**A Time Series Analysis: ERCOT Power Load Forecasting**

Sarah Alqaysi

Bikram Jill

Jack McCullers

Travis Lloyd

University of San Diego

ADS-506 Applied Time Series Analysis

6 November 2021

# TABLE OF CONTENTS

[TABLE OF CONTENTS 2](#_Toc89683692)

[Problem Statement 3](#_Toc89683693)

[Data Description 3](#_Toc89683694)

[Literature Review 3](#_Toc89683695)

[Introduction 3](#_Toc89683696)

[Body 4](#_Toc89683697)

[Conclusion 5](#_Toc89683698)

[Data Exploration 5](#_Toc89683699)

[Data Wrangling 5](#_Toc89683700)

[Pre-processing 5](#_Toc89683701)

[Model Strategies 6](#_Toc89683702)

[Results and Final Model Selection 9](#_Toc89683703)

[Conclusion 10](#_Toc89683704)

[Findings 10](#_Toc89683705)

[Suggestions 10](#_Toc89683706)

[References 11](#_Toc89683707)

[Appendix A 11](#_Toc89683708)

# Problem Statement

Load forecasting is an important aspect of any power grid. Due to the lack of large-scale storage options, system operators must forecast the daily load (demand) ahead of time and ensure adequate power generation is secured. Load forecasts are used to determine which power-generating resources will need to be turned on, which will need to be on standby in case of increased demand and overall affect the economics of the power grid. The time-series data in this study shows historical load profiles over time and our goal will be to determine if there are any models that can explain the load profile historically (and perhaps be useful in predicting the near-term future load profiles).

# Data Description

The data shows hourly historical (actual) load. This is displayed by region in Texas, as well as the overall number. The study will take data from 2017-2020 to have 4 complete years to analyze.

# Literature Review

## Introduction

Load forecasting is an important aspect of any power grid. Due to the lack of large-scale storage options, system operators must forecast the daily load (demand) ahead of time and ensure adequate power generation is secured. One example to support the importance of load forecasting is the push for Government investments in infrastructure to support the push for electric vehicles. According to a New York Times article addressing this issue, “today, fewer than 1 percent of cars on America’s roads are electric” (Plumer, pg 2). Load forecasts are used to determine which power-generating resources will need to be turned on, which will need to be on standby in case of increased demand and overall affect the economics of the power grid.

The time-series data for this study shows historical load profiles over time and the goal will be to determine if there are any models that can explain the load profile historically (and perhaps be useful in predicting the near-term future load profiles). The dataset, ERCOT Hourly Load Data, was pulled directly from the ERCOT website. The team will be looking specifically at the years 2017-2020.

## Body

The first source found was a paper completed for the 2018 International Conference on Machine Learning. In this paper, the team of researchers were focused on establishing different machine learning models for load forecasting in China. Their paper supports the use of a Support Vector Machine model that outperforms their other explored options. This set the baseline for the team that accurate traditional and non-traditional time-series models could be applied to load datasets such as the team’s chosen one.

The second source found was another paper completed for the 2018 International Conference on Machine Learning. In this paper, the team of researchers provided an overview of the actual forecasting methods and models used in renewable energy resources. This provides alternate and available forecasting tools to show which is the most efficient. The team plans to focus their efforts on providing a discussion on their efforts to fit two traditional time-series models as well as a neural network model. The team has the option to explore forecasting load output for the neural network model. As the team specifically focuses on electrical grid loads for Texas, this source serves as an example of load forecasting for other renewable energy sources. The team’s efforts on this project will provide a base for further exploration of this topic in future time-series modeling applications.

The third source found was an article from IEEE Transactions on Power Systems November 2013 issue. The paper introduced a novel functional time-series methodology for short term load forecasting. This was applied to data of historical daily loads in Cyprus. This source allows the team and future researchers the ability to pull future sources from this same IEEE Transaction on Power Systems journal. This is because they have many publications on load forecasting as it pertains to creating time-series modeling. The team decided to focus on this source because it provided an example time-series model applied to short term load forecasting. Short term load forecasting can be defined as aiming to estimate the projected load for the next thirty minutes to the next two weeks. The team has decided to focus only on years 2017-2020, however, this source provides the team the understanding at looking at smaller increments because the dataset provides daily load figures with time stamps associated with them.

## Conclusion

This study identified sources are important in understanding what load forecasting is and the role machine learning plays with the creation of models to support the objective. The study plans on using these sources to help support the models created within this project. This study also focuses on how to determine if there are any models that can explain the load profile historically.

# Project Overview

The purpose of this project is to analyze the power load data from the state of Texas, from years 2017-2020, and try to fit multiple, traditional time-series models to the data as well as one neural network model. The team will provide for commentary on the findings for each of the models.

The team chose to explore this data because it provided a unique challenge in forecasting for a state that was recently impacted from a severe winter storm that saw the inability to provide power to many counties of the state. It also provided the opportunity to see how one could properly forecast power loads as the push for the exploration of more renewable energy sources as well as the drive to implement increasing number of electic vehicles on the road.

# Data Exploration

**Figure 1**

*Name*

# Data Wrangling

## Pre-processing

**Figure 2**

*Name*

# Model Strategies

To begin with, P/ACF of the raw series and subsequent transformed series were evaluated. As can be seen in Figure XXXX; the raw data shows high cyclicality, and the series is certainly not stationary. This is to be expected, power demand has daily cycles (power demand being higher at certain hours of the day than others) and seasonal cycles (Winter has higher power demand than warmer months due to air-conditioning usage).

In order to overcome this, the first and second-order differenced data was observed, however the P/ACF plots still showed cyclicality. In particular, there was a continuous correlation of lag 24 (and multiples of it). Once again, this made sense in the context of the data, as the demand at any given time would be highly correlated to the demand 24, 48, 72 etc. hours before it.

As such, the data was differenced on its lag 24 (seasonal difference), which finally showed a P/ACF plot that could be modelled. Based on the plot shown, an ARIMA (24, 24, 0) model appeared to be most appropriate as the ACF tailed off and the PACF cut off for this final plot. Another model that was tested which is the GARCH (1,1) with ARIMA (24,24,0). The results included Akaike (AIC), Bayes (BIC), Shibata and Hannan-Quinn criteria for the model estimation. Basically, the lower these values, the better the model is in terms of fitting. And it was shown that results were in the (-4) range, which is good.

A second evaluation metric is the Ljung-Box test for testing the serial correlation of the error terms. The null hypothesis states there is no serial correlation of the error terms. Basically, if the p-value is lower than 5%, the null hypothesis is rejected. The model results show that the p-value is higher than 5% on the on "Standardized Squared Residuals", meaning that there is no serial correlation of the error term. Lastly, another interesting one to check (Figure 4), is *Adjusted Pearson Goodness-of-Fit* which measures the goodness of fit of the error. The null hypothesis says that the conditional error term follows a normal distribution. If the p-value is lower than 5%, the null hypothesis is rejected. The model results show three of the p-value higher than 5% and one lower. Figure 5 shows key plots of the model parameters, including graphs of ACF, Sample and Theoretical quantiles and the model Conditional SD plot.

**Figure 3**

*P/ACF Plots of ERCOT Time Series*

Chart

Description automatically generated with medium confidence A picture containing text, antenna

Description automatically generated

Chart, box and whisker chart

Description automatically generated with medium confidenceA picture containing chart

Description automatically generated

**Figure 4**

*GARCH Model: Adjusted Pearson Goodness-of-Fit Test*

Text

Description automatically generated

**Figure 5**

*GARCH Model: Adjusted Pearson Goodness-of-Fit Test*

Graphical user interface

Description automatically generated

# Results and Final Model Selection

Based on information gathered in the P/ACF exercise, the ARIMA (24, 24, 0) model was fit and the results can be seen in Figure XXXXX. Overall, this model fit quite well with a low MAPE (0.07) and low AIC (-216,565.9). What this shows is not only was the ARIMA model a good fit, it suggests that power demand is highly predictable according to the time of day. In the broader context of this assignment, this shows that forecasting power load is achievable.

**Figure 6**

*ARIMA (24, 24, 0) Model Summary and Forecast*

Text

Description automatically generated

# 

# Conclusion

## Findings

## Suggestions

In terms of next steps, having a model that can fit and predict power demand is useful for power grid planning and commercial exercises.

For planning purposes, Independent System Operators can use the load forecast to determine their power generation needs, which need to be confirmed in advance of actual power usage.

For commercial enterprises, particularly trading firms, having an accurate load forecast is one component of predicting power prices which could then be traded against. Load forecasts represent the demand side of power usage, which could then be extended to predict which generation units would need to be turned on to meet this demand. These two forces create the market price of electricity every hour of the day and could be speculated against.

# References

Jurj, D. I., Micu, D. D., & Muresan, A. (2018). Overview of Electrical Energy Forecasting Methods and Models in Renewable Energy. *2018 International Conference and Exposition on Electrical And Power Engineering (EPE), Electrical And Power Engineering (EPE), 2018 International Conference and Exposition On*, 0087–0090. <https://doi-org.sandiego.idm.oclc.org/10.1109/ICEPE.2018.8559807>

Paparoditis, E., & Sapatinas, T. (2013). Short-Term Load Forecasting: The Similar Shape Functional Time-Series Predictor. *IEEE Transactions on Power Systems*, *28*(4), 3818–3825.

Tsafack, I. (2021). *GARCH models with R programming : a practical example with TESLA stock*. idrisstsafack.com. <https://www.idrisstsafack.com/post/garch-models-with-r-programming-a-practical-example-with-tesla-stock>

Yang, J., & Wang, Q. (2018). A Deep Learning Load Forcasting Method Based on Load Type Recognition. *2018 International Conference on Machine Learning and Cybernetics (ICMLC), Machine Learning and Cybernetics (ICMLC), 2018 International Conference On*, *1*, 173–177. https://doi-org.sandiego.idm.oclc.org/10.1109/ICMLC.2018.8527022

# Appendix A

Following is the R Markdown file for this project.