

## WEATHER NORMALIZED LOAD DEMAND FORECASTING FOR DISTRIBUTION PLANNING

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### ABSTRACT

*Distribution planning is greatly dependent on an accurate forecast of load demand. A critical task in forecasting demand is to accurately estimate the peak load that would occur should the condition that brings about the peak demand occur. This paper describes experience with forecasting yearly peak demand on a summer-peaking USA utility with a clear sensitivity to temperature. A weighted temperature-humidity index was investigated, but the peak substation load was found to correlate better with peak daily temperature.*

### INTRODUCTION

The annual load demand forecast is an essential part of distribution planning. A critical task in forecasting demand is to accurately estimate the peak load that would occur should the condition that brings about the peak demand occur. The service territory under consideration has a summer peaking load. After suffering severe demand peaks in 1999 and 2001, the demand began to drop on many key substations from 2002-2004. Was this decline due to an actual decline in customer demand potential or simply mild weather? Planners believed that the latter was the case and that some substations would be loaded well above their firm rating if high temperatures were experienced again. A project was begun to perform a weather-normalized load forecast to better estimate the load at higher temperatures. This paper describes the weather normalization process that was developed and how it evolved. The resulting forecast can be used to conduct a planning study employing methods presented in an earlier paper.[1]

The overall process is:

1. Determine the design weather metric.
2. Determine the sensitivity of the load at each substation to the weather metric.
3. Correct the actual peak load to the design weather metric.
4. Develop the forecast from a linear regression of the corrected peak loads.

The first method investigated was based on the regional transmission grid operator's weather normalization process. [2] This method employs a Weight Temperature-Humidity Index (WTHI) based on a 3-day loading cycle for its

weather metric. Hourly temperature and humidity data were available from 2002 onward. Thus, this was a practical method to consider.

Results obtained using the WTHI to correct the actual load measurements were reasonable. However, upon further analysis, it was observed that the peak load of individual substations was more closely correlated to the peak daily temperature alone. The peak load simply occurred on the hottest day even if days before or after were much cooler. The process was repeated using daily peak temperature alone as the criterion with significantly better forecasts. The peak loading of critical substations was predicted quite accurately for 2005 and 2006. Details of the process are described in the following sections.

### SYSTEM DESIGN TEMPERATURE

The purpose of the design weather metric is to establish the load level that the system should be designed to deliver. The design weather metric was determined from over 50 years of daily peak temperature and humidity data for the Bridgeport Sikorsky observation station.[3] The value chosen was the highest value of the selected metric that occurred approximately once per decade. For the initial analysis, this criterion yielded a design WTHI value of 37. When the process was repeated using peak daily temperature alone, a design temperature of 100°F (37.8°C) was selected. Over the last 50 years, this temperature has been recorded for this area four times with the two most recent being the peak load years of 1999 and 2001. The decision was made to base the system design capacity on the highest temperature observed.

### TEMPERATURE SENSITIVITY

The next step in the process is to determine the sensitivity of the peak loading demand to the selected weather metric, which is temperature. Hourly loading and temperature data were available from 2002 onward for this project. Figure 1 shows a scatter plot of these points for three years for a critical substation (Substation B). This general shape is quite typical for utilities in the same geographical region.

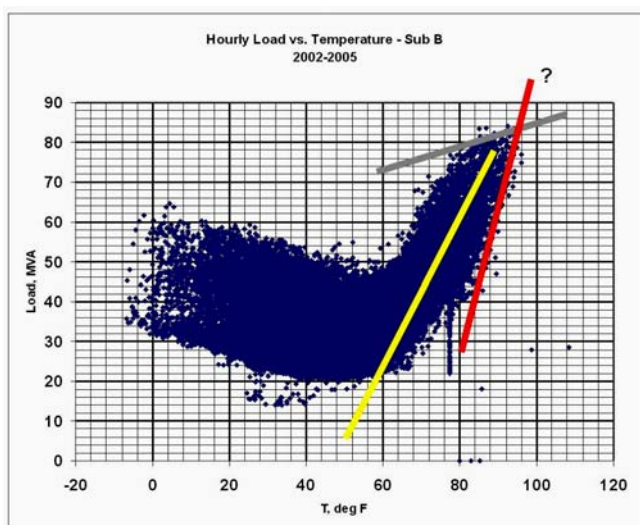


Figure 1. 3-year (2002-2005) Scatter Plot of Hourly Loads and Temperatures, Substation B.

While it appears that there is a clear trend for temperatures above 60°F, what we are really interested in for the load forecast is the sensitivity of the peak load to temperature. As shown, there are three seemingly obvious candidates for the slope of the trend: The slope of the peak loads (top), the slope of the peak temperatures (right side), and one in the middle. Which one should the distribution planner choose?

Without studying the problem, many would likely choose the middle slope because it appears to be the general trend. However, this slope of over 2 MVA/°F results in an overly conservative high forecast. The slope of the line fitted to the peak temperatures is even more conservative. The slope of the peak loads line (top line) yields a more reasonable forecast, but the value of approximately 0.25 MVA/°F turns out to be too low.

While it was observed that the peak load occurred on the day with the peak temperature, the peak load and peak temperature are not coincident in the same hour. As Figure 2 indicates for two key substations (referred to as A and B), the load peak lags the temperature peak significantly. The temperature peaks early in the afternoon while the load demand peaks 2-5 hr later. Interestingly, the load demand drops off quickly as the temperature drops, which is a common characteristic seen throughout the region.

The main finding of this analysis is that fitting lines to a hourly load-temperature plot like the one in Figure 1 is not a reliable way to determine the sensitivity of the peak load to the temperature.

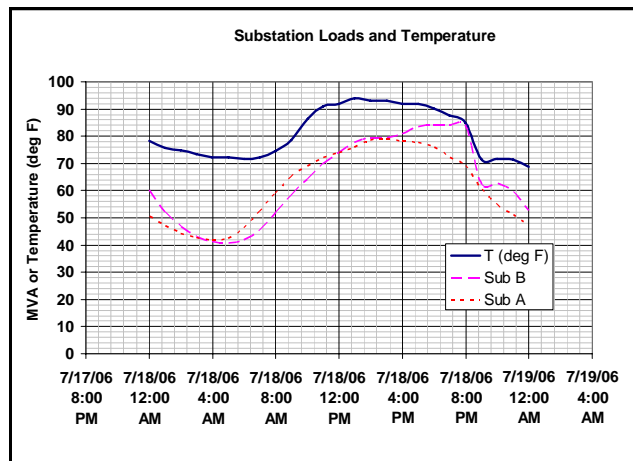


Figure 2. Substation Loads and Temperature Variation

Figure 3 provides more insight. This is a plot of the course of the hourly load-temperature characteristic during its daily cycle. This course defines the shape of the scatter plot in Figure 1. The points along the right edge of the scatter plot are established by rising temperatures from morning through early afternoon. In the case shown, the peak load occurs three hours after the peak temperature and remains at nearly the same value for four hours before dropping off rather quickly. This establishes the top and left sides of the scatter plot in the region above 60°F.

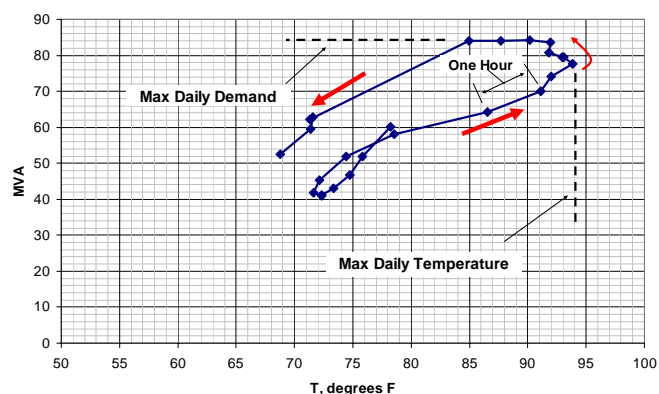


Figure 3. Typical Hourly Variation of Load Demand with Temperature For Substation B

Thus, it is difficult to determine which slope to use from the hourly load-temperature data. Once the coincidence of the peak substation demand with the hottest day had been observed, the hourly load-temperature data were converted to a set of points matching the peak load and temperature over 24-hr periods. The result is shown in Figure 4 for Substation A. This yields a clearer picture of the sensitivity of peak load to temperature. This curve can generally be fit quite easily with a 4<sup>th</sup> or 5<sup>th</sup> order polynomial and the slope at peak demand and temperature quickly estimated with sufficient accuracy.

Another noteworthy issue that appears in Figure 4 is the

sparse scattering of points below the dense cluster of the main peak daily load-temperature points. These usually represent days in which part of the substation load was temporarily transferred to another station during the daily peak. These points are inconsequential to the issue at hand where the important thing is what happens to the peak demand on the hottest days. Therefore, one further step we do is to filter out these points. Several means have been implemented for accomplishing this in a load data processing tool implemented in the PQView® program.[4] A favored technique is to discard outliers more than a specified number of standard deviations (usually between 1 and 2) from the mean at each temperature.

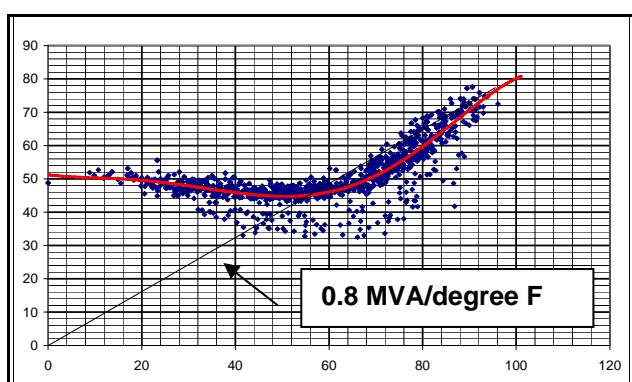


Figure 4. Substation A Peak Daily MVA Demand Vs. Peak Daily Temperature 2002-2005.

**PEAK LOAD FORECAST**

For Substation A, the sensitivity of peak load to temperature on the hottest days is 0.8 MVA/°F as shown in Figure 4.

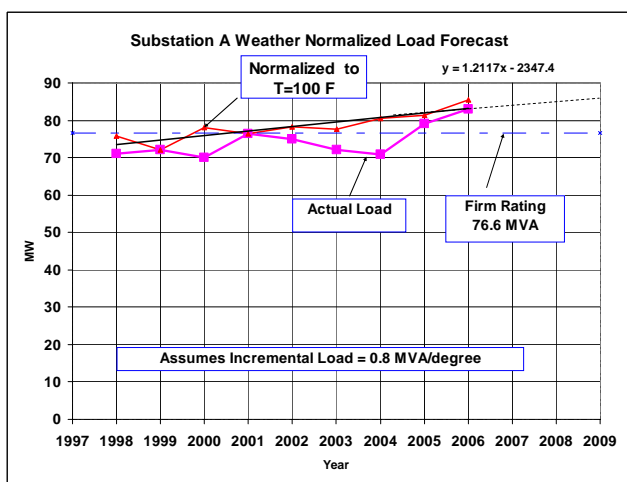


Figure 5. Temperature-normalized Load Forecast for Substation A

Applying this to the actual recorded peak load and peak temperature for each year yields the load forecast shown in Figure 5 with supporting data in Table I.

Once the actual measured load demand is corrected to the design temperature, regression over several years of data is employed to discern growth trends. The temperature-

corrected peak load shows a very consistent growth rate of 1.2 MVA per year since 1998. The substation had reached its firm rating in 2001 and the installed load on the substation continued to grow despite the fact that the actual peak loadings for the next three years declined due to mild weather. The technique described here resulted in a remarkably accurate prediction of the loading in 2005 and 2006 when more severe summer temperatures returned.

Table I. Annual Peak Load Data For Chart in Figure 5

Year	Peak Load MVA	Peak Temp, deg F	Temp Correction MVA	Load @ T=100F
1998	71	94	4.8	75.8
1999	72	100	0	72
2000	70	90	8	78
2001	76.5	100	0	76.5
2002	75	96	3.2	78.2
2003	72	93	5.6	77.6
2004	70.9	88	9.6	80.5
2005	79	97	2.4	81.4
2006	83	97	2.4	85.4

A similar excellent result was achieved for Substation B. In fact, for most of the utility’s other substations, a quite clear linear growth pattern appeared after the load was normalized to the design temperature.

**APPLYING THE FORECAST**

The forecasted trend is subsequently used as the base forecast to assess the risk of un-served energy over 5-10 year planning horizons. One could simply compare the peak demand and with the substation firm rating to decide when to invest in new capacity. However, this does not provide information about the risk involved with exceeding the firm rating of the substation. The firm rating is the amount that cannot be exceeded should one of the transformers in the substation fail.

One method of evaluating the risk simply extends the traditional peak demand method by computing annual energy in addition to the power at peak load. This requires computing 8760 hourly power flows rather than just one. However, the extra effort provides rich insight into the planning problem and the type of solution that might be applicable.

Starting with the weather-normalized load forecast, the planning area is simulated. Figure 6 shows the results of a hypothetical area planning study by depicting the amount of energy that would be served above the firm rating of the substations in the planning area over five years. The 3-D plots clearly show the extent of the problem: the risk of unserved energy is very high in the summer months and, especially by the 3<sup>rd</sup> and 4<sup>th</sup> years, is quite broad in terms of both the number of months and the number of hours of the

day exposed to the risk. At other times of the year, there is sufficient capacity. The amount of energy starts out small in 2006, but by 2009 the energy served above firm rating exceeds the vertical scale and the characteristic appears flat-topped.

If the chart had indicated that the excess energy stayed small, planners might be more inclined to consider incremental solutions to cover contingency cases or even defer investment all together. This chart gives an indication of how many hours a year the capacity is needed and when it is needed. To solve this problem, the capacity must be available in the late afternoon in the summer months. Our experience tells us that the rapid growth in excess energy indicates that a large capacity addition, such as a new substation, is likely the most economic solution.

This analysis is repeated for any proposed solution. A good solution to the problem should be able to completely eliminate or at least significantly reduce the risk indicated by this analysis.

## CONCLUSION

We have described a case study where normalizing substation loading to a selected design temperature yields improved load forecasts. Normalizing to temperature alone gives a more accurate forecast than a temperature-humidity index in this case. The more accurate forecasts significantly bolster the planner's case for making investment in additional capacity. The linear regression of the historical data is used as the base growth forecast; specifically-identified.

The clear coincidence of peak load with temperature is likely an indication that power consumers simply choose to not be uncomfortable on hot days. Few new structures are built without air conditioning. Also, owners of older residences are continuing to add air conditioning at a steady pace.

Using a temperature normalized forecast can give planners a more accurate perception of the planning risk and of possible solutions to reduce the risk to acceptable values.

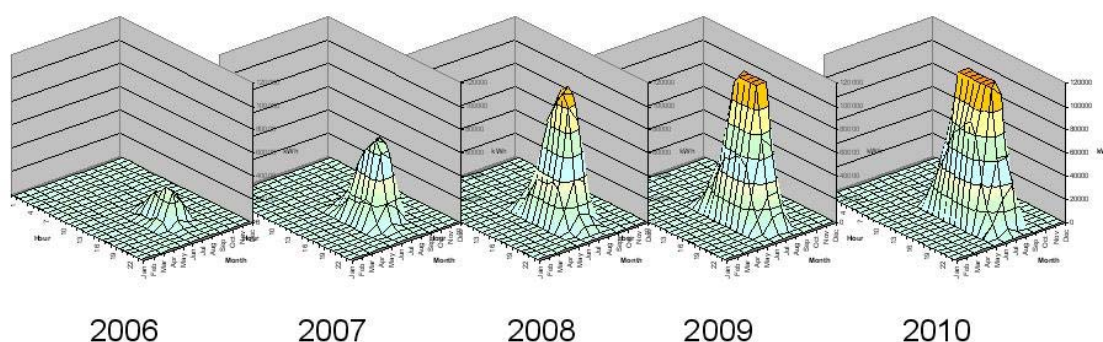


Figure 6. Shape of the Annual Energy Exceeding Firm Ratings for a five year Planning Horizon Resulting from Weather-Normalized Forecast

## ACKNOWLEDGMENTS

The authors would like to credit Elder Romero with recognizing the dominant dependence of the peak substation load on temperature alone.

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