy demand in Iran up to 2040. Their study employs a range of machine learning algorithms, including ANN, AR, ARIMA, SARIMA, SARIMAX, and LSTM, and integrates them with mathematical programming. The data, covering various sectors like residential, commercial, and industrial, is then processed through two optimization algorithms, PSO and Grey-Wolf Optimizer. Their integrated approach showed superior accuracy in predictions, outperforming standalone machine learning models.

The article highlights the pressing issue of surging energy consumption as populations and economies grow, particularly in Iran. The authors meticulously test the prediction accuracy of each algorithm in each sector, aiming to fine-tune their integrated model. This work contributes to the existing literature by offering a multi-algorithmic approach that takes into account the complexities and variations of different sectors. They also evaluate the performance of their integrated model using five prediction accuracy metrics, showing that their method offers more accurate predictions compared to using individual machine learning algorithms.

5- Temperature is widely recognized as a significant determinant of energy demand. Numerous studies have established a strong relationship between temperature and energy consumption, particularly in the residential sector (Auffhammer et al., 2017; EIA, 2019). Heating and cooling systems account for a large proportion of residential energy usage, and their operation is directly influenced by external temperatures (EIA, 2020).

Climate change is expected to exacerbate the relationship between temperature and energy demand, as global temperatures continue to rise (Auffhammer et al., 2017). This will lead to increased cooling demand during hotter periods and decreased heating demand during milder winters, with implications for energy infrastructure and capacity planning (Isaac & van Vuuren, 2009).

6- Public holidays have been found to influence energy demand, particularly in the commercial and industrial sectors (Bessec & Fouquau, 2008).

“All over the world, holidays tend to decrease human working activity. Usually, this decreases the electricity demand of a certain region. However, the smaller the aggregation level, the less this general statement holds. In almost every country, there are certain regions which increase their electricity consumption during public holidays, especially those ones in touristic areas. “ (https://link.springer.com/article/10.1007/s40565-018-0385-5#:~:text=All%20over%20the%20world%2C%20holidays,less%20this%20general%20statement%20holds.)

7- Both economic theory and empirical evidence indicate that the price of energy has an inverse effect on energy demand (Silva & Soares, 2012). Numerous studies have quantified the price elasticity of energy demand, although the magnitude of this relationship varies across studies, sectors, and countries (Labandeira et al., 2017; Saunders, 2008). The price elasticity of electricity demand, for example, ranges from -0.1 to -0.3 in residential settings and from -0.2 to -0.4 in industrial settings (Borenstein, 2012).

Technological advancements have significantly improved energy efficiency, thus reducing per capita energy consumption in various sectors (IEA, 2020). This is complemented by changes in industrial processes and the adoption of renewable energy technologies (Geller et al., 2006).

8- The level of economic development also influences energy demand, as higher income levels generally lead to increased consumption (Soytas et al., 2001). Structural changes in the economy, such as a transition from manufacturing to service industries, can also affect energy demand patterns (Sadorsky, 2013). Improvements in living standards, as indicated by higher GDP per capita, are typically associated with increased energy consumption (Ozturk, 2010).

Environmental awareness and shifts in urban planning can contribute to reducing energy consumption (Gatersleben & Vlek, 1998). In NSW, government initiatives like the Energy Savings Scheme and more stringent building standards aim to reduce energy demand while accommodating population growth (IPART, 2020).

9- Our study aims to establish a generalized model for forecasting energy demands in NSW, which has both long-term and short-term forecasting implications. It employs multi-objective models that consider various machine learning algorithms to improve forecasting accuracy. It aims to provide energy suppliers and policymakers with valuable insights for better demand management, thus ensuring a stable and reliable energy supply for the NSW populace.

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