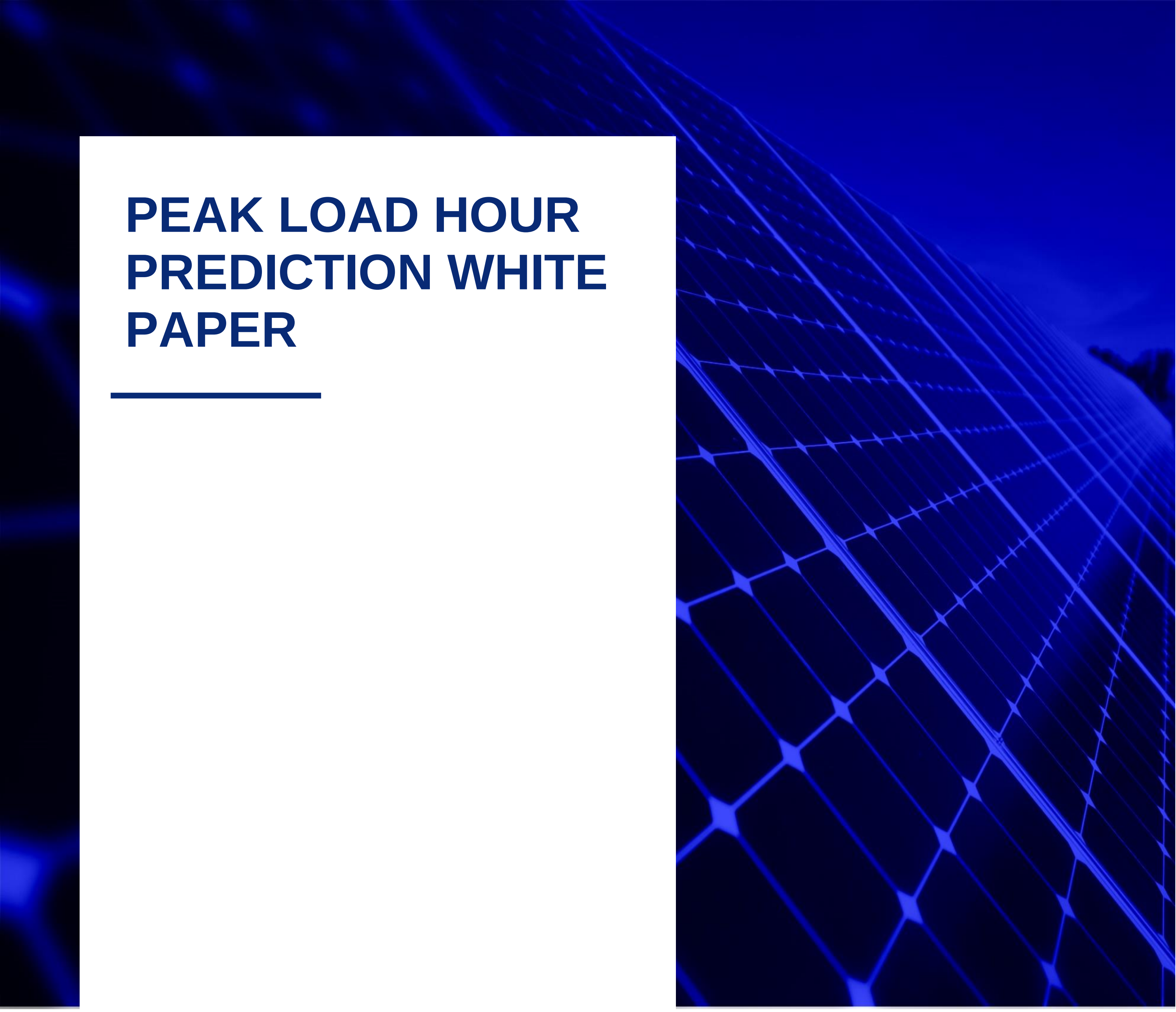

PEAK LOAD HOUR PREDICTION WHITE PAPER

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Introduction

Electric load forecasting is an area that has been extensively researched over the past few decades. Most of the research in this area is focused on developing models that can forecast the electricity load profile with higher level of accuracy. But having an accurate forecast of electricity load is not enough. While we can forecast the electricity demand reasonably well today, determining whether this demand is the monthly peak demand is still not easy.

A good forecasting strategy for peak demand days would help Exergy in determining when to turn on back-up generators and perform peak shaving. This type of scheduling would reduce the peak loads drawn from the grid and would hence result in financial savings. There are different demand response strategies adopted to reduce the electricity consumption during the peak hours, but the challenge comes in determining when to effectively deploy these programs to maximize the financial savings. Since the electricity demand highly varies from one region and utility to the other, it is imperative to have forecasting models specific to each region and utility to predict the peak load periods accurately.

Forecasting of electric loads poses several problems due to the high amount of variability associated with the electricity consumption. The energy consumption depends on several exogenous variables including ambient temperature, the type of day and many other factors. The historical data for energy demand generally has seasonality associated with it. So, in order to make a good forecasting strategy for predicting the peak load, it is critical to take into account the different seasonalities in the data and the effect of exogenous variables while developing models.

This whitepaper aims at achieving the following goals:

- Develop forecasting models using statistical and machine learning techniques (artificial neural network) to predict the electric load requirements.

- Develop classification models to classify peak days and usual days.

Artificial Neural Network Model

Artificial Neural Network (ANN) is a machine learning based modeling technique that makes use of advanced computational power to extract the non-linear relationships between response and predictor variables by learning from the historical data. These models are trained over longer periods of time than compared to the models discussed in the earlier sections which help them in adapting to new circumstances smartly and therefore making accurate forecasts with varying forecasting horizons.

The architecture of an ANN model is inspired from the anatomy of human brain. An ANN model consists of interconnected units known as artificial neurons which are arranged in multiple layers for information exchange between them. Each of these artificial neurons have some weighted inputs, a transfer function and an output associated with it. The choice of transfer function is made as per the characteristics of the data.

There are different learning algorithms that can be used to train the ANN models, these include Back Propagation Algorithm, Levenberg-Marquardt Algorithm, Particle Swarm Optimization and Genetic Algorithm. The details of these individual training algorithms are beyond the scope of this paper. In general, the training algorithms work to find the weights that minimize the prediction errors.

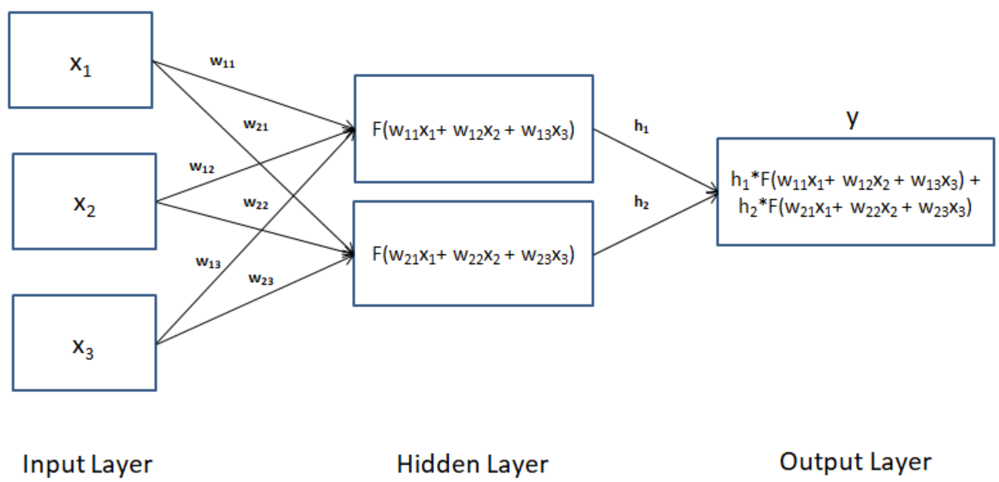

Figure 1 An example of a simple ANN model

Although ANN models outperform the other modeling techniques majority of the time, there are certain challenges associated with these models. First, these models require a lot of training in order to generate good forecasts, and at the same time it is necessary to ensure that they are not over trained for model fitting. Second, these models require more computational resources than compared to other modeling techniques. Third, it is quite arduous to interpret a trained neural network because of the non-intuitive transformation of the data through the layers of the network. However, we believe that the benefits of using ANN outweigh the challenges associated with it.

Methodology

For ANN training, we would explore the following data as input variables:

Continuous Variables:

Variables Name	Variables Meaning
x_{temp}	Temperature of the region at time t
x_{ws}	Wind speed of the region at time t
x_{rh}	Relative humidity of the region at time t
x_{prDem}	Previous day demand

Categorical Variables:

Variables Name	Variables Meaning
x_{hr}	Hour of the day
x_{dow}	Day of the week
x_{dt}	Weekday, weekend or holiday
x_{dom}	Day of the month
x_{moy}	Month of the year
x_{precip}	Precipitation or not

For classification, since peak hours occurs at most 5 times in a year, using logistic regression or KNN would not be feasible. It is important to set a limiting value for peak classification. This limiting value can be defined using simple statistical equation:

$$Value_{lim} = \mu + 3.291\sigma$$

Where,

$Value_{lim}$: limiting value for peak classification,

μ: average interval demand,

σ: standard deviation.

Peak Hour: If the maximum electric load demand predicted was greater than the limiting value of electric load, that particular hour was defined as a peak hour. The limiting value for peak day estimation was calculated by taking the average hourly electricity demand and two times the standard deviation of electricity demand. The data points where the demand exceeded the limiting value were known as peak data points. As per the Central Limit Theorem, these points would be normally distributed with mean μ and standard deviation σ. Therefore, the probability of observing a peak data point is less than 0.1%, but any hour that contained 1 peak data point was classified as a peak hour.

Usual Hour: All other hours were classified as the usual days.

Figure 2 provides a flow chart showing the generic approach used for creating forecasting models.

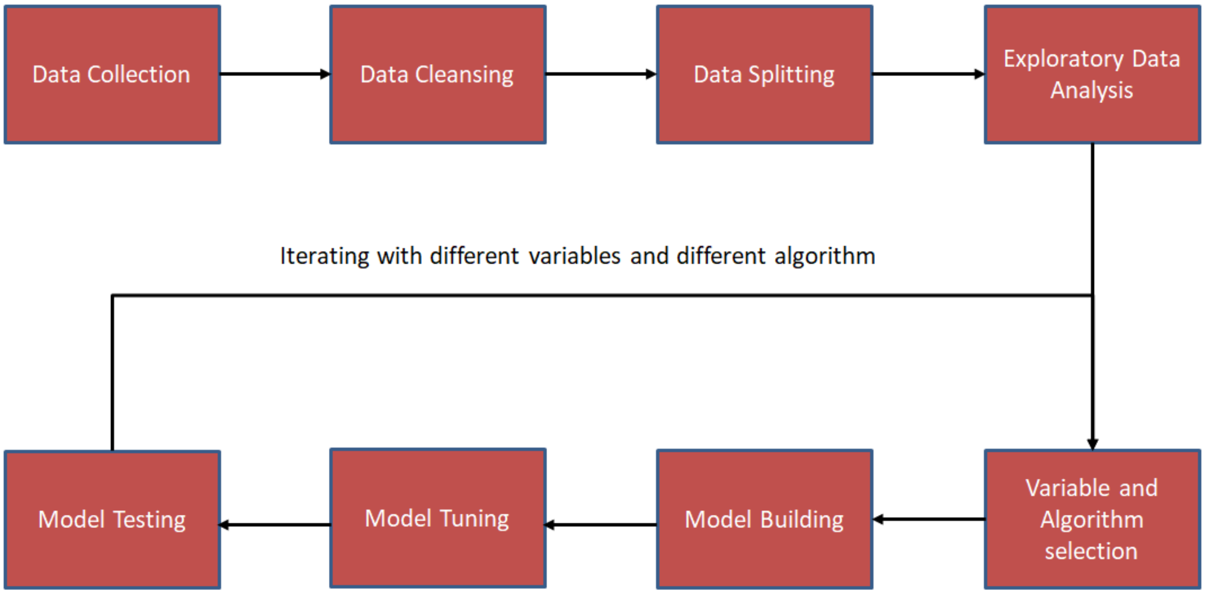

Figure 2 Flow chart showing steps in generating a forecasting model

Conclusion and Future Work

This white paper provided modeling methodology for predicting demand and classifying peak load hours. This paper provides a foundation for further model research, testing and deployment in many different areas. It would be interesting to see how this methodology performs for different RTOs across the United States.

Further research in the areas of developing forecasting models would provide opportunities for scheduling demand response plans on individual customer's level. The current methodology made use of the hourly interval data to develop forecasting models; it would be interesting to see how the forecasting accuracy for these models changes with change in the time intervals of the data.

The limiting value used in this study for classifying peak days depends upon the mean and standard deviation of the monthly electricity demand. Performing a sensitivity analysis on these descriptive statistical measures would further improve the robustness of the classification approach. Different modeling assumptions made in this research could be varied and their effect in predicting the type of days could be studied. There can be additional research opportunities in determining the optimal demand response action in response to the predicted peak hours.