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Forecasting electricity demand 7 days ahead in New South Wales

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07/10/2023

Table of Contents

Abstract:

Electricity is the primary source of energy driving innovation and development in the 21st century. Demand for electricity is correlated with temperature. Further, demand for electricity shows patterns of variation between months of the year as well as days of the week. In Australia, future demand for electricity is forecasted by the Australian Energy Market Operator (AEMO) which provides forecasted demand in 30-minute intervals. In this report, we compare the performance of deep learning and statistical models to predict demand to the model used by AEMO. Specifically, we investigate the application of LSTM model, a SARIMA-regression model, and a Polynomial Regression model and compared their performance. Due to the limitation of computing resources and time, our models generate and compare an average daily formatted demand for electricity. We found that the SARIMA-regression model performs best in predicting future demand, followed by LSTM and lastly Regression Models.

1. Introduction

Forecasting electricity demand is crucial in ensuring the reliability of deregulated markets like the the National Electricity Market (NEM). On a macro level, it allows industry and government to make informed decisions on systems planning, investments on infrastructure and policy design. On a micro level, it assists businesses to balance the supply and demand, which influences the price settings in the market. In cases where electricity supply surpasses demand, any excess energy produced goes to waste. Conversely, if there is an energy shortfall, it can lead to disruptions in the system. Hence accurate forecasts of electricity demand are crucial. It's widely recognized that as the forecasting horizon extends, the task of achieving precise load forecasts becomes increasingly challenging (Behmiri, et al., 2023). Furthermore, while a substantial body of research exists on short term forecasting, there is comparatively limited research, in the Australian context, that addresses medium load forecasting (Eshragh, et al., 2022).

Our client, Endgame Economics, is a leading expert in forecasting electricity demand. They provided a dataset on New South Wales (NSW) electricity demand and forecasts from the Australian Energy Market Operator (AEMO), as well as temperature data from 2010 to 2022. They advised us on many ways this data can be harnessed. Since there are identified gaps in the literature on medium term forecasts and we are interested in how generating plants might plan to purchase fuels we opt to leverage past electricity demand data to address this query: **What will be the anticipated electricity demand for the upcoming week, based on recent electricity demand patterns and temperature conditions?**

We investigate the use of historical demand data and/or temperature data to reliably predict next week's electricity demand. We proceed by establishing 4 models: Predict demand 1) using historical demand data and temperature, 2) using historical demand data, time features and temperature as predictors. 3) using historical demand data and time features as predictors and 4) using historical demand data alone.

We investigate the use of both statistical techniques and a deep learning technique to determine which offers better accuracy in predicting demand. More specifically, compare the performance of Polynomial Regression, Seasonal Autoregressive Integrated Moving Average (SARIMA)-regression and Encoder Decoder Long Short-Term Memory (LSTM) model. As a benchmark, we compare the results with the AEMO forecasts.

We find that the 7-day forecasts are best predicted by SARIMA-regression over the Encoder-Decoder LSTM. Having said that, we also find that the specific technique employed by the Encoder-Decoder LSTM is reliable on the first two days. Hence, even though the overall 7-day performance of LSTM may not be the best, it may still be useful as a 2-day forecast.

2. Literature Review

Numerous scholars have explored electricity demand ("load") forecasts by employing a diverse array of modeling methodologies. The literature identifies 3 broad horizons, each of them is characterized with different methodologies and practical applications. Short-term load forecasting (STLF) typically refers to predicting electricity demand within hourly, multi-hourly, daily, often using minute-by-minute or hourly intervals. STLF serves various essential purposes, including optimizing the scheduling of power generation units to align with their operational constraints and grid limitations. It aids in efficiently distributing the load, ensuring reliable energy allocation within the grid, analyzing the likelihood of incidents, and conducting studies on short-circuit events and grid stability (Liu, et al., 2020).

Medium term load forecasting (MTLF) is quite varied depending on the requirements or the behaviour of the data being analysed. According to a comprehensive assessment of MTLF methods conducted by (Wang, et al., 2022) the horizon can range from several months to a one/two years. Other definitions in the literature are as follows:

	Horizon	**Steps**
(Askari & Keynia, 2020)	Monthly	Daily
(Oreshkin, et al., 2021)	Yearly	Monthly
(Shah, et al., 2020)	Few months	Weekly
(Eshragh, et al., 2022)	One Year	Weekly
(Behmiri, et al., 2023)	Few days to a year	Daily
(Liu, et al., 2020)	Weekly or Monthly	

MTLF is useful for managing the consumption peak in special seasons like winter or summer, the optimum management of the product units, scheduling for inspection and repairing, and stable service to customers. In mid-term scheduling by considering the energy, a decision can be made on the rate of fuel-saving and contract with associates regarding time and how to apply the water and thermal power plants.

Long-term load forecasting (LTLF) is typically characterized by a yearly forecasting horizon and weekly or monthly forecasting intervals. LTLF plays a critical role in making high-level strategic decisions, primarily focused on determining the scale of investments required for long-term programs in the future. Key factors taken into account when conducting this type of forecasting encompass aspects such as population growth, subscriber counts, annual income, average energy prices, fuel costs, investment considerations, revenue generated from exports, and value-added assessments.

2.1 Medium term load forecasts methods

MTLF methods can be categorised into two broad groups:

Conditional Modeling: This category centers on economic analysis, management, and long-term planning for energy load and energy policy forecasting. It relies on incorporating external factors like gross national product, consumer price index, exchange rates, and average wage into the modeling process. (Ghiassi, et al., 2006)

Autonomous modelling: This classification primarily relies on historical demand data, atmospheric temperatures, and variables characterized by seasonal patterns. It is better suited for use in economies that exhibit stability and are not prone to abrupt demand-altering changes. (Amjady & Keynia, 2008)

2.1.1 Statistical approach

The approach classifications mentioned earlier predominantly depend on traditional statistical and econometric modeling methods, although certain approaches incorporate more advanced machine learning techniques. Traditional methods primarily encompass variations of Autoregressive Integrated Moving Average (ARIMA), exponential smoothing (ETS), and linear regression. While these models can handle seasonal time series data, they often necessitate supplementary processes like decomposition, local modeling approaches, or the incorporation of periodic components. Traditional models are subject to inherent limitations associated with their limited adaptability and a shortage of expressive power to model non-linear relationships. (Shah, et al., 2020)

A recent Australian study applied seasonal ARIMA (SARIMA)-regression to the NSW, Victoria and SA data. They examined historical demand data and exogenous variables such as maximum temperature, minimum temperature and solar exposure while forecasting the weekly peak demand over a one-year horizon. They found that SARIMA-regression performs better than Recurrent Neural Networks based Global Forecasting Methods (RNN-GFM). SARIMA-regression model generated, on average, a MAPE of 3.41% across all states and the environmental factor improved the forecast accuracy by 46.3%. (Eshragh, et al., 2022). In addition, a study from Thailand found no statistically significant difference between ANN, MLR and SARIMA (Kandananond, 2011)

Another study of Italian electricity demand argued that forecasting one-week ahead appears to be as hard as forecasting six-months ahead. For shorter horizons, ARIMA components provide an advantage. Forecasts from feed-forward-NN (FNN) models outperform forecasts from linear regression models at all horizons but the difference is only significant in the short term (Behmiri, et al., 2023).

2.1.2 Machine learning

Researchers have explored more adaptable machine learning and computational intelligence models in response to these challenges. Neural networks has several advantages, including the capacity to model non-linear relationships, learn from data, exhibit a universal approximation property, and exploit massive parallelism. Some examples of applying NN architectures to solve the MTLF problems include multilayer perceptron (MLPs) (Askari & Keynia, 2020), weighted fuzzy NNs and NNs combined with linear regression and AdaBoost. (Ringwood, et al., 2001), (Wang, et al., 2022).

Deep learning (DL) has achieved remarkable success in addressing intricate forecasting challenges in recent years. DL overcomes the inherent limitations of classical NNs such as their restricted expressive power and inability to discern general patterns across multiple instances. Modern DL architectures are constructed through combinations of foundational components, such as MLPs, RNNs and CNNs. One significant problem with RNNs is the vanishing gradient problem, particularly when processing lengthy sequences. To mitigate this challenge, the Long Short-Term Memory network (LSTM) was introduced. The LSTM architecture comprises a cell and several non-linear gates that regulate data flow within the cell, determining which information to retain and propagate to the subsequent time step. Research has demonstrated that LSTMs can outperform traditional statistical and machine learning models, such as ARIMA, Support Vector Machines (SVM), and classical NNs (Butt, et al., 2021).

A variation of LSTM which follows a sequence-to-sequence network is applied by (Fatema, et al., 2021) on AEMO data. They forecasted both the electricity demand and price based on their historical values. The proposed model was found to be better then SVM, Regression Trees and Neural Nonlinear AutoRegressive Network with Exogenous variables (NARX).

Another variation of the LSTM model was considered by (Zou, et al., 2019). The Stacked Bi-Directional LSTM (SB-LSTM) was assessed for both day-ahead and week-ahead demand forecasting. SB-LSTMs incorporate multiple hidden layers of bidirectional LSTM units, where each bidirectional LSTM layer comprises two hidden layers that process input data in opposite directions to generate both forward and backward information. The research involved the inclusion of calendar variables, meteorological data, and historical load records from the 28 days preceding the forecasted day or week. The findings revealed that the SB-LSTM methodology can yield accurate results for both day-ahead and week-ahead load forecasting, although the margin of error is somewhat greater in the latter case.

In (Dudek & Pełka, 2021), the authors found pattern similarity-based machine learning methods for MTLF is superior to LSTM. Other authors found the reliability of Support Vector Regression coupled with various optimisation techniques. For instance, (Zare-Noghabi, et al., 2019), who exclusively utilized time-related features as input for demand forecasting, recommended SVR in conjunction with the Symbiotic Organism Search Optimization (SOSO) method. Similarly, (Li, et al., 2022) proposed optimization using the Sparrow Search Algorithm.

Other recent machine learning models suitable for short term and medium term forecasts found in the literature are mostly a hybrid of machine learning models.

A day-ahead and week-ahead study by Islam et al, 2022 employed a hybrid of Artificial Neural Network (ANN), LSTM and Recurrent Neural Network (RNN). Similarly, Zheng et al (2017) used Empirical Mode Decomposition (EMD) and LSTM while employing XGBoost for feature selection. A study using Chinese data integrated XGBoost with gradient boosting decision tree (GBDT) and light gradient boosting machine (LightGBM) to build an XLG-LR fusion model to predict power demand (Ji et al, 2022).

The models in our project takes the form of autonomous modelling and draws inspiration from (Eshragh, et al., 2022), (Fatema, et al., 2021) and (Behmiri, et al., 2023).

3. Material and Methods

3.1 Software

The software used was Python on Colab Pro.

3.2 Description of the Data

The data for this project are provided in three separate data files. These files were.

a. **Temperature –** this csv file of size 8,195 KB contains data on date, time and temperature values for New South Wales for a period of 12 years, from the 1st of January 2010 to 1st of August 2022. The temperature is measured at 30 mins intervals. This csv file contains 19 values of temperature which are outliers. After these outliers removed, this file contains 247,627 values of temperature.
b. **Demand –** this csv file of size 8,253 KB contains data on the actual demand of electricity in New South Wales at 5 minutes interval for a period of 12 years from 1st of January 2010 to 1st of August 2022. There are no missing values in this file. This file contains 1,323,398 values of demand of electricity.
c. **Forecast Demand –** this csv file of size 769,555 KB contained data on forecasted future demand of electricity at 30-minute intervals for a 11-year period form 1st of January 2010 to 1st of August 2022. This file also provides an update date and time for each forecasted future demand is updated. There are multiple updates for a future forecasted demand. Each update had a unique id. There are a total of 11,619,503 values in this data file.

The three files are further checked for missing values and outliers. The temperature, demand and forecast demand file was then merged on the time and date values in this file. The resultant file has 11,584,033 values. The date and time column are split to make a separate column for date and time each. This file is further condensed by choosing only one demand value and a forecast demand value for every unique date and time. As a result, the condensed file contains demand, forecast demand and temperature values at 30-minute intervals between 1st of January 2010 and 1st of August 2022. 216,137 values.

The demand and temperature data over the 12 yr period is summarized in the table below.

Table 1. Statistical summary of temperature and demand

Statistical measure	Temperature	Demand
Minimum	-1.3	4,316.63
Maximum	44.7	14,605.19
Mean	17.38	8,070.17
Median	17.7	7,998.06
Mode	19	8,636.38
Standard Deviation	5.85	1,312.64
No. of Unique Values	627	179,782

3.3 Pre-processing Steps, Data cleaning and Assumptions

As the problem suggests we need to transform the 30-minute demand into daily aggregates. While this transformation is not required, it aligns with our interest in understanding daily demand and helps with efficiency. We have utilized the "resample()" function on a Pandas DataFrame to calculate the mean of all observations for each day. Because the forecasted data has some missing the values, merging the 3 datafiles as above results to missing actual demand. There is data missing for 3 entire days in February 2018, 10 entire days in April 2018, and 12 entire days in May 2018. Hence a separate datafile was created to feed into the LSTM model, where the mean of the daily demand was calculated first before merging. While the statistical models accept missing datapoints, LSTM does not accept missing data. Therefore there is a negligible discrepancy between the dataset used for the statistical models and LSTM model.

3.4 Modelling Methods (Prediction Models)

In technical terms, the problem described above falls into the category of a multi-step time series forecasting challenge due to the need to predict multiple time steps ahead. In addition, since we are including temperature as a contributing factor, the problem transforms into a multivariate multi-step time series forecasting model. As such, statistical models such as the Polynomial Regression and SARIMA-regression and deep learning methods such as Encoder-Decoder LSTM are suitable methods to solve this type of problem.

Polynomial Regression

Polynomial regression is a suitable statistical model to forecast demand of electricity based on temperature as the relationship between temperature and demand is not linear. Here the demand can be modelled by applying a higher degree of polynomial to temperature and other input features such as days of the week and month of the year.

A polynomial model can be trained using the sklearn package. In this package the polynomial features functions are used to convert the input features into the polynomial features of a chosen polynomial degree. These polynomial features are themselves used as an input feature to fit a linear model between these features and the response feature, demand.

SARIMA-regression

SARIMA forecasts future demand by using a linear combination of past values of demand. The Seasonal (S) part of SARIMA refers to the seasonal trend in the demand of electricity.

The Auto Regressive (AR) part of SARIMA refers to the fact in this model we are regression demand values against its own values. In other words, we used lagged values of demand as input values to forecast future demand of electricity.

The Integrated (I) part of SARIMA refers to differencing applied to may a non-stationary series into a stationary one. The Augmented Dickey Fuller test can be applied to test for stationarity.

Lastly the Moving Average (MA) part of SARIMA refers to using past errors in forecasting rather than actual values of forecasted demand in a regression model to forecast future demand (Hyndman & Athanasopoulos, 2018).

LSTM

Simple LSTM Architecture

The LSTM model was selected because it can capture complex connections and relationships between variables over extended periods (long-term). This contrasts with traditional feedforward neural networks, which struggle to learn long-term information due to the vanishing gradient problem.

As shown in figure 1 below, in a typical LSTM algorithm, both long-term memory (*c[t − 1]*) and short-term memory (*h[t − 1]*) are processed using multiple gates designed to filter data. Three key gates—namely, the input gate, the forget gate, and the output gate - along with the cell state, allow learning by retaining useful information and rejecting ones that are not. The memory cell state is updated by forget and update gates. As a result, LSTM is good at storing information over various time intervals, making it an excellent choice for time-series data forecasting.

The forget gate in LSTM is responsible for collecting long-term data. Irrelevant information is removed through a sigmoid activation function that ranges from 0 (open status) to 1 (close status). The input gate filters and prioritises incoming data to assess its relevance, controlling the flow of both short-term and long-term information within the cell through binary activation functions. Finally, the output gates determine the value of the upcoming hidden state based on prior inputs. (Khosravi, et al., 2023)

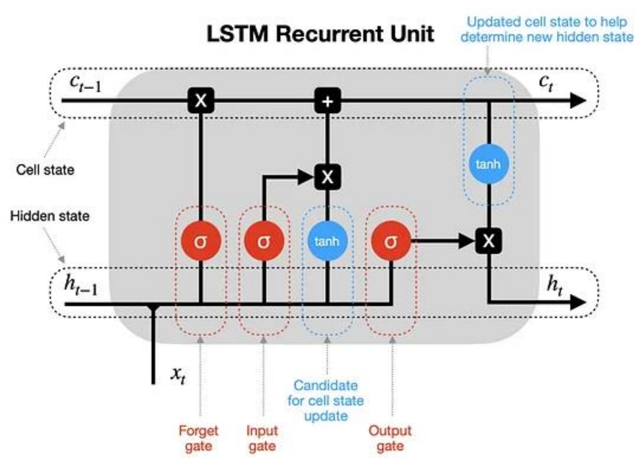


Fig 1: Long Short-Term Memory (LSTM) Architecture. (Dobilas, 2022)

Encoder-Decoder Multi-step Multivariate LSTM

In an Encoder-Decoder model, an LSTM model is trained to map an input sequence and an output sequence, without any requirement to have equal lengths. This model comprises two LSTMs, which can be considered as an encoder and a decoder. Adding a decoder means that we are allowing the model to know the prediction for the prior day in the sequence and accumulate internal state while outputting the sequence.

The LSTM encoder is responsible for reading the input sequence and converting it into a fixed-length vector via its hidden layers. This is referred to as the context vector. This context vector is then provided as input to the LSTM decoder, and the final encoder state serves as the initial decoder state for generating the output sequence.

Adding a repeat vector layer duplicates the context vector obtained from the encoder and feeds it as input to the decoder. This duplication is performed for a specified number of future time steps, 7 days in our case. The decoder generates an output for each time step, which is then processed. The time-distributed dense layer applies a fully connected dense layer to each time step separately. This layer acts as a wrapper that allows the application of a neural network layer to every time slice of the input.

The Encoder-Decoder LSTM codes used in this study was heavily referenced from (Brownlee, 2018).

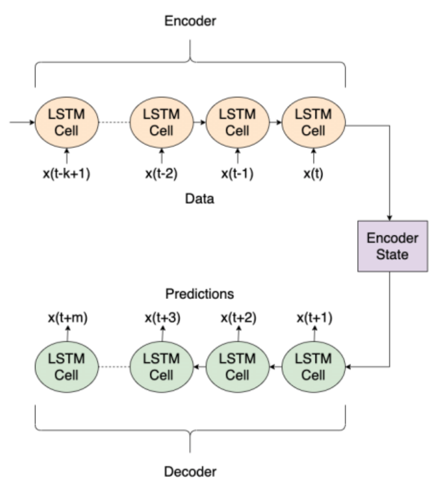


Figure 2. Encoder-Decoder LSTM architecture (Chandra, et al., 2021)

The training data for LSTM is between the 3rd of January, 2017 (Tuesday) to 28th of January, 2020 (Monday) (1,120 days) while the test data in from the 29th of December, 2020 (Tuesday) to the 1st of January, 2022 (368 days). Separating by date avoids data leakage. This is a useful and flexible way to set up the training data because the required forecast from August 2,2022 falls on a Tuesday. It can later be adjusted to a different start day.

Throughout the report, Encoder-Decoder or Sequence-to-Sequence LSTM is simply referred to as LSTM.

3.5 Evaluation methods

Commonly used metrics to evaluate forecast accuracy are the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The total electricity demand is measured in megawatt-hours (MWh), and it is preferable to employ an error metric that shares the same units although RMSE tends to penalise more than MAE. MAPE is also calculated for comparability with other studies. Relatively lower values of these metrics indicate better performance. These are all applied to Linear Regression, Polynomial Regression, SARIMA-regression and LSTM. In addition, the Akaike Information Criterion (AIC) values is used to compare performance of SARIMA models generated by the grid search.

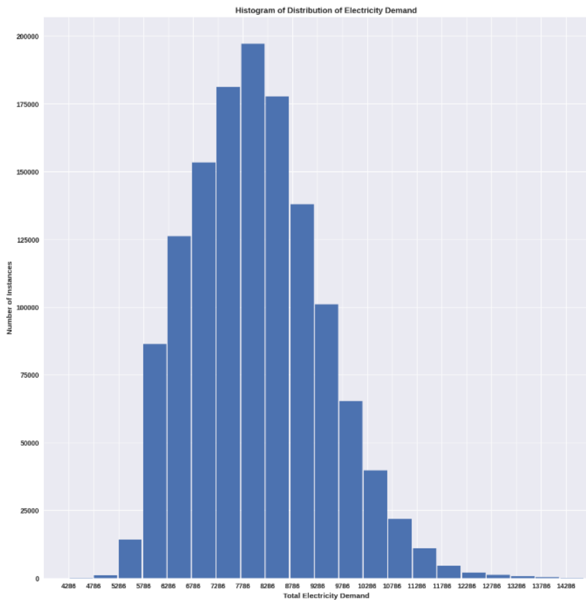
The evaluation methodology for LSTM follows the 'walk-forward' validation. It allows for the computation of the accuracy for the next day versus the next 3 days. It can also output a single score across the 7 days. (Brownlee, 2018)

4. Exploratory Data Analysis

In time-series forecasting, it is important to recognize that each observed data point is linked to its preceding data point. Consequently, we cannot treat each observation as an independent data point (Hyndman & Athanasopoulos, 2018).. This section conducts an exploratory data analysis of the demand and temperature and aims to identify of trends and patterns.

4.1 Distributions

Figure 3 is a histogram of demand of electricity in MWh from 2010 to 2022. It shows that demand is normally distributed with a mean of 8,153 MWh, the minimum and maximum of (5,050.81, 14,605.19) MWh. Figure 4 is a histogram of temperature values from 2010 to 2022. It shows that the temperature in NSW in the last 12 years also follows a normal distribution with a slight right sew illustrating some sparse extreme days. Temperature in NSW averages to about 17.5 C, the minimum and maximum temperatures recorded as (-1.3 C, 44.7 C).



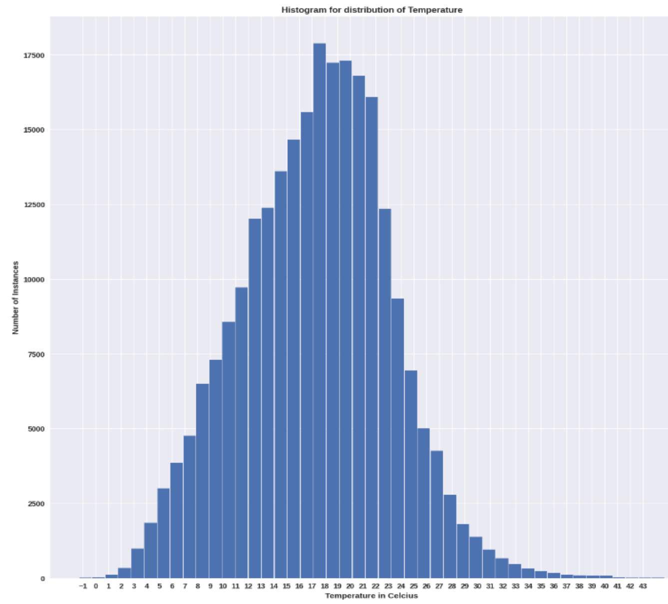


Figure 3. Histogram of actual demand **Figure 4. Histogram of temperature**

4.2 Relationship between demand, temperature and time

The actual daily demand for the years 2019 to 2022 is displayed in Figure 5 below. The data exhibits a notable seasonal pattern. Within each year, a 'W' shape emerges owing to elevated demand around the winter and summer months. We can also observe some volatility across the January-March period and November-December period and are therefore expected to pose challenges to forecasting.

This behaviour is further illustrated by Figure 6 which also compares monthly average forecasted demand and actual demand of electricity over a year. Demand for electricity surges on the cold months of June to July, followed by a moderate demand in the hottest months of January and February and further by November and December. Forecasted demand is higher than actual demand of electricity in July. On the other hand, actual demand of electricity is higher than forecasted demand of electricity in December and January. This graph shows that the maximum difference between forecasted demand and actual demand of electricity is seen in the summer and winter months where the temperature is either very low or very high. The times series does not exhibit an obvious trend but is examined in succeeding sections.

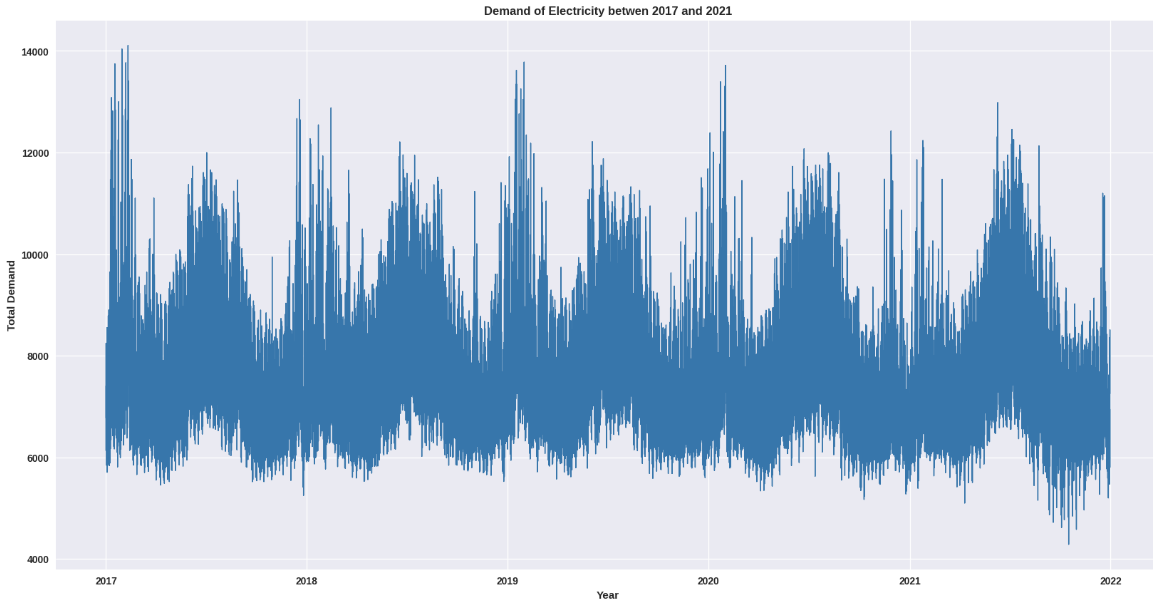


Figure 5. Average daily demand from years 2017 to 2022

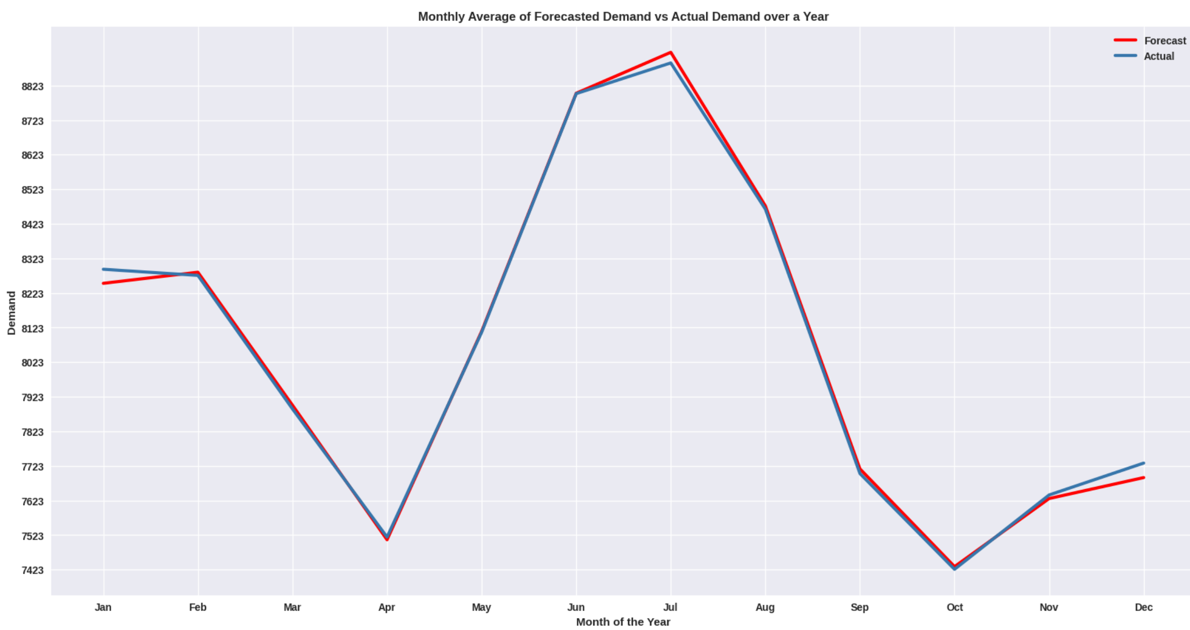


Figure 6. Average monthly demand, actual versus forecasts

A strong weekend/weekday pattern is also exhibited by demand as shown on Figure 7 below. Both actual and forecasted demand of electricity are lower on weekends compared to weekdays. Demand tends to be overestimated by the AEMO on Tuesday and Wednesday and underestimated on Saturday and Sunday.

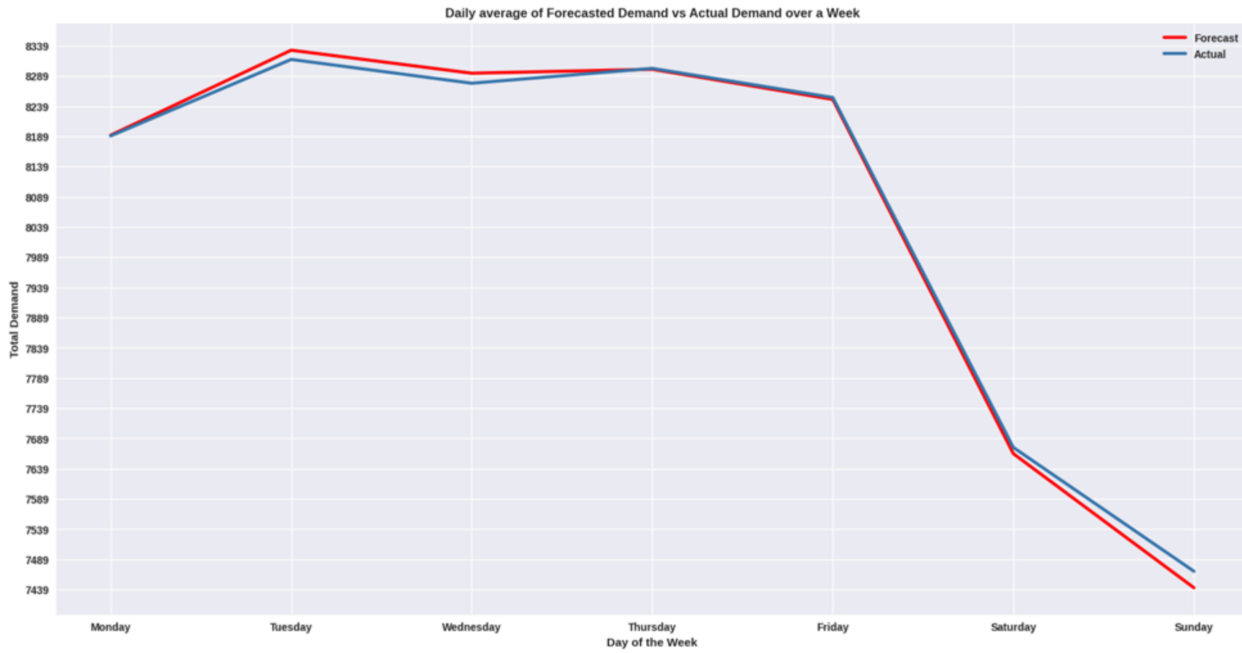


Figure 7. Daily demand, actual versus forecasts

The figure below shows that temperature also has a strong seasonal pattern which drives the behaviour of demand for electricity.

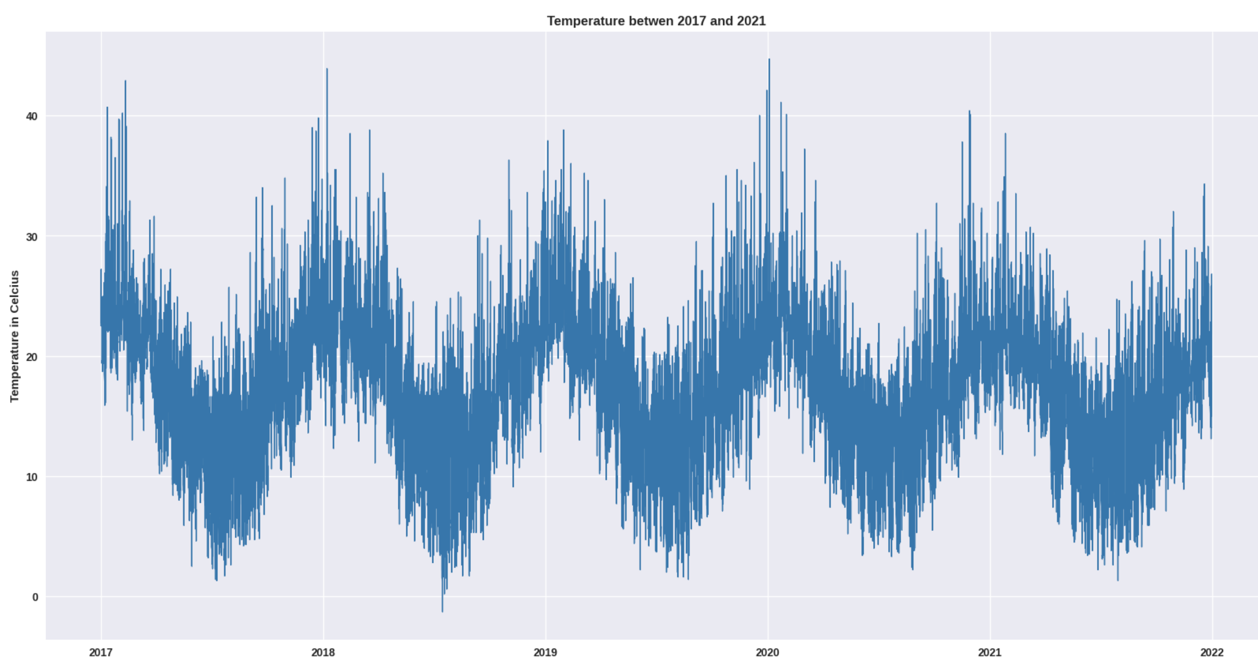


Figure 8. Yearly average temperature, 2017 to 2022

Figure 9 shows the demand of electricity with temperature over the 11-year period. The red dots represent demand on weekdays, Monday to Friday and the blue dots represent weekends. Demand for electricity is higher on weekdays than weekends. Further, demand of electricity is lesser when the temperature is between 16 C to 21 C. Demand of electricity increases as the temperature goes higher than 21 C and lower than 16 C

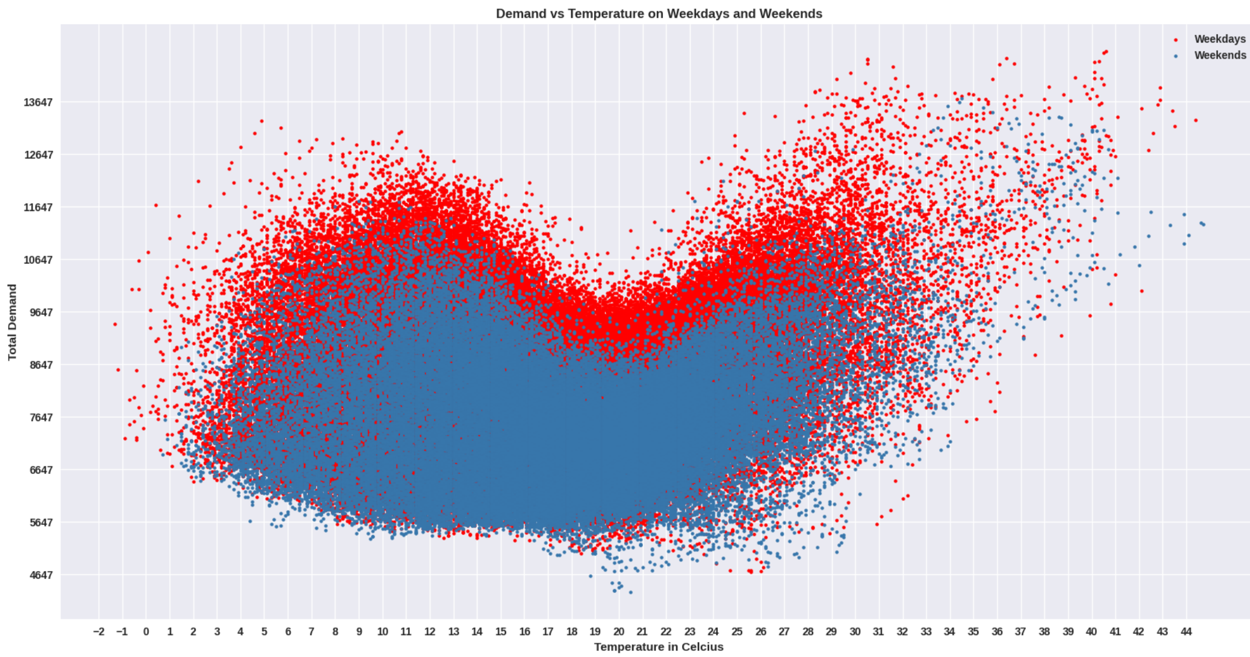


Figure 9. Actual demand against temperature, by weekend versus weekdays, 2010-2022.

Figure 10 compares the forecasted demand and actual demand of electricity with temperature. The red line represents forecasted demand, and the green line shows the actual demand of electricity. As confirmed from the previous graphs, this graph also shows that the demand of electricity increases when the temperature is too low or too high and is minimum between the temperatures of 16 C and 20 C. The blue dots in the graph represent the difference between forecasted and actual demand of electricity with changes in temperature. This graph shows that actual demand of electricity is higher than forecasted demand as we experience extreme temperatures. Further, this graph also shows that electricity demand is more accurately forecasted between 10 C and 25 C. The AEMO forecasts is more likely to deviate from the actual demand at extreme temperatures resulting to a volatile nature of demand occurring around the early months of the year and the later months of the year. The same can be expected in our study.

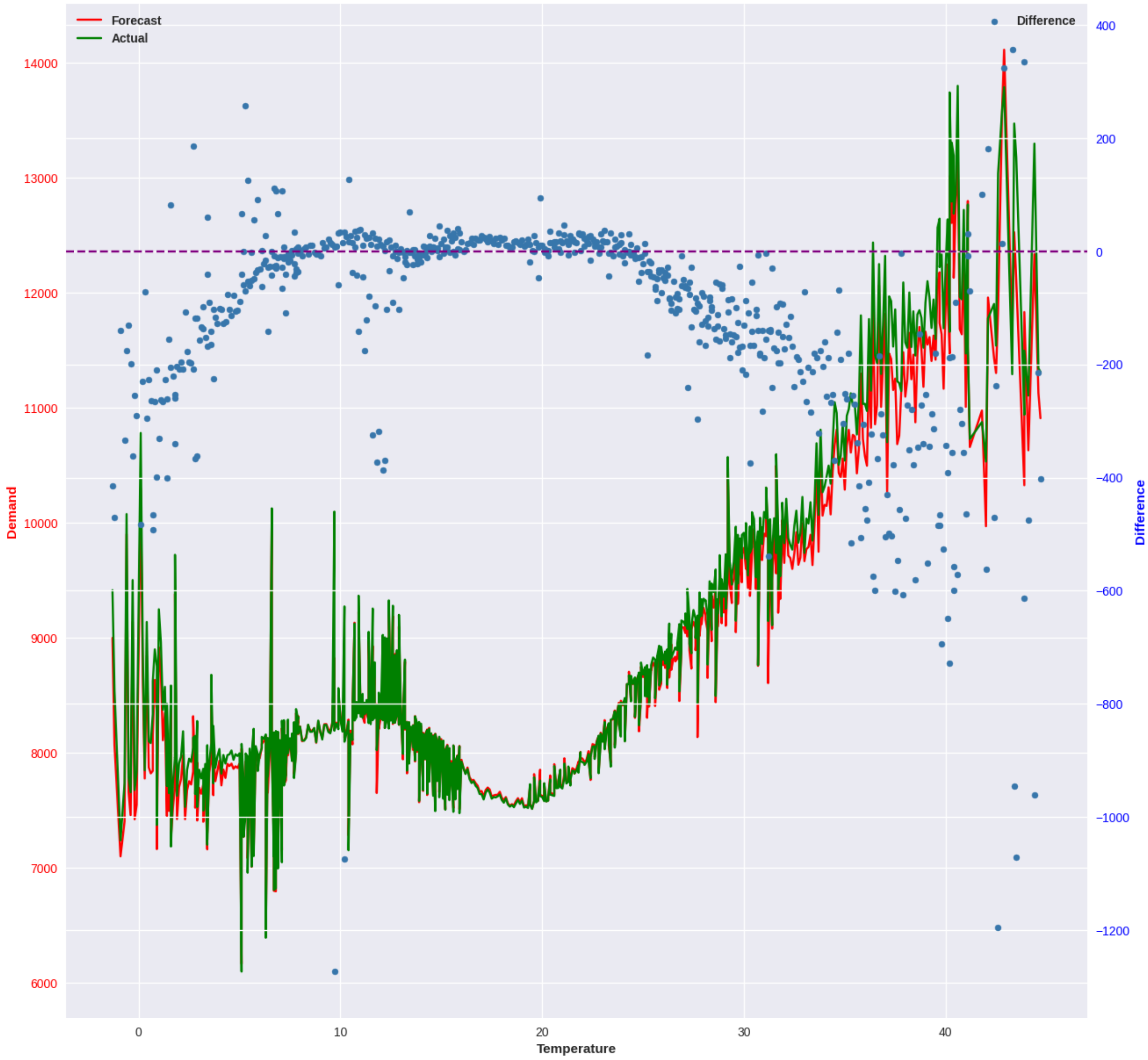


Figure 10. Difference between the actual demand and AEMO forecasts

5. Analysis and Results

In this study we apply Linear, Polynomial Regression, SARIMA-regression and LSTM to build models that can forecast electricity demand. These techniques are capable of outputting average daily data over the next 7 days which takes the form of a 1 week worth of time series from 1 August, 2022 to 8 August, 2022. LSTM outputs daily to 7 days while Linear, Polynomial Regression and SARIMA-regression output daily up to 1 year. As established in the previous section, the demand time series have strong day and month component therefore we consider these time features in our models.

5.1 Statistical models

5.1.1 Linear regression

A linear regression model is trained using the daily mean temperature, days of the week and the months of the year as a feature. The days of the week and the months of the year for each sample in the data set is hot encoded using the sklearn package into a binary 1 or 0. There were a total of 20 input features for this model. The linear regression model is trained on this data set and model accuracy was measured by using 10 - fold cross validation.

The linear regression model generated is presented as follows:

Demand = 7173.263+ 50.71x_1 + 180.51x_2 + 123.77x_3 - 399.21x_4 - 600.57x_5 + 234.70x_6 + 254.04x_7 + 206.75x_8 - 563.58x_9 + 647.39x_{10} - 542.04x_{11} -43.76x_{12} - 58.61x_{13} + 1128.56x_{14} + 1018.72x_{15} - 351.19x_{16} + 217.28x_{17} - 544.46x_{18} - 656.66x_{19} - 251.61x_{20} + ϵ_i

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

where

x_1 = Temperature	x_2 = Friday	x_3 = Saturday	x_4 = Sunday
x_5 = Monday	x_6 = Tuesday	x_7 = Wednesday	x_8 = Thursday
x_9 = January	x_{10} = February	x_{11} = March	x_{12} = April
x_{13} = May	x_{14} = June	x_{15} = July	x_{16} = August
x_{17} = September	x_{18} = October	x_{19} = November	x_{20} = December

This model generated an RMSE of 594.21, MAE of 480.48, MAPE of 5.61%.

5.1.2 Polynomial Regression

As seen from figure 9, the relationship between temperature and demand is not linear and therefore a polynomial regression model may be more suitable for modelling demand using temperature, days of a week and months of a year as input features. The days of the week and the months of the year for each sample in the data set was hot encoded using the sklearn package into a binary 1 or 0. There were a total of 20 input features for this model. There was a total of four polynomial regression models made to model demand. Four each of these models, the appropriate power of the polynomial was determined by looping through a powers 1 to 5 to train the date set. A mean RMSE value was generated by using 10 - fold cross validation at each power. The power with the lowest RMSE was chosen to train the final polynomial regression model. The two models trained were:

Model 1 - this polynomial regression model had only one feature, temperature as the input feature.

Model 2 – this polynomial regression model had all twenty features, temperature, seven days of the week, and twelve months of the year as the input features.

The two models had the following parameters.

Table 2. Parameters of polynomial models 1 and 2

Model	Polynomial Power	No. of Coefficients	Intercept	RMSE	MAE	MAPE
Model 1	4	4	1942.36	513.01	416.74	6.12%
Model 2	2	162	1.74E+13	470.35	387.91	4.43%

The regression equation for model 1 is:

Demand = $2331.52x^4 - 247.77x^3 - 9.83x^2 - 0.12x + 1942.36 + \epsilon_i$

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

Here x = Temperature Model 2 is not presented to save space. However, they are available in the codes provided. Please see the appendix. The predictions compared to actual test data is shown in figure 11. It is observed that the predictions tend to fit the actual data well.

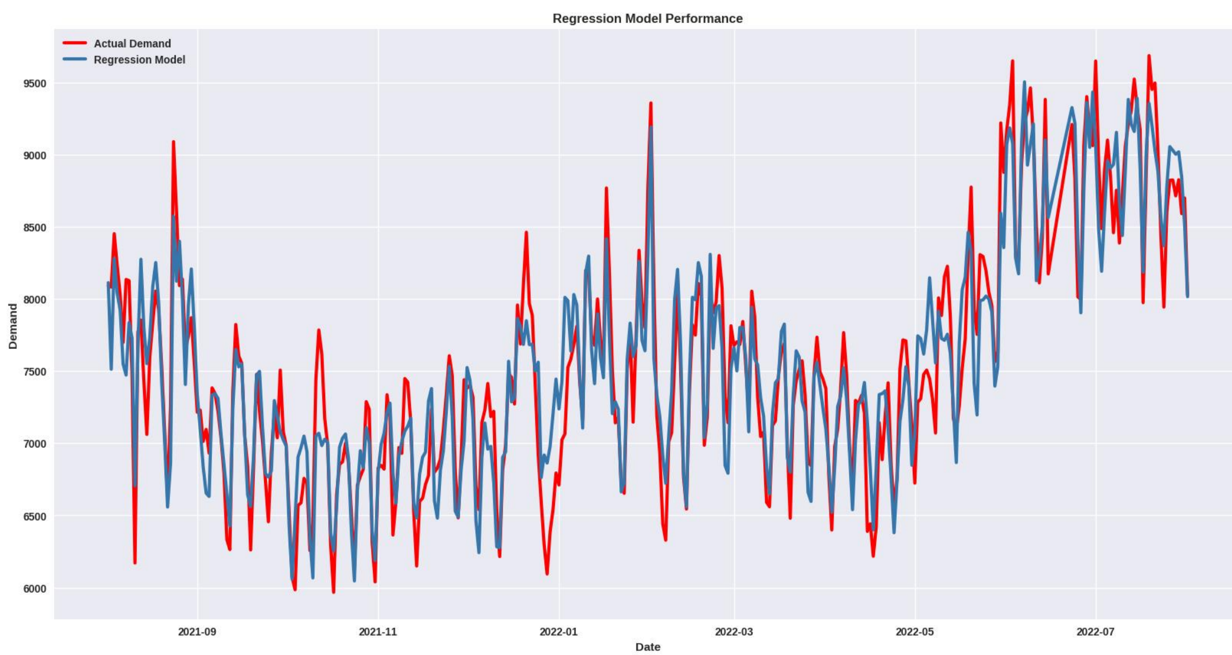


Figure 11. Demand predictions from the Polynomial regression overlayed on actual demand

5.1.3 SARIMA-regression

An essential requirement of modelling with SARIMA is that feature training data should be stationary and there should be no observable trend in the training data. If the data is not stationary, then we use differencing methods to ensure that the data is stationary. A new set of values are generated by taking the difference of the value at that time and the corresponding value at that set interval of time in the past.

An Augmented Dickey Fuller test is used to check for stationarity. In this test, under the null hypothesis is it is assumed that the data is stationary, and the alternative hypothesis assumes that the data is non stationary. We choose a p-value of 0.05 to accept or reject the null hypothesis.

Using the given data of demand over a year, the Augmented Dickey Fuller test generated a p-value of 0.0.005, which is lesser than 0.05 and therefore we can accept the null hypothesis and conclude that the demand data is stationary.

The daily average demand and average Temperature over a year from, 2nd of August 2021 to 1st of August 2023 (729 days), was used to train the SARIMA model.

The SARIMAX function in the statsmodels package is used to train the SARIMA model.

The SARIMAX function used exogenous regressor inputs as temperature. We train and compare two models:

- A model without using exogenous regressor inputs as temperature.
- A model using exogenous regressor inputs as temperature and therefore accounting for the trend of temperature.

The SARIMAX function trains the SARIMA model with seven hyperparameters

p: Autoregressive order.
d: Differencing order.
q: Moving average order.
P: Seasonal autoregressive order.
D: Seasonal differencing order.
Q: Seasonal moving average order
S: Length of the seasonal cycle.

The first six hyperparameters p, d, q, P, D, Q were set through grid search, by taking values ranging from 0 to 5 for each of the six hyperparameters. The RMSE and Akaike Information Criterion (AIC) values were used to compare performance of SARIMA models. The optimum values generated for the hyperparameters were:

p = 4, d = 1, q = 2, P = 6, D = 0, Q = 0

Figure 12 shows that the demand of electricity has a weekly pattern, that is, demand during weekdays tend to be higher than demand during weekends. Therefore, we set the hyperparameter S (length of the seasonal cycle) to 7. The 7-day pattern can also be confirmed from the following seasonal decomposition plot.

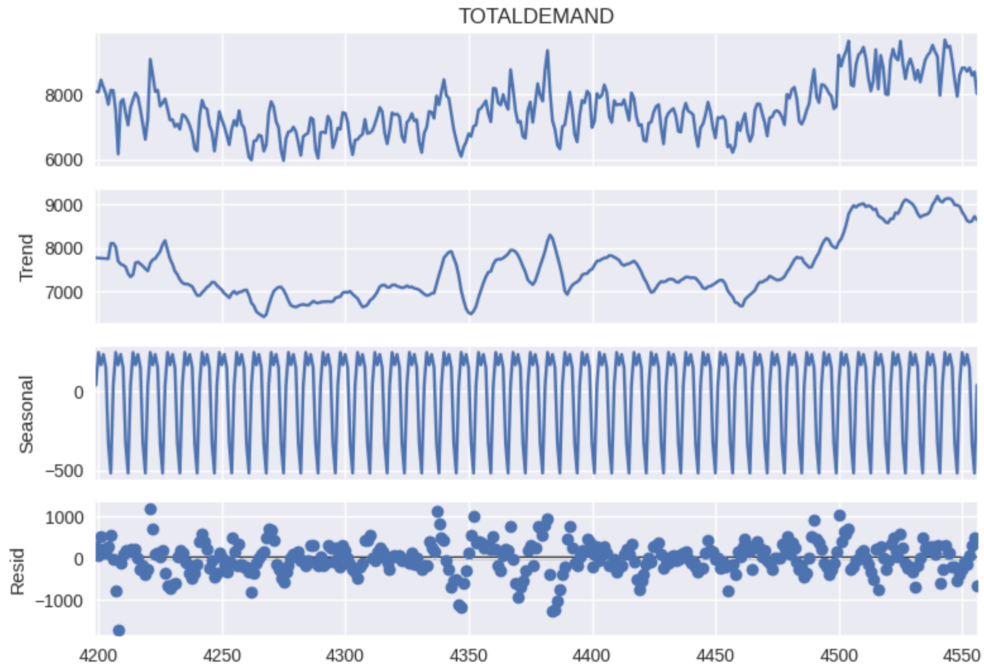


Figure 12. Seasonal decomposition plot

The significance of each coefficient of the AICs chosen model was assessed and the final selected combinations are presented in Figure 13 below. It can be seen that Prob(Q) = 0.23 > 0.05. Therefore we should not reject the null hypothesis that the residuals are uncorrelated. Further, Prob(JB) = 0.00 < 0.05 therefore should reject the null hypothesis that the residuals are normally distributed.

SARIMAX Results

Dep. Variable:	TOTALDEMAND	**No. Observations:**	358
Model:	SARIMAX(4, 1, 2)x(6, 0, [], 7)	**Log Likelihood**	-2556.298
Date:	Tue, 03 Oct 2023	**AIC**	5140.597
Time:	23:10:20	**BIC**	5194.846
Sample:	0	**HQIC**	5162.176
	- 358		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.0038	3.297	-0.001	0.999	-6.465	6.458
ar.L2	0.1657	1.052	0.158	0.875	-1.895	2.227
ar.L3	0.1352	0.315	0.429	0.668	-0.483	0.754
ar.L4	0.0952	0.425	0.224	0.823	-0.738	0.928
ma.L1	-0.3180	0.084	-3.781	0.000	-0.483	-0.153
ma.L2	-0.0960	1.052	-0.091	0.927	-2.158	1.966
ar.S.L7	-0.3144	0.181	-1.733	0.083	-0.670	0.041
ar.S.L14	-0.2843	0.157	-1.810	0.070	-0.592	0.024
ar.S.L21	0.1483	0.104	1.432	0.152	-0.055	0.351
ar.S.L28	0.7321	0.097	7.534	0.000	0.542	0.923
ar.S.L35	0.3035	0.170	1.784	0.074	-0.030	0.637
ar.S.L42	0.4101	0.180	2.283	0.022	0.058	0.762
var.TEMPERATURE	54.2559	16.472	3.294	0.001	21.972	86.540
sigma2	6.456e+04	7147.448	9.032	0.000	5.05e+04	7.86e+04

Ljung-Box (L1) (Q):	1.46	**Jarque-Bera (JB):**	43.48
Prob(Q):	0.23	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.61	**Skew:**	-0.34
Prob(H) (two-sided):	0.01	**Kurtosis:**	4.57

Figure 13. Output of the SARIMAX model

The statistical validity of the estimated models is verified through an examination of the residuals. The following figure illustrates the autocorrelation function (ACF) and a Q-Q plot depicting the residuals obtained from the fitted SARIMAX model. Notably, there is no discernible pattern within the residuals. The histogram is symmetrically centered around zero, and the kernel density estimate (KDE) curve closely resembles a normal distribution curve. Additionally, the straight-line distribution of residuals in the normal Q-Q plot confirms their normal distribution.

Furthermore, the correlogram indicates that correlations for lags greater than 1 are not statistically significant, with 95% of them falling below the threshold. These four plots collectively demonstrate that the SARIMAX model is optimally suited for predicting future electricity demand.

The two SARIMA model generates the accuracy in table 3. SARIMA-regression model using exogenous regressor inputs as temperature performs better than the SARIMA model not accounting for temperature. Both these models however do not perform as well as the AEMO forecasting model.

Table 3. SARIMA-regression and SARIMA performance

	SARIMA without Temperature	SARIMA With Temperature	AEMO
RMSE	360.13	337.79	132.88
MAE	263.19	247.55	99.62
MAPE	3.49%	3.3%	1.4%

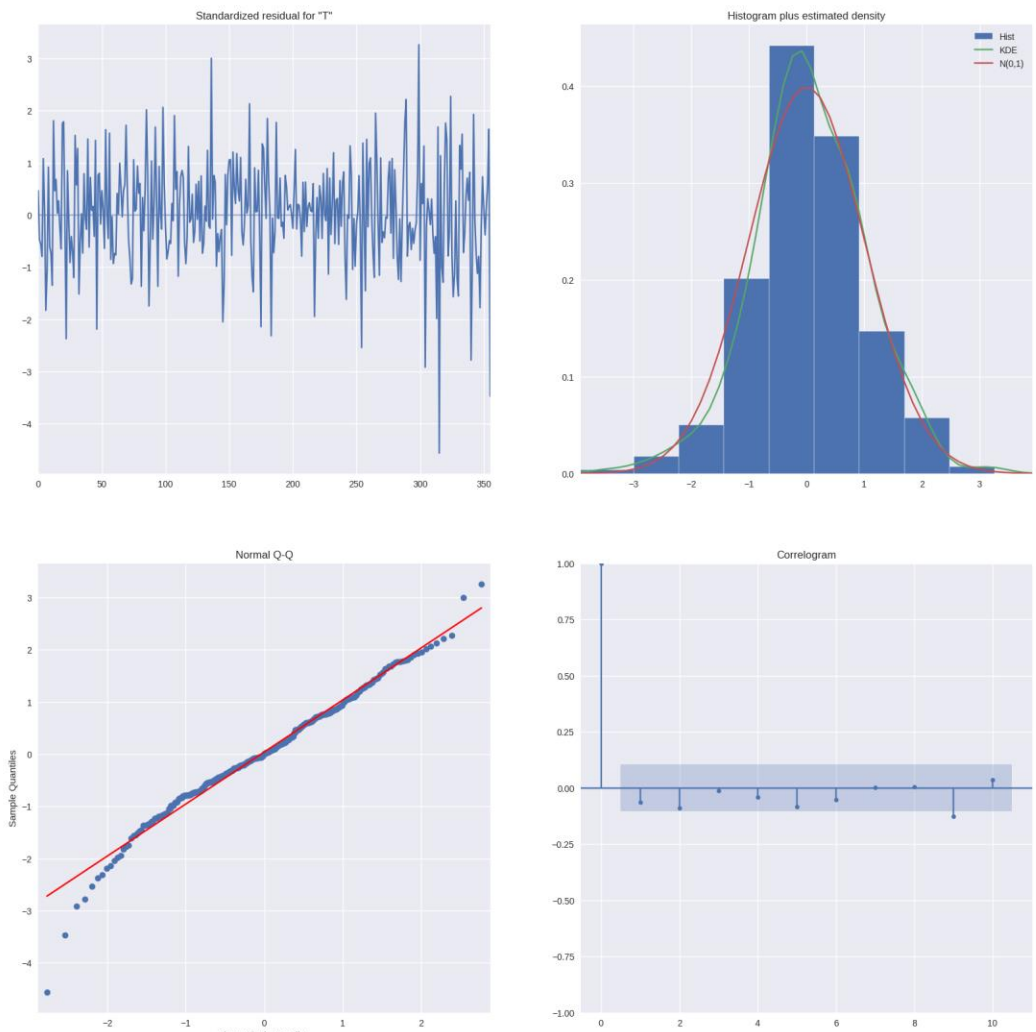


Figure 14. SARIMA-regression diagnostic plots

The predictions compared to actual test data is shown in figure 14. It is observed that the predictions tend to fit the actual data well.

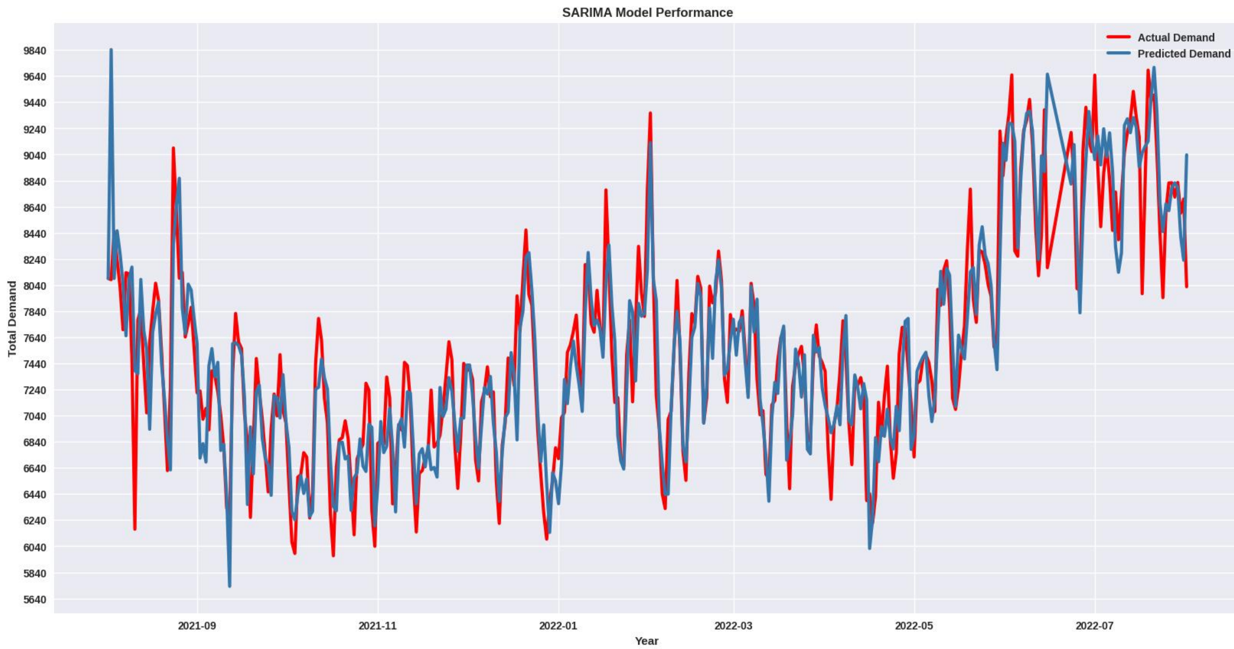


Figure 15. Demand predictions from the SARIMA-regression overlayed on actual demand

5.2 LSTM

The LSTM model employed in this study comprise of two sub-models:

- The encoder to read and encode the input sequence
- The decoder that reads the encoded input sequence and make a one-step prediction for each element in the output sequence.

As the number of features in the model are not that significant (maximum of 21 including the actual demand) we do not perform feature selection. However, feature engineering was necessitated by the model. Minmaxscaler was applied to the entire dataset before training was done. In the previous section, it is shown that the trend for demand is stationary hence differencing is not needed.

The LSTM model was trained using the Keras deep learning library in Python, employing the ReLU activation function and utilizing the MSE loss functions. To predict the future 7 days, the past 7 days were used. Hyperparameters were fine-tuned through an iterative trial-and-error approach to optimize the LSTM model's performance, considering factors such as the number of neurons, batch size, and epoch size.

Several simulations of the forecasting model are executed to establish the LSTM. Since LSTM is stochastic by nature, the experiment was run independently 5 times with different values of hyperparameters on Model 2. Also note that the codes provided will return different values because a random seed was not set. It was conducted this way because the multivariate Model 2 is theoretically the best model and the same hyperparameters are applied for comparative reasons. The final model with the best RMSE was selected and the values are given in the selected values column of the table below.

Table 4. Hyperparameter values used in training the LSTM

Model Parameter	Experimental values	Selected Values
Epochs	[1,50,100]	50
Batch_size	[1, 8, 10, 16, 32, 100, 200, 1000]	16
LSTM encoder layer	[1,5,8,10,15,100,150,200]	150
Activation 1	relu, tanh	relu
LSTM decoder layer	[5,8,10,20,100,150,200]	200
Activation 2	relu, tanh	relu
TimeDistributed Fully Connected Layer	[5,8,10,50,100,150,200]	200
TimeDistributed Activation	relu	relu
Training algorithm	adam, SGD	adam
Learning rate	0.001,0.0001	0.001
Weight decay	1e-6	1e-6
Loss	MSE, Huber	MSE
Drop out	0.2	No Dropout

The lowest RMSE, MAE and MAPE are achieved by Model 1 where demand was predicted using temperature as the predictor. The RMSE is 528.74, MAE is 415.04 and the MAPE is 5%. The rest of the results are displayed on table 5. However, its performance is still inferior of the AEMO forecasts.

Table 5. Performance metrics of Models 1,2,3 and 4

Models	Metric	LSTM	AEMO
Model 1: Predict future demand using Temperature as an explanatory variable	RMSE	528.74	141.17
	MAE	415.04	107.24
	MAPE	6%	1.32%
Model 2: Predict future demand using Temperature and Time Features as explanatory variables (Weekdays, Months)	RMSE	583.63	141.17
	MAE	428.49	107.24
	MAPE	6%	1.32%
Model 3: Predict future demand using Time Features as an explanatory variable (Weekdays, Months)	RMSE	564.22	141.17
	MAE	417.13	107.24
	MAPE	6%	1.32%
Model 4: Predict future demand using Historical Demand	RMSE	548.37	141.17
	MAE	426.45	107.24
	MAPE	6%	1.32%

The LSTM performs well on the first and second days of the forecasts as can be seen on the figure below. The model returns a relatively lower RMSE on the first and second days of the forecast with 443.02 and 456.38 RMSE respectively. The RMSE, MAE and MAPE tend to increase progressively the further away the day is from the last datapoint. This is explained by the fact that data is harder to predict the further away it is from the last datapoint. Therefore we see a higher overall RMSE of 528.74. All daily RMSEs are derived from the difference between all days of the week across the whole training dataset. For example, RMSE was obtained for all Tuesdays of the training data. Please see the appendix for a full list of accuracy for the LSTM model. The resulting metrics of this LSTM architecture is provided in table 7 in the appendix.

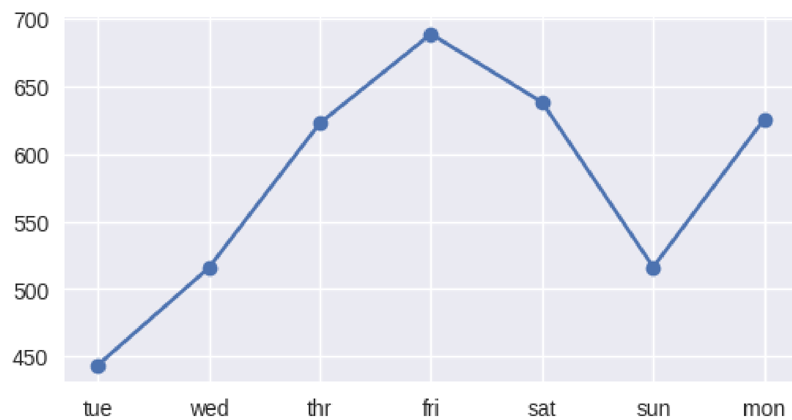


Figure 15. Daily RMSE of LSTM 7-day period

The above set of hyperparamaters are then applied to Models 2, 3 and 4. The predictions compared to actual test data is shown in figure 16. It is observed that the predictions overestimate demand pre May 2022. It suggests that the lookback or previous timestep should be lengthened from 7 days to possibly 28 days to allow the LSTM encoder to learn more.

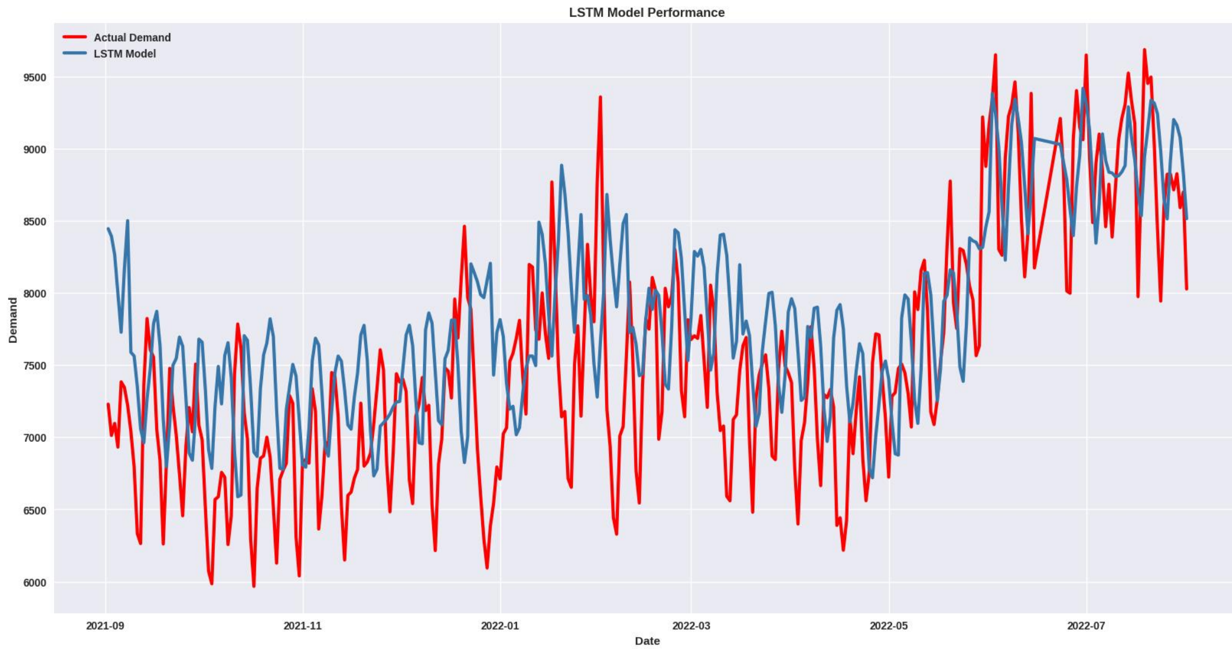


Figure16. Demand predictions from the LSTM model overlayed on actual demand

6. Discussion

The performance metrics are displayed in Table 6. It can be observed that the implementation of SARIMA-regression and LSTM returns the best accuracy when temperature is added as a predictor across the 3 metrics.

SARIMA-regression performed very well with RMSE of 337.79, MAE of 247.55 and MAPE of 3.3% upon inclusion of temperature as a regressor. This was a 6% improvement in RMSE and MAE from the SARIMA without temperature resulting to RMSE of 360.13, MAE of 263.19 and MAPE of 3.49%.

LSTM did not perform as well as SARIMA-regression but it performed the best on the Model 1 when temperature is added as a predictor with RMSE of 528.74, MAE of 415.04 and MAPE of 5%. Adding the time features to temperature as another predictor in Model did not improve the RMSE, MAE and MAPE in fact the RMSE increased by 10% and MAE increased by 3%, MAPE by 1%.

On the otherhand, inspecting the Polynomial regression reveals a surprising story. Polynomial Regression performs the best on Model 2 where both the temperature and time features are used as predictors. Adding time features to temperature as predictors yielded a 23.6% improvement in RMSE but an insignificant amount in MAE. For comparison, a multiple linear regression was also conducted with both temperatures and time features as predictors but did not perform any better, in fact it had the highest value across the 3 metrics.

This behaviour could be attributed to the fact that LSTM already incorporates the time features implicitly, therefore adding weekday and month information to the model maybe redundant and further introduces errors. However, it is apparent that adding temperature as a feature improves the accuracy of the LSTM. This observation is consistent across the prediction models investigated in this study.

Overall, SARIMA-regression with temperature as the regressor performed the best. This is our preferred model to forecast the next 7 days. However, none of the models fared better than the AEMO model. This could be due to the fact that the AEMO model inputs more granular data than our daily data. Figure 17 illustrates the final 7-days prediction using the best models for each predictive model. We see that SARIMA-regression and Polynomial Regression tend to follow the same shape but Polynomial Regression tend to be significantly lower than SARIMA-regression. On the other hand, LSTM has the same level as SARIMA-regression but is significantly lower on the last day.

Table 6. Performance metric of the best models under each of Polynomial Regression, SARIMA-regression and LSTM

Metric	Multiple Linear Regression	Polynomial Regression	SARIMA-regression	LSTM
RMSE	594.21	470.35	337.79	528.74
MAE	480.48	387.91	247.55	415.04
MAPE	5.61%	4.43%	3.3%	6%

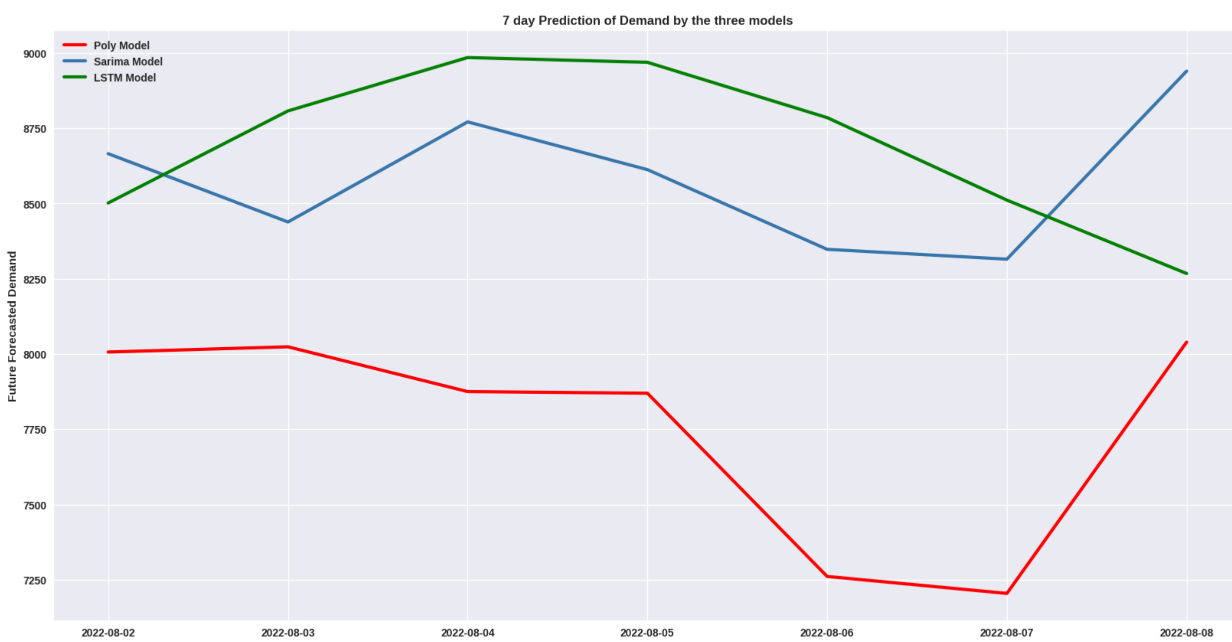


Figure 17. Final forecasts by prediction model

7. Conclusion and Further Issues

Precise demand forecasting plays a pivotal role in network access, enabling power plants to schedule unit maintenance, and assisting firms in formulating electricity pricing. These decisions carry significant weight when it comes to weekly load forecasting. We chose this specific time horizon due to the limited literature available on the topic while also highlighting the significant influence of temperature on the dynamics of electricity demand in New South Wales over a week.

Our primary aim in this study is to be able to forecast the week ahead from the 2nd of August, 2022. We achieved that by applying classical statistical methods and a popular deep learning method that accept multivariate predictors and outputs a multi-step forecast for comparison. More precisely, we have developed a SARIMA models, Polynomial Regression and LSTM for the week-ahead demand while incorporating temperature as a predictor and chose the best model for each. The results revealed that the SARIMA model with temperature regressor generated the lowest RMSE (337.79), MAE (247.55) and MAPE (3.3%). Polynomial regression did well when temperature, days and months are included as predictors. This model resulted to RMSE (470.35), MAE (387.91) and MAPE (4.43%). LSTM with a temperature feature follows which generated an RMSE (528.74), MAE (415.04) and MAPE of 5%. Multiple Linear Regression was the least performer with RMSE (594.21), MAE (480.48) and MAPE(5.61%).

Our findings are consistent with a recent NSW study where the authors also found a better performance of SARIMA-regression over RNN. Although the data used in their study was an aggregated weekly peak demand, their MAPE result for SARIMA-regression was 2.48% while the RNN MAPE was 5.07%, we can see that the SARIMA-regression MAPE (3.3%), Polynomial Regression MAPE (4.43%) and LSTM MAPE (5%) in our study is on par with their study (Eshragh, et al., 2022). While our models may not have outperformed the AEMO forecasts, the result provides assurance that the forecasts generated in our study, particularly the SARIMA-regression achieves reasonable accuracy.

The temperature regressor in this work is historical and is not forecasted. Therefore, in order to implement the SARIMA-regressor, forecasted temperature is needed. Since we expect temperature to be strongly seasonal and stationary, we do not expect the SARIMA-model to decline in accuracy significantly. On the other hand it is not required for LSTM because LSTM has the capacity to use the past 7 days of

Temperature is a very important determinant of demand. Our models clearly exhibit improvement in accuracy when temperature is added. We recommend using the forecasts outputted by the SARIMA-regressor model. However due to the RMSE and MAE of the SARIMA-regressor model still being significantly higher than the AEMO model, we therefore recommend investigation of other predictive models.

We suggest for this work to be used for planning. If the client is interested in day-ahead forecasts, the LSTM model offers reasonable performance in the first two days ahead, in this case these are Tuesdays and Wednesdays.

LSTM could benefit from further tuning with more granular data, eg. Hourly instead of daily. It can also be further tuned by using a longer lookback than 1 week. Adding more LSTM layers or employing a bidirectional stacked LSTM may also improve the performance of the model. It could also be hybridized with other deep learning methods such as the Convolutional Neural Networks (Brownlee, 2018).

We suggest investigating other available weather variables such as wind speed and humidity. Other improvements could also be the use of maximum daily load rather than mean daily load and the use of Holiday predictors. With regards to accuracy, all our the models need to be tested against an independent dataset.

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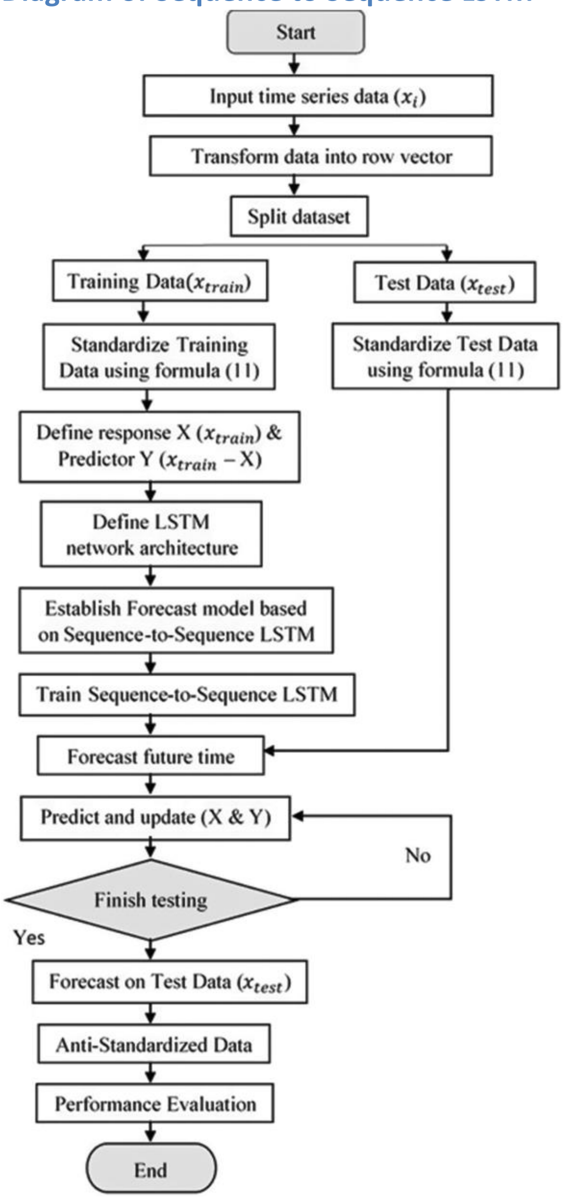
Appendix

Codes

https://github.com/mayanknagory/Capstone

Diagram of Sequence to Sequence LSTM



Source: Detailed flow of Encoder-Decoder Model, aka Sequence to Sequence model (Fatema, et al., 2021)

Table 7: Performance metrics for LSTM by day

	Overall	Tue	Wed	Thurs	Fri	Sat	Sun	Mon
				Model 1				
RMSE:	528.736	443.02	456.38	502.2	545.82	512.42	617.76	594.34
MAE:	415.0434	339.4	360.24	393.78	433.24	407.26	490.72	480.7
MAPE:	5%	0%	2%	8%	10%	8%	10%	10%
				Model 2				
RMSE:	583.6344	418.7	536.2	690.42	721.56	587.74	496.32	569.8
MAE:	428.49	314.56	408.7	506.82	520.26	424.72	380.68	443.7
MAPE:	6%	0%	8%	10%	10%	10%	10%	10%
				Model 3				
RMSE:	564.2224	422.88	524.08	654.4	682.5	572.3	491.16	553.5
MAE:	417.1296	322.46	401.4	476.3	489.88	411.66	373.74	444.52
MAPE:	6%	0%	6%	10%	10%	10%	10%	10%
				Model 4				
RMSE:	548.3684	423.24	470.86	541.98	570.9	529.8	651.1	614.26
MAE:	426.4454	328.48	379.66	418.74	437.9	416.96	515.68	487.8
MAPE:	6%	0%	4%	10%	10%	10%	10%	10%