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I'm Normal, You're Normal, but is Your Weather Normal?

Investigating adverse effects of weather on electric power demand: load normalized against the effects of weather vs. weather normalized load

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ABSTRACT

The traditional view is that a utility's long term forecast must have a standard against which it is judged. Weather normalization is one of the industry standard practices that utilities use to assess the efficacy of a forecasting solution. While recent advances in probabilistic load forecasting techniques are proving to be a methodology that brings many benefits to a forecast, many utilities still require the benchmarking process to determine the accuracy of their long term forecasts. Due to climatological volatility and the potentially large annual variances in temperature, humidity and other relevant weather variables, most utilities create normalized weather profiles through various processes in order to estimate what is traditionally called a weather normalized load profile. However, new research shows that due to the nonlinear response of electric demand to weather variations, a simple normal weather profile in many cases may not equate to a normal load. In this paper, we will introduce a probabilistic approach to deriving normalized load profiles for monthly peak and energy through a process we label "*load normalization against the effects of weather.*" We will compare this approach to the traditional weather normalization process. The proposed method has been successfully deployed at utilities for their long term operation and planning purpose and risk management.

INTRODUCTION

Electricity demand is a result of the interaction between the dynamic weather condition and human activities, which can vary widely during a given time. Erratic sales and revenue histories that result from this relationship can make it difficult to understand the true underling growth trend and electric utilities may do some form of "weather adjustment" to smooth out variation. Adjustments are made primarily for temperature extremes, but adjustments may also be made for extraordinary events such as catastrophic storms. Only the effects of temperature will be considered in this discussion.

The purpose of weather adjustment is to adjust sales, revenues and internal financial tracking to show the results of the forecast's efficacy assuming that normal weather had occurred. The calculation of normal weather is not uniform across all utilities. In some states, the public utilities commission determines a standard for weather adjustments.

This paper will compare a traditional *weather adjustment* of calculating adjustments to load for temperature extremes with the newer *load normalization against weather*. The latter uses statistical methods to estimate a load model and evaluates that model based on a normal or mean weather concept. The purpose of this paper is not to determine whether one methods is superior to

any other, but rather to examine the differences between the methodologies and compare the results.

Traditional Weather Adjustment

In the past, customer usage meters were read only once per month in billing cycle intervals that did not necessary follow the actual calendar month. The advent of automated meter reading (AMR) allowed for more efficient, more frequent meter reading, but utilities continued relying on billing cycles. The challenge for load forecasters using monthly billing cycle sales is deriving reliable correlations between load adjusted for accounting practices and explanatory variables that are likely not contemporaneous with the billing cycle.

Whether load forecasters are using billing cycle sales or actual calendar month energy in their models, a traditional weather adjustment to forecasts is to find the product between coefficients derived from a monthly load regression analysis and the difference between actual and normal temperature statistics. An example for calculating cooling and heating degree day temperature statistics are shown below.

(1). Average temperature = (max temperature + min temperature)/2

(2). Cooling Degree Days (CDD) = Average Temperature - 65

where the average is greater than 65 degrees

(3). Heating Degree Days (HDD) = 65 - Average Temperature

where the average is less than 65 degrees

Degree days based on 65 degrees is a common form of the calculation, but other base numbers can be used. Forecasters may also use one base for heating and another for cooling to recognize a temperature band where customer demand is unresponsive.

In addition to heating and cooling degree days, monthly forecast models may also include trend variables, price of electricity, or other explanatory variables as shown below.

(4). Monthly sales = α + (β_1 * CDD) + (β_2 * HDD) + (β_3 * economic growth) + (β_4 * Price) + … + u

Weather adjustment to actual sales is provided in the following formula:

(5). Adjustment = β_1 * (Normal CDD – Actual CDD) + (β_2 * (Normal HDD – Actual HDD)

We built a basic monthly forecast model for total SECI using the methodology described above, but by only regressing heating and cooling degree days on monthly energy. Five years of hourly data was accumulated into monthly energy and degree days to mimic traditional monthly forecasts for this analysis. The resulting parameter estimates of the specified model are as follows.

SECI Energy (MWH) = 659,706 + 1375*CDD + 1,555*HDD

Degree days were based on the 65 degree break point without any testing of other specifications. Other specifications for break point may have been statistically more efficient and yielded different results. During 2015, the actual cooling degree days were 3,570 versus a 30 year mean of 2,873. Actual heating degree days were 540 versus a 30 year mean of 726. The 2015 temperature adjustment is then:

2015 Adjustment = 1,375*(2,873-3,570) + 1,555*(726-540) = -670,520 MWH = -671 GWH

Load Normalization against Weather for Hourly Point Forecast

Advanced Metering Infrastructure (AMI) is now becoming widespread, and with several utilities approaching 100% penetration. With AMI the utility now has hourly data of a finer granularity for each customer and can determine true monthly consumption. That hourly data also allows utilities to expand their modeling to the hourly grain, constructing their own models or using a sophisticated commercial product as SAS® Energy Forecasting. Models for hourly forecasting are typically much more complex, including not only hourly temperatures but polynomial effects, lags and moving averages, and other special effects. As a result, calculating a weather adjustment from an hourly forecast model is now a more burdensome and complex process. Repeating formula (5) for each hour is not an option most forecast analysts would pursue.

While it is difficult to calculate an adjustment for temperature it is relatively easy to create a normal temperature forecast for the target year. In practice normal temperature models are often the entire year of history that comes closest to the mean HDD and CDD over a long historic period. Another approach is to collect data by months based on the same criteria. A more statistically based method is to use the ranked average methods with a long history of temperature. One major shortfall of the ranked average model is that it groups the severe temperatures at the beginning or end of the months where they are most likely to occur. High temperatures at the end of December meet the statistically lower temperatures at the beginning of January, creating a jagged pattern that may be statistically correct but not realistic for modeling.

A model created by ranked average can be mapped to a given historic year using that year's temperature profile. The hourly forecast model using the hourly temperatures is generally sensitive to differences in weekday and weekend response to temperature difference. The choice of year to use as pattern for a ranked average model can influence forecast results.

We built a normal temperature using the ranked average method over 30 years with historic temperature data. The ranked average model was plotted to the temperature pattern of 2008 which had near normal annual HDD and CDD. Multiple forecast models were developed using actual load and temperature data for 2012 through 2014. A 2015 holdout period was used to select the best model since 2015 was the target adjustment year to create a normal forecast. The results are below.

Ranked Average Temp Model --- Forecast Year 2015 (GWh)

Actual Energy	13,771
Forecast Using Normal Temp Model	13,329
Temperature Adjustment	-441

<u>Load Normalization against Weather for Hourly Probalistic Forecast</u>

Because electricity demand is the result of the interaction between dynamic weather condition and human activities, the normal weather described in the previous section may not lead to a normal load. Alternatively, we would like derive normal load against weather. This method to derive normal load does not require normal weather as the input and was first introduced by Hong et al [1]. This alternative methodology utilizes the historical temperature series of the past *n* years to generate *n* point forecasts for each of the forecasted hour. The median of the forecasts derived using the empirical distribution of the point forecasts is considered as the normal load against weather.

In this study we used the forecast equation developed in SAS® Energy Forecasting for the point forecast described above, as well as using SAS® to develop the regression models for the Traditional Weather Normalization Methodology. The equation for the point forecast was used to create a probabilistic forecast using 30 years of historic temperature data from 1985 through 2014. The hourly forecasts were accumulated to total year 2015 energy, based on the source year of the temperature data.

The mean of the 30 forecasts were calculated as below:

SAS EF Point Forecast --- Year 2015 (GWh)

Actual Energy	13,424
Forecast Using Normal Temp Model	13,771
Temperature Adjustment	-347

As we stated in the introduction the purpose of this paper was to examine the effects of two newer temperature adjustment methodologies to compare the results with a general monthly approach that have traditionally been used historically. The purpose is not to determine whether or not one method is superior to another, but to examine the differences between the methodologies.

METHOD	Temperature Adjustment
Traditional Monthly Method	-671 GWH
Hourly Point Forecast with Normal Year Temperature Model	-441 GWH
Hourly Probabilistic Forecast with 30 Years of History	-347 GWH

The traditional method is fairly fixed process. Variations for this method include adding more explanatory variables or adding more observations to the training period.

Further work should be focused on the range of point forecasts that will come from changing the pattern year used to map the ranked average method. The probabilistic mean forecast was based on the annual sums for each of the temperature source years. Mean forecasts could also be built from monthly mean values or from a finer granularity of data.

REFERENCES

T. Hong, J. Wilson, and J. Xie . 2014. “Long term probabilistic load forecasting and normalization with hourly information,.” IEEE Trans. Smart Grid, <vol. 5, no. 1, pp. 456–462.

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