EISPC
EASTERN INTERCONNECTION STATES' PLANNING COUNCIL

Load Forecasting Case Study

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The information and studies discussed in this report are intended to provide general information to policy-makers and stakeholders but are not a specific plan of action and are not intended to be used in any State electric facility approval or planning processes. The work of the Eastern Interconnection States' Planning Council or the Stakeholder Steering Committee does not bind any State agency or Regulator in any State proceeding.

Executive Summary

University of North Carolina at Charlotte (UNCC) teamed with Illinois Institute of Technology (IIT), ISO-New England, and North Carolina Electric Membership Corporation (NCEMC) to prepare a Load Forecasting Case Study for the Eastern Interconnection States' Planning Council (EISPC) in response to the NARUC solicitation NARUC-2014-RFP042–DE0316. The work was supported by the Department of Energy, National Energy Technology Laboratory, under Award Number DE-OE0000316.

The study includes two parts:

1) A comprehensive review of load forecasting topics for states, planning coordinators, and others. This was covered in Chapters 1 through 6. In addition, a list of recommended actions is summarized in Chapter 8.
2) Three case studies in three regions to assist Planning Coordinators and their relevant states with applying state-of-the-art concepts, tools, and analysis to their forecasting regime. The case study is presented in Chapter 7 and a glossary of terms can be found in Chapter 9.

This study is intended to be both a primer on load forecasting as well as provide an in-depth discussion of load forecasting topics with a real-world demonstration that will be useful to state commissioners, planning coordinators, utilities, legislators, researchers, and others. This study is also intended to simplify and demystify the many complex concepts, terms, and statistics used in load forecasting.

A few key takeaways from this study include:

1) Load forecasting is the foundation for utility planning and it is a fundamental business problem in the utility industry. Especially with the extraordinary risks confronting the electric utility industry due to a potentially significant change in the resource mix resulting from environmental regulation, aging infrastructure, the projected low cost of natural gas, and decreasing costs of renewable technologies, it is crucial for utilities to have accurate load forecasts for resource planning, rate cases, designing rate structures, financial planning, and so forth.
2) The states have varying degrees of authority to foster improvements in the databases, the forecasting tools, and the forecasting processes. A comprehensive load forecasting process often involves complicated data requirements, reliable software packages, advanced statistical methods, and solid documentation to construct credible narratives to explain the potential future energy use of customers. Load forecasting is not a static process. Rather, utilities and policymakers should be continually looking for ways to improve the process, the databases, and advance the state-of-the-art in forecasting tools. It is imperative that utilities devote substantial time and resources to the effort to develop credible load forecasts.
3) Deployment of smart grid technologies has made high granular data available for load forecasting. An emerging topic, hierarchical load forecasting, which produces load forecasts with various hierarchies, such as geographic and temporal hierarchies, is of great importance in the smart grid era. While customizing the models for each sub-region or utility would enhance the

forecasting accuracy at the sub-regional level or utility level, the accuracy gained at a lower level can be often translated to the enhanced forecasts at the aggregated levels.

4) Many factors influence the load forecasting accuracy, such as geographic diversity, data quality, forecast horizon, forecast origin, and customer segmentation. The same model that works well in one utility may not be the best model for another utility. Even within the same utility, a model that forecasts well in one year may not generate a good forecast for another year. In order to establish the credibility in load forecasting, utilities have to follow forecasting principles to develop a consistent load forecasting methodology.
5) The recent recession has brought many utilities a paradigm change in how customers use electricity and how much they use. The North Carolina Electric Membership Corporation case study in Chapter 7 was designed to show how the same forecasting methodology would lead to different results and varying degrees of forecasting accuracy in three supply areas of the same state (North Carolina).
6) It is inappropriate to evaluate long-term load forecasts based on ex ante point forecasting accuracy. Long term load forecasts should be probabilistic rather than point estimates. The evaluation should also be based on probabilistic scoring rules.
7) All forecasts are wrong. While the ability to predict the future with as much accuracy as possible would be ideal, a more realistic expectation, especially for long-term forecasts, is the insights on the various risks that may confront a utility.

Scope of the Work

This work includes two parts: Part I White Paper and Part II Case Study.

Part I White Paper

- Task 1: History, requirements, and uses of state-of-the-art load forecasting:
    - Why load forecasting is important
    - Brief historical perspective on the evolution of load forecasting (e.g. the NERC Fan)
    - How load forecasts are used for financial forecasts
    - How load forecasts are used for transmission and other resource planning (including resource adequacy)
    - How load forecasts are used for the following:
        - Development of cost-of-service
        - Development of rate design
        - Development of customized programs to selectively encourage/discourage use. This should include a discussion of using load forecasting in concert with measurement and verification of demand response and energy efficiency.
    - Load forecasting for a traditional vertically-integrated utility and a market participant
    - Potential advantages of using common approaches to load forecasting over broader regions to resolve planning and coordination issues -including ameliorating seams issues. To this end, the Subcontractor shall address problems of rolling-up individual forecasts to construct a regional forecast, duplication, inconsistent data, different economic drivers or drivers that aren't entirely tailored to a specific utility or region.
- Task 2: Issues and considerations to take into account when incorporating risk analysis into load forecasts:
    - Concerns about over-forecasting
    - Concerns about under-forecasting
    - Treatment of weather in load forecasts
    - Incorporating feedbacks and elasticity into load forecasts
    - Treatment and quantification of economic forecast risk
    - Deliverable: Discussion of the five bulleted issues/considerations in Task 2 that should be taken into account when incorporating risk analysis into load forecasts.
- Task 3: Discussion of different types of load forecasting (e.g., econometric, end-use):
    - Forecasting for different classes of customers: residential, commercial (non-agricultural and agricultural), industrial, and other loads (including potential loads like electric vehicles, customer-owned generation, and energy storage.
- Task 4: Explanation of how to select the appropriate forecast horizon for:
    - Financial planning
    - Transmission planning
    - Generation planning
    - Other resources
- Task 5: Discussion of how to select the appropriate tools with regard to:
    - A cursory assessment of the current load forecasting models
    - What types of tools that would be needed to advance the state-of-the-art in planning software
    - The data requirements for supporting new generation of load forecasting models

- Task 6: Explanation of the database requirements for various types of forecasts (this should include a discussion of data sources, concerns about various types of information, and suggestions for improvements including actions that might be taken by state commissions to improve the quality and quantity of data):
  - End use and total home/facility load research
  - End-use/appliance surveys
  - Demographic data
  - The potential benefits of expanded use of the North American Industrial Classification System (NAICS) or Standard Industrial Classification Code (SIC)
  - The use of borrowed data to supplement in-house data
  - Consistency of data such as the treatment of demand response as a load or resource or both
  - Treatment of Demand Response (including measurement and verification issues)
  - Treatment of energy efficiency (including measurement and verification issue, treatment of new technologies, changes in building/home codes and attendant effect on energy use).
  - Treatment of customer-owned generation (including measurement and verification issues)
  - What might be possible with information from "smart meters" and a "smart grid"?
- Task 7: A brief assessment and recommendations of actions states might take to facilitate improved load forecasting for their Planning Coordinator(s) or jurisdictional entities.

Part II Case Study

- Task 8: Create a collaborative Case Study with the Planning Coordinator and the relevant states to apply Part I. Part II should also address the broader applicability of the processes, databases, and analysis to other regions.
- Task 9: Provide a Glossary of Terms for Parts I and II with illustrations where appropriate. The Glossary shall include an explanation and examples of important statistical concepts and formulas. The Subcontractor shall provide these examples for Part I. Consideration should be given to embedding a podcast-type link into the Study to provide a richer and longer term learning potential.
- Task 10: To ensure broad dissemination of the Study, the Subcontractor shall participate in up to two in-person meetings as well as potentially a webinar, at EISPC's discretion. The purpose of the Subcontractor's participation in the meetings and a potential webinar will be to provide updates on the progress of the Study- including obtaining inputs from EISPC on the drafts of the Report.

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List of Acronyms

AC	Alternating Current
AEO	Annual Energy Outlook
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive and Moving Average
BGE	Baltimore Gas and Electric Company
BI	Business Intelligence
CA CEUS	California Commercial End-Use Survey
CA RASS	California Residential Appliance Saturation Study
CAIDI	Customer Average Interruption Duration Index
CBECS	Commercial Building Energy Consumption Survey
CBP	County Business Patterns
CC	Customer Count
CDD/HDD	Cooling Degree Days / Heating Degree Days
CEA	Consumer Electronics Association
CELT	Capacity, Energy, Loads, and Transmission
CERA	Cambridge Energy Research Associates
ComEd	Commonwealth Edison Company
DER	Distributed Energy Resources
DG	Distributed Generation
DMS	Data Management System
DR	Demand Response
DSM	Demand-side Management
DST	Daylight Saving Time
ECPC	U.S. Economic Classification Policy Committee
EE	Energy Efficiency
EIA	Energy Information Administration, U.S. Department of Energy
EISPC	Eastern Interconnection States Planning Council
EPACT92	Energy Policy Act
EPIC	Energy Production and Infrastructure Center, UNC Charlotte
ETL	Extraction, Transformation, and Loading
EVs	Electric Vehicles
FERC	Federal Energy Regulatory Commission
G&T	Generation and Transmission
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product

GEFCom2014	Global Energy Forecasting Competition 2014
GIS	Geographic Information System
GMP	Gross Metropolitan Product
GMT	Greenwich Mean Time
GSP	Gross State Product
GUI	Graphical User Interface
HID	High Intensity Discharge
IEEE	Institute of Electrical and Electronic Engineers
IRP	Integrated Resource Planning
ISO	Independent Systems Operator
ISO-NE	ISO New England
LOLP	Loss of Load Probability
LTLF	Long Term Load Forecasting
MECS	Manufacturing Energy Consumption Survey
MLR	Multiple Linear Regression
MTLF	Middle Term Load Forecasting
MW	Megawatt
MWh	Megawatt hour
NAICS	North American Industrial Classification System
NARUC	National Association of Regulatory Utility Commissioners
NASA	National Aeronautics and Space Administration
NEEP	Northeast Energy Efficiency Partnerships
NERC	North American Electric Reliability Council
NOAA	National Oceanic and Atmospheric Administration
NSF	NERC Summary Forecasts
OMB	the Office of Management and Budget
PAC	Planning Advisory Committee
PECO	Philadelphia Electric Company
PURPA	The Public Utility Regulatory Policies Act
PV	Photovoltaic
RECS	Residential Energy Consumption Survey
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCADA	Supervisory Control and Data Acquisition
SIC	Standard Industrial Classification Code
STLF	Short Term Load Forecasting
UCM	Unobserved Components Model
UEC	Unit Electricity Consumption
Vermont TRM	Efficiency Vermont Technical Reference User Manual
VSTLF	Very Short Term Load Forecasting

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1. Overview of Load Forecasting: from History to the State-of-the-Art

1.1 Why Is Load Forecasting So Important?

1.1.1 From Forecasting to Load Forecasting

Forecasting is a necessary and important function in virtually any industry. Airline companies forecast the number of passengers to schedule flights. Breweries forecast the beer consumption to plan production. Retailers forecast the fashion goods demand to decide what discount to offer to customers. Banks forecast mortgage transactions to commit workforce in branch offices.

Electric utilities run the power grid, known as the most complex man-made system on earth, to deliver electricity to more than five billion people around the globe (Hong, 2014). When turning on the switch, one expects the light to be on. However, the business from generating the electrons to delivering them to power the light bulbs and other electrical appliances is not that simple. While many other industries have some form of inventory to store and buffer their products and services, those of the electric power industry, electricity, cannot be massively stored using today's technologies. As a result, electricity has to be generated and delivered as soon as it is consumed. In other words, the utilities have to balance the supply and demand every moment.

Load forecasting, mainly referring to forecasting electricity demand and energy, is being used throughout all segments of the electric power industry, including generation, transmission, distribution, and retail. Applications of load forecasts spread power supply planning, transmission and distribution systems planning, demand side management, power systems operations and maintenance, financial planning, rate design, and so forth. Due to the fundamental role of load forecasting in the utility business operations, inaccurate load forecasts may result in financial burden to or even bankruptcy of a utility company. While load forecasting provides a key input to power systems operations and planning, inaccurate load forecasts can lead to equipment failures or even system-wide blackout.

Overall, electricity storage limitations and societal necessity of electricity lead to several interesting features of load forecasting, such as the complex seasonal patterns, 24/7 data collection across the grid, and the need to be extremely accurate (Hong, 2014). This study is intended to demystify or simplify complex concepts, terms, and statistics used in load forecasting. This study will also address questions such as: How do load forecasts fit in with other aspects of the planning processes? Since the future is uncertain, how much confidence can be placed in load forecasts? How should the quality, rigor, and results of load forecasts be evaluated? What can be done to improve the quality and credibility of load forecasts?

1.1.2 Classification of Load Forecasting Problems

There is no single forecast that can satisfy all of the needs of a utility. A common practice is to use different forecasts for different purposes. With so many applications, it is unrealistic to establish a forecasting problem for each application. Therefore, we have to take a scientific approach to classifying the load forecasting problems. The classification of various forecasts not only depends upon the business needs of utilities, but also on other factors that drive the electricity consumption.

Based on the forecasting horizon, we can classify load forecasting problems into the following four groups:

- Very short term load forecasting, forecasting horizon ranging from a few minutes ahead to a few hours ahead.
- Short term load forecasting, one day to two weeks ahead forecasting.
- Medium term load forecasting, two weeks to three years ahead forecasting.
- Long term load forecasting, three to fifty years ahead forecasting.

A more liberal classification is to use the two week horizon as the cut-off point to separate short term load forecasting and long term load forecasting. The main justification for this cut-off is that temperature, an important driving factor of load, can be hardly predicted beyond two weeks.

This load forecasting case study is primarily focusing on medium/long term load forecasting. Due to the emerging trend toward integrated load forecasting, necessary coverage of very short and short term load forecasting is also provided.

1.2 Evolution of Load Forecasting: A Brief History

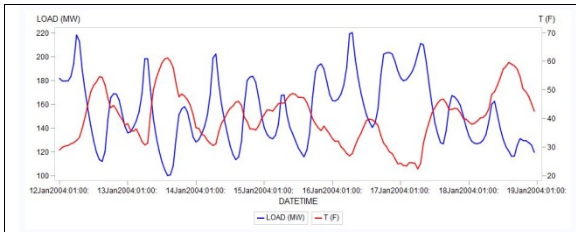
As a fundamental business problem in the utility industry, load forecasting practices have gone through several important stages, such as using a simple counting method at the inception of the power industry, the engineering approach with charts and tables in the pre-PC era, and the computer based methods in the late 20th century. Smart grid investment and technologies bring challenges to the load forecasting community, such as consideration of demand response (DR) programs and distributed energy resources. The century-old energy forecasting finds its new life in the smart grid era (Hong, 2014). In this section, we review the evolution of load forecasting practices in a chronological order.

1.2.1 Pre-PC Era

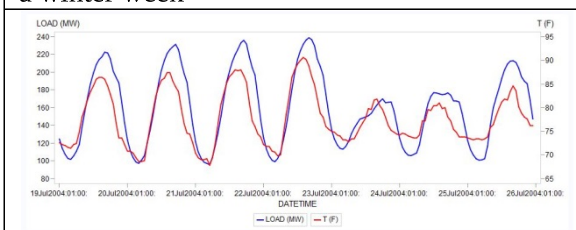
When Thomas Edison and his company developed the Pearl Street Station in 1882, his motivation was to promote the sales of light bulbs. This first steam-powered station initially served about 3000 lamps for 59 customers. When lighting was the sole end use of electricity, load forecasting was straightforward. The power companies could just count how many light bulbs they installed and planned to install. Then they roughly knew the level of load in the evening. This ancient method is still being used today for forecasting the load of street lights.

As more and more electric appliances, such as electric iron, radio, and electric washer, were being invented and became popular, the forecasting problem gradually turned to be non-trivial. Some special events, such as a presidential speech, caused a spike in the load curve, because millions of people were listening to the radio at the same time.

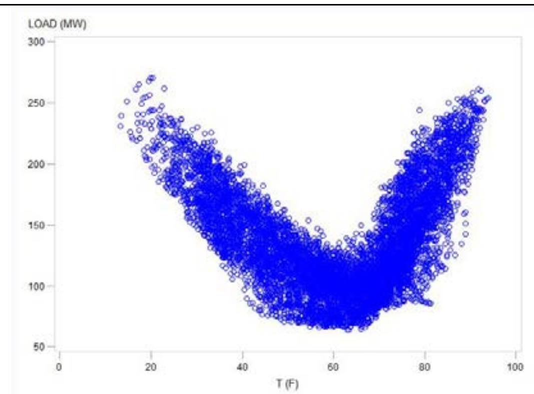
In 1940s, electricity demand was highly affected by weather, principally due to high penetration of air conditioners. Figure 1-1 shows the relationship between load and temperature via two line plots and a scatter plot. In the winter, load and temperature are negatively correlated primarily due to space heating needs. In the summer, the correlation is positive primarily due to the space cooling needs. Since then, weather variables, such as temperature and humidity, have been widely used to forecast electric load.



a. Line plots of hourly load and temperature in a winter week



b. Line plots of hourly load and temperature in a summer week



c. A scatter plot of hourly load and temperature. The scatter shows an asymmetric “U” shape. On the left, the lower the temperatures are, the higher the loads are, which is primarily due to heating needs. The opposite happens on the right, which is primarily due to space cooling needs.

Figure 1-1: Relationship between load and temperature

Because there were no statistical software packages at that time, an engineering approach was developed to manually forecast the future load using charts and tables. Some of those elements, such as heating/cooling degree days, temperature-humidity index, and wind-chill factor, are inherited by today's load forecasting models. The similar day method, which derives a future load profile using the historical days with similar temperature profiles and day type (e.g., day of the week and holiday), is still used by many utilities.

1.2.2 NERC Fan

Since 1974, as part of its effort to improve system reliability, the North American Electric Reliability Council (NERC) has published 10-year electric load forecasts. Accordingly, forecast data collected for electric utility service territories are combined to obtain regional and finally national totals. NERC does not prepare the forecasts; rather it coordinates and aggregates the utility data. The forecasts are often referred to as the NERC summary forecasts (NSF). An NSF graph since 1974 along with actual energy sales shown in Figure 1-2 provides a dramatic picture. The rate of growth in 1951-1973 was 7.8% compounded. Although the 1974-1983 forecasts projected a growth rate of 7.5%, it is clear from the figure that actual growth after 1973 fell far short of 7.5%. In fact through 1982 the actual growth rate was only 2.2%. Subsequent forecasts were successively less steep with the projected growth rate for 1982-1991 falling to 3.2%. This forecast pattern is often referred to as the NERC Fan. The shortfall of actual electricity sales relative to forecasts and persistent downward revisions of projected growth rates raised several questions. Should electricity forecasts be more accurate, given the information and techniques available to forecasters at the time? Was the rate of downward revision of forecasts appropriate?

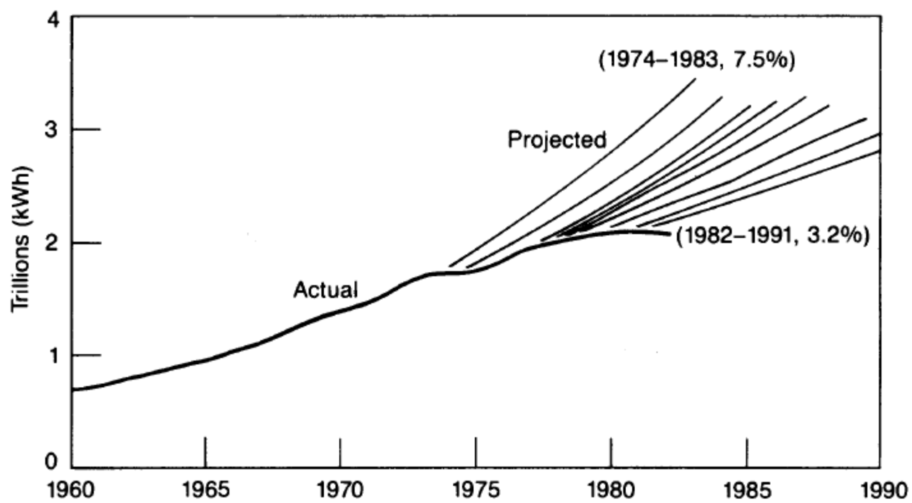


Figure 1-2: NERC Fan: Actual (1960-1982) and Projected (1974-1990)

1.2.3 Spatial Load Forecasting

In the 1980s, computer applications ramped up. A significant amount of research was devoted to long term spatial load forecasting about when, where, and how much load growth will occur (Willis & Northcote-Green, 1983). The forecasting horizon ranges from several years to several decades. Such forecasts have been widely used in transmission and distribution planning. Most of them fall into three categories: trending, simulation, and hybrid methods.

Trending methods look for some function to fit the past load growth patterns and estimate the future load. The most common trending method is to apply a polynomial regression model to historical load data. The advantages of the trending method include ease of use, simplicity, and a short-range response to recent trends of load growth. However, the method often fails to provide a useful estimate of the long-range load, due to over-fitting or extrapolation of high-order polynomials.

Simulation methods attempt to model the load growth process to reproduce the load history, as well as to identify the temporal, spatial, and magnitude information of the future load growth. They model an urban development process based on land-use information from government, customer rate classes from utilities, and load curve models of consumption patterns. Depending on the quality of data, this approach has had fair to very good short-range accuracy and good to excellent long-range usefulness for planning. Its drawback is expensive development and training costs.

Hybrid methods combine the favorable features of trending and simulation. An ideal hybrid method should respond to the recent trend of load history in the short-range, keep the long-range defensibility provided by the simulation methods, and all this without requiring many skills and interactions from the user. A modern hybrid method was originally developed by Hong (2008). The method divides the entire service territory into thousands of 50-acre small areas. The small areas are then used to build a hierarchy with multiple levels. Load growth at each small area or region is assumed to be an S curve. The input information includes historical load at the 50-acre small area level, long term load forecast at the corporate level, and land use development plans. The parameters are estimated by minimizing the errors in historical fit and the difference between sum of lower level forecasts and the corresponding high level forecast. This method has been commercialized and deployed to many utilities in North America. Figure 1-3 shows the results from a case study of a medium size U.S. utility, where the maps of the actual load and load forecast are plotted in Microsoft Excel.

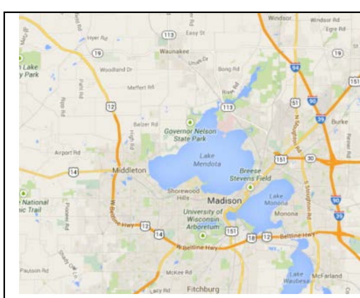
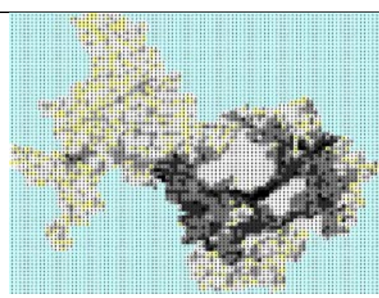
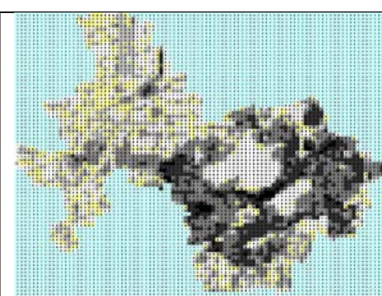
		
A medium size city of U.S.	Actual load today	Forecasted load 20 years later

Figure 1-3: Long term spatial load forecasting

1.2.4 Short Term Load Forecasting

Computers not only helped improve the practices of spatial load forecasting, but also those of short term load forecasting (STLF). Late in the last century, the power industry went through a major structural change, which made accurate short term load forecasts even more critical. First statistical techniques, such as regression analysis and time series analysis, were applied to STLF. Then Artificial Intelligence (AI) became one of the hottest terms in the scientific community, resulting in hundreds of papers reporting AI based approach to STLF. In 1990s, Electric Power Research Institute (EPRI) sponsored a project that developed several artificial neural networks based short term load forecasters (Khotanzad, & Afkhami-Rohani, 1998). Some research generated from this EPRI project was later commercialized and became a popular STLF service provider.

The models based on AI techniques, such as artificial neural network (ANN), fuzzy logic, and support vector machine, were black-box models that appealed to organizations unwilling to build an in-house team of forecasting analysts. Many utilities were still not comfortable with black-box approaches and instead developed forecasts using the classical methods such as the similar day method, and statistical techniques such as multiple linear regression. Some utilities with an in-house forecasting team also built black-box models or purchased forecasts for comparison purposes. The most recent and comprehensive research on regression-based short term load forecasting was developed by Hong (2010). The methodology in (Hong, 2010) was soon adopted by many utilities, retailers, and trading firms worldwide and became part of the engine of a commercial energy forecasting solution offered by SAS. Table 1-1 summarizes the key attributes of different approaches to short term load forecasting.

Table 1-1: Comparison among short term load forecasting techniques

	Pros	Cons
Multiple Regression	Interpretable; easy to implement, update, and automate; good accuracy	Relies on explanatory variables; needs explanatory variables, a designated functional form, and at least two years of history
Autoregressive Integrated Moving Average (ARIMA)	Few parameters to estimate; does not require a long history; good accuracy in (very) short term	Low accuracy in longer term; high cost to implement, update, and automate; difficulty to interpret moving average
Artificial Neural Network (ANN)	Minimum statistical or domain knowledge required; good accuracy during normal days	Heavy computation; over-parameterization; difficult to interpret; low accuracy during extreme weather conditions

1.2.5 The Smart Grid Era

In the past decade, the electric power industry has undergone a grid-modernization process, installing millions of smart meters, sensors, and communication devices. With the introduction of Smart Grid, the usual challenges to load forecasting remain and are further complicated by demand response and distributed generation.

Smart grid technologies bring great potential for a greener and more reliable grid at reduced cost. One way to achieve these goals is through demand response (DR), which is defined by US Federal Energy Regulatory Commission (FERC) as "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*."

To effectively design and implement the DR programs, utilities have to perform a series of analytical tasks, such as forecasting electricity price, forecasting load at individual customer level with or without DR programs, and after-the-fact estimation of the consumption pattern changes due to various DR programs. A major challenge in this area is to estimate the normal consumption pattern, or baseline. Because time is irreversible, there is no way for a utility to conduct an experiment to get the actual value of normal consumption pattern for an event day (the day when DR programs are triggered). There are over a hundred baseline estimation methods. Most of them are based on a simple average of the load profiles of several days prior to the date when DR programs are triggered. These methods are shown to be insufficient at individual customer level. There is not yet a proven solution to this problem.

With the generation from wind turbines, rooftop PV panels, and solar farms, the century-old load forecasting problem finds another new challenge, the influence of negative loads from distributed energy resources. Figure 1-4 shows one week of solar generation at 5-min interval. The solar generation pattern depends on cloud coverage. The generation profile is a nice bell curve if it is a sunny day. On a cloudy or partially cloudy day, the generation is quite unpredictable. Many large and medium utilities today operate their systems with one day ahead load forecast error at 3% or lower. While it is a challenge to achieve a similar accuracy in forecasts of their wind or solar generation, utilities are addressing the challenge and making continued improvement in their wind and solar forecasting practice.

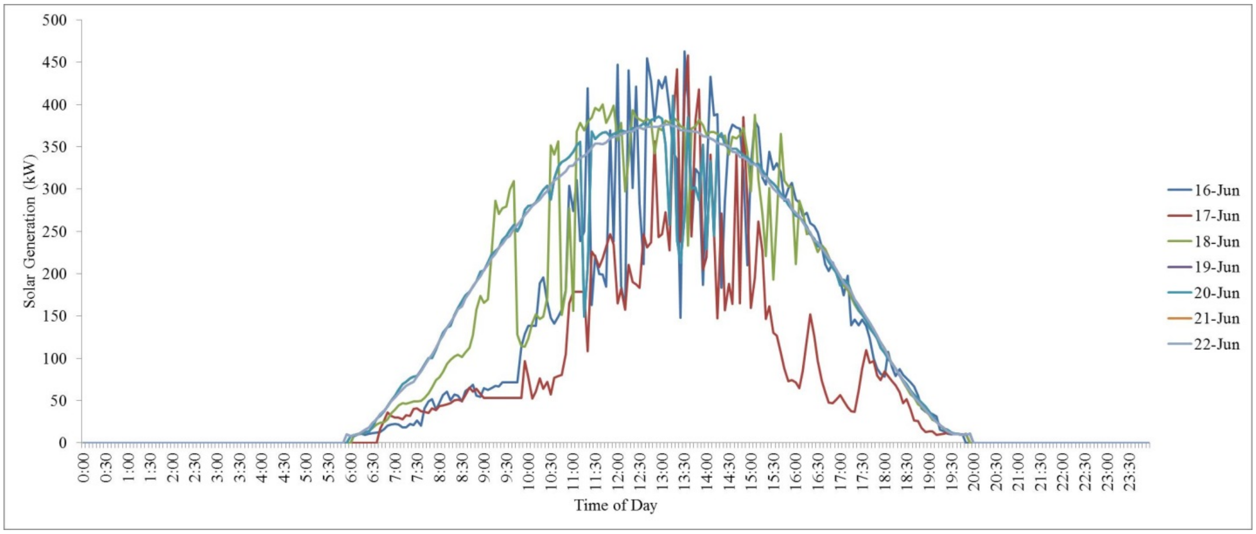


Figure 1-4: One week of solar power generation at 5-minute interval

Major advances are being made in renewable-generation forecasting by both meteorologists and forecasters. The meteorologists sample the state of the fluid at a given time and apply the equations of fluid dynamics and thermodynamics to estimate the state of the fluid at some time in the future. This numerical weather prediction approach requires significant computing resources as well as working knowledge of meteorological science. Further analysis is needed to translate wind and solar forecasts into renewable generation forecasts. The statistical alternative uses meteorological forecasts as one of its modeling inputs, among others, such as lagged wind power and calendar variables. A recent review of the state-of-the-art is in (Zhang, Wang & Wang, 2014).

1.2.6 Global Energy Forecasting Competitions: A Crowdsourcing Approach

While the research community has been publishing thousands of energy forecasting papers, few of them have been actually used in the field. To tackle the emerging challenges in energy forecasting, the Institute of Electrical and Electronic Engineers (IEEE) Working Group on Energy Forecasting organized the Global Energy Forecasting Competitions in 2012 (GEFCom2012) and 2014 (GEFCom2014). The competitions brought together many new ideas to the load forecasting field from hundreds of data scientists in many different industries. A more comprehensive introduction of GEFCom2012 is in (Hong, Pinson & Fan, 2014).

Among various energy forecasting problems tackled in these competitions, two of them covered load forecasting: hierarchical load forecasting in GEFCom2012 and probabilistic load forecasting in GEFCom2014. In both tracks, the competition organizers provided the contestants real world electricity demand and weather data. The hierarchical load forecasting track was to mimic short term load forecasting in the smart grid environment, where the forecasters have access to load data at various levels in the system. In the probabilistic load forecasting track, the contestants were asked to provide load forecasts in 99 quantiles to offer a more comprehensive description of the uncertainties in future electricity demand.

1.3 Business Needs of Load Forecasting

1.3.1 Financial Forecasting

Similar to other business entities, utility companies have to be financially stable in order to efficiently operate the power grid. Developing revenue forecasts is a must-have business requirement for a successful utility finance department. The revenue forecasts eventually drive the various budgeting decisions, such as how much should be spent on upgrading infrastructure; how much raises and bonuses will be offered to the employees; how many people to hire or lay off; whether to acquire or sell a business unit; how to set the strategy for investing renewable generation; how much rate increase or decrease should be requested in the next rate case, and so forth.

There are several ways that load forecasts are being used in revenue forecasting:

1) Comparing budget to actual revenue. Because weather cannot be accurately predicted in the long term, utilities have relied on the forecast of normalized load to make their budgets. At the beginning of a year, a utility reviews the previous forecast and analyzes the sources that result in the difference between the budgeted and actual revenue, such as modeling error, extreme weather conditions and error in economy forecasts.
2) Comparing revenues year over year. Since weather is a main driving factor of electricity consumption, the energy consumptions of the previous years can be affected by weather more than the natural growth of the economy. Utilities need to understand where the load would have been without the effect of change in weather conditions.

Since the income of a utility is primarily from electricity sales, revenue forecasting, at the conceptual level, can be conducted by multiplying the energy consumption with the rate. The load forecast, as one of the multipliers, is an important input to a utility's financial forecasting process.

$$\text{Revenue (\$)} = \text{Rate (\$/MWh)} \times \text{Energy (MWh)}$$

The actual financial forecasting process is much more complicated than the above equation. Because a utility has many revenue classes, the load forecasting process has to provide the matching energy consumption for each revenue class.

Before the smart grid era, the load data for financial forecasting was mainly from two sources:

1) Monthly readings from the meters, which was delivered to the customers on their monthly bills;
2) Daily or hourly reads from a small sample (from a few dozen to a few hundred) of interval meters.

In the old days, there were two major challenges for load forecasting at revenue class level:

1) Data processing. For example, for a utility with 40 revenue classes, the historical load data has to be arranged into 40 groups to have one to one mapping for each revenue class. The data for each group may require a substantially different processing procedure. Extensive load research studies are often involved when estimating the demand profile of some revenue classes. Sometimes the raw data can be missing due to meter malfunction or database shut-down.
2) Unbilled energy. When sending bills, often utilities group the customers into twenty plus billing groups. In other words, not all customers receive their bills on the same day of the month. Also, the number of days on different monthly bills can be different due to weekends and holidays that fall on the billing dates.

Deployment of smart meters has helped ease the load forecasting process in some sense. Although there are still data quality issues at smart meter level, the modern communication systems and data warehousing technologies have shown a great potential of resolving the two challenges mentioned above.

1.3.2 Power Systems Planning

In many organizations, planning and forecasting are seamlessly integrated together. The forecasting function of a utility is usually assigned to the planning department. Nevertheless, the distinction between the two should not be omitted. Planning provides the strategies given the forecasts. Forecasting estimates the results given the plan. Planning relates to what the utility should do. Forecasting relates to what will happen if the utility tries to implement a given strategy in a possible environment.

Power system planning is a process to determine new or upgrading existing power system components to reliably satisfy load in the foreseeable future. Power system planning stages include electrical load forecast, generation planning, and transmission and distribution planning. The electrical load forecast forms the basis of power system planning and provides information on expected load growth, load profiles, and load distribution. A comprehensive power system planning model may include many sub-models, such as:

- a load forecasting model that uses historical demand data, forecasted population and economic trends, and the effects of planned energy efficiency programs on forecast values;
- a reliability module that calculates the value of loss of load probability (LOLP) for each year in each plan and compares this value to the specified reliability criterion on LOLP;
- a financial model that calculates the annual revenue requirements for a new generating project, based on the project's capital cost and construction spending curve, the utility's cost of debt and equity, the utility's target capital structure, the book and tax life of the project, the income taxes paid by the company, and the specific ratemaking treatment used by the utility;

- a production simulation model that identifies generation expansion plans, simulates and evaluates alternative plans, identifies the plan with the lowest total net present value of revenue requirements, and reports the generation projects that are included in that plan; and
- an output module that summarizes the output of the various models in more convenient formats.

A. *Generation Planning*

The aim of generation planning is to seek the most economical generation expansion scheme to achieve a certain reliability level according to the forecast of increased demand in a certain time period. The following questions are to be answered in generation planning:

- When to invest in new generating units?
- Where to invest in new generating units?
- What type of generating units to install?
- What capacity of generating units to install?

The following quantitative analysis should be conducted by the generation planning models in order to find and justify the generation expansion scheme:

- The feasibility of the generation structure
- The cost of primary energy resources and fuel for the scheme
- The cost of investment flow and annual operation of the scheme
- The reliability indices of electricity supply
- The sensitivity of the scheme to an increase in the fuel price and generating unit investment
- The effect of delaying certain key projects

Generation planning and analysis can be performed by using a spectrum of methodologies that range from very simple analysis, such as levelized bus-bar cost, to much more detailed analysis involving reliability, production cost, investment cost, and financial analysis.

Generation capacity expansion programs use the predicted annual energy and peak load demand to assess the need to build new generating units. In system reliability studies, the major reliability indices include the probability of the system being able to meet the peak demand and the probability of the system being able to meet the hourly load demand. Those reliability indices are calculated based on the load forecast.

B. *Transmission Planning*

The fundamental objective of transmission planning is to develop the system as economically as possible and maintain an acceptable reliability level. The system development is generally associated with determination of a reinforcement alternative and its implementation time. A decision on retirement or replacement of aging system equipment is also an important task in transmission planning. Generally speaking, transmission planning is the process of identifying areas of the current transmission grid that are in need of expansion to maintain reliability and accommodate new generation and/or growing load. Transmission planning ensures that the transmission infrastructure can deliver power from the generators to the loads, and that all the equipment will remain within its operating limits during both normal operation and system contingencies. An adequate transmission plan answers the following questions:

- Where to build a new transmission line?
- When to build it?
- What type of transmission line to build?

Transmission planning is generally divided into two stages: scheme formation and its evaluation. The task of scheme formation is to determine one or more alternatives satisfying the power transmission requirements according to the available and needed transmission capacity. The task of scheme evaluation is to make overall economic and technical assessment of formed schemes including power flow, stability analysis, short-circuit current capacity, reliability and economic calculations, and to decide a final scheme. During scheme evaluation, the network configuration can further be improved using the information obtained from the computation.

Transmission planning can be divided into three stages in terms of timespan: long-term planning, medium-term planning, and short-term planning. Long-term planning is associated with a long period, such as 20 to 30 years. It often focuses on a high-level view of system requirement. The solutions discussed in long-term planning are preliminary and may need significant changes or even redefinitions in subsequent planning stages because of very uncertain input data and information. Medium-term planning can refer to a timeframe between 10 and 20 years. In this stage, preliminary considerations and solutions from long-term planning are modified according to actual information obtained in previous years, and study results are utilized to guide short-term projects. Short-term planning deals with the issues that have to be resolved within 10 years. Concrete alternatives must be investigated in depth and compared. Planning studies at this stage generally lead to a capital plan for future projects.

Transmission planning methods may be grouped into two categories: heuristic and mathematical optimization methods. The heuristic method is based on intuitive analysis and relatively close to the way in which engineers think. The optimization method formulates the design requirements of planning as an operational mathematical planning model solved by an optimization algorithm such that an optimal planning scheme is obtained satisfying all constraints.

C. Distribution Planning

The objective of distribution planning is to determine the size, location, and time of installation of new distribution equipment, taking account of capacity constraints of lines, drop in voltage, and the degree of assurance with which demands can be met. Distribution planning is a complex task in which planners must ensure that there is adequate substation capacity (transformer capacity) and feeder capacity (distribution capacity) to meet the load demands.

Distribution systems are the part of electricity delivery infrastructure that serves the load and are optimized for the lowest cost that meets the desired reliability of service. Reliability in distribution planning is defined and evaluated quite differently compared with reliability evaluation in generation planning. Typical reliability indices used in distribution planning include System Average Interruption

Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Customer Average Interruption Duration Index (CAIDI).

D. Integrated Resource Planning

Integrated resource planning (IRP) is designed to evaluate new energy resources that consider a full range of alternatives, including conventional generation, renewable generation, power purchases, and energy conservation and load management programs to provide adequate and reliable service. The plan must consider necessary features for system operations, such as diversity, reliability, dispatch ability, and other risk factors. The overall IRP objective is to evaluate demand and supply resources on a consistent and integrated basis. IRP has the potential to take a society-wide perspective, incorporate public participation in meaningful ways, and create plans that are low-cost, low-risk, and with outcomes that minimize environmental and social impacts.

Alternatives examined by system planners in an IRP setting include:

- Adding generating capacity (thermal, renewable, customer-owned, or combined heat and power),
- Adding transmission and distribution lines, and
- Implementing energy efficiency (EE) and demand response programs.

Steps taken in the creation of an IRP include:

- Forecasting future loads,
- Identifying potential resource options to meet those future loads,
- Determining the optimal mix of resources based on the goal of minimizing future electric system costs,
- Receiving and responding to public participation (where applicable), and
- Creating and implementing the resource plan.

1.3.3 Other Use of Load Forecasts

A. Cost-of-service Allocation

The purpose of conducting a Cost of Service Study is to determine a utility's full costs of providing electricity for various categories of customers, at different points in the supply chain and within different geographical areas. A utility's full cost of service includes its efficient operating costs plus an appropriate return on the assets necessary to produce, deliver, and sell electricity to its customers and meet growing demand through prudent investment. The Cost of Service is used by the utility to determine and understand its internal cost structure so that the utility can better control its costs, manage its business on a commercial basis, improve customer service and its financial performance. The Cost of Service is used by the regulator to make informed policy decisions, develop the utility's revenue requirements, and set appropriate tariff levels that enable the utility to provide service and meet demand growth over time.

B. Development of Rate Design

Retail electricity rates have traditionally been characterized by three fundamental properties. First, they have been set at the same level for broad classes of customers (e.g., all residential customers) whose usage patterns can vary widely. Second, retail rates are typically set at a fixed level that reflects the broad average of the hourly costs to serve customers in the class over a year or a season. Third, retail rates focus largely on recovering utilities' historical embedded costs rather than reflecting forward-looking market costs. The development of appropriate rates requires a projection of the kilowatt-hour consumption in each rate class over a horizon of about one or two years.

C. Demand Response

Demand response, a valuable feature of smart grid, is growing dramatically as an effective demand management method. Demand response represents a scenario in which households and commercial consumers participate in grid management through appropriate modifications of their consumption profiles during certain time periods in return for a monetary reward. Sometimes, the participation is mediated by aggregators, who design consumption profile modifications to make up standardized products to be sold on energy markets. Demand response signals to consumers generated by aggregators would require load forecasting algorithms which explicitly take into account demand response effects. However, traditional load forecasting tools have limitations to reflect demand response customer behaviors into load predictions. With the deployment of advanced metering infrastructure (AMI), an avalanche of consumption data has become available. AMI data introduce a fresh perspective on load forecasting.

D. Energy Efficiency

Energy efficiency refers to using less energy to provide the same service. Energy efficiency is a way of managing and restraining the growth in energy consumption. Utilities increasingly treat energy efficiency as a resource analogous to conventional power generation, and are changing generation investment plans based on anticipated efficiency acquisitions. Indeed, energy efficiency policy, along with demand side management policy, is among the causes of steadily slowing electricity sales growth in recent decades. The expanding implementation of these programs is stimulating changes to forecasting procedures.

1.4 Load Forecasting for a Traditional Vertically-integrated Utility and a Market Participant

1.4.1 Regulation and Deregulation

The electric power industry consisted of many municipally owned utilities and privately owned multiservice utilities competing with each other locally, until Samuel Insull first set up a successful example of the business model for the industry. He consolidated his company with others, so that he could sell electricity to a broader market using bigger and more efficient generators. Moreover, he also sought new customers to diversify the pattern of electricity consumption and fill in more off-peak loads. By 1907, his company Commonwealth Edison was already known as one of the most progressive and lowest cost utilities in the world. As a result, Insull's strategies became the strategies of the electric power industry in the United States. Small utilities gradually merged with or purchased electricity from large, vertically integrated, private multiservice utilities. To further exploit the benefits of large and efficient equipment, private electric utility ownership also consolidated into large utility holding companies.

As the service territories of the large utilities started to grow beyond the city boundaries, and even across state lines, state regulation and Federal involvement were brought to the electric power industry. Federal and state regulation recognized electric utilities as natural monopolies, which allowed them to grow with little competition to sell electricity to broader segments of the market, and to charge rates that were reasonable and yet sufficiently high to keep the utilities financially healthy. On the other hand, the utilities were obligated to provide service, with as few interruptions as possible and without discrimination, to all customers who sought to buy power.

Abuses by holding companies appeared in the 1920s, which eventually led to Federal intervention. In the 1930s, the early years of the Great Depression, the Federal Government became a regulator of private utilities and a major producer of electricity, and oversaw the holding companies in order to avoid financial abuses. The electric utility industry was still a host of natural monopolies. The benefits and regulation, together with technological development, helped keep the rapid and healthy growth of the industry through the 1960s.

Several challenges such as environmental concerns, high inflation, and increased fossil-fuel prices which resulted in the energy crisis of the 1970s appeared, and led to the introduction of the electric power industry deregulation. In 1978, the U.S. Congress passed The Public Utility Regulatory Policies Act (PURPA), a law meant to promote greater use of renewable energy by opening the wholesale markets to nonutility electricity producers, primarily private businesses and industrial manufacturers that generated their own electricity. In 1970, the electric utilities produced 93% of the total generation. The share steadily increased to 97% in 1979. Due to the growth of non-utilities in the 1980s, this number declined to 91% in 1991. In 1992, Congress passed the Energy Policy Act (EPACT92) that further promoted competition in the bulk power market.

1.4.2 Implications of Deregulation on Load Forecasting

One role of regulation was to ensure that the utilities could raise enough capital for building infrastructure so that the projected load could be met. Sometimes, the customers had to pay higher rates than in previous periods to maintain the financial health of the utilities. The legitimate status of a natural monopoly allowed the utilities to grow, to use larger and more efficient equipment, and to invest in technological development, which further reduced the unit cost of electricity. As a result, the retail price of electricity was decreasing prior to the energy crisis of the 1970s, as shown in Figure 1-5. Hearings to approve rate increases, so called “rate cases,” were initially not an issue for utilities. This changed with deregulation. Although the industry is deregulated, to avoid financial abuses, the utilities are still being watched by the government. Regulators have the authority to approve or deny requests in rate cases. To favor the voters, of which most are the customers of utilities, politicians have the tendency to reduce the rates rather than increase them. This makes the defense of rate cases more and more challenging for utilities. Since it is the “projected load” that reflects the future income and potential costs of a utility and thus determines the rate, a formal load forecasting process becomes a necessity for a utility to succeed in a rate case.

Uncertainty and the difficulty of defending rate cases, together with many other factors derived by deregulation, changed the operating strategy of the industry from “build and grow” to “wait and hold.” Beginning in the late 1980s, utilities slowed down infrastructure development and only performed system expansion or equipment maintenance and upgrade when they had to. In the short run, (i.e., one to three years), this new strategy helped them achieve better financial benefits than the “build and grow” strategy would have done. Meanwhile, the load/capacity ratio was being pushed higher and higher to accommodate the increasing electricity demand. After a decade of consistently executing the new strategy, the equipment was operating near its limit, which further required the utilities to deploy a formal forecasting process to help justify decisions about operations, maintenance, and planning.

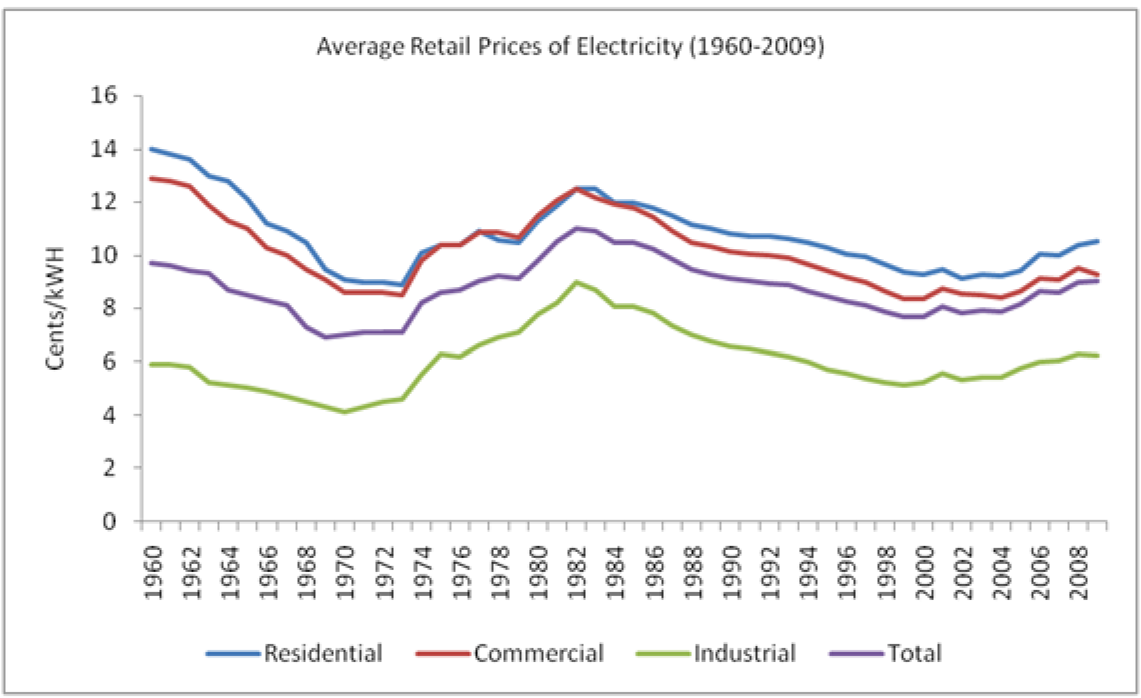


Figure 1-5: Average retail prices of electricity

Deregulation creates competitive markets for parties to buy and sell electricity. In order to make proper decisions for energy purchases, utilities have to have a good idea of their future electricity demand and price. Failing to do so would result in losing money in the markets. While the market price is not transparent to the end users in real-time, utilities have to be responsible for the costs, which creates the potential for them to be financially unhealthy due to inaccurate forecasts.

Counter-intuitively, in the deregulated industry, regulatory commissions become more active than before. Energy efficiency and demand response programs are encouraged by the regulators or mandated in many states. In the competitive market, electricity prices rise as the demand goes up. On the other hand, as the system approaches its limits, outages are more likely to occur during high demand periods. Demand response programs are set up to help utilities manage system peaks as well as to avoid outages. Since power systems are generally sized corresponding to the peak demand, reducing peak demand could also result in savings in plant and capital costs. Nevertheless, none of these benefits could be realized without fairly accurate load forecasts indicating when the peak load would occur and how much the peak load would be.

With more and more solar panels and wind turbines interconnected to the grid and being treated as negative loads, the load forecasting problem becomes even harder, because the production of these energy resources is highly dependent upon weather, such as cloud cover, wind speed and direction, etc., which cannot be easily predicted.

1.5 Hierarchical Load Forecasting

1.5.1 Top-down Load Forecasting

Traditionally, utilities take a top-down approach to long term load forecasting. The forecasts are developed by the analysts in a forecasting team providing services to the corporate offices. While the data is often collected from different corners of the organization and may be broken down by geographical areas, the forecasts are not generated by regions. Usually the finest resolution of the forecasts is at revenue class level. Different revenue classes may not share the same model.

The top-level load forecasts are typically developed as follows:

1) Developing weather indices for the entire service territory. Some frequently used weather indices include hourly temperature, max/min daily temperature, max/min monthly temperature, average daily temperature, average monthly temperature, heating degree days (HDD), cooling degree days (CDD), and so forth.
2) Developing macroeconomic indices for the entire service territory. Some frequently used macroeconomic indices include Gross State Product (GSP), Gross Metropolitan Product (GMP), Gross Domestic Product (GDP) by county, GDP by industry sectors, number of customers served by the utility, total population in the territory, price of electricity, interest rate, housing stock, and so forth.

3) Developing model(s) for each revenue class. Different revenue classes may have different response to the variables mentioned above. For instance, residential load usually has a higher correlation with temperature variables than the industrial load.
4) Developing scenarios through the forecasting horizon. The scenarios can be based on weather conditions, economy growths, energy policies and so forth.
5) Developing scenario based load forecasts for each revenue class. Then aggregating the revenue-class level load forecasts by scenario to obtain the scenario based top-level load forecasts.

After the top-level load forecasts are developed and approved by the corporate senior management team, they are then broadcasted to the organization for their planning and budgeting activities.

The main advantage of taking this top-down approach includes the following three aspects:

1) Efficient. The forecasting process is conducted with minimal number of iterations. There is minimal redundancy and duplication in the process.
2) Consistent. Since the forecasts are being developed by the same team year after year, there is usually a good business continuity inherited in this process. Very often the forecasts are well documented. Since all the data streams come to the same central location, all the forecasts can be developed based on the same version of data.
3) Serving corporate management needs. Being developed by the team serving corporate senior management, the forecasts are born to be useful for corporate business management.

1.5.2 Bottom-up Load Forecasting

A major shortcoming of the aforementioned top-down load forecasting process is the lack of accuracy on local forecasts. If two customers belong to the same revenue class, their historical load will be summed together for top-down load forecasting regardless of where these two customers are located. If a utility's territory is large enough, customers in different corners of the territory may very well be in different climate zones. The "one size fits all" approach may not generate good models for any sub-regions. Moreover, the local planners often have more insights about the local business and recent movement of the big loads. Such information is often lost or ignored in the stream up to the corporate office.

Therefore, some utilities take a bottom-up approach to load forecasting:

1) At the beginning of the planning cycle, each local planner or planning team conducts a local planning study to come up with a local load forecast.
2) The local load forecasts are then aggregated, or rolled up, to the corporate level.
3) The forecasting team at the corporate service office converts the bottom-up load forecasts to revenue class level forecast.

The major difference between the top-down forecast and bottom-up forecast is that the former aggregates historical data first, while the latter aggregates the forecast. Most of the time, if not always, the aggregated forecasts are too high to be useful. This is mainly due to the following reasons:

1) Planners tend to be conservative and try to avoid the consequences of under forecasting, so that local load forecasts are often higher than necessary.

2) The sum of extreme local load forecasts is an unrealistic extreme at the top level, because the sub-regions will never peak at the same time.

In addition, the bottom-up forecasting process suffers where the top-down approach excels:

1) Inefficient. There will be multiple teams with similar skill set developing forecasts for different sub-regions. Very often, the same data set has to be duplicated dozens of times by the teams for each local load forecast. The forecasting process rarely stops at step #3 without iterations. Since the aggregated local forecast is often too high, there has to be another round(s) of negotiations between the local and top levels.

2) Inconsistent. It is very difficult to ensure that each local forecasting personnel or team is using the same data sources and following the same standard when generating future scenarios.

3) Not meeting corporate management needs. While each load forecast has been developed to maximize the benefit of a sub-region, they are not designed to serve the business needs of the corporate.

1.5.3 Hierarchical Load Forecasting

Over the past decades, the utility industry including the research community has been looking for an optimal solution to load forecasting, which can preserve the pros of top-down approach. Meanwhile, such a solution should well capture the salient features at the sub-regional level. The latter condition requires developing customized models for each of the sub-regions. When the number of sub-regions is getting large, the solution will have to rely on modern IT infrastructure.

The answer is hierarchical load forecasting, or load forecasting with hierarchical information, such as geographic hierarchy, temporal hierarchy, circuit connection hierarchy, and revenue class hierarchy. Hierarchical load forecasting provides load forecasts at various levels of the hierarchy, which offer the utilities more insights into the power systems and the customer usage patterns than the traditional top-down or bottom-up load forecasts. The availability of data varies depending upon the stage of smart meter deployment. In the U.S., most utilities, even without any smart meters, have hourly load data down to distribution substations via Supervisory Control And Data Acquisition (SCADA) systems. The ones with smart meters deployed have hourly or sub-hourly load data down to the households. Utilities need forecasts at low voltage level so that they can better perform distribution system operations, such as circuit switching and load control. Even at the Independent Systems Operator (ISO) level, leveraging the hierarchical load and weather information at zonal level can help enhance the load forecasting accuracy of the aggregated loads (Lai & Hong, 2013). Hong, Pinson & Fan (2014) proposed six challenges to hierarchical load forecasting. Two of the major challenges are how to utilize the hierarchical structure of the load, and how to utilize multiple weather stations spread across a large geographic area.

The literature on hierarchical load forecasting is limited. There are a few major milestones in this area. Hong (2008) implemented a hierarchical trending method for spatial load forecasting at a medium size U.S. utility, which involved fitting S curves for the 3000 plus small areas and their aggregated levels through a constrained multi-objective optimization formulation. Fan, Methaprayoon, & Lee (2009) reported the results of a multi-region forecasting project at a Generation and Transmission (G&T) co-op. While the project aimed at high voltage load forecasting, the methodology was to look for optimal combination of the regions to improve forecasting accuracy. Average of all weather stations was used in that study. Hong et al. (2010) presented a simulation study showing the effect of historical temperature data uncertainties on load forecasting accuracy. Lai & Hong (2013) reported an empirical hierarchical load forecasting case study based on ISO New England data, which included several ways of averaging weather stations and grouping loads.

IEEE Working Group on Energy Forecasting organized the Global Energy Forecasting Competition (GEFCom2012), which included a track on hierarchical load forecasting. The competition problem was to backcast and forecast the loads of 20 zones and their sum with temperature information from 11 weather stations. Hong, Pinson & Fan (2014) offered an overview of the methodologies used by 11 entries of the hierarchical load forecasting track. The 4 winning teams also published their solutions in the International Journal of Forecasting (Charlton & Singleton, 2014; Lloyd, 2014; Nedellec, Cugliari, & Goude, 2014; Ben Taieb & Hyndman, 2014).

2. Incorporating Risk Analysis into Load Forecasts

2.1 Concerns about Over-forecasting and Under-forecasting

2.1.1 All Forecasts Are Wrong

Forecasting, by nature, is a stochastic problem rather than deterministic. There is no "certain" in forecasting. Things like "the sun will rise tomorrow" are not forecasts. Since the forecasters are dealing with randomness, the output of a forecasting process is supposed to be in a probabilistic form, such as a forecast under this or that scenario, a probability density function, a prediction interval, or some quantile of interest. In practice, many decision making processes today cannot yet take probabilistic inputs, so the most commonly used forecasting output form is still point forecast, e.g., the future expected value of a random variable.

Due to the stochastic nature of forecasting, the response variable to forecast is never 100% predictable. When guessing the head or tail of a coin, the guess may be right a few times, but the probability that it is always right is zero. The question like "why is the forecast different from the actual?" should not be asked, because some differences between the forecasts and actual values are expected. Instead, it is questionable if the forecasts are exactly the same as actual. On the other hand, it is fair to ask "why does the forecast fail to capture XYZ features from the actual?" It requires the person who raises the question to identify the missing features first. There are plenty of other factors that may cause wrong forecasts, such as bad data, inappropriate methodologies, and substandard software, etc. It's the forecaster's job to apply best practices to avoid these avoidable issues.

2.1.2 Concerns about Biased Forecasts

A forecast bias refers to consistent differences between the actual observations and the forecasts of those quantities. A normal property of a good forecast is that it is not biased. If a forecast is consistently higher than actual observations, it is called “over forecasting”. If it is consistently lower than actual observations, it is called “under forecasting”. The “NERC Fan” discussed in Section 1 is an example of over forecasting. Note that over or under forecasting does not mean that all the forecasted values throughout the forecast horizon are higher or lower than the corresponding actual ones. A typical measure of bias of forecasting procedure is the arithmetic mean or expected value of the forecast errors. Figure 2-1 below shows examples of unbiased forecast, over forecast, and under forecast.

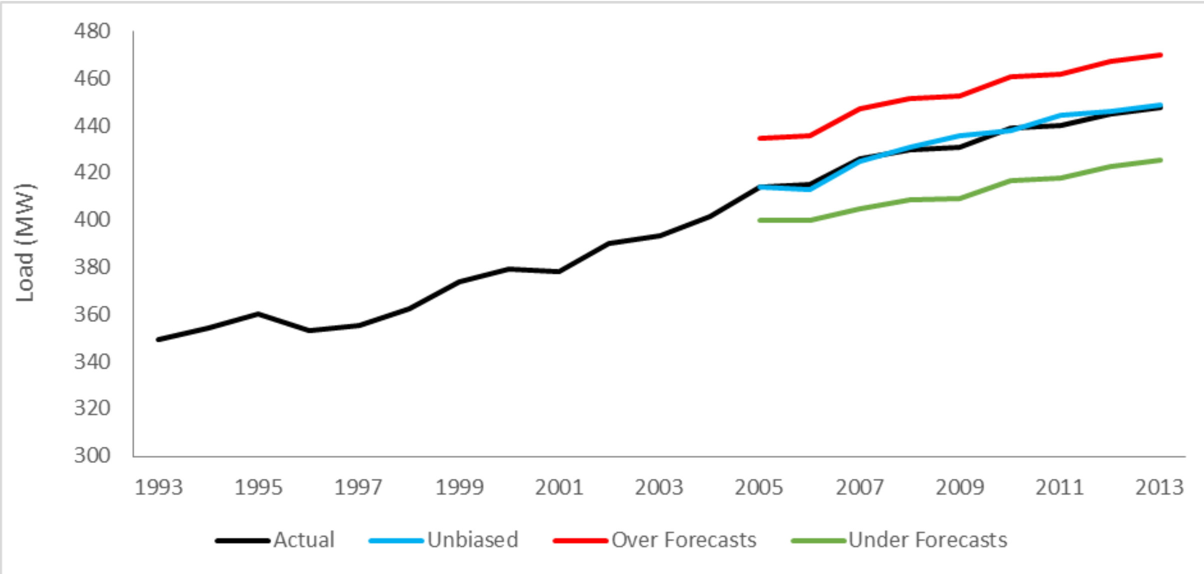


Figure 2-1: Three forecasts vs. actual load

Since the applications of load forecasts spread across the entire utility industry, over or under forecasting of the load has various consequences to the operations and planning of utility business and power systems. Table 2-1 lists the consequences of over and under forecasting by application.

Table 2-1: Consequences of over and under forecasting by application

Application	Over Forecasting	Under Forecasting
Financial forecasting	• Over estimating spending on upgrading infrastructure • Acquiring more business units than the actual situation • Increasing rates more than it should be to maximize profit • Hiring more people than necessary	• Under estimating spending on upgrading infrastructure • Acquiring less business units than the actual situation • Decreasing rates more than it should be to maximize profit • Hiring less people than necessary
Generation planning	• Investing in more generators or larger new generators • Better reliability with higher cost	• Investing in less generators or smaller new generators • Worse reliability with lower cost
Transmission planning	• Investing in more transmission lines or larger capacity of the lines than necessary • Better reliability with higher cost	• Investing in less transmission lines or smaller capacity of new lines than necessary • Worse reliability with lower cost • More congestion in the area which is significantly under forecasted
Distribution planning	• Investing in more distribution substations or higher capacity than	• Investing in less distribution substations or lower capacity than

	necessary • Building more distribution lines than necessary • Better reliability with higher cost	necessary • Building less distribution lines than necessary • Worse reliability with lower cost
Cost-of-service allocation	• Higher cost of service	• Lower cost of service
Rate design	• Set the rates not high enough • Forecasted electric sales higher than actual • Significant discrepancy between actual load and forecasted load	• Set higher rates than enough • Forecasted electric sales lower than actual • Significant discrepancy between actual load and forecasted load
Demand response (DR)	• More load to be shifted and less monetary reward for households and commercial consumers participating in grid management under the assumption of over forecasting	• Less load to be shifted and less monetary reward for households and commercial consumers participating in grid management under the assumption of under forecasting
Energy efficiency (EE)	• Promoting and investing in energy efficient programs more than necessary	• Not enough promotion for or investment in energy efficiency programs • Missing the best time to install the energy efficient equipment • Missing the opportunity to improve later on energy efficient technologies

2.2 Treatment of Weather in Load Forecasting

Weather refers to the present condition of the meteorological elements, such as temperature, humidity, wind, rainfall, cloud cover, thunderstorm, etc., and their variations in a given region over periods of up to two weeks. Climate encompasses these same elements in a given region and their variations over long periods of time. In load forecasting, weather is often used to refer to meteorological elements in general. As an important driver of the load, we discuss how we treat weather in load forecasting.

2.2.1 Load vs. Temperature: Piecewise Linear, Quadratic, or Cubic?

Among all of the meteorological elements mentioned above, temperature contributes the most to majority of load forecasting problems. Very often, temperature variables alone can help explain more than 70% of the variation of the load. The scatter plot in Figure 2-2 below shows a typical load and temperature relationship, which can be described as a "Nike" shape. On the left side, lower the temperature results in higher load. On the right side, higher temperature also results in higher load.

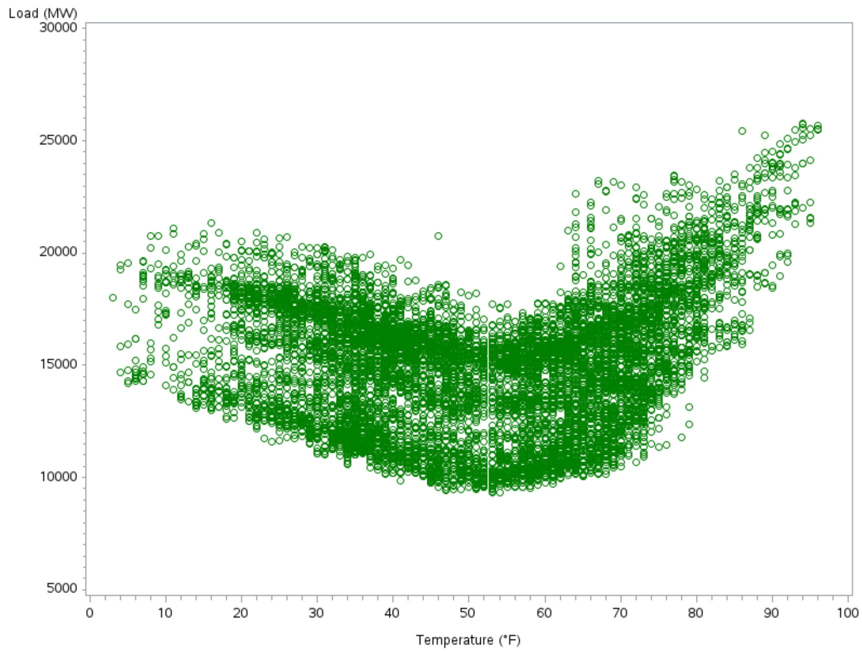
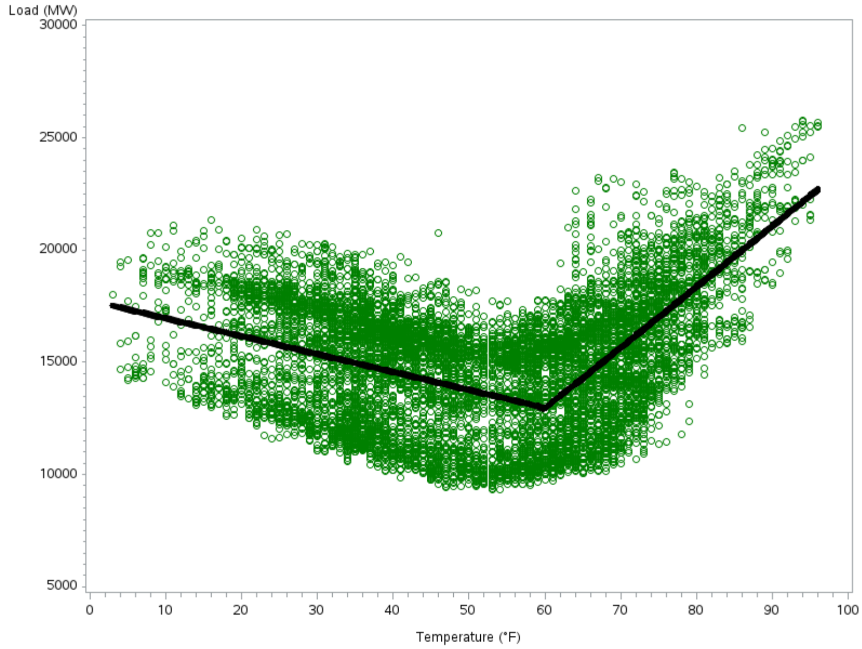


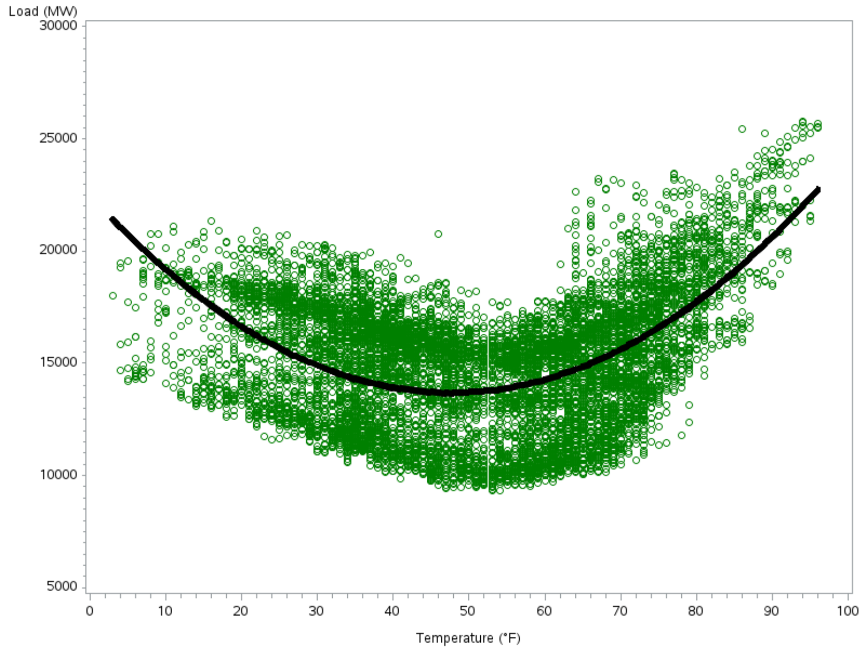
Figure 2-2: Scatter plot for a typical load and temperature relationship

As shown in Figure 2-3 below, there are several ways to model such a shape using regression analysis:

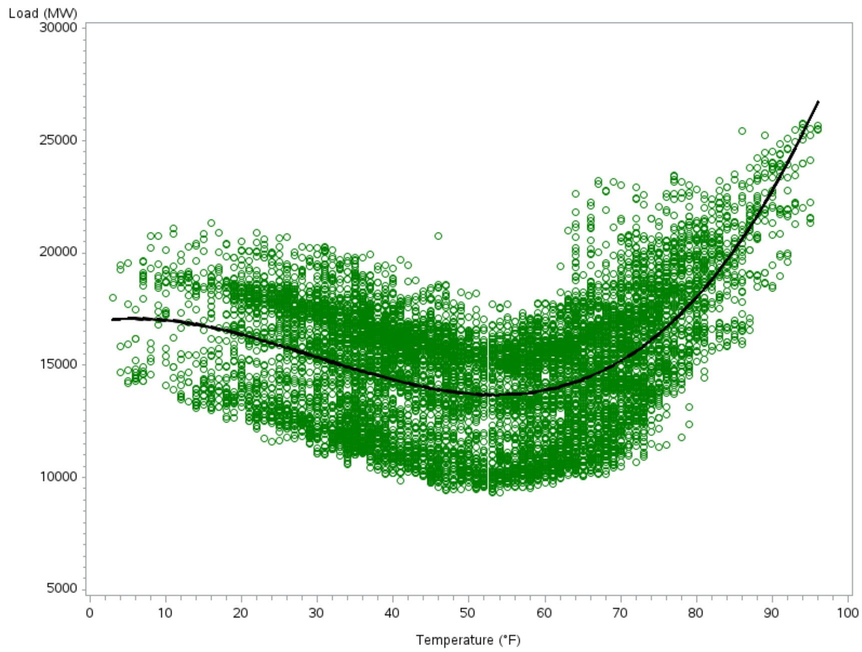
1) Piecewise linear models. As shown in Figure 2-3(a), the Nike shape can be modeled by first identifying a cut-off (or more than one cut-off points), and then using straight lines to fit the observations in each segment.
2) 2^{nd} order polynomial regression models. As shown in Figure 2-3(b), the Nike shape can be modeled with a 2^{nd} order polynomial function.
3) 3^{rd} order polynomial regression models. As shown in Figure 2-3(c), the Nike shape can be modeled with a 3^{rd} order polynomial function.


Load (MW)
30000
25000
20000
15000
10000
5000
0
10
20
30
40
50
60
70
80
90
100
Temperature (°F)

(a)


Load (MW)
30000
25000
20000
15000
10000
5000
0
10
20
30
40
50
60
70
80
90
100
Temperature (°F)

(b)



(c)

Figure 2-3: Three different functions for a typical load and temperature relationship

The advantage of polynomial regression models over piecewise regression models is that there is no need to identify the cut-off point(s), i.e., how many cut-off points are needed and where these cut-off points should be. For load forecasting, 3rd order polynomial models are preferred over the 2nd order polynomial models, because the Nike shape is usually asymmetric. The 2nd order polynomial models can only produce symmetric shapes.

2.2.2 Interactions between Temperature and Calendar Variables

Since temperature is generally high during the day and low at night, and is high in summer and low in winter, there exist interactions between temperature variables and calendar variables such as *Hour* of the day and *Month* of the day. As shown in Figure 2-4 below, the Nike shape in each of the 24 hours is slightly different. Same analogy applies to the load-temperature scatter in each of the 12 months as shown in Figure 2-5.

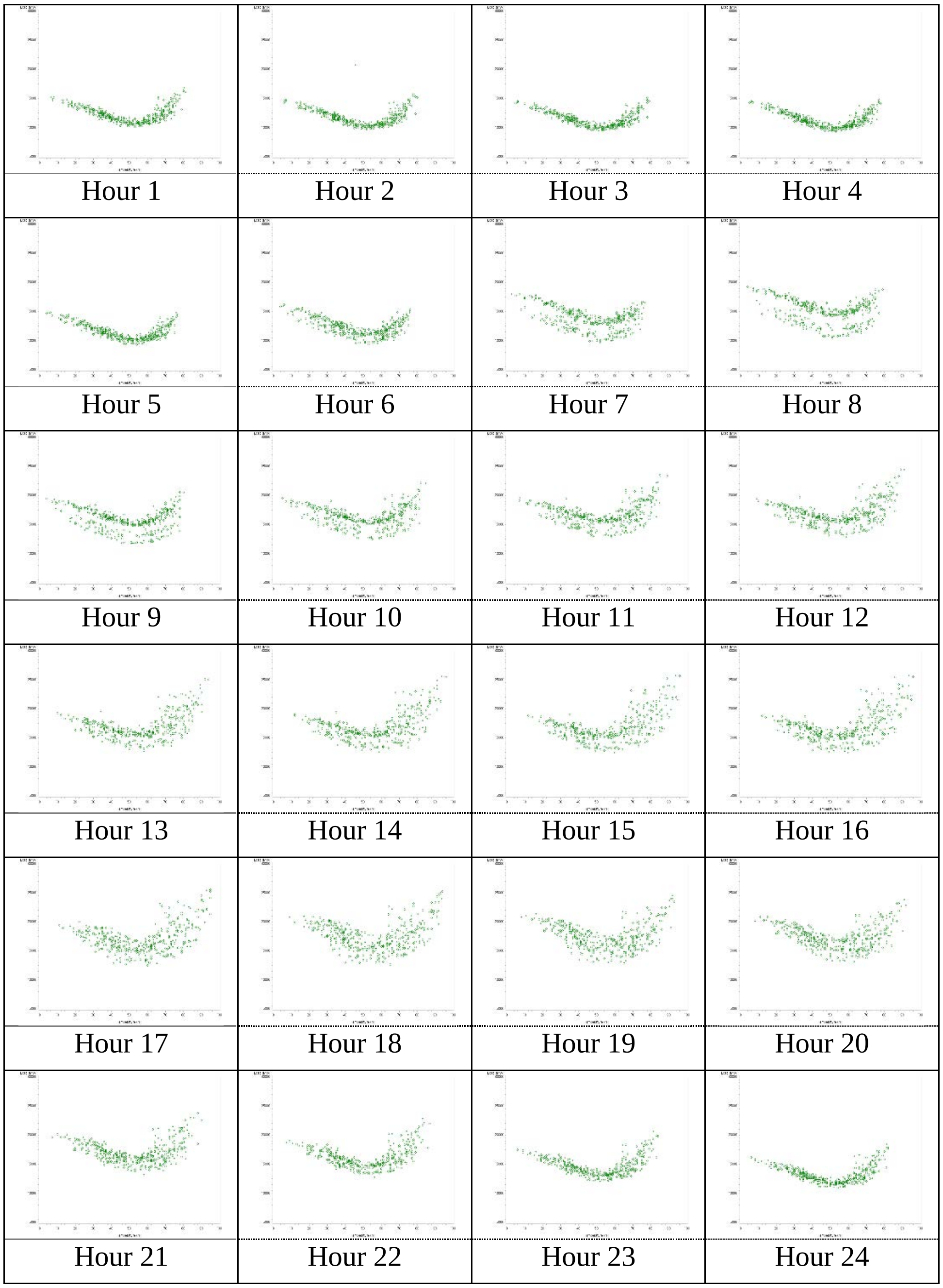


Figure 2-4: Hourly scatter plots for a typical load and temperature relationship

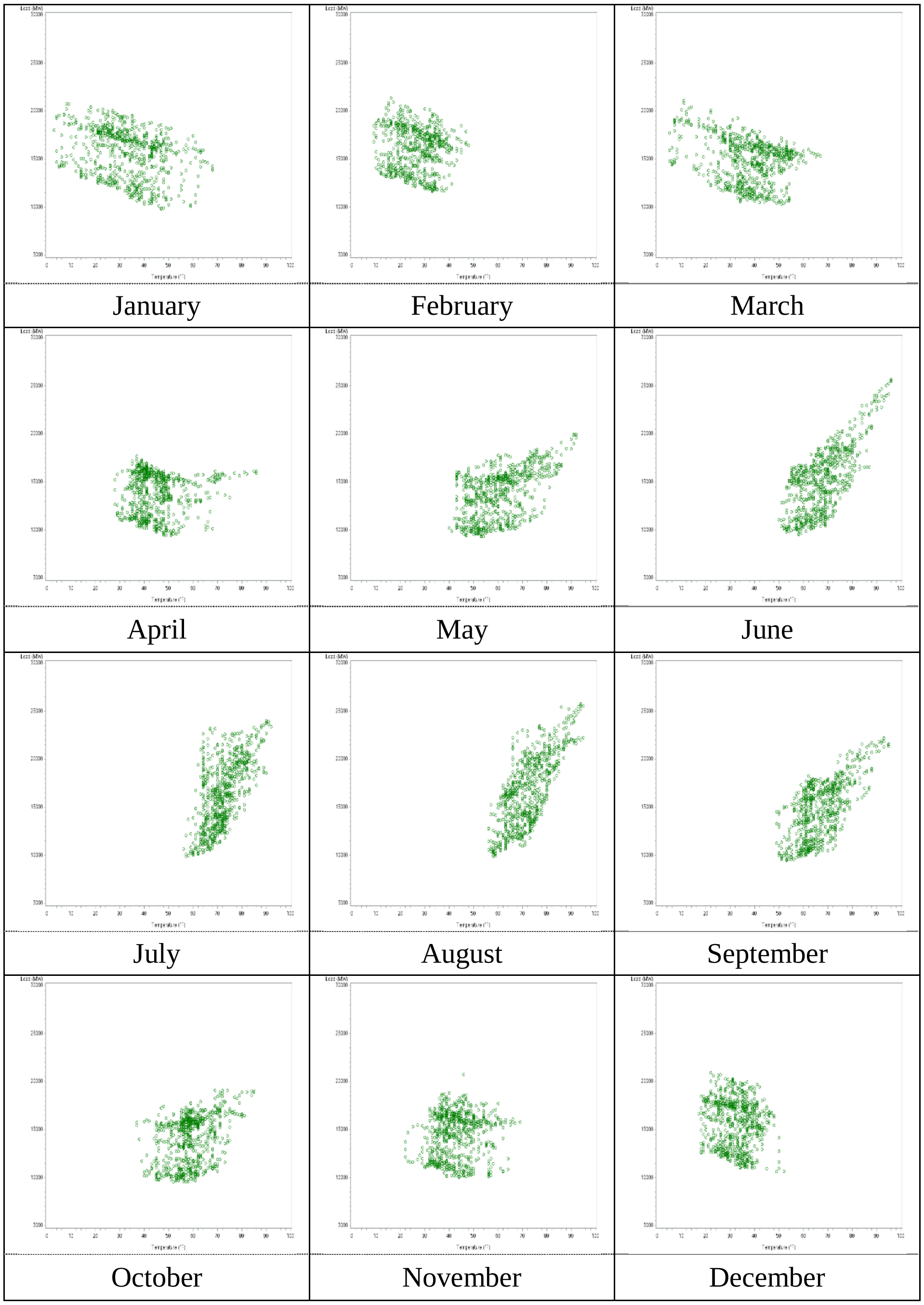


Figure 2-5: Monthly scatter plots for a typical load and temperature relationship

2.2.3 Lagged Temperature Variables

While the temperature of the current hour directly affects the load, the temperatures of the preceding hours also affect the load. This phenomenon was referred as recency effect in (Hong, 2010). Recency effect is a term originally used in psychology, which means that human beings tend to remember the most recent events more clearly than the previous ones.

Two most popular ways of using preceding hour temperatures are lagged temperature variables and average temperatures of previous days. That latter one can be written as:

$$T_{avg,d} = \frac{1}{24}\sum_{i=24d-23}^{24d} T_{t-i}$$

where $T(t)$ denotes the temperature of hour t; $T_{avg,d}$ denotes the average temperature of the dth 24-hour period.

In (Hong, 2010), the author also used exponentially weighted temperature to assign higher weights to the recent hour temperatures:

$$T_w = \frac{\sum_{k=1}^{24} \alpha^{k-1} T_{t-k}}{\sum_{k=1}^{24} \alpha^{k-1}}$$

where α is the base for the exponential weights with the typical range from 0.8 to 1..

2.2.4 Other Weather Variables

Other metrological elements, such as humidity, wind speed, cloud cover, also have varying degrees of effect on the load. It is worth mentioning that these weather variables are used differently for short term versus long term load forecasting.

In short term load forecasting, weather forecasts throughout the forecasting horizon are used to produce load forecasts. The accuracy of weather forecasts affects the accuracy of load forecasts. Although some of the weather variables, i.e. wind speed, can add some predictive power to the load forecasting model, they are very difficult to predict beyond a few hours. Therefore, there is a tradeoff between the information added from the additional weather variables and the noise introduced by the errors in these weather variables. Extensive out-of-sample tests and field tests should be performed to justify the inclusion of weather variables. The conclusion may vary depending upon the features presented by the data. Most utilities, for short term load forecasting solutions in the field, would use temperature variables. Some utilities may use additional weather variables.

Many key weather variables can hardly be predicted beyond two weeks. Therefore, weather forecasts in medium and long term load forecasting are rarely used. Instead, a simulation approach is preferred, where how the weather would look in the future is simulated based on the historical weather information. This simulation may create many weather scenarios, ranging from ten to thousands of scenarios. By plugging in the simulated weather scenarios to the load forecasting models, scenario based load forecasts can be generated. A rigorous study is not yet available to show that including weather variables other than temperature variables would definitely benefit long term load forecasting.

When developing models based on low resolution load data, weather variables should be converted to match the resolution of the load data. For instance, if load data is at monthly interval, the corresponding weather variables should have the same or lower resolution, such as heating degree days, cooling degree days, monthly max/min temperature, and monthly average temperature.

2.3 Incorporating Feedbacks and Elasticities into Load Forecasting

2.3.1 Feedbacks in Load Forecasting

Since forecasting is a stochastic problem by nature, we rarely see two forecasters producing exactly the same forecasts. Because all forecasts are wrong, we often see forecasters arguing about the forecasts and trying to convince the others to believe one forecast or the other. In load forecasting, there is often disagreement between different departments or different forecasting teams. A list of several situations when feedbacks should be included in revision of the original forecast is provided below:

1) Errors were found in one of the key data sources.
2) Additional important information was not considered in the forecast. For instance, a large data center is moving into the service territory.
3) Forecasts are shown to be higher than physical limit of the end use.

We have to recognize the difference between load forecasting with feedbacks and fraudulent forecasting. Feedbacks are used to correct and/or improve existing forecasting processes without any consideration of personal agenda. Fraudulent forecasts are often developed from non-scientific forecasting process that violates forecasting principles to satisfy the personal agenda of someone. An example of fraudulent forecasting:

One of the high tech companies asked the utility for a new distribution substation to ensure a highly reliable service to its data centers. After analyzing the power systems near downtown, the planning team concluded that the annual load growth has to be as high as 3% to justify the addition of the substation. This high tech company lobbied the executives of the utility, who then put a big pressure on the forecasting team. Under the pressure, the forecasting team added two dummy variables to the recent two years with low peak demand to create the 3% annual growth.

An easy way to spot the fraudulent forecast and plan is to check which one comes first. In a legitimate case, the plan should always come after the forecast. Otherwise, it is a fraudulent case.

2.3.2 Price Elasticities in Load Forecasting

Price elasticity of demand is a measure used in economics to show the responsiveness of the quantity demanded of a good or service to a change in its price. More precisely, it gives the percentage change in quantity demanded in response to a one percent change in price. Considering electricity as a good or service, we would expect to estimate the price elasticity of electricity demand. In theory, the higher the rate is, the more conservative the electricity consumption behavior is.

In reality, because electricity is already a societal necessity, it has been priced at a relatively low rate to be only a very small portion of a family's total spending. Small fluctuation of electricity rate may not change the electricity consumption behavior of many customers. Namely price elasticity would be zero in this case. On the other hand, rising electricity price may change the behavior of low-income families, for whom the electricity bill takes a large portion of the family's spending. Overall, family income could be a driving factor of price elasticity.

In load forecasting, price elasticity has to be considered on a case by case basis:

1) When load forecasting is conducted at the planning coordinator level, the effect of price elasticity is often not observable.
2) When load forecasting is conducted at revenue class level, the effect of price elasticity may be observed for some revenue classes.
3) When demand response programs, such as time of use rate or critical peak rebate programs, are implemented, price elasticity is dependent upon the scale of demand response implementation.

2.4 Treatment and Quantification of Economic Forecast Risk

Economic variables can be included in a load forecasting in different forms, such as additive, multiplicative, and interactions.

When the economic variables are treated in an additive form, e.g.,

$$\text{Load} = f(\text{weather variables}) + g(\text{calendar variables}) + h(\text{economic variables}) + e$$

A simple example can be written as follows:

$$\text{Load} = \beta_1 T + \beta_2 T^2 + \beta_3 T^3 + \beta_4 \text{Hour} + \beta_5 \text{Weekday} + \beta_6 \text{Month} + \beta_7 \text{GSP} + e$$

If economy (i.e., Gross State Product, GSP) forecast is off by δ, the load forecasting error due to GSP forecasting error would be $\beta_7\delta$.

When the economic variables are treated in a multiplicative form, e.g.

$$\text{Load} = f(\text{weather variables})\, g(\text{calendar variables})\, h(\text{economic variables})\, U$$

A simple example can be written as follows:

$$\text{Load} = (\beta_1 T + \beta_2 T^2 + \beta_3 T^3)(\beta_4 \text{Hour} + \beta_5 \text{Weekday} + \beta_6 \text{Month})(\beta_7 \text{GSP}) U$$

If GSP forecast is off by *x*%, the load forecasting error due to GSP forecasting error would be *x*%.

Very often, the load forecasting models are not as simple as the ones mentioned above. The economic variables can be included in the model as interactions with other variables, such as the example below:

$$\text{Load} = \beta_1 T\ \text{GSP} + \beta_2 T^2\ \text{GSP} + \beta_3 T^3\ \text{GSP} + \beta_4 \text{Hour} + \beta_5 \text{Weekday} + \beta_6 \text{Month} + \beta_7 \text{GSP} + e$$

In this case, sensitivity analysis should be performed to understand how errors in the economic forecast are translated into errors in load forecast.

3. Types of Load Forecasting

3.1 Residential Load Forecasting

Residential customers include private households that use energy for heating, cooling, cooking, lighting, small appliances. Among all customer classes, residential customers have the most weather responsive electricity consumption behavior. Although the load of an individual residential customer can be quite stochastic (Figure 3-1), residential load aggregated to the revenue class level is more predictable than the loads of other customer classes. Therefore, we usually apply advanced statistical models for residential load forecasting. A residential load forecasting model typically includes many variables such as weather, calendar, and population.

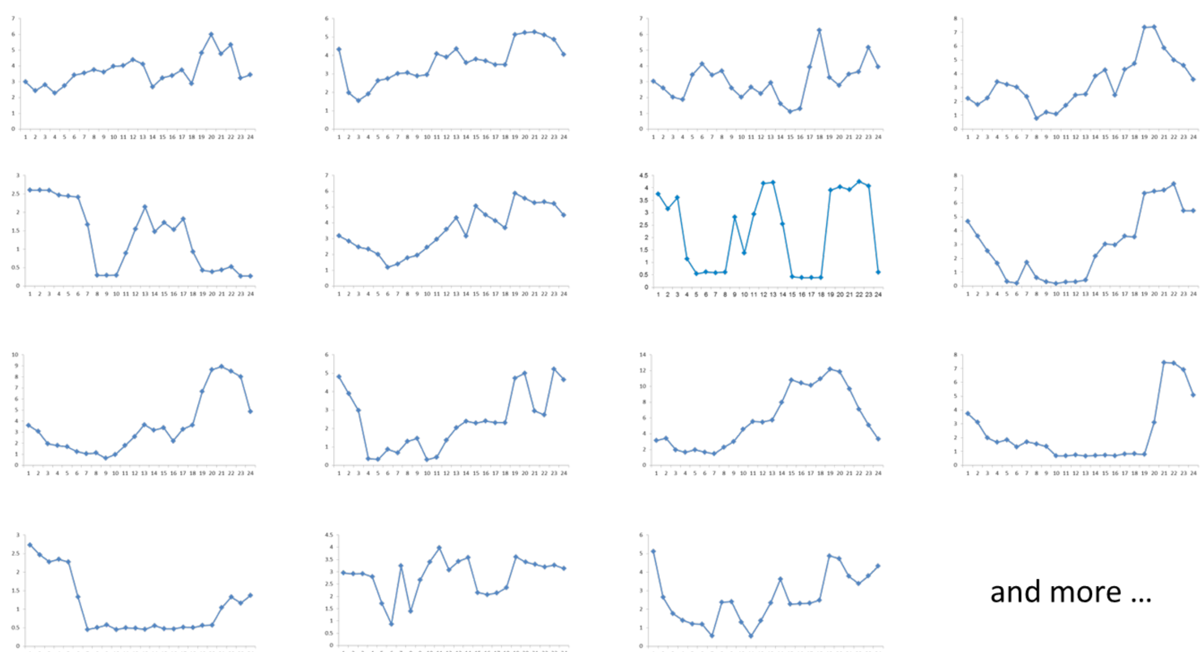


Figure 3-1: Diverse daily residential load profiles

Before the smart grid era, most meters were being read once a month. The energy usage of most residential customers was in monthly load series. Because the meters were not read at the same time, load forecasters had to first convert thousands of load series from billing month to calendar month. This task required load profiles at hourly or daily interval. To develop these load profiles, a utility had to install a small sample of interval meters taking daily or hourly readings. The number of interval meters had to be large enough to be used to infer the load profiles of all residential customers. The process of using readings from a small number of interval meters to develop load profiles of all residential customers is called load profiling.

Another important aspect of residential load forecasting is appliance saturation survey, which requests households to provide information on appliances, equipment, and general consumption patterns. The survey usually results in the number of households with end-use saturation. Such information is very important in estimating the peaks. For instance, without the constraints of end-use saturation, the demand would grow at the same rate as the temperature increases during hot summer days, which may lead to over-forecast of the peak load. Other than the saturation factor, the efficiency of air conditioning systems and differences in individual's temperature preferences are also important outcomes of the survey studies.

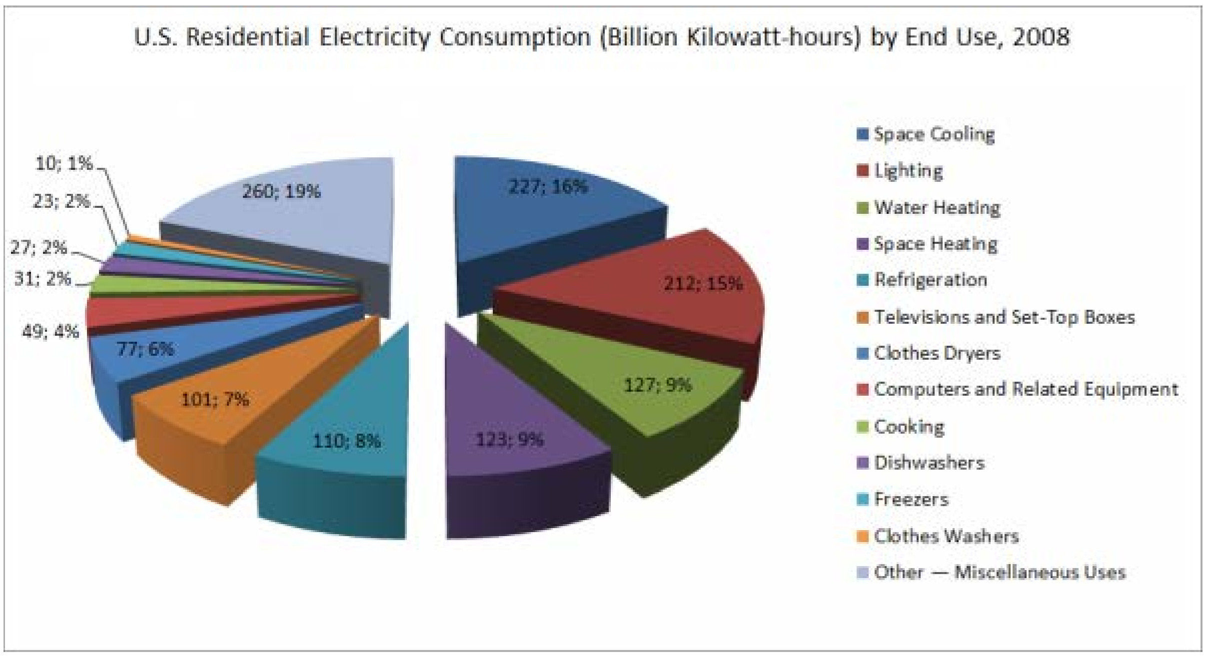


Figure 3-2: Sample U.S. residential electricity consumption

3.2 Commercial Load Forecasting

Commercial customers are those customers not involved in manufacturing, such as retail stores, restaurants, hotels, and educational institutions. Commercial customers can be roughly divided into two sub-classes, small commercial and large commercial customers. The cut-off is generally based on the peak load of 50kW during any 12-month period.

Load forecasting for small commercial customers is similar to residential load forecasting, because small commercial customers usually have close response to weather. Load forecasting for large commercial customers requires customized efforts depending upon the type of business. In addition to weather, most large commercial loads are significantly affected by the business schedules. Some of them have strong seasonal patterns. For instance, the load of hotels in a vacation area is mainly affected by tourism demand during holiday seasons, while the load of hotels in central business district responds to the local economy and major conferences.

The load of education institutions also has its own characteristics. At diurnal level, the schedule of students is different from working professionals. For instance, many students stay up late. Therefore, daily peaks of student dorms often occur close to midnight. At annual level, education institutions follow academic calendars. The load level is low during academic holidays.

Another special load is from agriculture customers, who need to pump water for irrigation, keep the animals warm during extreme cold periods, and dry grain. Since time of the day may not be critical to some of these agriculture needs, farmers given enough incentives can schedule some activities to a period designated by the utility. For agriculture load forecasting, detailed information about the type of farming or dairy operations in addition to historical load and weather information is needed.

In recent years, the growing demand of information technologies leads to increasing number of data centers. There are two key characteristics of a data center: 1) the CPUs have to be on all the time; and 2) the temperature of data centers has to be maintained within a certain range, i.e., 68 to 72 degrees Fahrenheit. Some data centers are operated at temperatures as low as 55 degrees. These characteristics make the data center load very much driven by temperature. Therefore, the load profile of data centers can be verypredictable.

3.3 Industrial Load Forecasting

There are several factors affecting the load of an industrial customer, such as facilities, business types, production levels, electricity rates, customer-owned generation, and production schedule. Figure 3-3 shows the industrial load zone of a U.S. utility. Since there are not only one or two major driving factors highly correlated with the load, the industrial load is very unpredictable. Industrial load forecasting can be performed based on the end use of industrial subclasses.

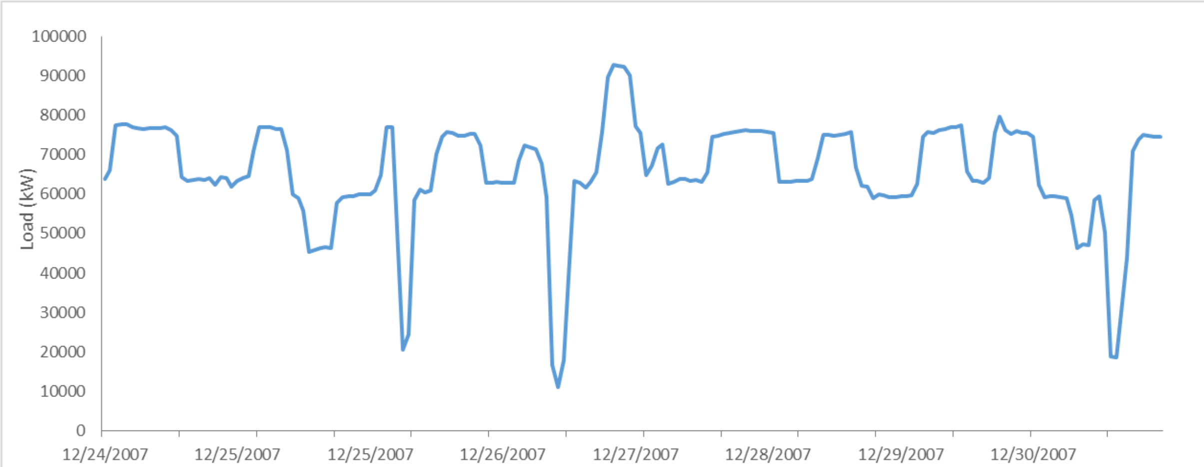


Figure 3-3: Hourly load profile of an industrial customer

3.4 Load Forecasting for Other Loads

3.4.1 Electric Vehicles

In the past several years, automobile manufactures have launched several models of electric vehicles (EVs) in North America. Although the manufacturers have announced plans for mass production of EVs in the near future, there are still uncertainties around the timing and extent of large-scale adoption of EVs.

EVs are one prominent example where miscellaneous sales growth could affect the forecast of energy sales. The EV sales are also a category of sales with a great deal of uncertainty. The EV sales are driven by many variables, such as driving-age population, government subsidies, gasoline and electricity price forecasts, and efficiencies for both electric and conventional vehicles.

The EV sales affect the EV load of a large region, while the EV sales and driving patterns together affect the EV load of a small area. The driving patterns are also affected by the availability of charging stations, local business schedule, driving distance, and so forth (Duan, Gutierrez, & Wang, 2014).

3.4.2 Customer-Owned Generation and Energy Storage

Traditionally, positive loads from low level(s) are aggregated to high level for electric load forecasting. When customer-owned generation is involved, it can be treated as negative demand. There are several types of customer-owned generation that require different treatments in load forecasting:

- Unmetered roof-top PV panels. Some utilities do not measure roof-top PV generation. Instead, the meter measures the net demand (actual demand minus solar generation). In this situation, the higher the penetration level of PV panels, the more challenging it is to forecast the load. Weather variables such as cloud cover and solar radiation can be included in the load forecasting models.
- Metered roof-top PV panels and small/medium solar farms. Some utilities measure both PV generation and net demand. In this case, the load forecasting process can be divided into two threads, forecasting the actual demand and forecasting solar generation. Since the solar generation series on a house can be quite noisy, it is recommended to aggregate the solar generation from household level to a region to obtain a less volatile profile for forecasting purposes. Some industrial and commercial customers have their own small/medium solar farms, which are metered by the utilities. The generation of those solar farms can be forecasted separately from the industrial/commercial load.
- Backup generators. Some industrial and commercial customers have their own backup generators to protect their business operations during power outages. Given enough incentives, some of these customers would enroll in the demand response programs. During special events, such as price spike periods, they can turn on the backup generators per request of the utilities. Since these DR programs are not being called regularly, DR effect can be estimated using historical load in the regular hours, and can be accounted for in future demand side management planning.

Renewable energy resources such as wind and solar energy are known to be highly intermittent and volatile, which creates significant challenges to power systems operations. One of the solutions is to place energy storage together with renewable generation. From the perspective of forecasting, energy storage acts as a smoother to the renewable generation series. In other words, smoothed renewable generation can be directly forecasted.

4. Selection of Load Forecasting Horizon

4.1 Basic Principles

4.1.1 Forecast Horizon Starts at Forecast Origin

Forecast origin is the last available point in the historical data. Forecast horizon is the distance between the forecast origin and the furthest point that is being forecasted. Figure 4-1 depicts a one-year ahead load forecasting process. At the beginning of spring 2014, the data up to end of year 2013 is available for load forecasting. Although the forecast is for the 12 months of 2015, the forecast horizon is in fact 2 years.

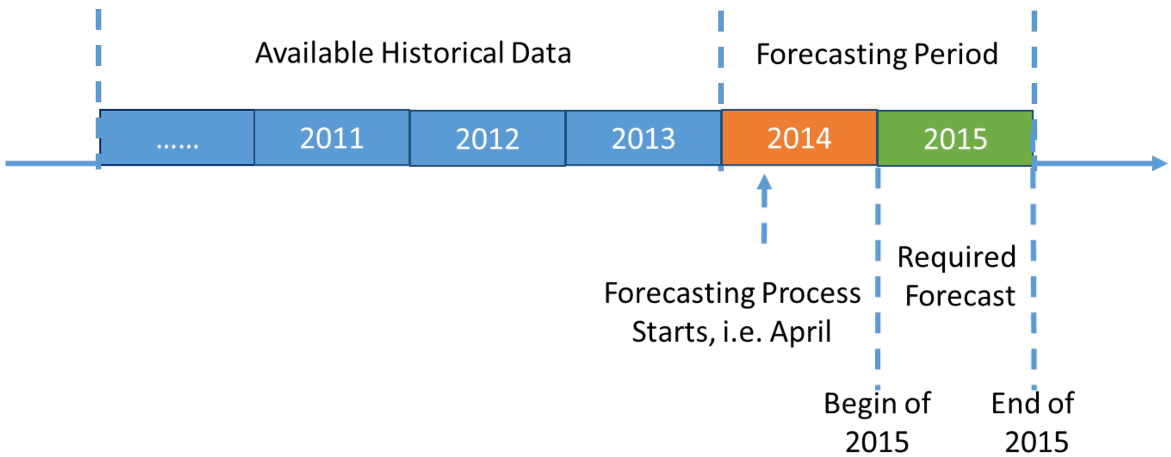


Figure 4-1: One-year ahead load forecasting

4.1.2 Forecast Horizon Should Serve Planning Horizon

The forecast horizon should cover the planning horizon. The planning horizon has to be longer than the lead time. Lead time is the time between the initiation and completion of a process. For instance, the lead time between the decision of replacing a 4kV service transformer and commissioning of a new transformer can be anywhere between a few weeks and two or three months, depending upon the urgency, availability of personnel, equipment supplies, and so forth. For the purpose of building a transmission substation, the lead time can be anywhere between three to five years. If the time to secure the land ahead of time is counted, the lead time can be up to 10 years.

4.1.3 Effective Forecast Horizon is Limited by Data History

In many utility applications, the planning horizon can be beyond 20 years. To cover such a long planning horizon, the forecasting horizon would be 20 years or longer. It should be recognized that the longer the forecast horizon goes, the more unpredictable the load is. There are many factors affecting the predictability through the forecast horizon. An important one is the length of data history. There are several aspects of the relationship between data history and forecast horizon:

1) The business cycle should repeat itself at least two times. To forecast the load of one year, at least two years of history is needed.
2) The data history should be two to three times of the forecast horizon. In other words, to forecast 20 years ahead, 40 to 60 years of history is ideal.

In reality, access to longer than 30 years of load history is rarely available. Even if the load data is available with long history, the very old data may not be useful. This is because the electricity consumption pattern has changed dramatically over the past few decades. In the U.S., forecasters have access to 10 to 15 years of high quality load data, and 30 to 40 years of high quality weather and economy data. These data are good enough for 5 years ahead load forecasting, but not really sufficient for the forecast horizon beyond 20 years.

There are two remedial methods to resolve the insufficient data issue in long term load forecasting:

1) Make the forecast updating cycle less than half of the length of the data history, i.e., 5 years.
2) Develop probabilistic load forecasts, to better describe the uncertainty associated with the load in the long term.

Both methods are being used in the industry today. The first one is already embedded into the business operations. The second one is usually implemented to produce scenario based load forecasts.

4.2 Forecasting Horizons for Utility Applications

Load forecast for financial planning is usually updated every 1 to 5 years with a forecast horizon of 1 to 20 years. For generation and transmission planning, the forecast horizon could be 5 to 30 years as new generators or transmission lines require a long lead time (e.g., over 5 years). The update of load forecast for generation and transmission planning is usually done every 1 to 2 years. The updating cycle and forecast horizon for distribution planning are similar to those for generation and transmission planning, except that the forecast horizon could be as short as 1 year since the lead time for equipment on the distribution level is generally much shorter than that on the transmission level. Load forecast for renewable energy planning has a similar updating cycle and forecast horizon to distribution planning but could have a forecast horizon of up to 30 years, which is typically the life cycle of a renewable energy project. Load forecast for integrated resource planning has longer forecast horizon and is updated less frequently. Table 4-1 below summarizes the forecasting horizon and updating cycle of representative utility applications.

Table 4-1: Forecasting horizon and updating cycle of representative utility applications

	Updating Cycle	Forecast Horizon
Financial Planning	1 – 5 years	1 – 20 years
Generation Planning	1 – 2 years	5 – 30 years
Transmission Planning	1 – 2 years	5 – 30 years
Distribution Planning	1 – 2 years	1 – 20 years
Integrated Resource Planning	3 – 10 years	10 – 50 years
Renewable Energy Planning	1 – 2 years	1 – 30 years

5. Selection of Load Forecasting Tools

5.1 A Brief Review of Load Forecasting Techniques and Methodologies

Many papers in the literature provided reviews of representative load forecasting techniques and methodologies (Abu-El-Magd & Sinha, 1982; Alfares & Nazeeruddin, 2002; Feinberg & Genethliou, 2005; Gross & Galiana, 1987; Hippert, Pedreira, & Souza, 2001; Hong, Pinson, & Fan, 2014; Hong, 2010, 2014; Liu et al., 1996; Metaxiotis, Kagiannas, Askounis, & Psarras, 2003; Moghram & Rahman, 1989; Taylor & McSharry, 2007; Taylor, 2008; Tzafestas & Tzafestas, 2001; Weron, 2006; Willis & Northcote-Green, 1983). Here the word "technique" refers to a group of models that fall in the same family, such as Multiple Linear Regression (MLR) models, Artificial Neural Networks (ANN). On the other hand, "methodology" represents the general solution framework that can be implemented with multiple techniques. For example, a variable selection methodology may be applicable to both MLR models and ANNs. While both techniques and methodologies are important to the load forecasting practices, the literature has been dominated by papers focusing on various techniques and their combinations. The original research on load forecasting methodologies is quite limited.

5.1.1 Techniques

In this section, five load forecasting techniques are reviewed, including linear regression models, semi-parametric additive models, artificial neural networks, and univariate models such as Autoregressive and Moving Average (ARMA) models, and exponential smoothing models.

A. Linear Regression Models

Regression analysis is a statistical process for estimating the relationships among variables. Regression models have been used for both STLF and long term load forecasting (LTLF) in the literature. Load or some transformation of load is usually treated as the dependent variable, while weather and calendar variables are treated as independent variables (or explanatory variables). The parameter estimation process relies on the user or forecaster to specify a functional form among these variables.

Hong (2010) proposed a modern approach to applying regression analysis to STLF, where the interactions (or cross effects) among weather and calendar variables were emphasized. The case study was based on a U.S. utility that deployed the models in the production environment. Several special effects were modeled using regression analysis, such as recency effect, weekend effect, and holiday effect. Hong, Wilson, & Xie (2014) developed a linear regression model for LTLF. The linear model was first augmented from a STLF model by adding a macroeconomic indicator. It was then applied to various scenarios to generate the long term probabilistic load forecast. The authors showed that the models based on hourly data had less ex post forecasting errors than the ones based on monthly or daily data.

B. Semi-parameter Additive Models

The semi-parametric additive model is in the regression framework but designed to accommodate some non-linear relationships and serially correlated errors. In particular, such models allow nonlinear and nonparametric terms using the framework of additive models. In load forecasting, these generalized additive models are used to estimate the relationship between load and the explanatory variables: temperatures, calendar variables, etc.

Hyndman & Fan (2010) developed two models to forecast long term peak demand for South Australia, a semi-parametric model for half-hourly demand and a linear model for annual median demand. The natural logarithms were used to transform the raw demand with major industry loads subtracted. The semi-parametric model captured calendar effects, temperature effects, and the effects from demographic and economic factors. The models were then used to generate density forecasts with simulated temperature as inputs.

Goude, Nedellec, & Kong (2014) applied generalized additive models to model electricity demand over more than 2200 substations of the French distribution network, at both short and middle term horizons. These generalized additive models estimated the relationship between load and the explanatory variables including temperatures, calendar variables, and so forth. This methodology demonstrated good results on a case study for the French grid.

C. Artificial Neural Networks

The ANNs have been extensively used for load forecasting since 1990s. ANN is a soft computing technique that does not require the forecaster to explicitly model the underlying physical system. By simply learning the patterns from historical data, a mapping between the input variables and the electricity demand can be constructed, and then adopted for prediction. A number of ANN architectures have been used for load forecasting, such as back propagation, Hopfield, Boltzmann machine, among which the most popular one is back propagation. Researchers have been reporting fairly good results with ANN models, though many of the good results were due to peeking the future. Hippert, Pedreira, & Souza (2001) offered a critical review of the literature in the ANN based load forecasting.

The most successful implementation of ANN models for STLF was from a project sponsored by the Electric Power Research Institute (Khotanzad and Afkhami-Rohani, 1998). The solution was named as ANNSTLF – Artificial Neural Network Short-Term Load Forecaster. This load forecasting system included two ANN forecasters: one predicted the base load and the other forecasted the change in load. The final forecast was computed by adaptive combination of these two forecasts. The ANNSTLF and its improved versions were later commercialized are used by a large number of utilities across the U.S. and Canada.

D. Univariate Models

Exponential smoothing assigns exponentially decreasing weights to the past observations over time. It does not rely on variables other than lagged loads, meaning less data requirements than other widely used techniques such as MLR and ANN. Since the electricity demand is highly driven by weather, changes in weather patterns can greatly affect the load profiles. When the weather condition is quite volatile, the techniques that do not leverage meteorological forecasts are often in a disadvantage situation.

ARMA models provide a parsimonious description of a stationary stochastic process in terms of two polynomials, one for auto-regression and the other for moving average. Since the hourly electricity demand series is well-known to be non-stationary, ARIMA models, a generalization of ARMA models, are often used for load forecasting purposes. The ARMA models can also be generalized to include exogenous variables, called ARMAX models.

5.1.2 Methodologies

A. Similar Day Method

The similar day method is to find a day in the history that is similar to the forecasted day. The similarity is usually based on day of the week, season of a year, and the weather patterns. As mentioned in (Hong, 2014), the similar day method is one of the earliest methods being applied to load forecasting. Even today, many system operators are still having the load and temperature profiles of the representative days hanging on the wall of the operations room. Modern similar day method is often implemented with some clustering techniques. Instead of one similar day, the algorithms may identify several similar days or similar segments of a day, and then combine them to obtain the forecasted load profile.

B. Variable Selection

For many techniques that rely on explanatory variables, an important step is to determine which explanatory variables to use and their functional forms. Hong (2010) proposed a variable selection mechanism and applied it to comparing three different techniques for STLF, such as linear regression, ANN, and fuzzy regression. The results showed that for each of the three techniques, the proposed mechanism was able to gradually reduce the forecasting errors. Several other papers also showed step-by-step refinement to the base models or captured the salient features one by one, though they did not plug in different techniques to the same modeling framework.

C. Weather Station Selection

Since weather is a major driving factor of electricity demand, it is important to figure out the right weather stations for a territory of interest. (Hong, Wang, & White, 2015) is the first original research paper devoted to weather station selection. Two case studies were provided, one based on a field implementation at NCEMC, and the second based on the data from the GEFCom2012. Although regression models were used to illustrate the proposed methodology, the models based on other techniques can also be plugged into this framework.

D. Hierarchical Forecasting

Due to the deployment of smart grid technologies, how to utilize the hierarchies to improve load forecasts becomes an important topic in today's load forecasting community. The literature on hierarchical load forecasting is limited. There are a few major milestones in this area. Hong (2008) implemented a hierarchical trending method for spatial load forecasting at a medium size U.S. utility, which involved fitting S curves for 3460 small areas and their aggregated levels through a constrained multi-objective optimization formulation. Fan, Methaprayoon, & Lee (2009) reported the results of a multi-region forecasting project at a Generation and Transmission (G&T) co-op. While the project aimed at aggregated level load forecasting, the methodology was to look for optimal combination of the regions to improve forecasting accuracy. Average of all weather stations was used in that study. Lai & Hong (2013) reported an empirical hierarchical load forecasting case study based on ISO New England data, which included several ways of averaging weather stations and grouping loads. The concept of hierarchy can be expanded from geographic/spatial hierarchy to temporal hierarchy. And there are many papers in the literature producing 24 forecasts for the 24 hours of a day with 24 different models. Note that none of these hierarchical forecasting methods is constrained on a specific technique. In fact, all of them can be implemented with regression models, semi-parametric models, ANNs, and so forth.

5.2 Load Forecasting Software Tools and Solutions

There are many tools available in the market that may be used for energy forecasting purposes. They all have different learning curves, levels of technical support, depth of forecasting procedures, and price tags. There is not yet one single tool that dominates all metrics. When considering which tools to use, utilities have to evaluate many factors, such as direct (i.e., license and service fees) and indirect costs (salaries and training costs for the users) of the software package, potential value-add, and implementation time. This section introduces several commercial load forecasting tools and solutions that have been widely used in the utility industry. A survey[1] conducted in Oct 2014 identified major vendors that are providing products and services in the load forecasting field.

[1] http://blog.drhongtao.com/2014/10/load-forecasting-software-packages-survey.html

5.2.1 SAS

SAS® Energy Forecasting is built on the SAS family of software products which have been used by electric utilities since 1976. The solution is tailored for electric utility energy and load forecasting, automatically stepping through as many as nineteen models to select the best forecast model. For inexperienced forecasters, the process can be highly automated with few decisions required, while experienced users can expand the models with additional variables or import models into the solution. The SAS Energy Forecasting process is transparent, with model results at all stages of the process available for review and to archive for regulatory documentation.

The solution is tailored for electric utility energy and load forecasting, automatically stepping through an intelligent model selecting methodology which is equivalent to enumerating thousands of model candidates to pick the best.

- Basic models are multiple regression where additional variables and combinations are sequentially tested for model improvement
- Models are tested at each iteration to prevent over-fitting
- Second stage models are developed using UCM, ARIMAX, Exponential Smoothing, and Neural Nets; testing for model improvement
- Automatic weather range scenarios
- Automatic economic growth scenarios

Users can choose the level of automation for the forecasting process.

- Default is fully automated, hands off forecast generation
- User is able to set automatic selection criteria in the model
- Custom models can be built within the software with any desired structure or frequency
- Existing externally developed models can be imported to use in the software, automating parameter estimation
- User can choose to re-estimate any model at any time, as often as needed

Model results and statistics are available at each step of the process.

- Outlier files are automatically generated and can be reviewed and visualized with a graphical user interface (GUI)
- Model result files are created at each step and can be reviewed and visualized with the GUI
- Model statistics and selection criteria are available for review and visualization within the GUI
- All results, statistics and outliers can be presented in presentation quality reports and graphs

All time forecasting horizons can be produced from the same integrated forecasting solution, from very short-term to long-term load forecasting, from next hour to 30 years or beyond.

- Next hour to 24 hours for energy market operations

- 7 to 14 day forecasts for energy market planning and contracting
- 2 years to 30 years or more for budgeting and capacity planning
- All forecasts at hourly detail, automatic conversion of energy and peak demands to daily, monthly, and annual.

SAS® Energy Forecasting is an integrated member of a larger suite of analytic and business intelligence offerings which are provided in the solution.

- Provides data management including data cleaning
- Provides analytic tools for related analysis
- Provides visualization and reporting during the model selection process
- Provides presentation quality visualization and reporting

SAS® Energy Forecasting can automatically generate forecasts on a very large-scale.

- Automatically perform large-scale enterprise forecasting tasks
- Define flexible hierarchies and models
- Perform automatic hierarchical forecasting and reconciliation up and down the hierarchy, preserving locked forecast values
- Generate exception reports based on sound statistical logic and business rules.

SAS® Energy Forecasting includes time series data management capabilities. Transactional data can be converted to a time series format and forecast all in one step, or the converted data can be fed into a forecasting data mart as part of an overall data processing function.

- Able to customize aspects of the large-scale forecasting process, including exception rules, the model repository and events, control over model selection, event identification and exception reporting
- Events management console
- Discretionary manual overrides of statistical forecast values, and locking of the overrides
- Automatic model selection, explanatory variable testing, and outlier detection
- Code generation (and saving) via GUI which can be used for subsequent batch processing.

5.2.2 Itron

MetrixND and MetrixLT are Windows applications designed specifically for utility forecasting processes. Some of the high level features are:

- Support for annual, quarterly, monthly, weekly, daily, hourly, and sub hourly data.
- Folder based project explorers to organize tables, variables, configured charts, and configured reports.

- Drag and drop functionality for building transformations, models, reports and other objects.
- Wide spread use of quick charts giving single-click access to graphical depictions of data, statistics, and diagnostics.
- User configured line charts, scatter plots, and hourly data charts.
- Import/export support for common formats and databases
- Inclusion of Microsoft Visual Basic for Applications with access to the full object model of the application, allowing construction of objects and execution of modeling tasks using VBA code.

MetrixND is a statistical package that supports data transformation, statistical model estimation, model evaluation, and post processing. Statistical methods supported include:

- Exponential smoothing
- Time series (ARIMA) modeling
- Regression models with or without time series residuals
- Neural Network models with or without time series residuals
- Regression with ARCH (Autoregressive Conditional Heteroskedasticity) /GARCH (Generalized Autoregressive Conditional Heteroskedasticity) volatility models

MetrixND includes additional objects to support the modeling process.

- Forecast Test – supports generation of dynamic out-of-sample forecast tests with rolling estimation periods.
- Simulation – generates model predicted values with input overrides to support calendar month estimation, weather normalization, and unbilled estimation.
- Statistics Comparison – comparison of model statistics across specifications

MetrixLT is a specialized system that performs

- Construction of billing cycle weighted weather variables
- Calculation of normal and rank and average weather values
- Calendar rotation of daily weather scenarios
- Aggregation of hourly loads and loss factor adjustments
- Calibration of hourly load forecasts to monthly energy and peaks
- Calibration of bottom-up hourly forecasts to system forecasts

MetrixND and MetrixLT are used by over 100 utilities in North America, including most of the large utilities and ISOs. Typical applications include the following:

- Hourly and sub-hourly short-term forecasting
- Solar and wind generation forecasting
- Monthly sales, peak, and revenue forecasting
- Calculation of normal monthly weather and daily weather scenarios

- Weather normalization of sales and peak demand
- Monthly sales and revenue variance analysis
- Calendar month sales estimation
- Estimation of unbilled energy
- Long-term energy demand forecasting
- Statistically adjusted end-use modeling
- Long-term hourly load forecasting
- Market price forecasting
- Individual customer forecasting

Forecast Manager (FM.Net) is a companion product that provides a time-series database platform for storing and managing historical and forecast data. This provides a centralized Microsoft SQL Server data base for financial and long-term forecasting. Variables in data tables and transformation tables are organized in an explorer framework that allows users to configure data flows based on their business processes. Data are accessed by MetrixND statistical models, and forecasts are stored in FM for archiving and comparison purposes.

Itron also provides an automated forecasting system (MetrixIDR) that uses MetrixND as the statistical engine. This system is used for short-term forecasting of hourly and sub hourly loads by ISOs, RTOs, and retail energy suppliers in North America, Australia, and Europe.

5.2.3 Integral Analytics

LoadSEER (Spatial Electric Expansion & Risk) is a spatial load forecasting software tool designed specifically for transmission and distribution (T&D) planners who face increasingly complex grid decisions caused by emerging microgrid technologies, extreme weather events, and new economic activity. The objective of LoadSEER is to statistically represent the geographic, economic, distributed resources, and weather diversity across a utility's service territory, and use that information to forecast circuit and bank level peak loads, sub-sections of the circuit, acre-level changes, and impacts from various scenarios over the planning horizon. Planners are able to decompose system impacts using map layers superimposed on the spatial representation of the T&D infrastructure. As shown in Figure 5-1, load growth forecasts, distributed renewable generation, demand response, distributed intelligent systems, and other demand or supply factors are spatially located relative to the existing capital infrastructure.

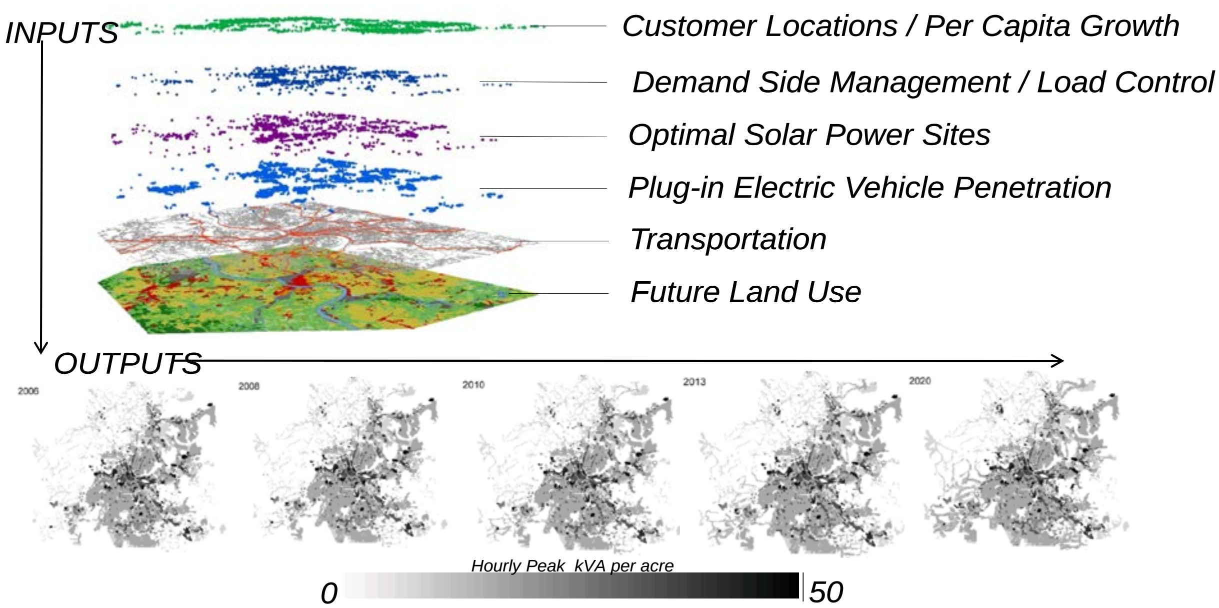


Figure 5-1: Map layer hierarchy

LoadSEER's powerful GIS mapping and load forecasting functionality uniquely blends traditional peak load regression based forecasting with more sophisticated econometric forecasting and rigorous geo-spatial forecasting. Multiple methods lead to increased confidence in the final forecast. This enables distribution planners to more accurately predict risks on their circuits due to local load growth and/or distributed generation changes, including electric vehicle adoption, increasing solar penetration, switching transfers, demand response, and other factors. The core algorithms automatically model geographic and economic drivers, along with weather, to provide engineers with the most representative circuit by circuit forecast models. In some cases, one circuit might respond to retail sales, while another might be sensitive to employment, personal income, housing starts, or various combinations. This process enables planners to analyze specific future scenarios such as transportation network expansion, suburban sprawl, urban redevelopment, new manufacturing, and additional employment centers. The final forecast results can be leveraged to enhance an existing suite of planning tools, including direct exports to power flow analysis tools, used in forecasting future transmission congestion, calculation of local avoided costs for optimal DER integration, and Distribution IRP requirements.

A major aspect of LoadSEER is to insure both short and long term consistency with system level financial planning, by streamlining regulatory data requirements, creating more defensible long term substation forecasting methods, and streamlining various aspects of the decision and approval process. Moreover, the software enables a much more accurate methodology for calculating avoided marginal costs of grid asset deferrals for use in more intelligently targeting DG, Smart Grid programs, and demand response and energy efficiency. The strategic benefits of LoadSEER include:

- Ability to forecast up to 100 economic influences, by circuit, in addition to weather. Economic risk often trumps weather risk at circuit level.
- Automated forecast model fitting, with recommended forecast results, so planning engineers can minimize time spent developing forecasts, yet still incorporate their local knowledge of growth.
- A GIS spatial forecast, based on 20 years of NASA satellite histories, modeling geographic influences unique to the regional customer base and the landscape.
- Ability to target DSM or DG to target circuits, without jeopardizing reliability.
- Comprehensive quality checking, process review, and log history for use in data requests and defensibility, as well as oversight and management during the forecast period.
- Ability to directly integrate solar forecasts, EV forecasts or other microgrid impacts, down to the customer level.
- Quick export to your power flow analysis tool, or DMS (Data Management System), with full hourly load shapes across all weather scenarios.

Key pros of LoadSEER include:

- Leverages multiple forecasting methods to triangulate on the truth.
- Very sophisticated approach to scenario analysis, especially for factors that do not exist in the past load history (new DG, EV, commuter rail lines, new economic centers, etc.)
- Provides direct integration to power flow tools, such as CYME and others.
- Provides hourly load shapes, with weather and economic risk incorporated, for use in DMS, switching/transfers, power flow modeling, and forecasting LMP congestion.
- Exports direct avoided T&D costs for use in DER, DG, EE, DR planning and execution.
- Accounts for historical transfers of load between circuits.
- Ease of use, and increased productivity, due to automation of forecasting process.
- Significantly more defensible within regulatory settings and management. Project justification.

Key cons of LoadSEER include:

- Data requirements more comprehensive, though software costs include data processing, so the burden falls on the IT Department more so than on Distribution Planning.
- Cost is generally higher than more traditional regression-only approaches.

5.2.4 Other Vendors

Two other tools are widely used by utility analysts, MS Excel (from Microsoft Office) and EViews (from HIS Inc.). Spreadsheets are probably the most widely used forecasting tool, for its ease of use and low cost. There are, however, several major issues with MS Excel, when it comes to long term forecasting in the regulatory environment:

1) Scalability. When the data set is large, it takes much time to open and save a spreadsheet.
2) Hard to audit. In order to audit an MS Excel model, one has to click through the cells to see the formula. Since the load forecasting models are fairly complex, it is very hard to audit an MS Excel based load forecasting model.
3) Not portable. Long term load forecasting usually involves dozens of, if not hundreds of, different data sources. When an MS Excel based load forecasting model is connected to various other spreadsheets in different folders, tremendous effort is needed to port the data and models from one computer to another while keeping the links valid.

EViews, a forecasting, econometric and statistical software package, was originally developed by Quantitative Micro Software 20 years ago, which was purchased by IHS Inc. in 2010. IHS is a global source of information and analysis in several major industries, including automotive, chemical, finance, technology and energy.

Designed with ease-of-use at the forefront of the development process, EViews features a graphical object-oriented user-interface, making it an easy to use statistical package.

While EViews is more general than a pure energy forecasting product, it is used by a large and growing community of forecasters in the energy and utility sectors. EViews is a tool used by a number of governmental agencies, including the Department of Energy and the Energy Information Administration (whose National Energy Model is built using EViews). The latest version of EViews, EViews 8.1, includes the ability to directly connect to the EIA's database to directly download, and keep up to date, energy data inside your EViews workfiles.

EViews is also used extensively by IHS' own analysts, including those working within IHS CERA (formally Cambridge Energy Research Associates), to forecast energy market demand globally.

5.2.5 Universities

Over the past several decades, thousands of papers have been published in the load forecasting arena. Most of them are authored by university professors and students. Although most papers in the literature are theoretical with minimal practical value, some of them are indeed the leading edge of load forecasting research and practice. In this section, several major universities that have developed notable long term load forecasting methodologies actually being used by the industry are discussed.

A. *University of North Carolina at Charlotte*

University of North Carolina at Charlotte (UNCC) has been working with many U.S. utilities on load forecasting projects. A key sponsor of UNCC is North Carolina Electric Membership Corporation, who have contributed to, tested, and deployed many load forecasting methodologies with UNCC. The lead faculty in the load forecasting area is Dr. Tao Hong, whose load forecasting methodology has been commercialized by SAS as its designed SAS® Energy Forecasting mentioned earlier. Key load forecasting publications of Dr. Hong include (Hong, Pinson, et al., 2014; Hong, Wang, & White, 2015; Hong, Wang, & Willis, 2011; Hong, Wilson, & Xie, 2014; Hong, 2010, 2014; Lai & Hong, 2013).

B. *Monash University (Australia)*

Monash University has been working with utilities in Australia and New Zealand on load forecasting projects. A key sponsor of Monash University's load forecasting work is Australian Energy Market Operator. The lead faculty in the load forecasting area is Dr. Rob Hyndman. Note that Monash University's load forecasting models are implemented as a package[2] of R, an open-source statistical software. Key load forecasting publications of Dr. Hyndman include (Fan & Hyndman, 2012; Hyndman & Fan, 2010, 2014).

C. *Purdue University*

The State Utility Forecasting Group (SUFG) at Purdue University has been assisting the State of Indiana for over 25 years through its forecasts of electricity consumption, prices, and resource requirements. The lead faculty is Dr. Douglas J. Gotham. Key load forecasting publications of SUFG are accessible through SUFG website[3].

[2] https://github.com/robjhyndman/MEFM-package
[3] http://www.purdue.edu/discoverypark/energy/SUFG/

5.3 Data Requirements for Supporting New Load Forecasting Models

New load forecasting models in the smart grid era should take advantage of modern automatic metering infrastructure, information technology, and advancement in atmosphere science. The following data sources are useful to support new load forecasting models:

- Load: hourly load history at end user level; hourly load history at distribution substation and transmission substation level; hourly wholesale load history.
- Weather: hourly weather history at weather stations within and surround the services territory.
- End use and appliance survey results.
- Demographic and economy information.
- Hierarchical information: connections among substations and meters; breakdowns of revenue classes; breakdowns of rate classes; billing group mapping; industry code mapping.
- Outage logs: record of all outages including location, customers affected, and duration.
- Demand response and energy efficiency programs: start and end time of all demand response programs, illustrations of all types of energy efficiency programs and implementation date.
- Negative demand: metered customer-owned generation history.
- System loss information: estimated transmission and distribution losses.

6. Database Requirements for Load Forecasts

The accuracy of load forecasting depends not only on the numerical efficiency of the employed algorithms, but also on the quality and quantity of available data. This section explains the database requirements for load forecasting.

6.1 End-Use Load Data Sources

A comprehensive end-use load model would account for a minimum of three classes of electricity customers: residential customers, commercial customers, and industrial customers. The U.S. Department of Energy's Energy Information Administration (EIA) administers three national consumption surveys, which targets specific populations that together comprise the vast majority – but not all – of the energy consumed in the U.S. Unlike survey research conducted by or in partnership with electric utilities, the EIA end-user surveys select entities for their surveys from sample frames of households, buildings, and manufacturing establishments, which have been assembled without access to customer accounts.

- Residential Energy Consumption Survey (RECS): A nationally representative sample of housing units. Specially trained interviewers collect energy characteristics on the housing unit, usage patterns, and household demographics.
- Commercial Building Energy Consumption Survey (CBECS): A national sample survey that collects information on the stock of U.S. commercial buildings, including their energy-related building characteristics and energy usage data.
- Manufacturing Energy Consumption Survey (MECS): A national sample survey that collects information on the U.S. manufacturing establishment, their energy-related building characteristics, and their energy usage and expenditures.

The following data sources can be useful in building residential end-use load model.

- *Residential Energy Consumption Survey (RECS):* The RECS collects household characteristics and usage patterns from a nationally representative sample of housing units using specially trained interviewers. This information is combined with data from energy suppliers to these homes to estimate energy costs and usage for heating, cooling, select appliances, and other end uses. The 2009 survey collected data from 12,083 households in housing units statistically selected to represent the 113.6 million U.S. housing units that are occupied as a primary residence, and includes reportable domains of Massachusetts and the group of remaining states in New England. The 2009 RECS was the core data source for the residential end-use shares for annual electricity consumption.

- *2009 California Residential Appliance Saturation Study (CA RASS):* The California Energy Commission sponsored a Residential Appliance Saturation Study in 2009. The study surveyed the following utilities: Pacific Gas and Electric Company, Southern California Edison, San Diego Gas and Electric Company, Southern California Gas Company, and Los Angeles Department of Water and Power. The survey collected data regarding the saturation and usage of appliances and electrical equipment and household energy consumption behaviors. The RASS data products include energy consumption estimates and saturation estimates by utility, climate zone, dwelling type, age group and income, as well as estimates of annual consumption for a limited number of electrical end-use categories.

- *Efficiency Vermont 2013 Technical Reference User Manual (Vermont TRM[4]):* In 2012 Efficiency Vermont published a Technical Reference User Manual, which documents the methods, formulas and default assumptions that Efficiency Vermont's energy efficiency programs uses in its impact estimates. Data comes from Vermont data when available; when not available, data comes from nearby regions, such as New England or other states in the Northeast, or from engineering calculations.

- *Assessment of Energy-Efficiency and Distributed Generation Baseline Opportunities:* Efficiency Maine Trust contracted The Cadmus Group to assess the energy-efficiency and distributed generation resources for Maine's residential, commercial, and industrial sectors for the 2012 to 2021 period. Field visits collected data on building characteristics and electric equipment saturation to establish a baseline. Data collected from the surveys allowed adjustment of assessments to current market conditions, especially in terms of saturations of electric equipment, specifically energy-efficient equipment.

- *Residential Miscellaneous Electric Loads: Energy Consumption Characterization and Savings Potential:* The Department of Energy contract TIAX to characterize residential Miscellaneous Electronic Loads including unit level, household level and annual level electricity consumption. The study used mostly engineering estimates to come up with Unit electricity consumption (UEC) and research to find residential saturation of these miscellaneous electric appliances.

- *Energy Consumption of Consumer Electronics in U.S. Homes in 2010:* Report prepared by Fraunhofer Center for Sustainable Energy Systems for the Consumer Electronics Association (CEA). This study was commissioned to determine the energy usage of mainstream consumer electronics in 2010. UEC estimates were produced using the power draw of the electronic devices and the hours of annual use.

- *Final Field Research Report:* This report summarizes the field measurements of the energy consumption of consumer electronics in the state of California and was prepared by ECOS Consulting and RLW Analytics. The study collected data of various plug loads in California households and analyzed the results of the field data collection to provide annual energy use estimates for many common household electronics.

[4] http://www.greenmountainpower.com/upload/photos/371TRM_User_Manual_No_2013-82-5-protected.pdf

- *Residential Lighting End-Use Consumption Study:* This 2012 report was published by the Department of Energy. The aim of the study was to estimate national and regional lighting usage measures and consumption within U.S. households. These estimates were built using a "bottom up" approach using hours of use, household categorical cross-classifications, and lamp level characteristics.

The following data sources can be useful in building commercial end-use load model.

- *Commercial Buildings Energy Consumption Survey (CBECS):* The CBECS is a national sample survey that collects information on the stock of U.S. commercial buildings, their energy-related building characteristics, and their energy consumption and expenditures. Commercial buildings include all buildings in which at least half of the floor space is used for a purpose that is not residential, industrial, or agricultural, so they include building types that might not traditionally be considered "commercial," such as schools, correctional institutions, and buildings used for religious worship. CBECS data is available in summary tables, or through the use of the publicly available database of over 5,000 participating buildings in the 2003 sample. The micro data file contains estimates of annual energy consumption for several end-uses, heating and cooling degree-days, along with various building characteristics. The finest level of geography indicated on the CBECS data is Census Division. The New England states comprise one such division.
- *California Commercial End-Use Survey (CA CEUS):* The CA CEUS was conducted with a sample of 2,790 commercial facilities in the following service areas: Pacific Gas and Electric, San Diego Gas and Electric, Southern California Edison, Southern California Gas Company, and the Sacramento Municipal Utility District. Commercial buildings were selected based on Standard Industrial Classification (SIC) code provided by the utilities; the CA CEUS report defines the 'premise' sampling unit as "a collection of buildings and/or meters service a unique customer at a contiguous location". The sample was stratified by utility, CEC forecasting climate zone, building type, and annual energy consumption for 2000. The analysis year for this data was 2002. Using survey results, time-of-use data loggers, and billing analysis, the CEUS collected and reported estimates on building systems, electricity and gas consumption, equipment penetration, operating schedules, and other characteristics.
- *County Business Patterns:* The County Business Patterns (CBP) is an annual series published by the U.S. Census Bureau that provides subnational economic data by industry. This series includes the number of establishments, employment during the week of March 12, first quarter payroll, and annual payroll. This data is useful for studying the economic activity of small areas; analyzing economic changes over time; and as a benchmark for other statistical series, surveys, and databases between economic censuses. Businesses use the data for analyzing market potential, measuring the effectiveness of sales and advertising programs, setting sales quotas, and developing budgets. Government agencies use the data for administration and planning.
- *Commercial and Residential Sector Miscellaneous Electricity Consumption: Year 2005 and Projections to 2030:* TIAX LLC conducted a study of the electricity consumption of various commercial and residential end-uses. The U.S. Department of Energy's EIA and the Decision

Analysis Corporation commissioned this report. The study created consumption estimates for twenty-one commercial and residential electric loads for the years 2005 (base year), 2010, 2015, 2020 and 2030.

- *Commercial and Industrial Lighting Load Shape Project:* KEMA (now DNV GL) produced a report in 2011 for Regional Evaluation, Measurement and Verification Forum, a project facilitated by the Northeast Energy Efficiency Partnerships (NEEP). This report delivers weather normalized 8,760 lighting end-use load shapes for commercial lighting through a combination of short-term metering and external data sources.
- *2010 DOE Lighting Market Characterization Study:* In 2010 DOE's Solid State Lighting Program released a report containing measures of lighting usage in the United States. Commercial, residential and industrial lighting estimates, including energy use, installed number of lights and average lumen were all aspects of this study. The specific light categories that had estimates were: incandescent, halogen, compact fluorescent, linear fluorescent, high intensity discharge (HID), and other.

The following data sources can be useful in building industrial end-use load model.

- *Manufacturing Energy Consumption Survey (MECS):* The MECS is a national sample survey that collects information on the stock of U.S. manufacturing establishment, their energy-related operational characteristic, and their energy consumption and expenditures. While micro data are not available from the MECSdata tables of consumption of net electricity by end-use category and region and consumption of offsite-produced electricity by NAICS industry and region are publicly available. The MECS finest level of geography is census region, which for the New England states also includes New York, New Jersey, and Pennsylvania.
- *County Business Patterns:* The County Business Patterns (CBP) is an annual series published by the U.S. Census Bureau that provides subnational economic data by industry. This series includes the number of establishments, employment during the week of March 12, first quarter payroll, and annual payroll. This data is useful for studying the economic activity of small areas; analyzing economic changes over time; and as a benchmark for other statistical series, surveys, and databases between economic censuses. Businesses use the data for analyzing market potential, measuring the effectiveness of sales and advertising programs, setting sales quotas, and developing budgets. Government agencies use the data for administration and planning.
- *Economic Census:* The Economic Census is the U.S. Government's official five-year measure of American business and the economy. It is conducted by the U.S. Census Bureau, and response is required by law. The Economic Census provides state-level estimates of numerous measures of economic activity by NAICS industry code, including the cost and quantity of purchased electricity and dollars of value added.
- *Annual Energy Outlook:* The Annual Energy Outlook (AEO) is a product of the EIA. The AEO contains retrospective and prospective estimates of energy production, sales, and consumption by fuel, market sector, and other categories.

- *Farm Service Agency Crop Acreage Data:* This dataset is released monthly and contains mandatory self-reported cropland acreage data at a national, state, and county level. It includes data for planted cropland by type of crop, field state, and number of farms. At the time of this report the December 2013 monthly release was the most recent dataset.
- *2010 DOE Lighting Market Characterization Study:* In 2010 DOE's Solid State Lighting Program released a study report prepared by Navigant Consulting containing measures of lighting usage in the United States. Commercial, residential and industrial lighting estimates, including energy use, installed number of lights and average lumen were all aspects of this study. The specific lamp categories that had LMC estimates were: incandescent, halogen, compact fluorescent, linear fluorescent, high intensity discharge (HID), and others.

6.2 Other Data Sources

6.2.1 Weather Data

The quality of weather data is crucial to the accuracy of load forecasting. There are many missing values in the raw data from National Oceanic and Atmospheric Administration (NOAA). Even in the version with quality control, the weather data available through NOAA may not have enough quality to support load forecasting tasks. Therefore, many utilities purchase cleansed historical weather data record from commercial weather service providers. Traditionally, utilities only use a limited number of weather stations for load forecasting. Since there are thousands of weather stations in the U.S., a medium size utility may have access to dozens of weather stations. It is a best practice to explore the usage of many weather stations for the enhancement of load forecasting accuracy.

WeatherBank, Inc. (WBI) is a completely integrated, full-service, meteorological consulting company providing weather data and products, and custom programming solutions for businesses, government agencies, and the general public since 1972.

WBI archives all weather data on a real-time basis. But more than just archiving, over the past 25-years, WBI staff have designed, installed, and perfected a system to test and correct all missing data values, and all values outside or failing to pass its proprietary quality assurance/quality control checks. Thus, WBI renders to end-users complete data sets with no missing values. To load forecasters, this is a huge benefit over publically available data sets.

There are two time periods in WBI database: HOURLY metrics and DAILY metrics, beginning on January 1, 1950. There are nearly 3,500 weather stations available across North America. WBI has mapped every postal code in Canada and every zip code in the USA, to one of these weather stations (using multiple and redundant backup stations). WBI also provides normalized values of over 200 metrics on a rolling 10, 20 and 30-year basis (currently applying 1984-2014).

Since WBI manages this data in real-time along with their internal forecast engine, all data and most of the 200 metrics are also predicted hourly, extending months into the future. So essentially, historical + current + predicted data is seamlessly combined to form one, value-added data set.

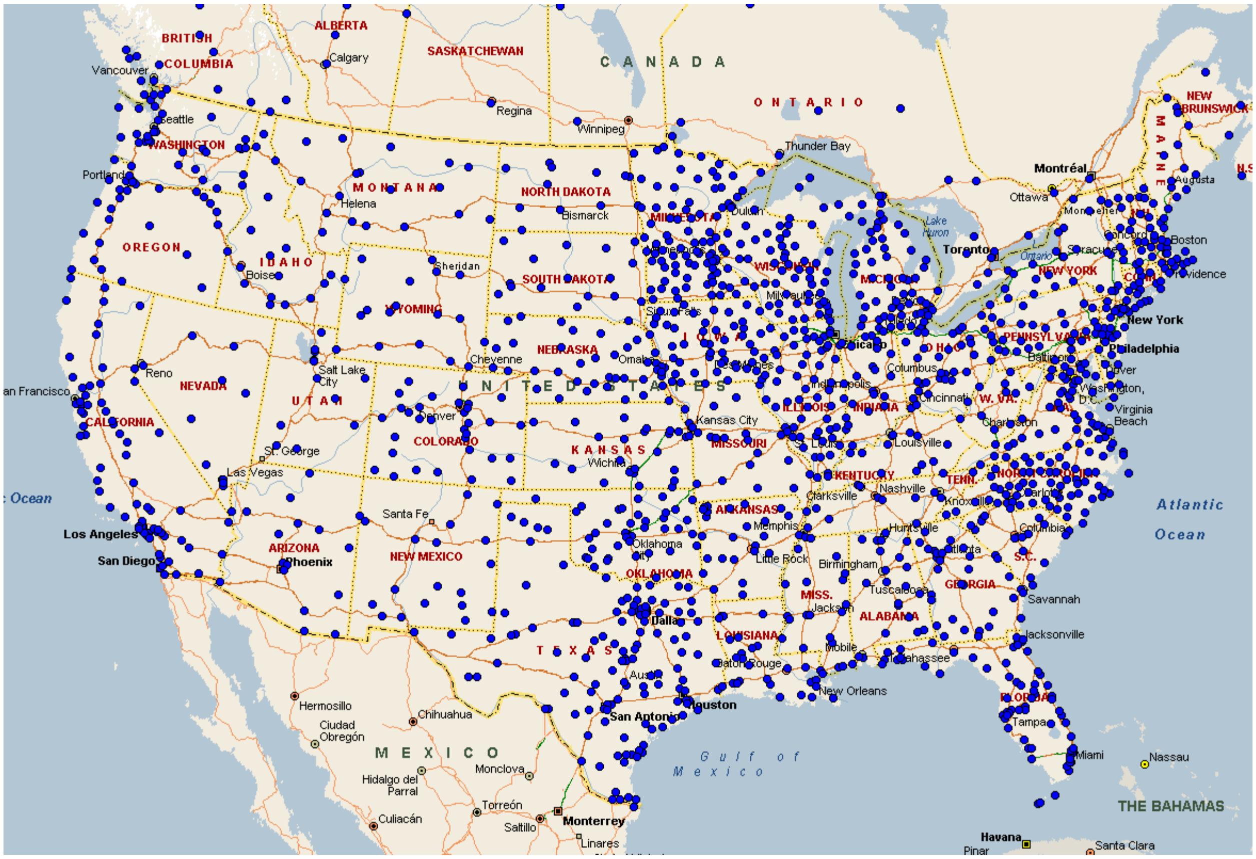


Figure 6-1: Weather stations in the U.S. (from WeatherBank)

6.2.2 Demographic Data

Long-term electrical load forecasting usually needs demographic information. Demographic variables include the total population and its composition by cohort. These variables do not tell much about how load varies hour to hour, but they are important indicators of the overall growth of the system. For instance, load forecasters can study how each age group responds to the emerging technologies, such as electric vehicles, new electronic devices, energy efficiency appliances, and so forth. Such information is important to adjustment of long term load forecasts. Forecasts of these demographic variables are normally available from government agencies and econometric forecasting services.

6.2.3 Industry Code

The North American Industry Classification System (NAICS) is the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. business economy. Since different industry sectors may have significantly different load profiles based on the usage of appliances and equipment, industrial load forecasting can be performed based on the end use of industrial subclasses, which can be obtained through extended use of NAICS.

NAICS was developed under the auspices of the Office of Management and Budget (OMB), and adopted in 1997 to replace the SIC system. It was developed jointly by the U.S. Economic Classification Policy Committee (ECPC), Statistics Canada, and Mexico's *Instituto Nacional de Estadistica y Geografia*, to allow for a high level of comparability in business statistics among the North American countries.

This official U.S. Government Web site provides the latest information on plans for NAICS revisions, as well as access to various NAICS reference files and tools. The official 2012 U.S. NAICS Manual[5] includes definitions for each industry, background information, tables showing changes between 2007 and 2012, and a comprehensive index.

6.2.4 Synthetic Data

More often than not, utilities are facing shortage of data for part of the load forecasting tasks. This may be caused by several factors, such as insufficient staff, lack of raw measurements, insufficient time for performing the analysis, etc. In such situations, utilities can "borrow" data from external sources to perform the analysis. Typical sources include national survey conducted by the government, case studies performed by consulting firms, public reports from other utilities and academic publications.

Notice that there is a fine line between synthetic data and faked data. Synthetic data is obtained by combining borrowed data with in-house data to reasonably approximate the electricity consumption of a utility of interest. Faked data is part of a fraudulent forecasting process, where people try to manipulate data to satisfy a personal agenda.

6.3 Treatment of Non-Conventional Load

There are three types of non-conventional load that should be handled carefully in load forecasting. They include demand response, energy efficiency, and customer-owned generation. Demand response is one of

[5] http://www.ntis.gov/products/naics.aspx

many resources needed to satisfy the increasing demand for electricity. In addition to providing capacity for resource adequacy for planning purposes, capacity and ancillary services provided by demand response help ensure resource adequacy while providing operators with additional flexibility in maintaining operating reliability. Energy efficiency refers to using less energy to provide the same service. It is a way of managing and restraining the growth in energy consumption. Demand response and energy efficiency policy are among the leading causes of steadily slowing electricity sales growth in recent decades. The expanding implementation of these programs is stimulating changes to forecasting procedures. Customer-owned generation refers to electric generation equipment on the customer's side of the meter. Sometimes this is referred to as self-generation or distributed generation (DG). Examples of electric generation equipment used by customers include solar photovoltaic, wind turbines, small portable gasoline powered generators, diesel or natural gas powered generators, micro turbines, and fuel cells. Customer-owned generation reduces a customer's demand for energy from the bulk power system and can even produce small amounts of electricity that can be fed back to the power grid to serve other consumers.

There are two ways to treat the above non-conventional load. They can be treated as behavior-modifying mechanisms to change the net load shape or as supply-side resources responding to the grid needs. The activities discussed in the load-modifying path seek to attenuate the peaks and valleys and make the ramps less steep, while the resource sufficiency path discusses ensuring needed flexible resources that will be included in future planning and procurement processes.

Load-modifiers are those resources or programs not seen or optimized by the market, but they modify the fundamental system load shape, preferably in ways that harmonize with grid operations. An effective load-modifying program helps create a flatter system load profile, attenuating high energy peaks and valleys and reducing extreme upward and downward ramps. A more favorable load profile can benefit the system or market operator by creating a more manageable and stable system, and it can benefit ratepayers by deferring or avoiding the need for future capacity additions and lowering resource adequacy requirements.

Supply-side resources are those energy supplies available to the ISO to balance net load. These resources can take different forms, ranging from conventional generators to demand response. Supply-side resources are used to directly balance load, manage congestion, and satisfy reliability standards. Supply-side resources inject or curtail energy in specific locations, and can be modeled, optimized, and dispatched when and where needed by the ISO.

6.4 Use of Information from Smart Meters and Smart Grid

Traditional electrical meters only measure total consumption, and provide no information of when the energy was consumed at each metered site. Smart meters provide a way of measuring this site-specific information. The increasing usage of smart grid technologies provides forecasters with high resolution, layered information to improve the load forecasting process. Smart meters can also help measure, and verify data related to non-conventional load types mentioned in Section 6.6, including demand response, energy efficiency, and customer-owned generation.

Technical literature has presented a wide range of methodologies and models for improving the load forecasting accuracy. However, much of the work is based upon the forecasting of aggregated consumptions at system levels with minute information on consumption profiles for classes of customers. With the deployment of advanced metering infrastructure (AMI), an avalanche of consumption data has become available. AMI data introduce a fresh perspective on load forecasting. To attain the maximum AMI benefits, it is of utmost importance that utilities perform large-scale data analyses for transforming AMI data into useful information for load forecasting. With the availability of customer consumption patterns, advanced analytics techniques will enable electric utilities to extract insights from AMI data with previously unachievable levels of sophistication, speed, and accuracy.

Some of the aspects that need to be considered when incorporating smart meter data while developing load forecasting models for better accuracy are discussed as follows.

- As the smart meter installations are getting rolled out in phases by various utilities, the utilities have a hybrid group of customers with smart and traditional meters. The usage behavior of the smart meter customers is completely different to the traditional meter consumers due to the features and functions of smart meters. Hence, forecasters need to develop separate forecasting models for each type of consumers which can be seamlessly integrated to get the final forecasted value to be submitted to the power plant producers.
- The electricity consumption data is available for every 15-minute time interval with smart meters. This facilitates the forecasters to develop load forecasting models with finer resolutions. On the other hand, for the traditional meter consumers, development of forecasting models for different time intervals is not possible due to the lack of the data at such short intervals. So, forecasters need to analyze to see which time frame models from smart meter consumers need to be combined with traditional meter models to obtain the final forecast value.
- The amount of data available in the smart grid is very high. The forecasting models that are developed by forecasters should be able to handle these high volumes of data without getting confused and provide an accurate forecast. As some part of the data that is received from the smart meters can be erroneous, faster pre-processing techniques need to be employed to filter the bad data, before including in the forecasting models.

7. Collaborative Case Studies

7.1 Introduction

In this chapter, we will present three case studies based on data from three different companies including ISO New England (ISONE), Exelon Corporation (Exelon), and North Carolina Electric Membership Cooperation (NCEMC). The three companies are operated with distinct organizational structure, regulatory environment, and geographical territories. Table 7-1 outlines the key features of the three case studies. To avoid verbose presentation, we are not performing exactly the same features to all case studies.

We would also like to emphasize that all the results presented in this chapter are based on the years of data we specified. We do not recommend the utilities to directly apply the model results to other years or other territories. Instead, we do encourage the utilities to follow the methodology presented in this chapter and the key references highlighted in bold in the bibliography section. Note that we do not intend to replicate what the utilities are doing either. These case studies provide an independent view of projected demand and energy using the data with the easiest access to many utilities.

Table 7-1: Key features of the three case studies

	ISONE	Exelon	NCEMC
Territory characteristics			
Zones	8 zones in 6 adjacent states	3 operating companies in 3 separate states	3 adjacent supply areas in one state
Levels of hierarchy	3	1	2
Forecasting methodologies			
Weather station selection		√	√
Weekend and holiday effects	√	√	√
Forecasting results			
Forecast horizon (years)	2	3	5
Number of scenarios	10 (‘04-‘13)	15 (’96-’10)	30 (‘79-‘08)
Ex ante probabilistic forecasting	√	√	√
Ex post point forecasting w/ actual economy and temperature		√	√
Ex post point forecasting w/ forecasted economy and actual temperature			√
Other topics	Energy efficiency and demand response		

All of the results presented in this chapter are based on linear models. The main effects and cross effects are listed in Table 7-2. A similar model was presented in (Hong, Wilson, & Xie, 2014).

Table 7-2: A typical underlying linear model

Main Effect	Cross Effect
GSP (or GMP), T_t, T_t^2, T_t^3, *Month*, *Weekday*, *Hour*	T_t **Month*, T_t^2 **Month*, T_t^3 **Month*, T_t **Hour*, T_t^2 **Hour*, T_t^3 **Hour*, T_{t-1} **Month*, T_{t-1}^2 **Month*, T_{t-1}^3 **Month*, T_{t-1} **Hour*, T_{t-1}^2 **Hour*, T_{t-1}^3 **Hour*, T_{t-2} **Month*, T_{t-2}^2 **Month*, T_{t-2}^3 **Month*, T_{t-2} **Hour*, T_{t-2}^2 **Hour*, T_{t-2}^3 **Hour*, T_{t-3} **Month*, T_{t-3}^2 **Month*, T_{t-3}^3 **Month*, T_{t-3} **Hour*, T_{t-3}^2 **Hour*, T_{t-3}^3 **Hour*, T_a **Month*, T_a^2 **Month*, T_a^3 **Month*, T_a **Hour*, T_a^2 **Hour*, T_a^3 **Hour*, *Day*Hour*

7.2 ISO New England

7.2.1 Overview

ISO New England (ISO NE) is the independent, not-for-profit company authorized by the Federal Energy Regulatory Commission (FERC) to perform three critical, complex, interconnected roles for the region spanning Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and most of Maine. The three roles include operating the power system, administering wholesale electricity markets, and power system planning.

As shown in Figure 7-1, ISONE has 8 zones in 6 states, of which Massachusetts has 3 zones. In this case study, we will develop forecasts for 10 zones in total. Other than the 8 individual zones, we are treating Massachusetts as one zone and the ISO NE system total load as another zone. We develop ex ante probabilistic load forecasts for the calendar years 2014 and 2015 based on data on and prior to 2013 for each of the 10 zones. The load and temperature data is available through ISO NE website [6]. Gross State Product (GSP) is used as the macroeconomic indicator for the 6 states. The sum of the GSP of the 6 states is used as the macroeconomic indicator for ISO NE total load. Gross Metropolitan Product (GMP) of Boston is used as the macroeconomic indicator of the North East Massachusetts zone. GSP of Massachusetts is used as the macroeconomic indicator of the other two zones of Massachusetts. The historical economy data is from U.S. Bureau of Economic Analysis [7] as show in Figure 7-2. The economy forecast of 2014 and 2015 is based on a simple linear regression over the most recent 5 years.

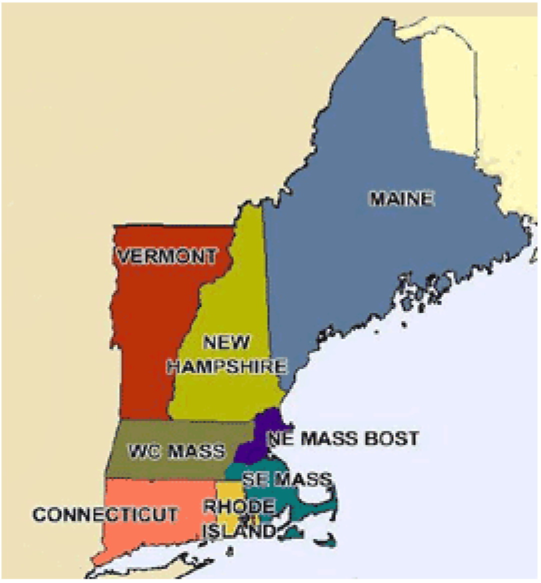


Figure 7-1: ISO New England service territory map

[6] http://www.iso-ne.com/markets-operations/iso-express
[7] http://www.bea.gov/

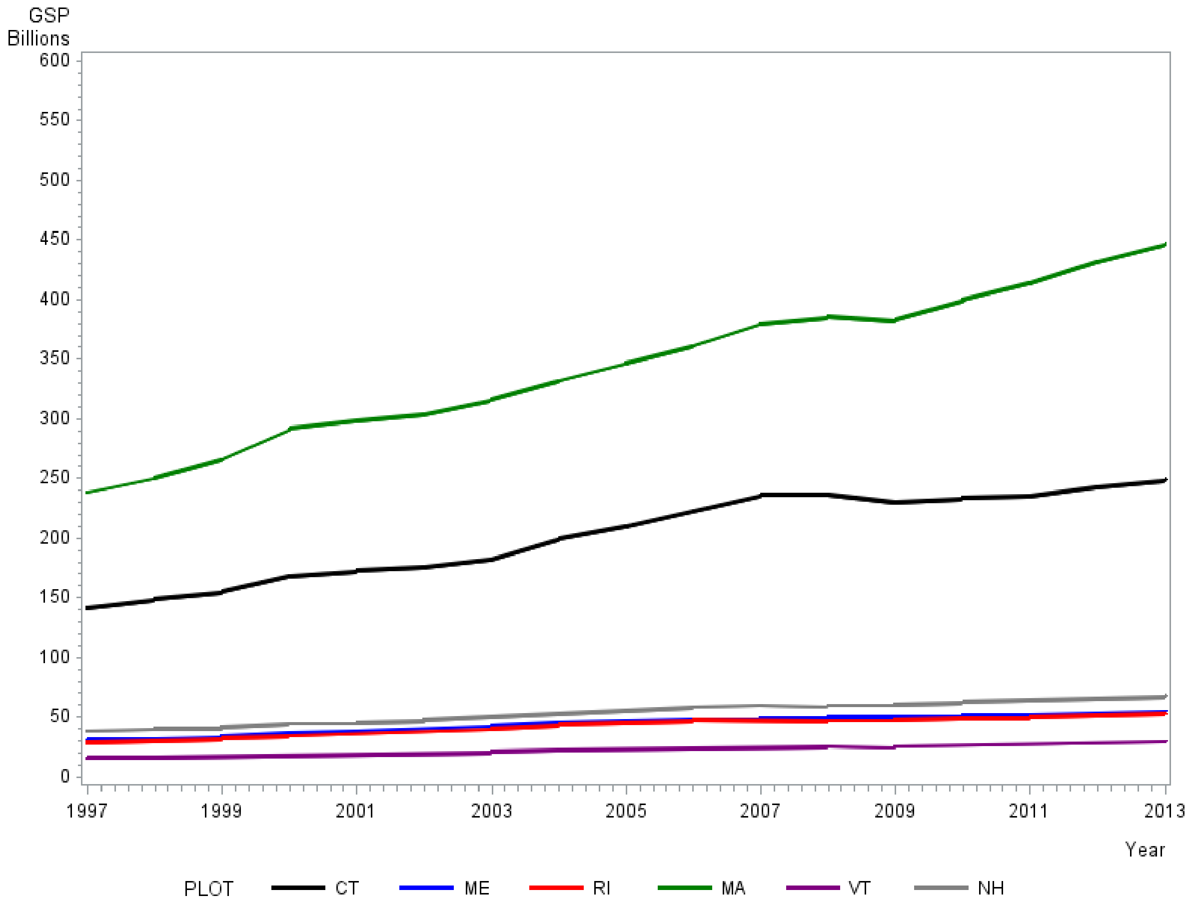


Figure 7-2: Macroeconomic indicators for ISO New England (1997-2013)

7.2.2 Weekend and Holiday Effects

Although the 6 states covered by ISO NE are located close to each other, their weekend and holiday effects appear to be quite different. Table 7-3 lists the weekend effects, which include how to group days of a week together for each of the 10 zones. Table 7-4 lists the holiday effects of ISO NE system-level load, which include how different holidays and their surrounding days are being altered to better reflect the holiday load profiles.

Table 7-3: Weekend effect modeling for ISO New England

Zone	Combination[8]
ISONE	None
VT	None
ME	Wednesday and Thursday
NH	None
CT	None
RI	Tuesday and Wednesday
MASS	None
SEMASS[9]	Tuesday and Wednesday
WCMASS[10]	Wednesday and Thursday
NCMASSBOST[11]	None

[8] Combining the codes of few days of a week to treat them the same in the model.
[9] Southeast Massachusetts
[10] West-central Massachusetts
[11] North-central Massachusetts (Boston area)

Table 7-4: Holiday effect modeling for ISO New England

							MASS			
Holiday[12]	**ISONE**	**VT**	**ME**	**NH**	**CT**	**RI**	**ALL**	**SE**	**WC**	**NC**
Before	Sat	None	Sat	None	None	Sat	Sat	Sat	Sat	None
New Year's Day	Sun	Sun	Sun	Sat	Sun	Sun	Sun	Sat	Sun	Sat
After	None	None	None	None	None	None	None	None	Sun	None
Before	None	None	None	None	None	None	None	None	None	None
Birthday of MLK	None	Mon	None	Mon	None	None	None	None	None	Fri
After	None	None	None	None	None	None	None	None	None	Tue
Before	None	None	Sat	None	None	None	None	Sun	None	Sun
Washington's Birthday	Fri	None	Fri	None	Fri	Fri	Sat	Sat	Sat	Sat
After	Fri	None	Fri	None	Fri	None	Mon	Fri	Mon	Fri
Before	None	None	None	Sun	None	Sun	None	Sat	None	None
Memorial Day	Sun	Sun	Sun	Sun	Sun	Sun	Sun	Sun	Sun	Sun
After	Mon	Mon	Mon	Mon	Wed	Mon	Mon	Mon	Mon	Wed
Before	None	None	None	None	None	None	None	None	None	None
Independence Day	Sun	Sun	Sun	Sun	Sun	Sun	Sun	Sun	Sun	Sun
After	None	None	None	None	Mon	Sat	Sun	Sat	Sun	None
Before	None	Sun	None	Sun	None	Sun	None	Sun	None	None
Labor Day	Sat	Sun	Sun	Sun	Sat	Sat	Sat	Tue	Sun	Sun
After	Wed	Mon	Mon	Mon	Wed	Tue	Mon	None	Mon	Mon
Before	None	None	None	None	None	None	None	Sun	None	Sun
Columbus Day	None	None	None	Mon	None	Sun	Sat	Sat	Sat	Sat
After	None	None	None	None	None	Mon	Mon	Mon	Mon	Mon
Before	None	None	None	None	None	None	None	None	None	None
Veterans Day	None	None	None	None	None	None	None	None	None	None
After	None	None	None	None	None	None	None	None	None	None
Before	None	Mon	Mon	None	Thu	None	Thu	None	None	Fri
Thanksgiving Day	Sat	Sat	Sat	Sat	Sat	Sat	Sat	Sat	Sat	Sat
After	Sat	Sun	Sun	Sun	Sat	Sat	Sat	Sat	Sun	Sat
Before	None	Sat	Sat	Sat	None	None	None	None	Sat	None
Christmas Day	Sun	Sat	Sun	Sun	Sun	Sat	Sun	Sun	Sun	Sun
After	None	Sun	Sun	None	None	None	None	None	None	None

[12] The day codes of some holidays and their surrounding days are altered to model holiday effects. For instance, Memorial Day is a Monday holiday, though it may behave more like a weekend day (Saturday or Sunday). If so, we will change the day code of the Memorial Day from Monday to Saturday (or Sunday).

7.2.3 Ex ante Probabilistic Forecasting Results

This section presents the ex ante probabilistic forecasting results of ISO NE. The dashed lines are the monthly energy (or peak) from 10 weather scenarios derived from weather history from 2004 to 2013. The black, red, and green lines are the median, 90th percentile, and 10th percentile monthly energy (or peak) of the 10 scenarios. The actual load is represented by the black dots. Note that the case study was conducted in Fall of 2014, so the actual load history (in black dots) is available through September 2014.

A. ISO New England (ISO NE)

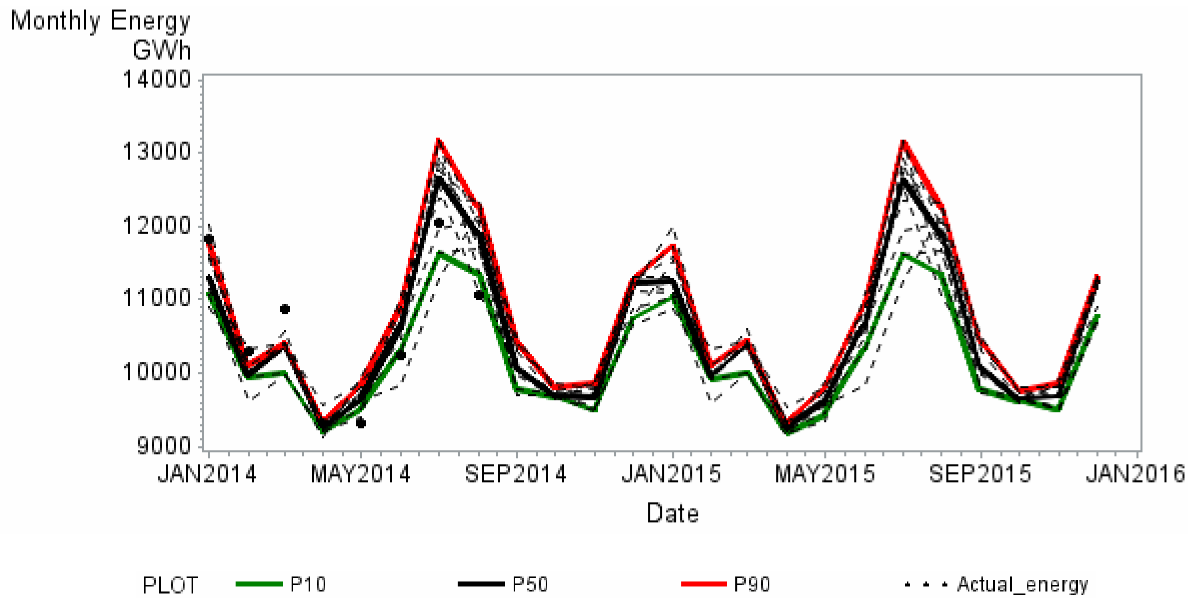


Figure 7-3: Ex ante probabilistic forecasts of ISO NE monthly energy (2014 – 2015)

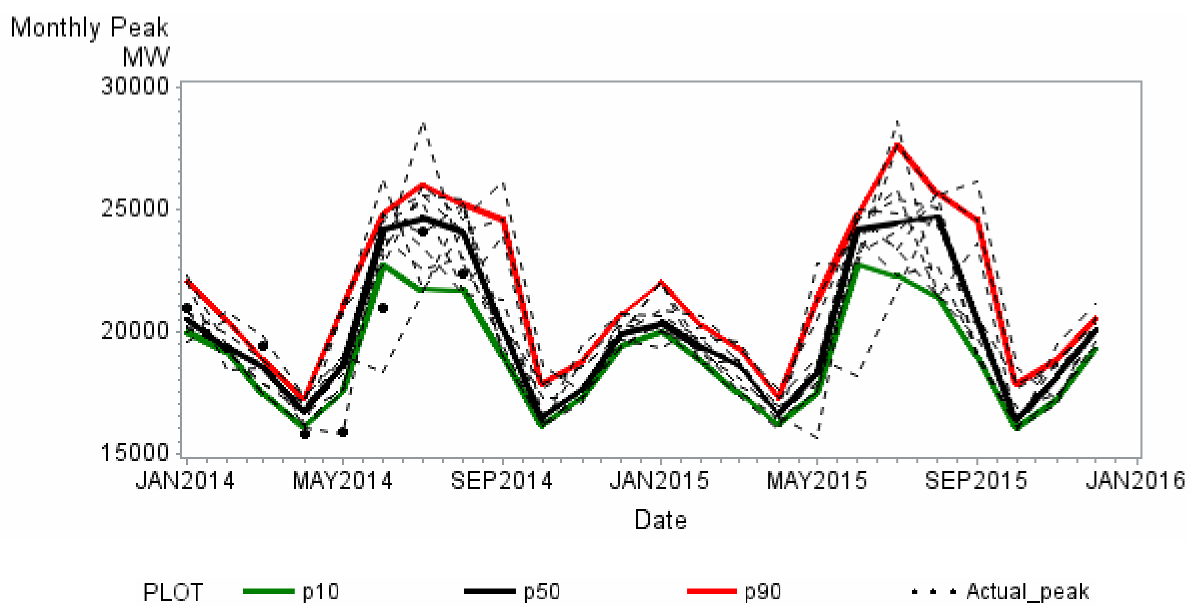


Figure 7-4: Ex ante probabilistic forecasts of ISO NE monthly peak (2014 – 2015)

B. Connecticut (CT)

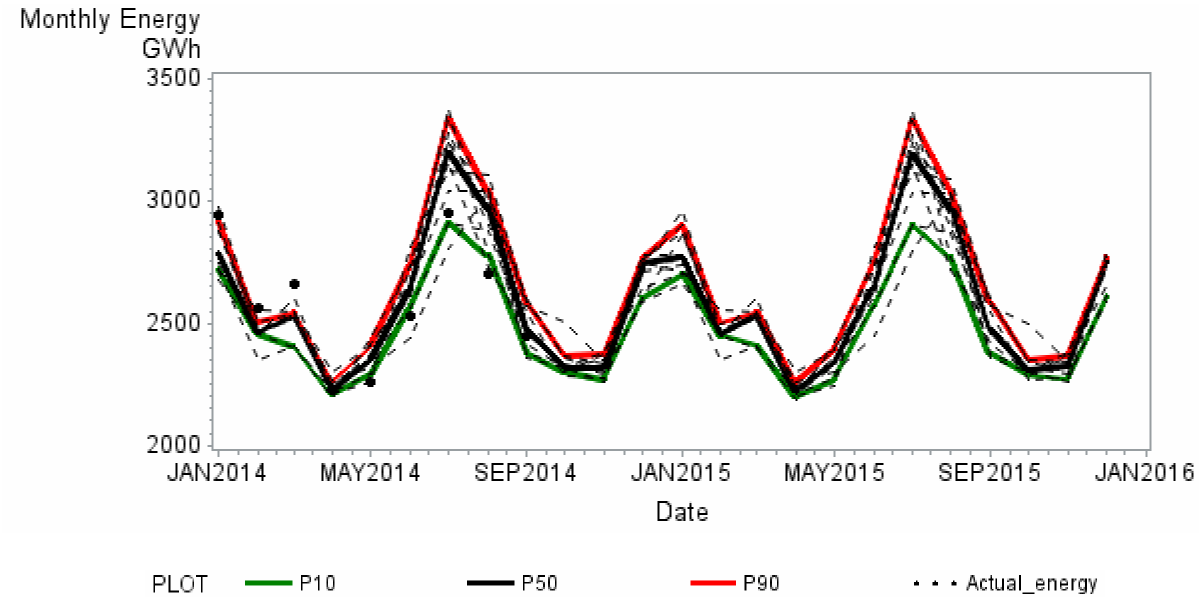


Figure 7-5: Ex ante probabilistic forecasts of CT monthly energy (2014 – 2015)

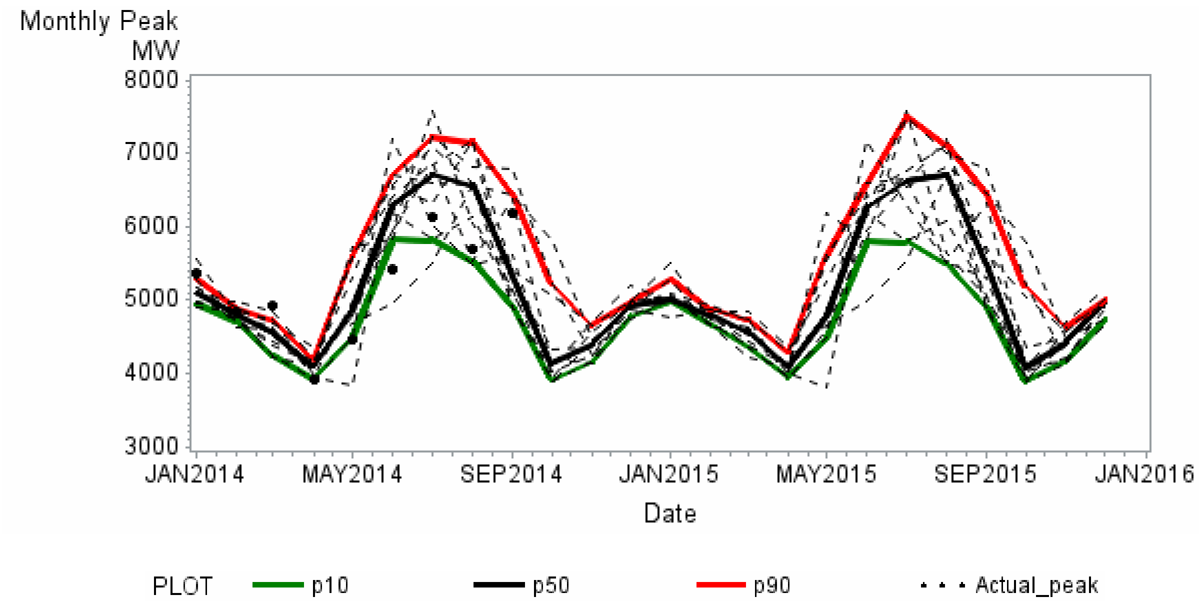


Figure 7-6: Ex ante probabilistic forecasts of CT monthly peak (2014 – 2015)

C. Maine (ME)

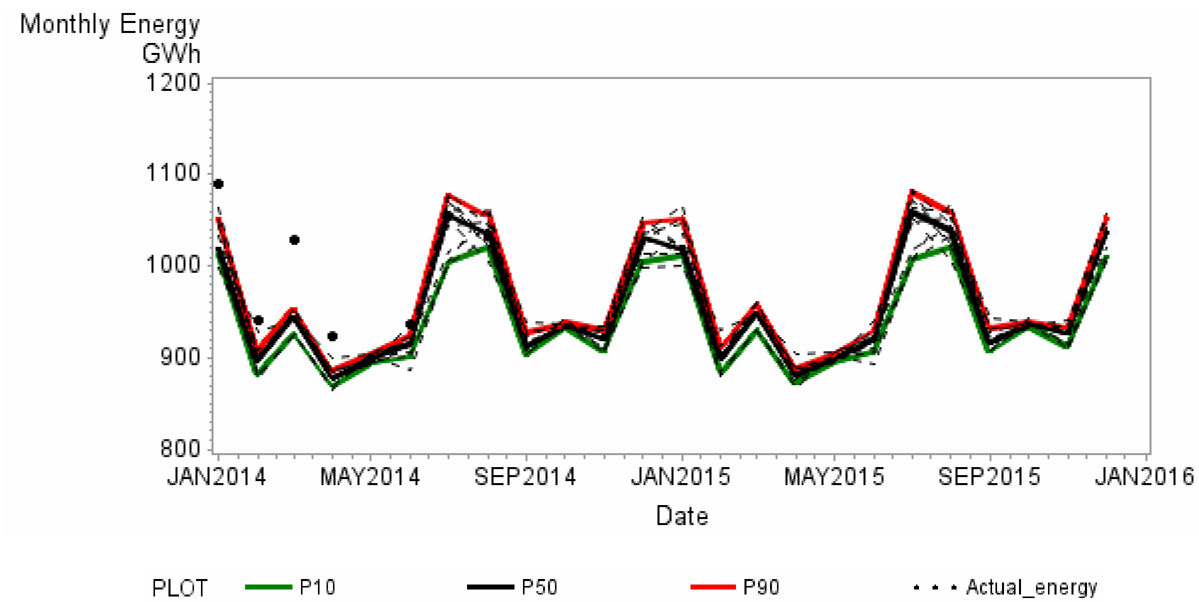


Figure 7-7: Ex ante probabilistic forecasts of ME monthly energy (2014 – 2015)

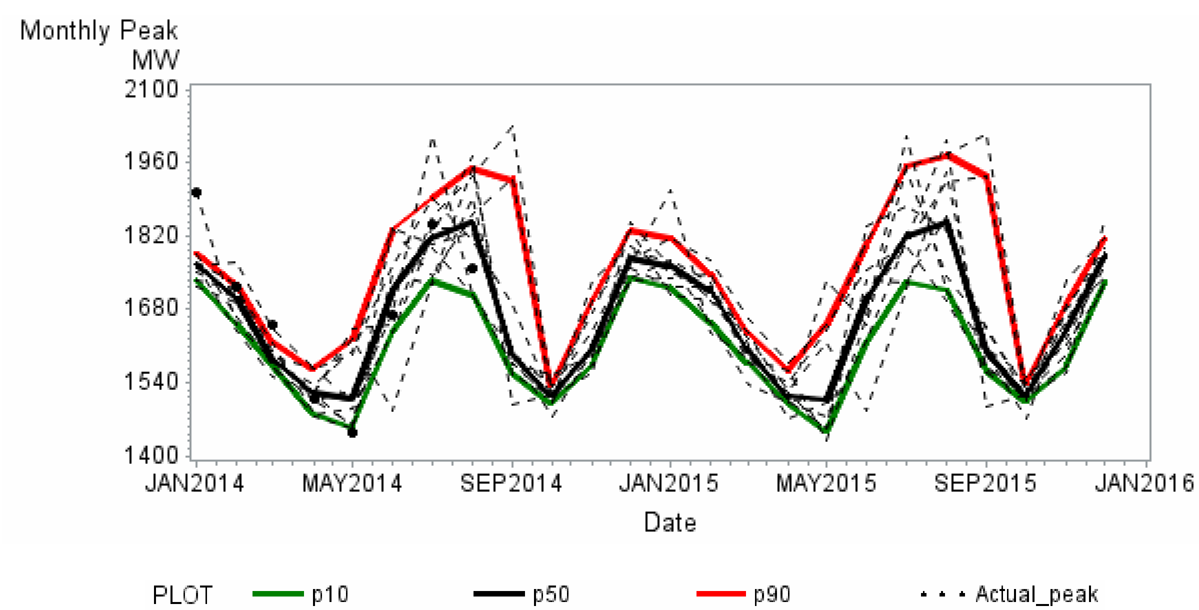


Figure 7-8: Ex ante probabilistic forecasts of ME monthly peak (2014 – 2015)

D. New Hampshire (CT)

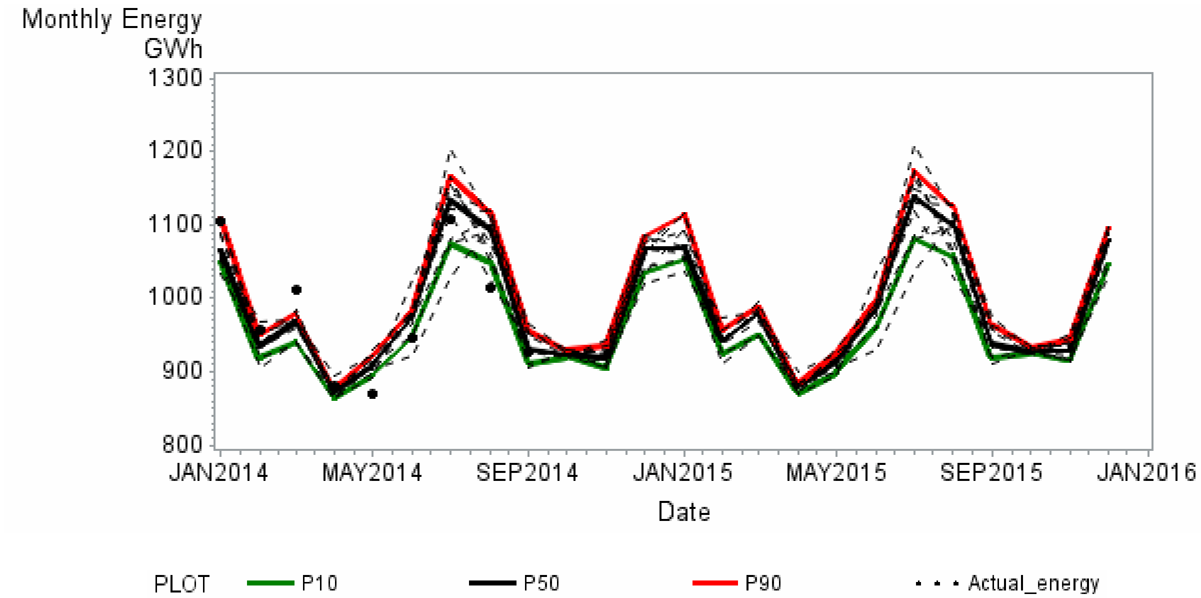


Figure 7-9: Ex ante probabilistic forecasts of NH monthly energy (2014 – 2015)

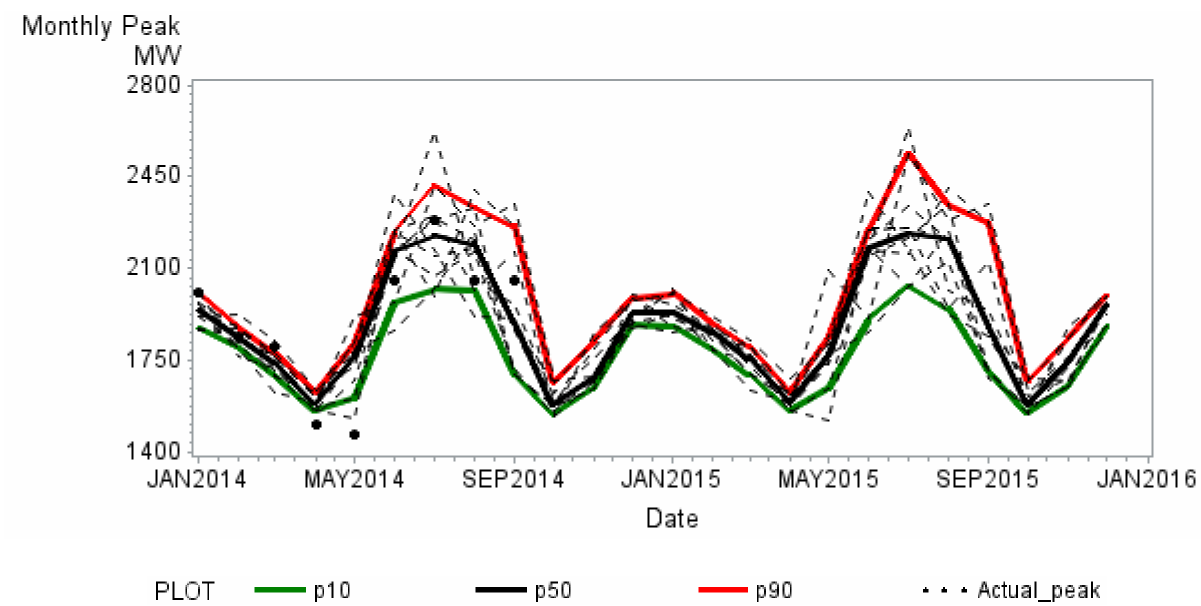


Figure 7-10: Ex ante probabilistic forecasts of NH monthly peak (2014 – 2015)

E. Rhode Island (RI)

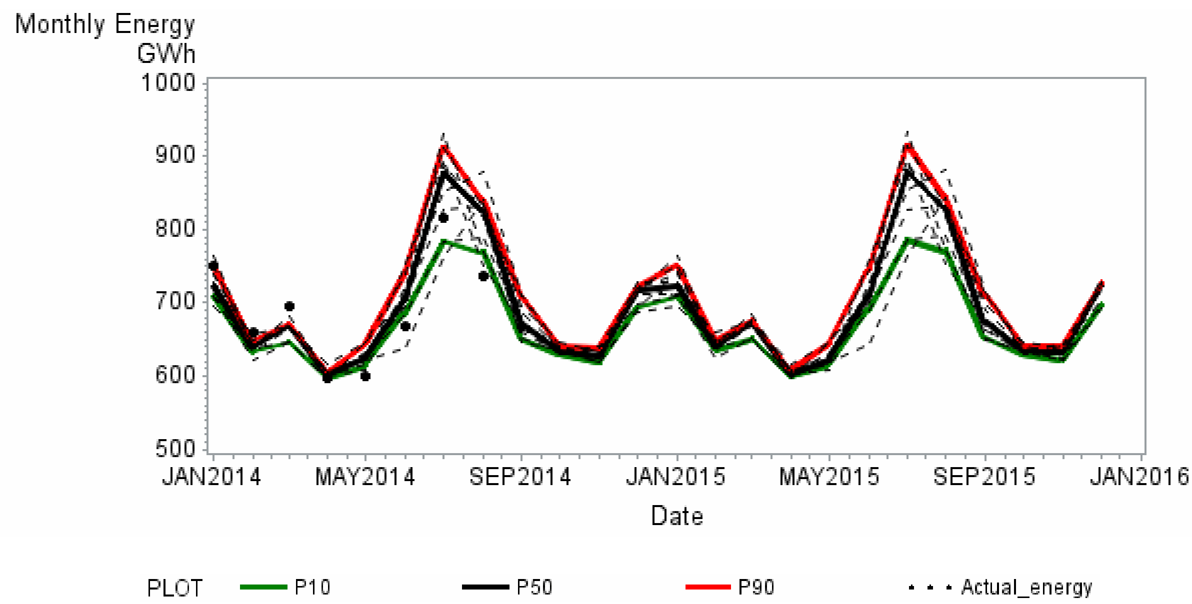


Figure 7-11: Ex ante probabilistic forecasts of RI monthly energy (2014 – 2015)

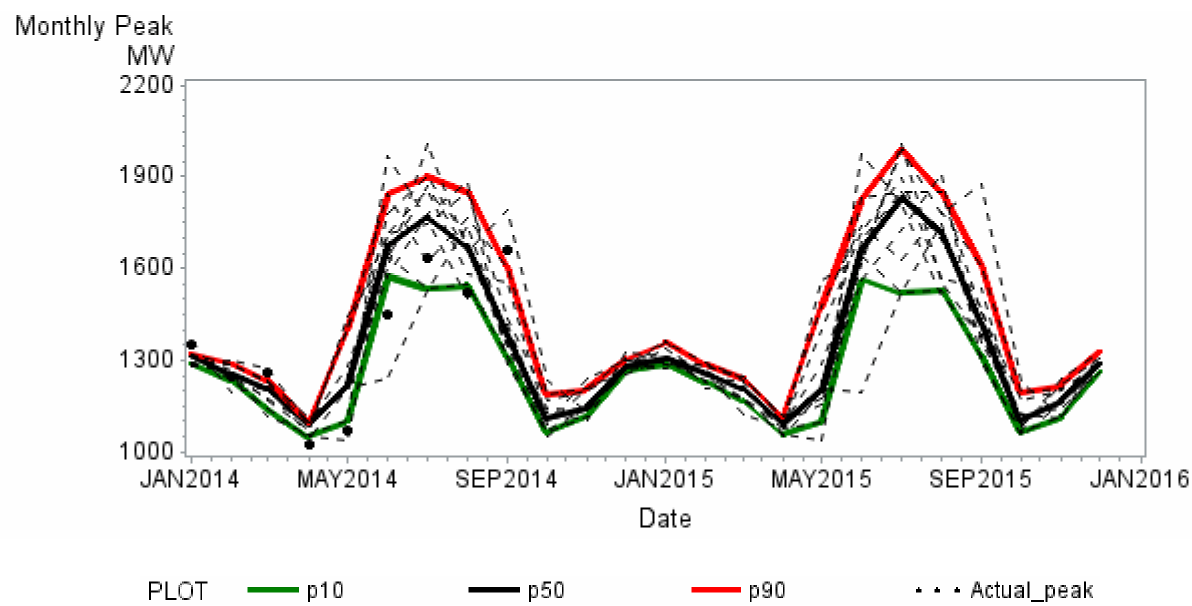


Figure 7-12: Ex ante probabilistic forecasts of RI monthly peak (2014 – 2015)

F. Vermont (VT)

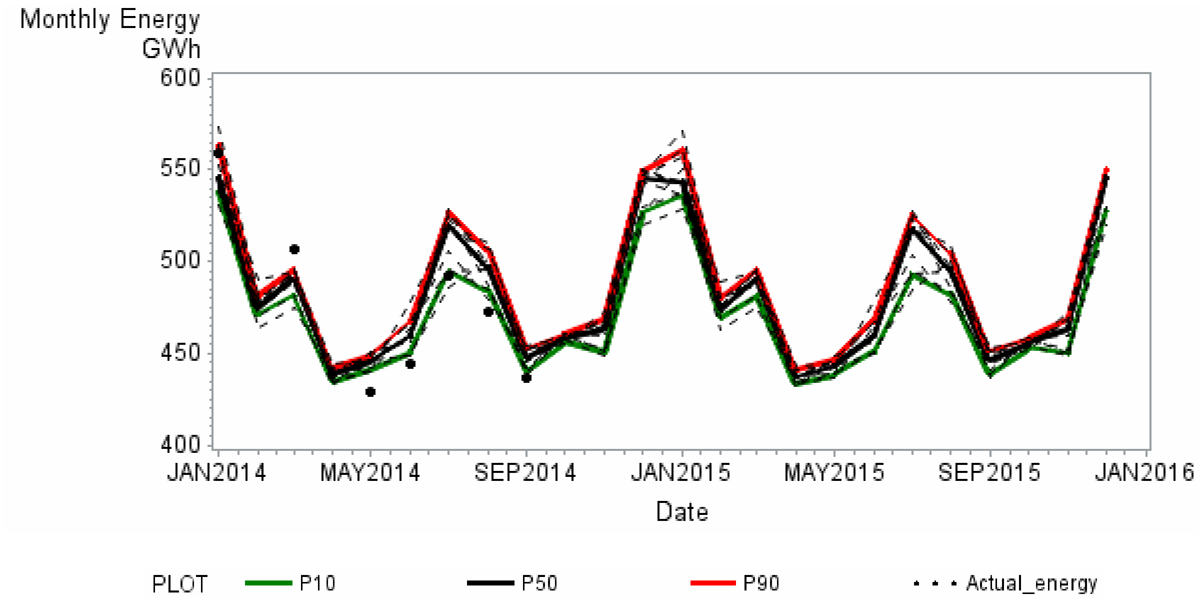


Figure 7-13: Ex ante probabilistic forecasts of VT monthly energy (2014 – 2015)

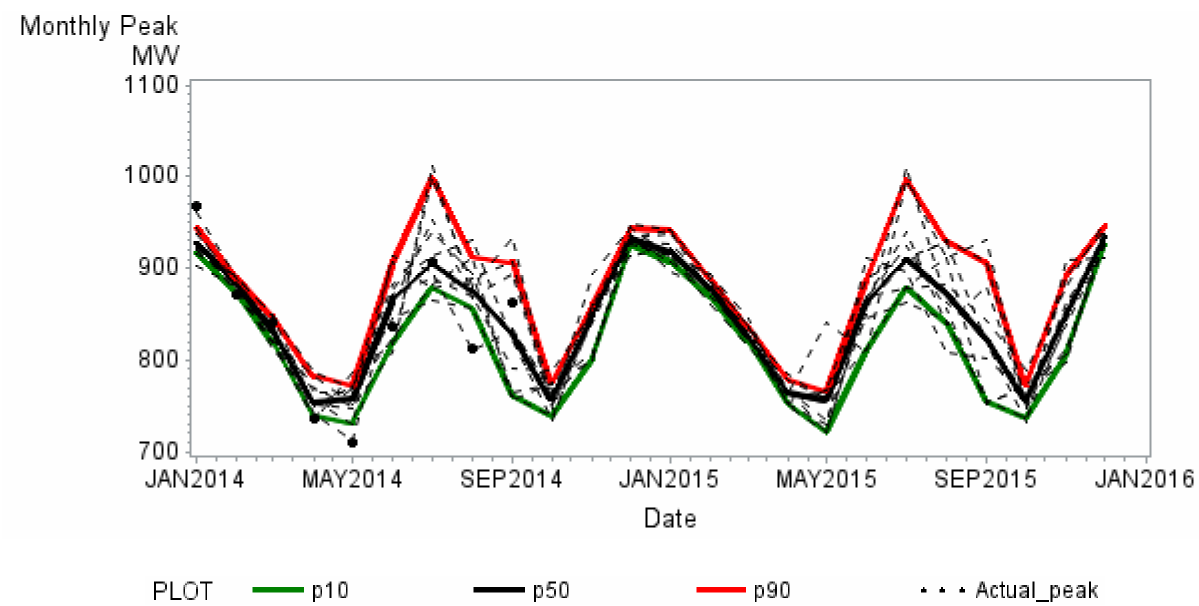


Figure 7-14: Ex ante probabilistic forecasts of VT monthly peak (2014 – 2015)

G. Massachusetts (MASS)

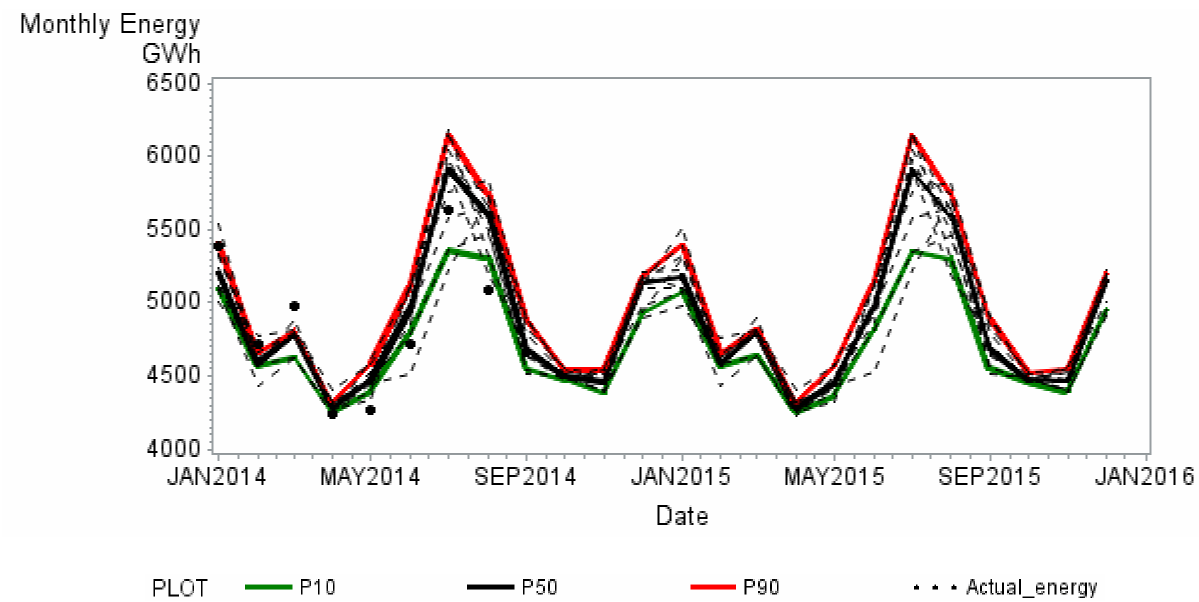


Figure 7-15: Ex ante probabilistic forecasts of MASS monthly energy (2014 – 2015)

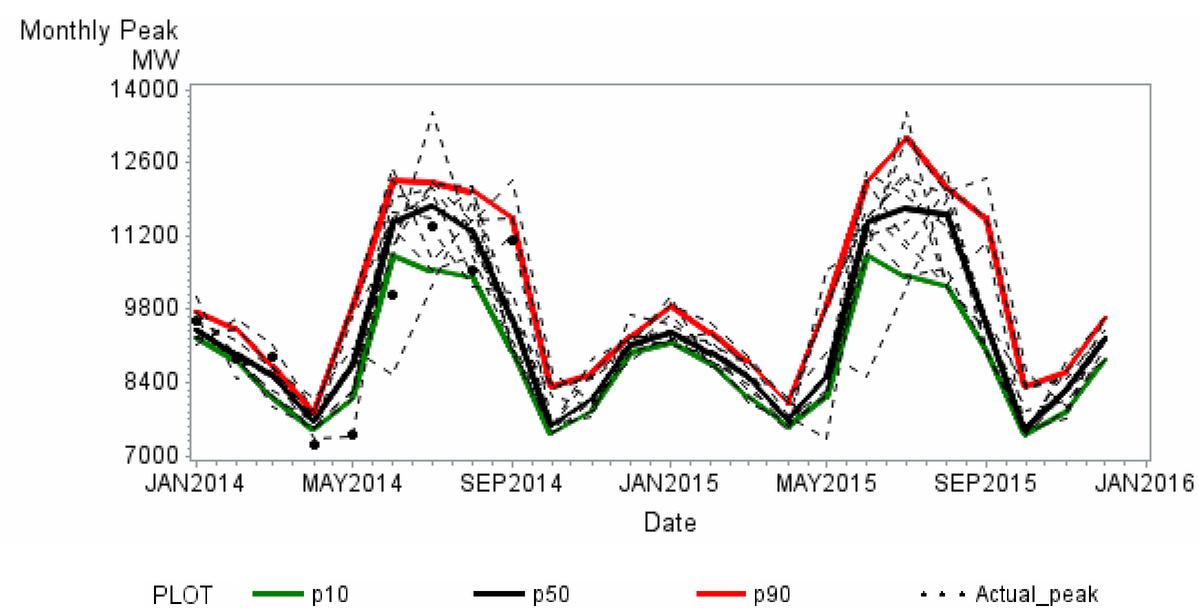


Figure 7-16: Ex ante probabilistic forecasts of WCMASS monthly peak (2014 – 2015)

H. North Central Massachusetts (NCMASS)

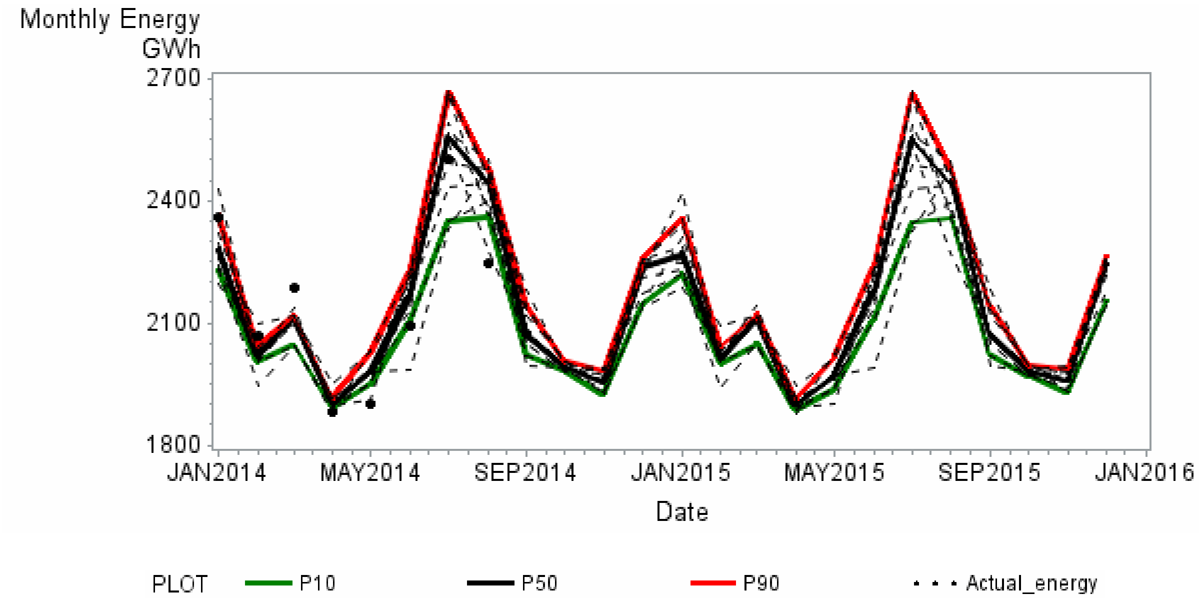


Figure 7-17: Ex ante probabilistic forecasts of NCMASS monthly energy (2014 – 2015)

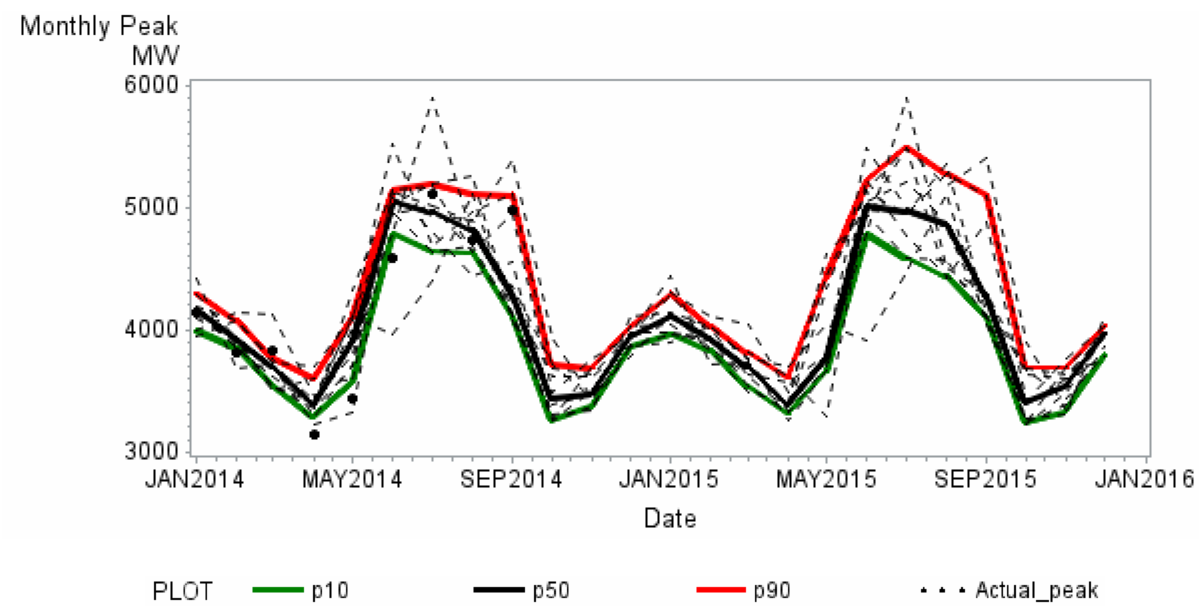


Figure 7-18: Ex ante probabilistic forecasts of NCMASS monthly peak (2014 – 2015)

I. Southeast Massachusetts (SEMASS)

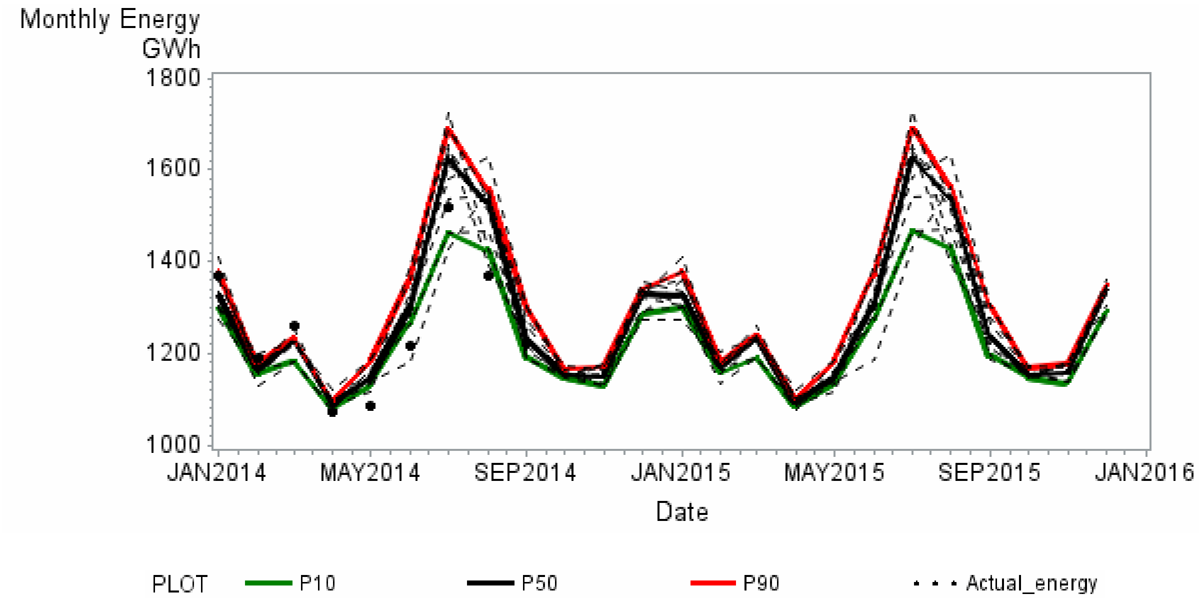


Figure 7-19: Ex ante probabilistic forecasts of SEMASS monthly energy (2014 – 2015)

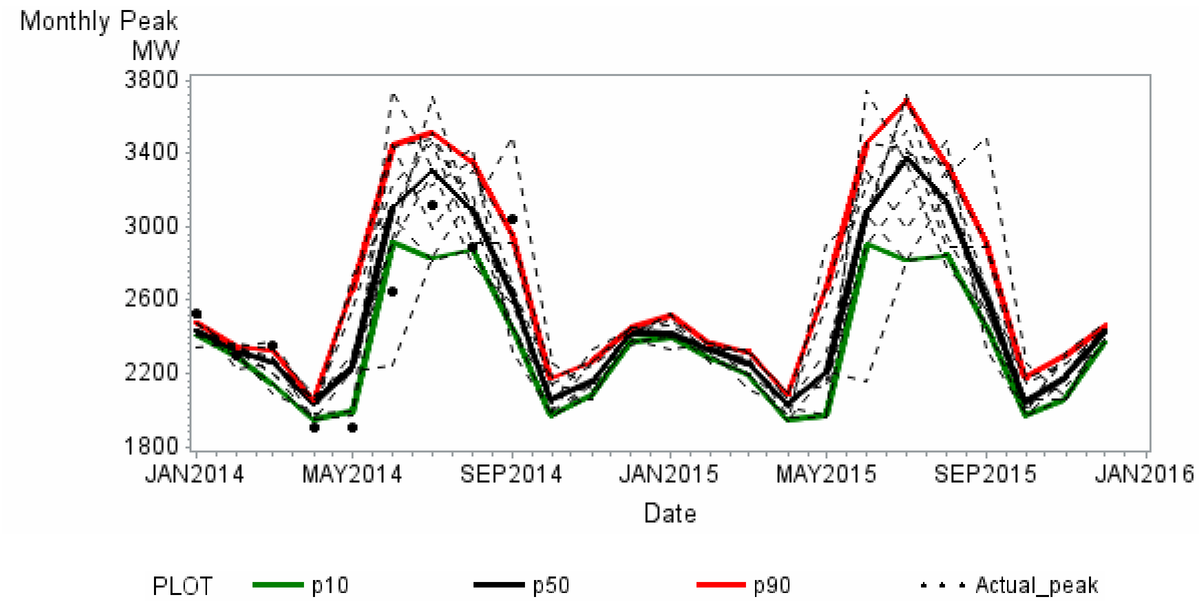


Figure 7-20: Ex ante probabilistic forecasts of SEMASS monthly peak (2014 – 2015)

J. West Central Massachusetts (WCMASS)

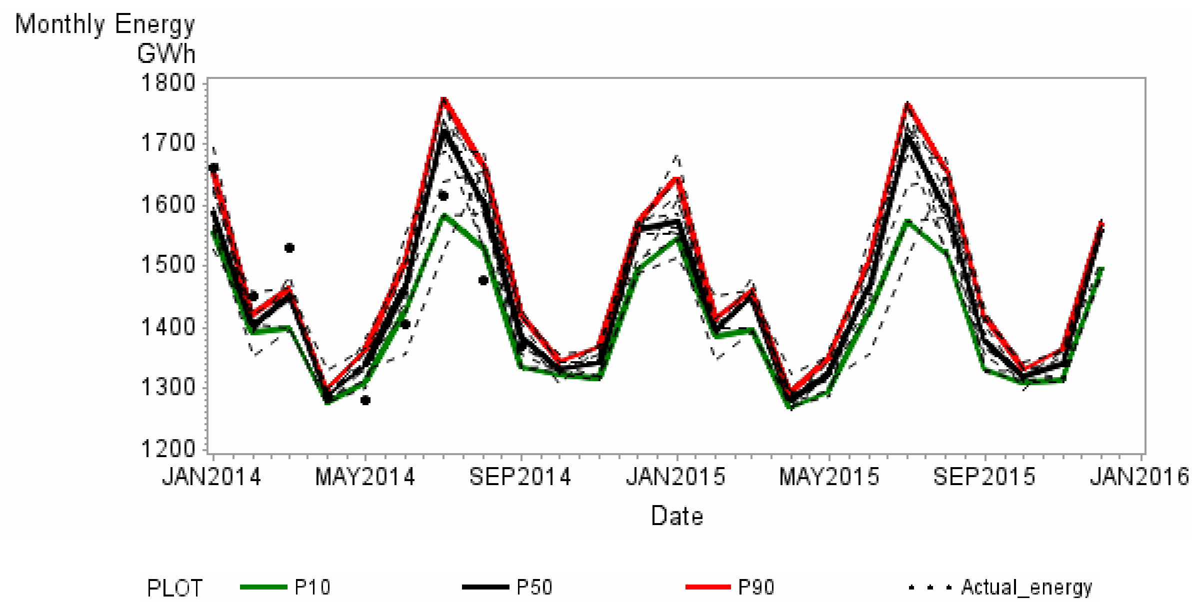


Figure 7-21: Ex ante probabilistic forecasts of WCMASS monthly energy (2014 – 2015)

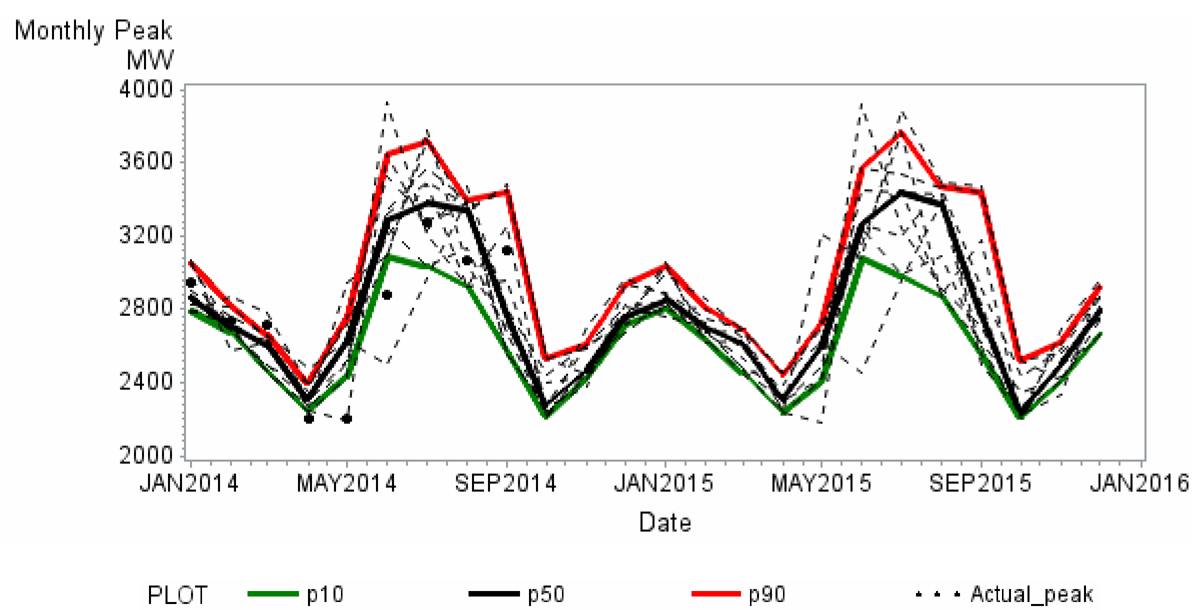


Figure 7-22: Ex ante probabilistic forecasts of WCMASS monthly peak (2014 – 2015)

7.2.4 Energy Efficiency and Distributed Generation

ISO NE also conducts rigorous in-house forecasting activities regularly. ISO NE's forecast report of Capacity, Energy, Loads, and Transmission (the CELT Report) is available to the public[13]. The 10-year projections provided in the CELT Report are used in power system planning and reliability studies. The detailed documents that support the CELT Report are also accessible below. The energy and peak load forecasts integrate state historical demand, economic, and weather data, and the impacts of utility-sponsored conservation and peak-load management programs.

ISO NE develops energy efficiency (EE) forecasts[14] annually with stakeholder input from the Energy-Efficiency Forecast Working Group. The EE forecast is used in ISO studies looking beyond the Forward Capacity Market timeframe, such as long-term transmission planning studies and economic planning studies, and incorporated into the CELT Report and Regional System Plan.

The Distributed Generation (DG) forecast[15] projects the anticipated growth and impact of distributed generation resources on New England's power system. DG is electricity provided by relatively small installations that are directly connected to retail distribution or customer facilities—not the regional power system. An example would be a photovoltaic (PV) system (i.e., solar panels) installed on-site by a homeowner or business. With DG's growing implementation in New England, its effects on the power system—both for operations and system planning—are also expected to grow. For example, DG may be able to alleviate or prevent constraints in regional power system transmission or distribution, and reduce or eliminate the need to install new transmission or distribution facilities.

The DG forecast is developed annually by the ISO with stakeholder input from this working group. The ISO regularly updates the Planning Advisory Committee (PAC) on DG forecast working group developments. For the forecast, DG resources are considered to be those with typically 5 megawatts or less in nameplate capacity that are interconnected to the distribution system (typically 69 kilovolts or below) according to state-jurisdictional interconnection standards. These may include both those installations that are located behind a customer load (i.e., behind-the-meter) and those that are interconnected directly to the distribution system without a customer load being present.

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[13] http://www.iso-ne.com/system-planning/system-plans-studies/celt
[14] http://www.iso-ne.com/system-planning/system-forecasting/energy-efficiency-forecast
[15] http://www.iso-ne.com/system-planning/system-forecasting/distributed-generation-forecast

7.3 Exelon

7.3.1 Overview

Headquartered in Chicago, Exelon does business in 48 states, the District of Columbia, and Canada. The company is one of the largest competitive U.S. power generators, with approximately 35,000 megawatts of owned capacity comprising one of the nation's cleanest and lowest-cost power generation fleets. Its Constellation business unit provides energy products and services to more than 2.5 million residential, public sector, and business customers, including more than two-thirds of the Fortune 100. Exelon's utilities deliver electricity and natural gas to more than 7.8 million utility customers in central Maryland (BGE, Figure 7-23), southeastern Pennsylvania (PECO, Figure 7-24), and northern Illinois (ComEd, Figure 7-25).

In this case study, we will develop forecasts for each of the three operating companies. In addition to ex ante probabilistic load forecasts for the calendar years 2011 to 2013 based on data on and prior to 2010, we also develop the ex post point forecasts for the same years. The load is available through PJM website[16]. The weather data is provided by WeatherBank Inc.[17] GMP of Baltimore, Philadelphia, and Chicago is used as the macroeconomic indicator for each operating companies BGE, PECO, and ComEd respectively. The historical economy data is from U.S. Bureau of Economic Analysis [18]. The economy forecast of 2011 to 2013 is based on a simple linear regression over the most recent 10 years (2001 – 2010). The economy data (both actual and forecasted values) are shown in Figure 7-26, Figure 7-27, and Figure 7-28.

[16] http://pjm.com/markets-and-operations/data-dictionary.aspx
[17] http://weatherbank.com/
[18] http://www.bea.gov/

Figure 7-23: BGE electric service territory map

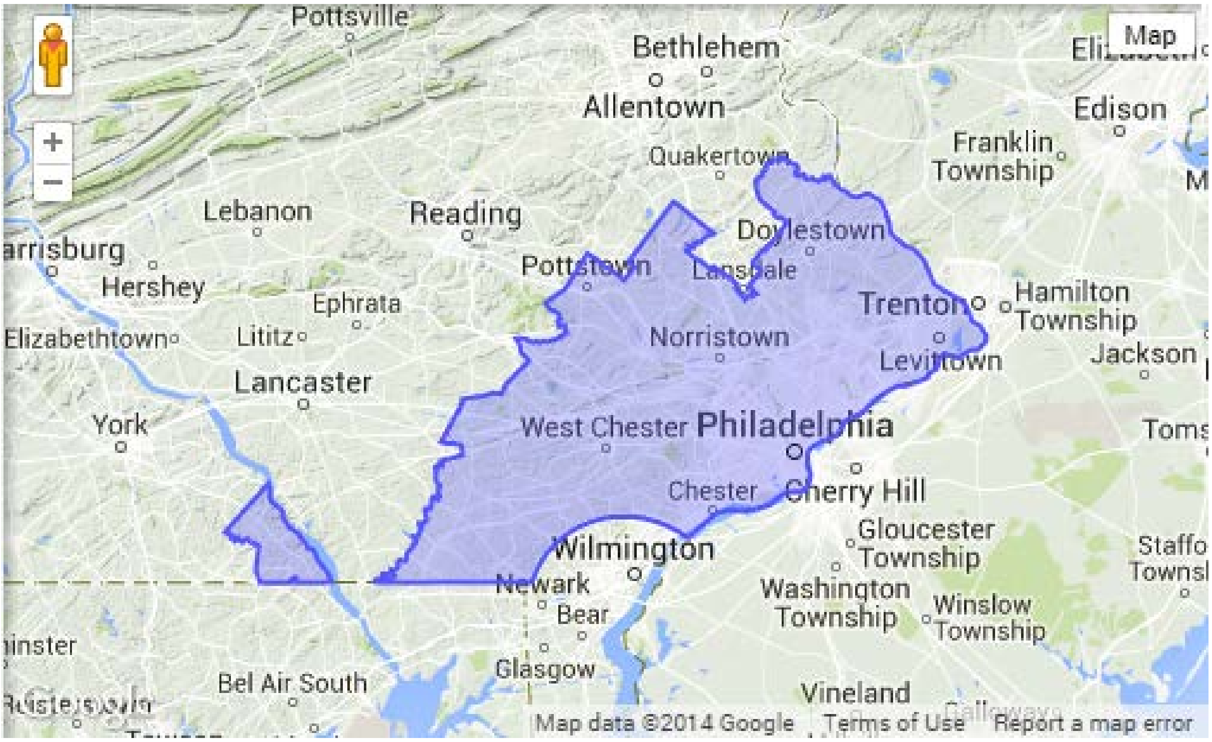

Figure 7-24: PECO electric service territory map

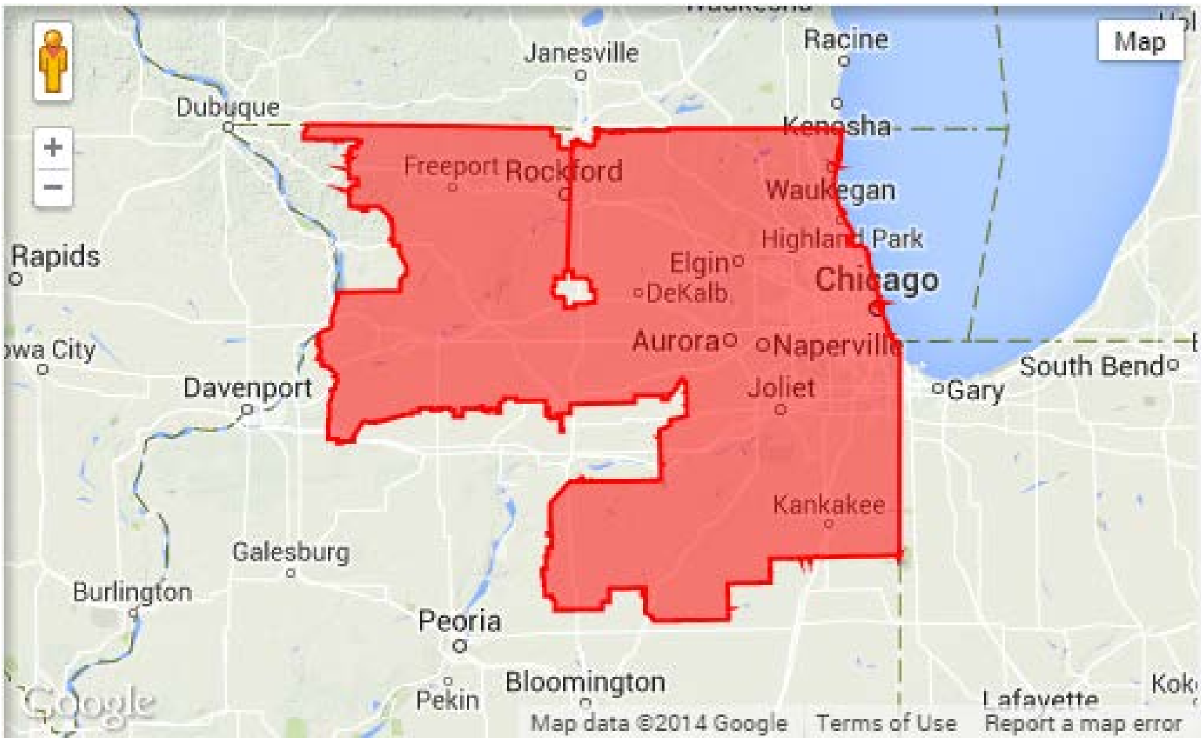

Figure 7-25: ComEd electric service territory map

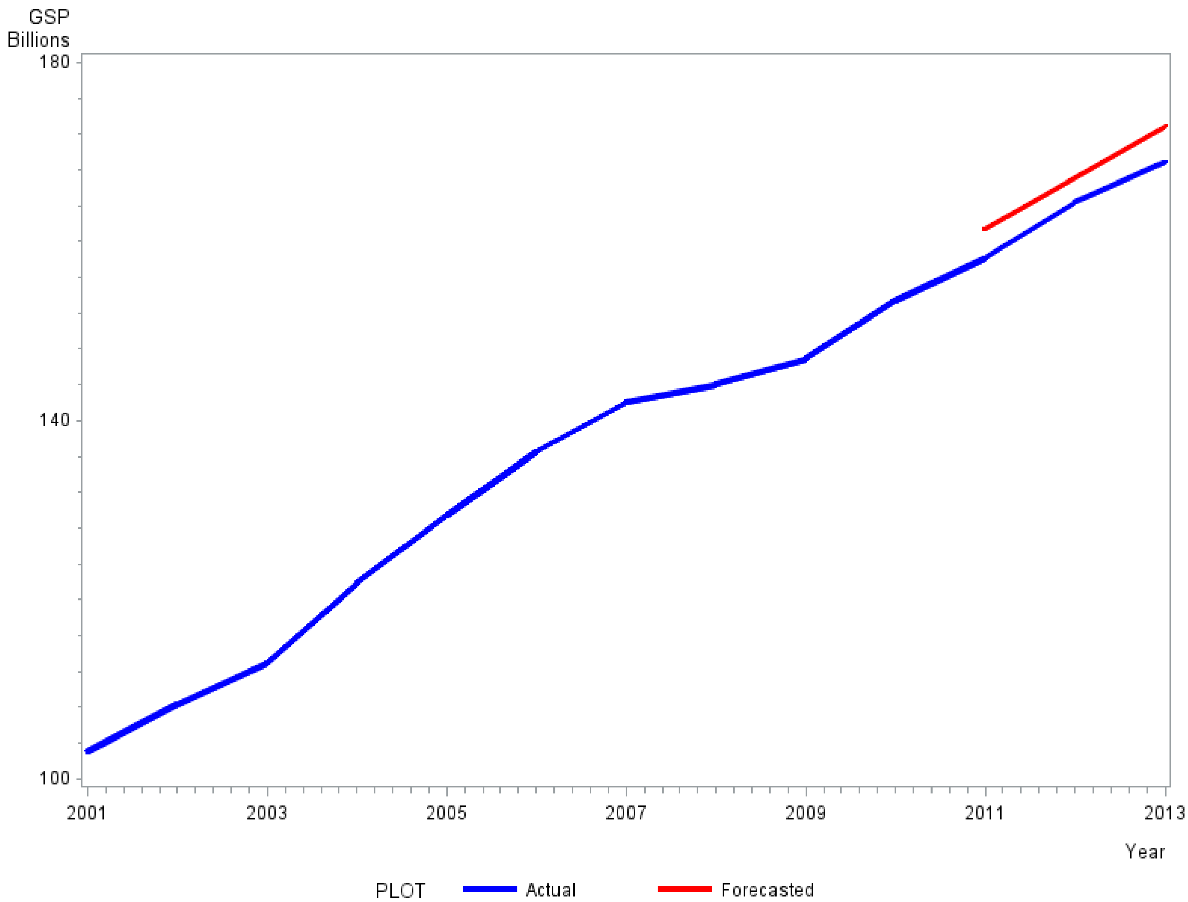

Figure 7-26: Actual and forecasted GMP of Baltimore

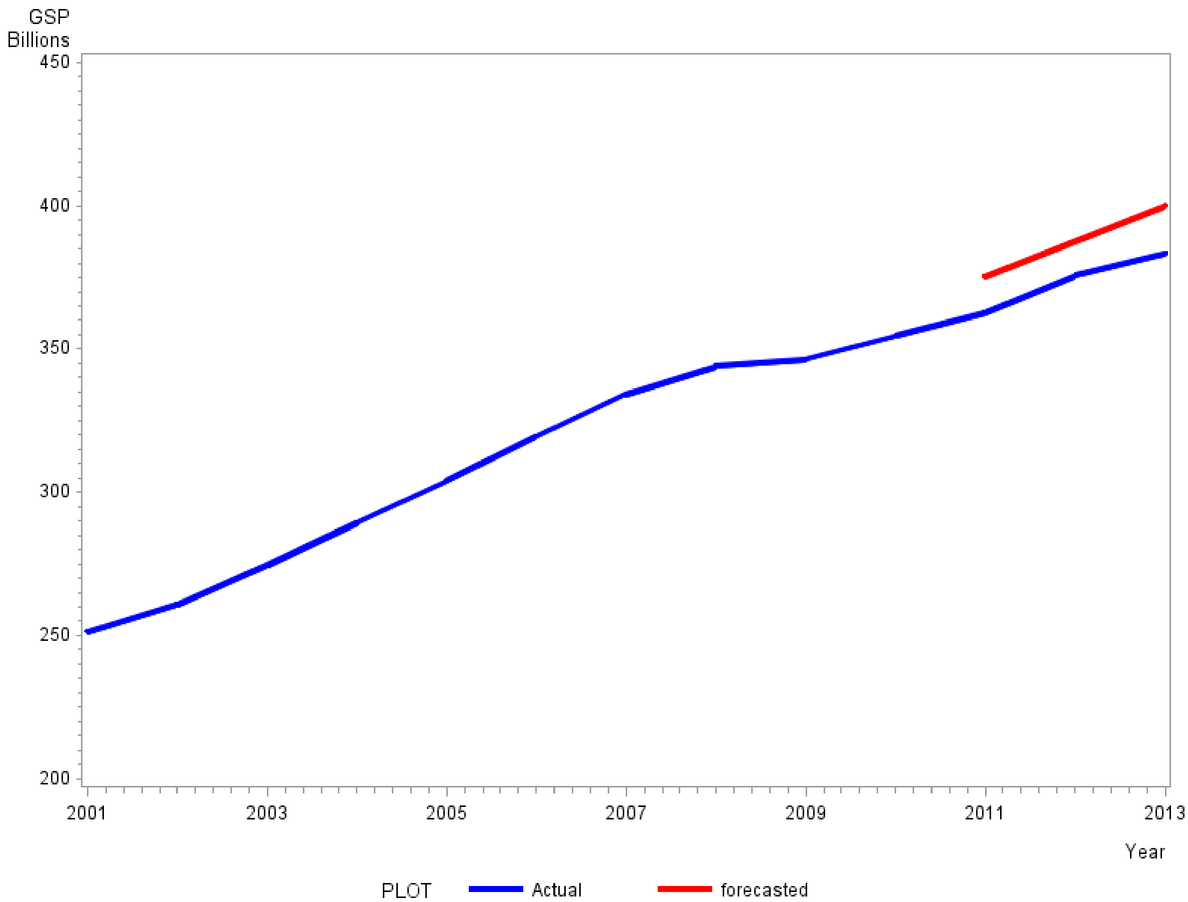

Figure 7-27: Actual and forecasted GMP of Philadelphia

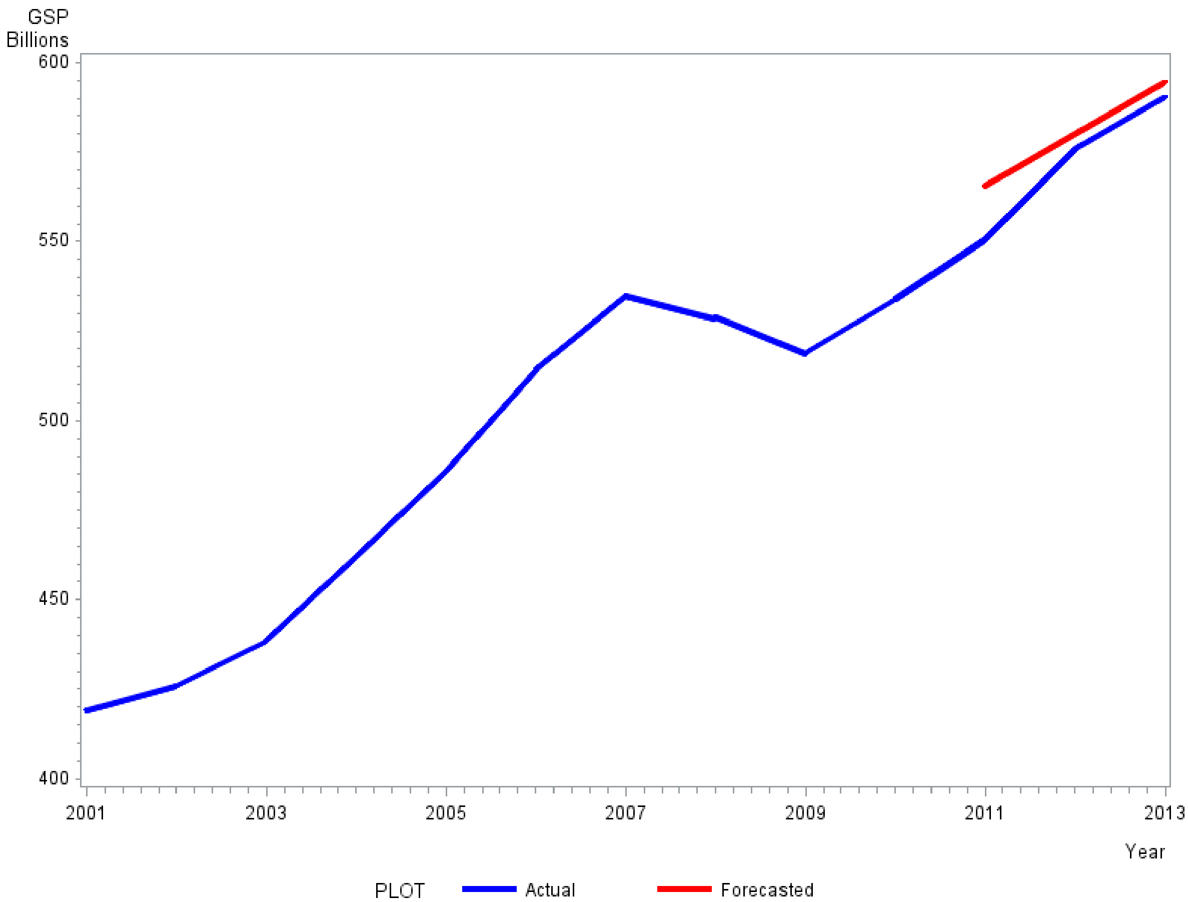

Figure 7-28: Actual and forecasted GMP of Chicago

7.3.2 Weather Station Selection for ComEd

Following the methodology presented in (Hong et al., 2015), we perform the weather station selection for ComEd as an example. Table 7-5 lists the weather station selection results based on different years from 2007 to 2013. It can be seen that the combination of weather stations varies year by year. In other words, for different years, due to the change in meteorological conditions, the weather stations that can be used to best represent the territory also change.

Table 7-5: Weather station selection for ComEd by year

Weather Stations	2007	2008	2009	2010	2011	2012	2013
KC75							
KSQI							√
KVYS	√					√	√
KPNT							
KRPJ							√
KDKB	√	√	√	√	√	√	√
KC09	√	√				√	√
KARR	√					√	√
KJOT	√					√	√
KLOT	√	√	√		√	√	√
KORD	√	√	√	√	√	√	√
KPWK	√	√	√	√	√	√	√
KIKK					√		√
KIGQ	√	√	√		√	√	√
KGYY	√						√
KFEP							
KDPA	√	√	√			√	√
KEFT					√	√	√
KRFD	√	√	√		√	√	√
KJVL	√						√
KBUU							
KENW							
KUGN							
KRAC	√						
KVPZ	√	√	√			√	√

7.3.3 Weekend and Holiday Effects

The three operating companies, Baltimore Gas and Electric Company (BGE), Philadelphia Electric Company (PECO), and Commonwealth Edison Company (ComEd) of Exelon are from three separated states not adjacent to each other. Their weekend (Table 7-6) and holiday (Table 7-7) effects appear to be different as expected.

Table 7-6: Weekend effect modeling for BGE, ComEd and PECO

Zone	Combination
BGE	Tuesday and Wednesday
ComEd	Wednesday and Thursday
PECO	Tuesday and Wednesday

Table 7-7: Holiday effect modeling for BGE, ComEd, and PECO

Holiday	BGE	ComEd	PECO
Before	Sat	Sun	Sat
New Year's Day	Sun	Sun	Sun
After	Mon	Mon	None
Before	None	None	None
Birthday of MLK	None	None	Fri
After	None	None	Mon
Before	None	Sun	None
Washington's Birthday	Sat	Fri	Fri
After	None	Wed	Thu
Before	None	Sun	None
Memorial Day	Sun	Sun	Sat
After	None	Mon	None
Before	Fri	Fri	Fri
Independence Day	Sat	Sun	Sun
After	None	None	None
Before	None	None	None
Labor Day	Sun	Sun	Sun
After	Mon	Mon	Thu
Before	None	None	None
Columbus Day	None	None	None
After	None	None	None
Before	None	None	None
Veterans Day	None	None	None
After	None	None	None
Before	Fri	Fri	None
Thanksgiving Day	Sat	Sun	Sat
After	Sat	Sun	Sat
Before	Sat	Sat	Sat
Christmas Day	Sun	Sat	Sun
After	Sat	Sat	Sat

7.3.4 Ex ante Probabilistic Forecasting Results

This section presents the ex ante probabilistic forecasting results of BGE, PECO, and ComEd. The dashed lines are the monthly energy (or peak) from 10 weather scenarios derived from weather history from 1996 to 2010. The black, red, and green lines are the median, 90th percentile, and 10th percentile monthly energy (or peak) of the 10 scenarios. The actual load is represented by the black dots.

A Baltimore Gas and Electric Company (BGE)

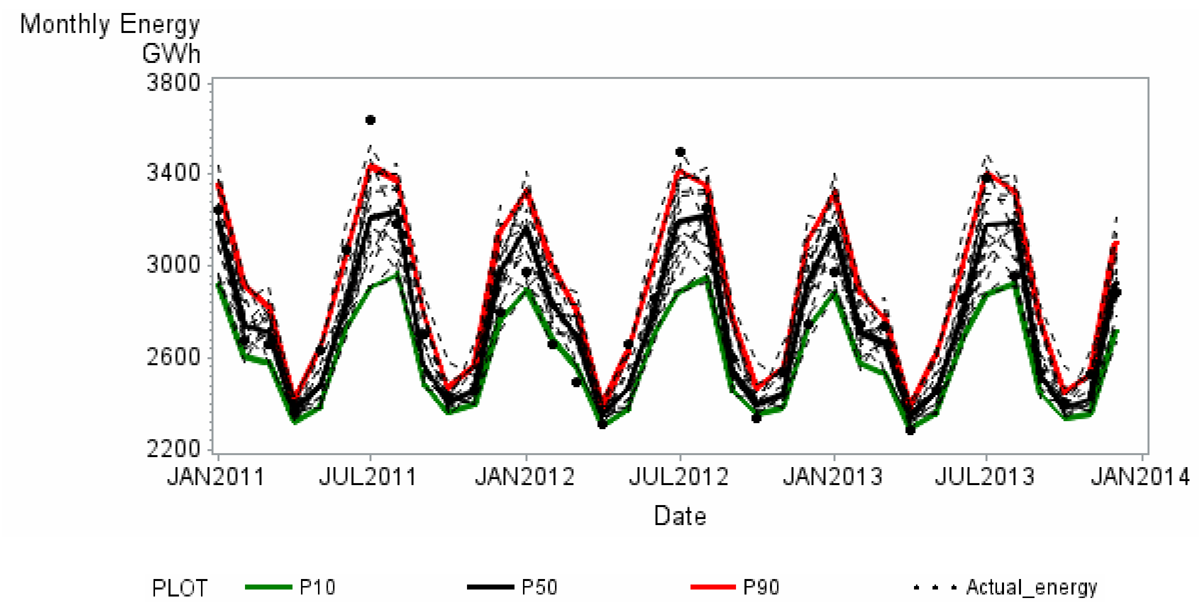

Figure 7-29: Ex ante probabilistic forecasts of BGE monthly energy (2011 – 2013)

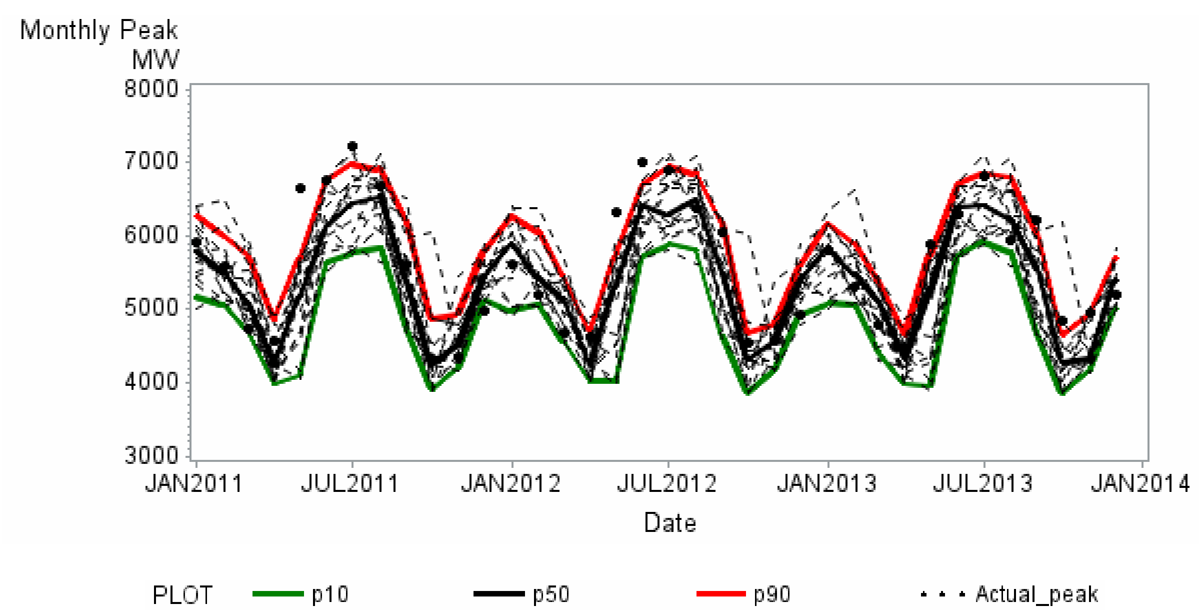

Figure 7-30: Ex ante probabilistic forecasts of BGE monthly peak (2011 – 2013)

B. *Philadelphia Electric Company (PECO)*

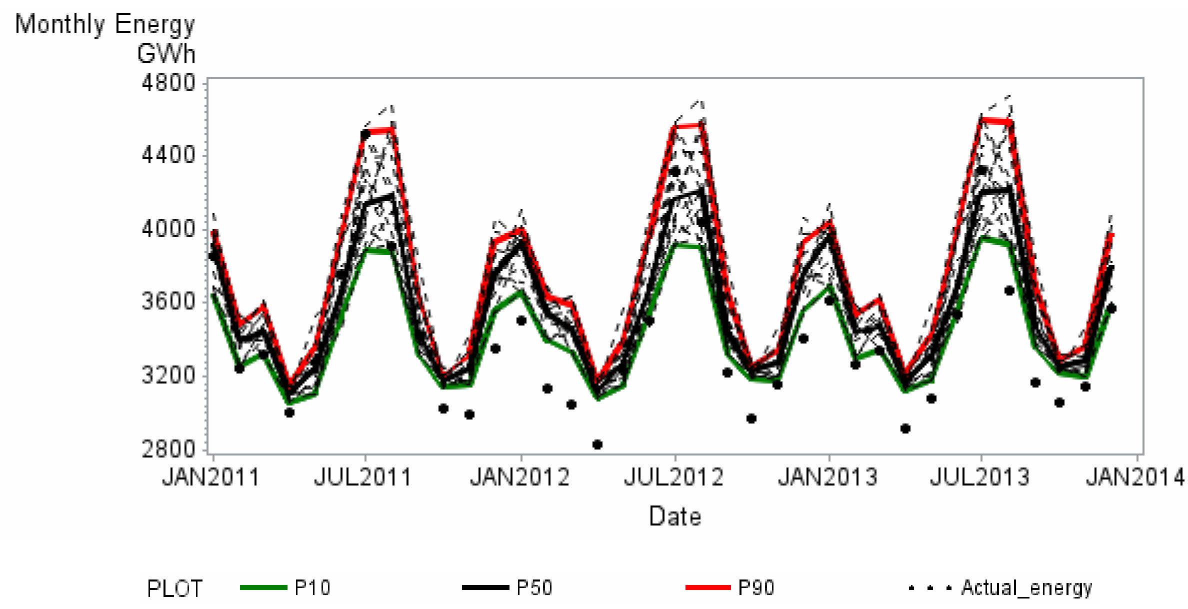

Figure 7-31: Ex ante probabilistic forecasts of PECO monthly energy (2011 – 2013)

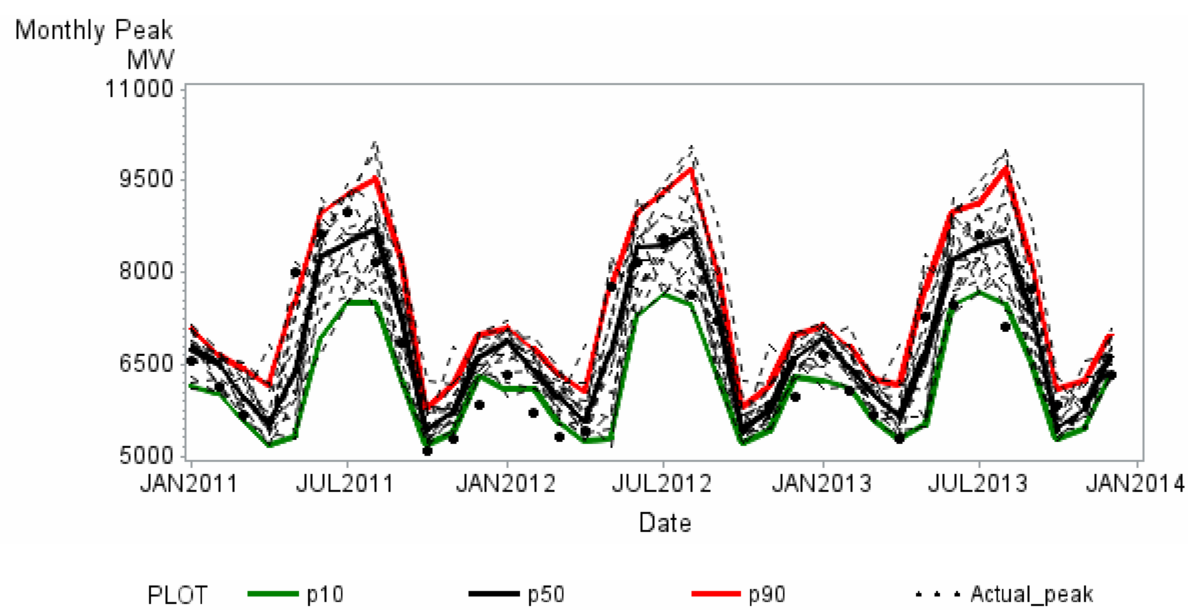

Figure 7-32: Ex ante probabilistic forecasts of PECO monthly peak (2011 – 2013)

C. Commonwealth Edison Company (ComEd)

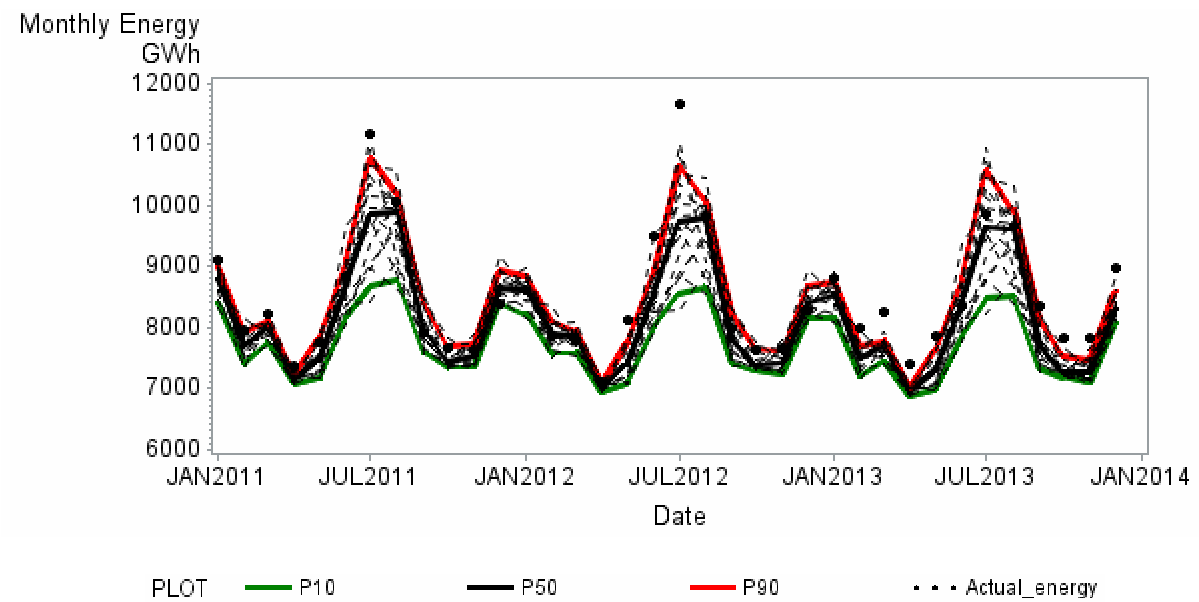

Figure 7-33: Ex ante probabilistic forecasts of ComEd monthly energy (2011 – 2013)

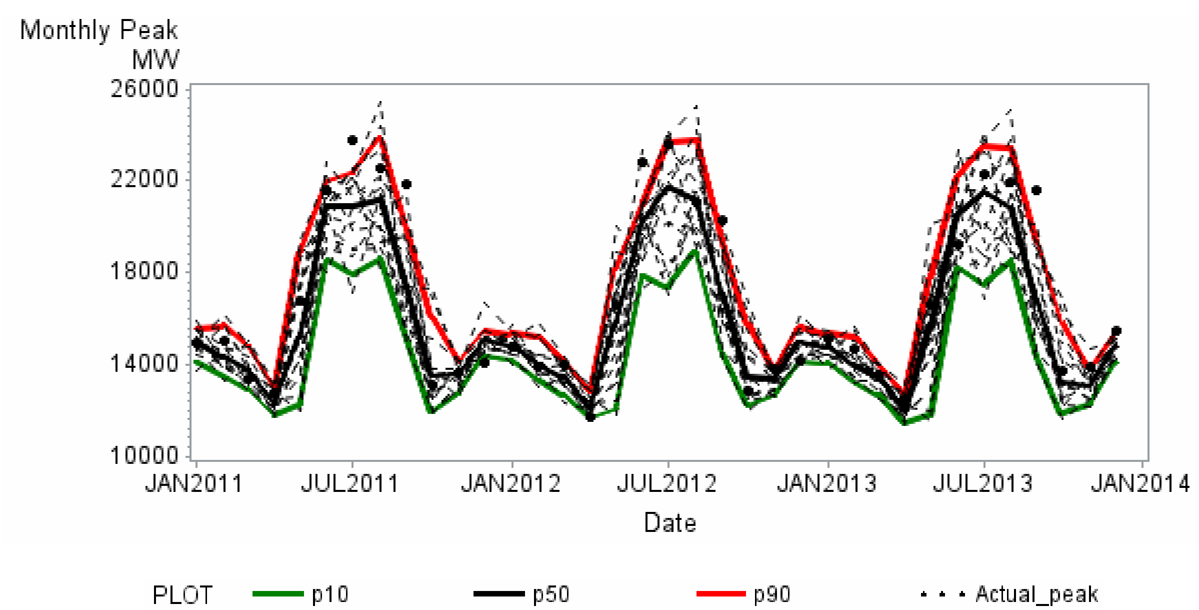

Figure 7-34: Ex ante probabilistic forecasts of ComEd monthly peak (2011 – 2013)

7.3.5 Ex post Point Forecasting Results

Ex post point forecasting helps understand the modeling error given actual weather and economy observations. This section presents the ex post point forecasting results of the three operating companies. The actual economy and temperature observations are used to generate the ex post forecasts. The actual load is represented by the black dots.

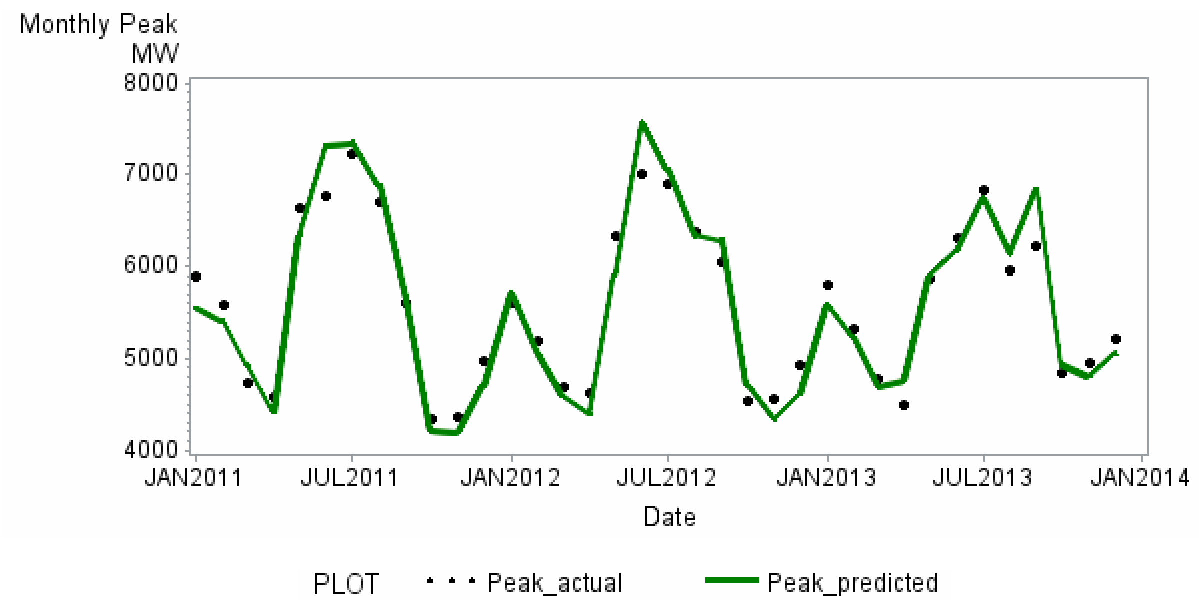

Figure 7-35: Ex post point forecasts of BGE monthly peak (2011 – 2013)

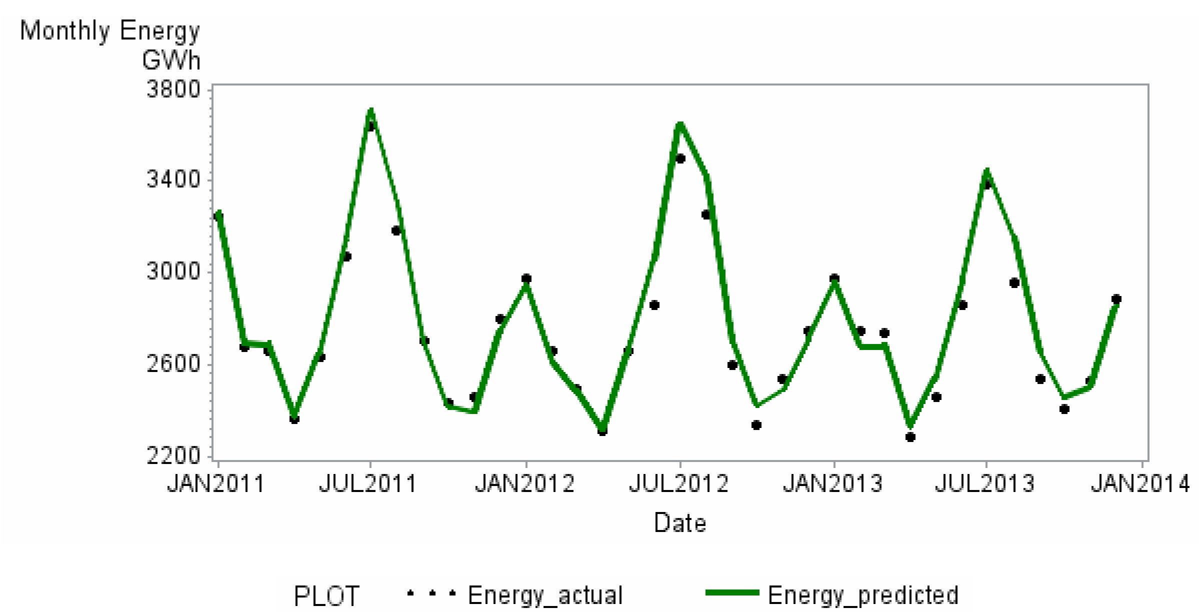

Figure 7-36: Ex post point forecasts of BGE monthly energy (2011 – 2013)

B. Philadelphia Electric Company (PECO)

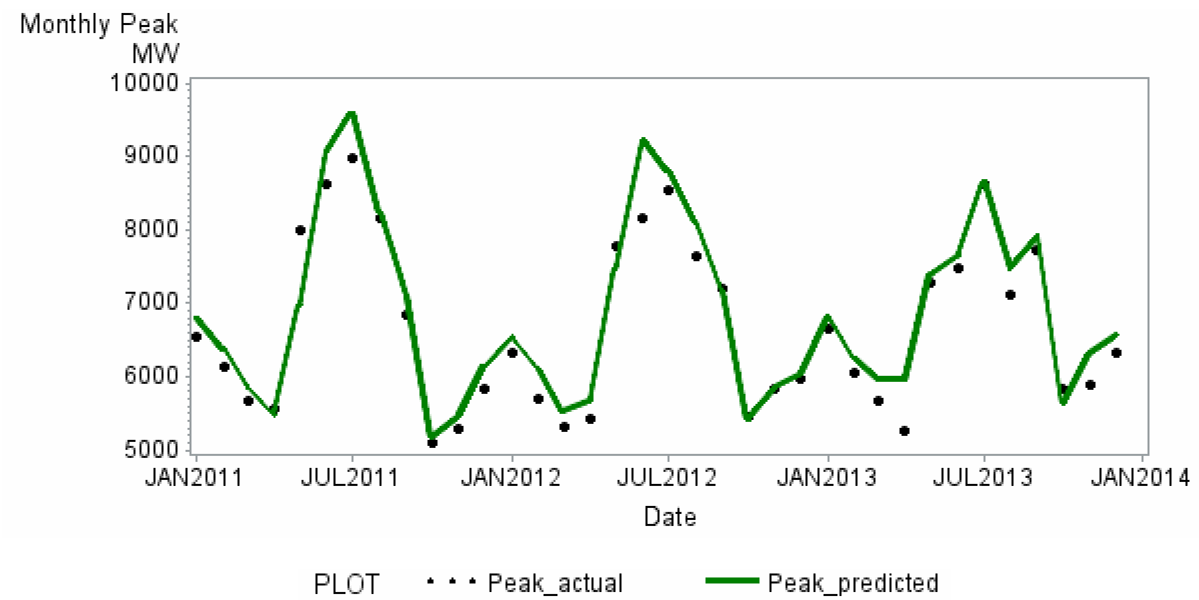

Figure 7-37: Ex post point forecasts of PECO monthly peak (2011 – 2013)

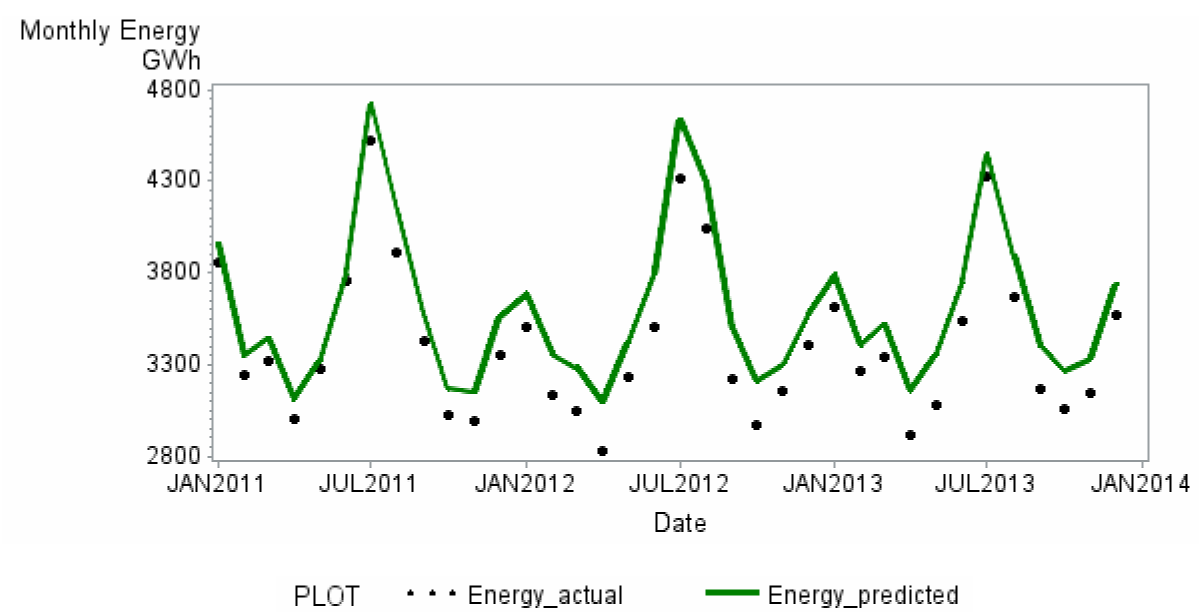

Figure 7-38: Ex post point forecasts of PECO monthly energy (2011 – 2013)

C. Commonwealth Edison Company (ComEd)

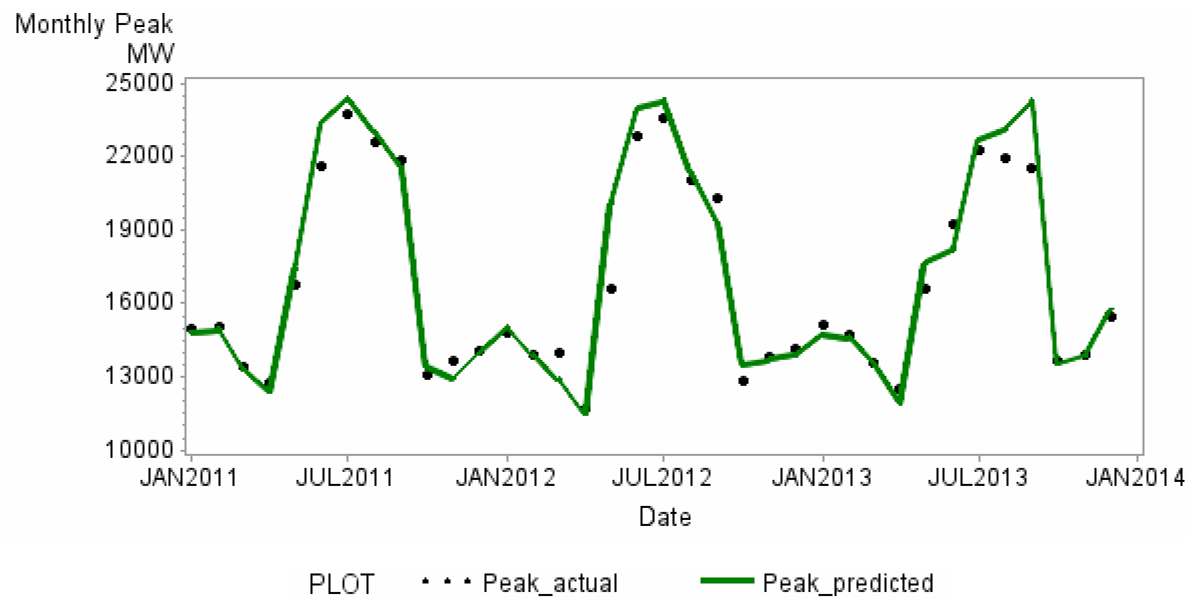

Figure 7-39: Ex post point forecasts of ComEd monthly peak (2011 – 2013)

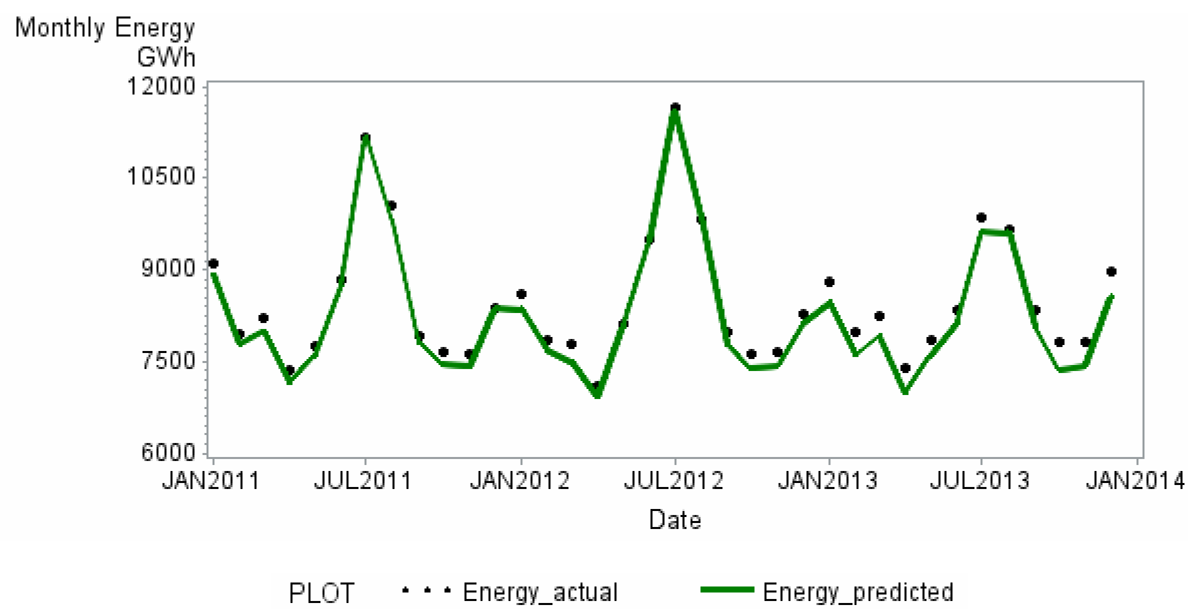

Figure 7-40: Ex post point forecasts of ComEd monthly energy (2011 – 2013)

7.4 NCEMC

7.4.1 Overview

As one of the largest G&T cooperatives in the US, NCEMC is comprised of a family of corporations formed to support 26 of North Carolina's electric distribution cooperatives. These cooperatives provide energy and related services to more than 950,000 households and businesses in 93 of North Carolina's 100 counties. Figure 7-41 shows the territory map of NCEMC. North Carolina can be divided into three distinct geographic areas, the Coastal Plain in the east, the Piedmont in the center, and Mountains in the west. For power supply purposes, NCEMC's territory is divided into three supply areas denoted as SA1, SA2, and SA3 respectively in this chapter. Some supply areas may cross multiple geographic areas.

In this case study, we will develop forecasts for each of the three power supply areas and NCEMC total load. The case study is set up intentionally to forecast the five years after 2008, when the recession started. In addition to ex ante probabilistic load forecasts for the calendar years 2009 to 2013 based on data on and prior to 2008, we also develop the ex post point forecasts for the same years. There are two ex post forecasts we are developing: one with actual temperature and actual economy, and the other one with actual temperature and forecasted economy. This setup allows people to see one of the worst cases with long term load forecasting: not only the economy forecast would be off, but also the energy consumption behavior may have changed due to the economy.

The load and weather data is provided by NCEMC. GSP of North Carolina is used as the macroeconomic indicator in this case study. The historical economy data is from U.S. Bureau of Economic Analysis [19]. The economy forecast of 2009 to 2014 is based on a simple linear regression over the most recent 12 years (1997 – 2008). The economy data (both actual and forecasted values) are shown in Figure 7-42.

[19] http://www.bea.gov/

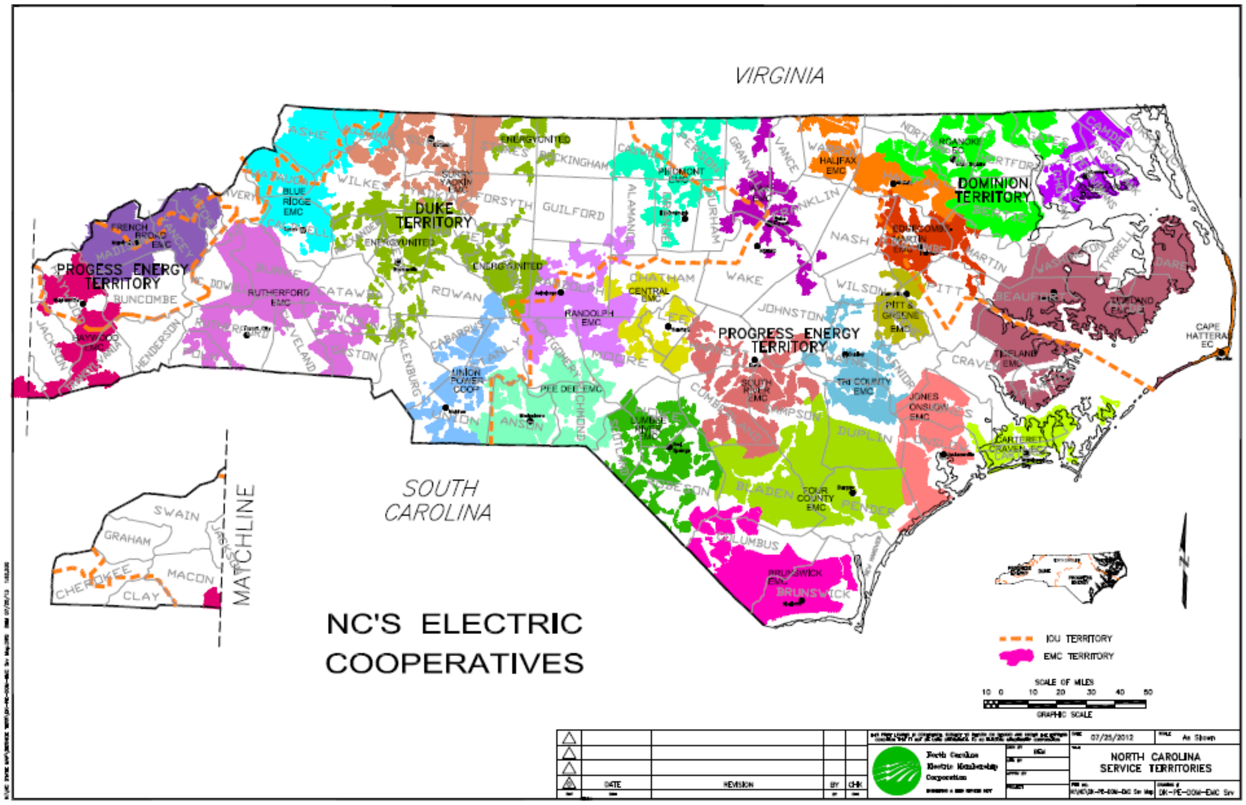

Figure 7-41: NCEMC electric service territory map

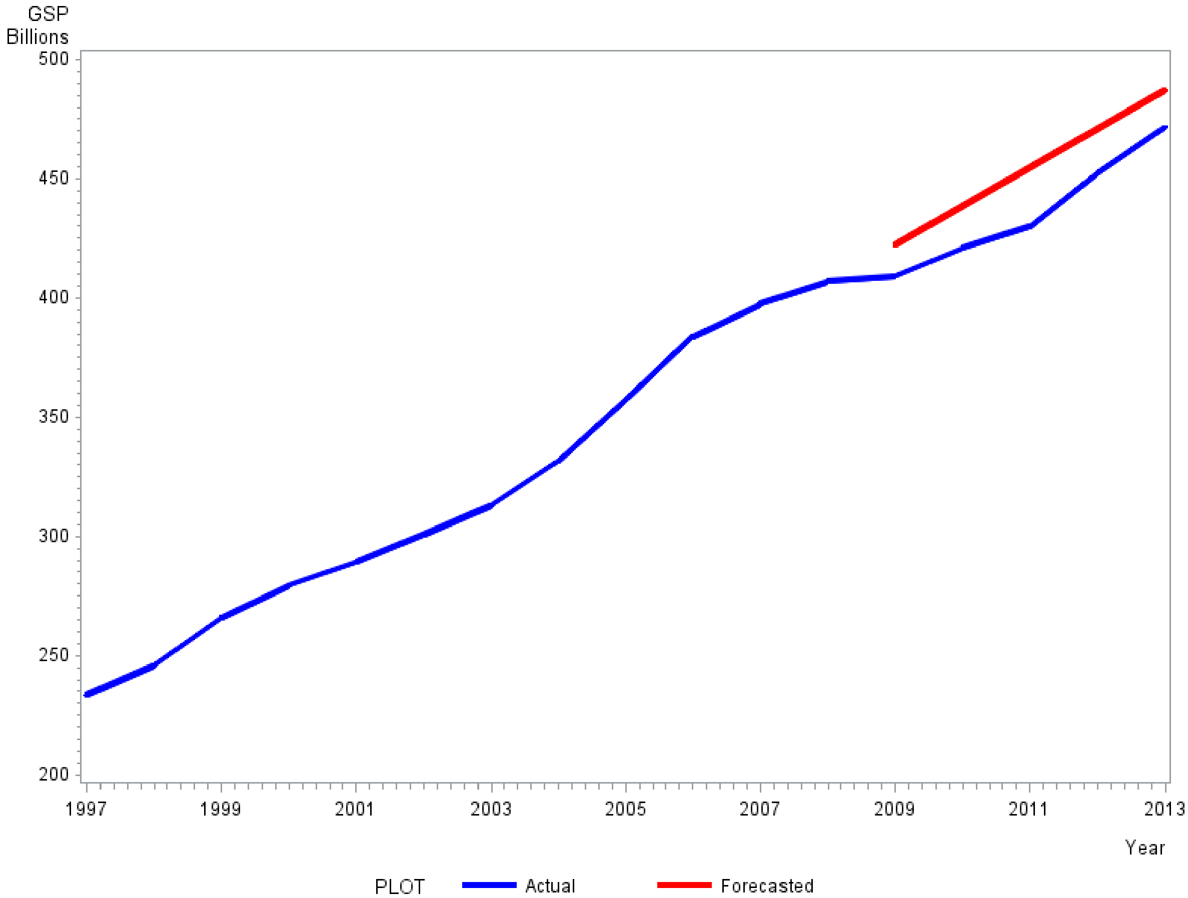

Figure 7-42: Actual and forecasted GSP of North Carolina

7.4.2 Weather Station Selection for NCEMC

Following the methodology presented in (Hong et al., 2015), we perform the weather station selection for NCEMC as an example. Table 7-8 lists the weather station selection based on 2008. It can be seen that the combination of weather stations varies from one supply area to another. In other words, for different supply areas, due to the change in meteorological conditions, the weather stations that can be used to best represent the territory also change. This is expected due to the aforementioned geographic diversity of the North Carolina.

Table 7-8: Weather station selection for NCEMC

Weather Stations	NCEMC	SA1	SA2	SA3
KAFP	√	√	√	
KASJ				√
KAVL				
KCLT	√	√	√	
KCPC	√	√		
KECG				√
KEWN	√	√		√
KEYF	√	√		√
KGEV				
KGSB	√	√		√
KGSO	√	√	√	√
KHBI	√	√	√	
KHKY			√	
KHNZ	√			√
KHSE				√
KIGX	√	√	√	√
KILM	√	√		√
KIPJ			√	
KMRH	√	√		√
KMRN				
KMWK				
KNCA	√	√		√
KORF				√
KPGV	√	√		√
KPOB	√	√	√	√
KRDU	√	√	√	√
KRWI	√	√		√
Total Number Selected	17	16	9	17

7.4.3 Weekend and Holiday Effects

The weekend and holiday effects are listed in Table 7-9 and Table 7-10 respectively. Although the territory of NCEMC falls in one state, the weekend and holiday effects vary from one supply area to another.

Table 7-9: Weekend effect modeling for NCEMC

Zone	Combination
NCEMC	Wednesday and Thursday
SA1	Wednesday and Thursday
SA2	None
SA3	Monday and Tuesday, Wednesday and Thursday

Table 7-10: Holiday effect modeling for NCEMC

Holiday	NCEMC	SA1	SA2	SA3
Before	Sat	Sun	Sat	None
New Year's Day	Sun	Sun	Sun	Sun
After	Mon	Mon	None	None
Before	None	None	Sat	None
Birthday of MLK	Sun	None	Sun	Sat
After	None	None	None	Wed
Before	None	None	None	None
Washington's Birthday	None	None	None	Sat
After	None	None	None	Fri
Before	None	None	Sat	Sat
Memorial Day	Sat	Sun	Sat	Sat
After	Mon	Mon	Mon	Wed
Before	Fri	Fri	Fri	Fri
Independence Day	Sun	Sun	Sun	Sun
After	Mon	Mon	Fri	Mon
Before	Sat	Sat	Sat	Sat
Labor Day	Sat	Sat	Sat	Sat
After	Wed	None	Wed	Fri
Before	None	None	None	None
Columbus Day	None	None	Wed	None
After	None	None	None	None
Before	None	None	None	None
Veterans Day	None	None	None	Sun
After	None	None	None	None
Before	Mon	Tue	Mon	Sat
Thanksgiving Day	Sat	Sat	Sat	Sun
After	Sat	Sat	None	Sat
Before	Sat	Sun	Sat	Sat
Christmas Day	Sun	Sun	Sun	Sun
After	Sun	Sun	Sun	Sat

7.4.4 Ex ante Probabilistic Forecasting Results

This section presents the ex ante probabilistic forecasting results of NCEMC and its three supply areas. The dashed lines are the monthly energy (or peak) from 30 weather scenarios derived from weather history from 1979 to 2008. The black, red, and green lines are the median, 90th percentile, and 10th percentile monthly energy (or peak) of the 10 scenarios. The actual load is represented by the black dots.

A NCEMC Total

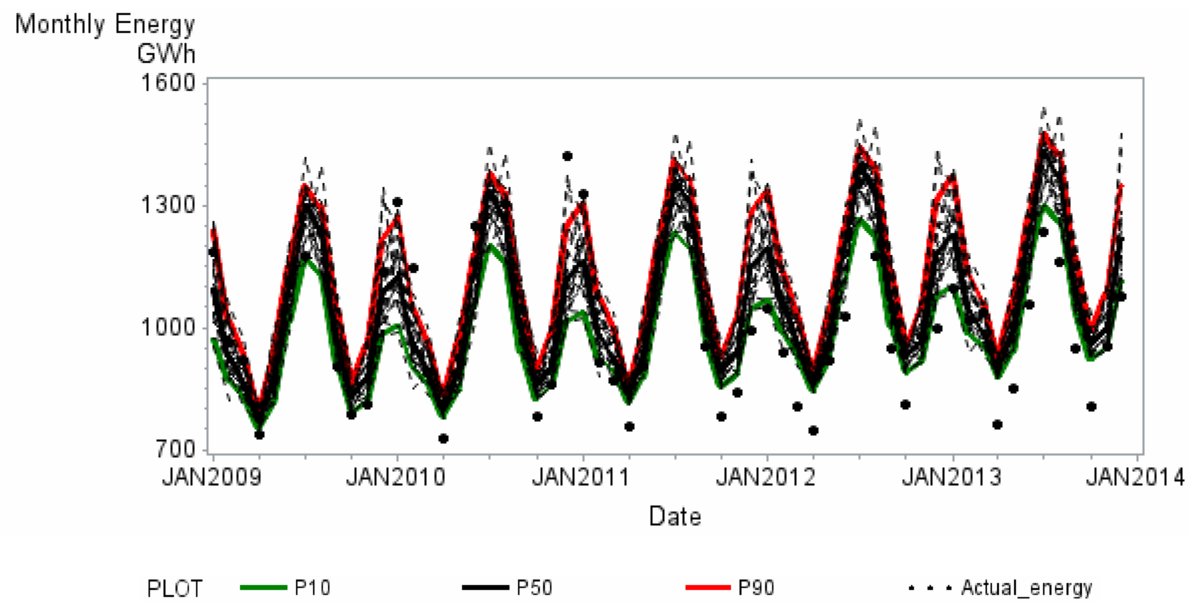

Figure 7-43: Ex ante probabilistic forecasts of NCEMC monthly energy (2009 – 2013)

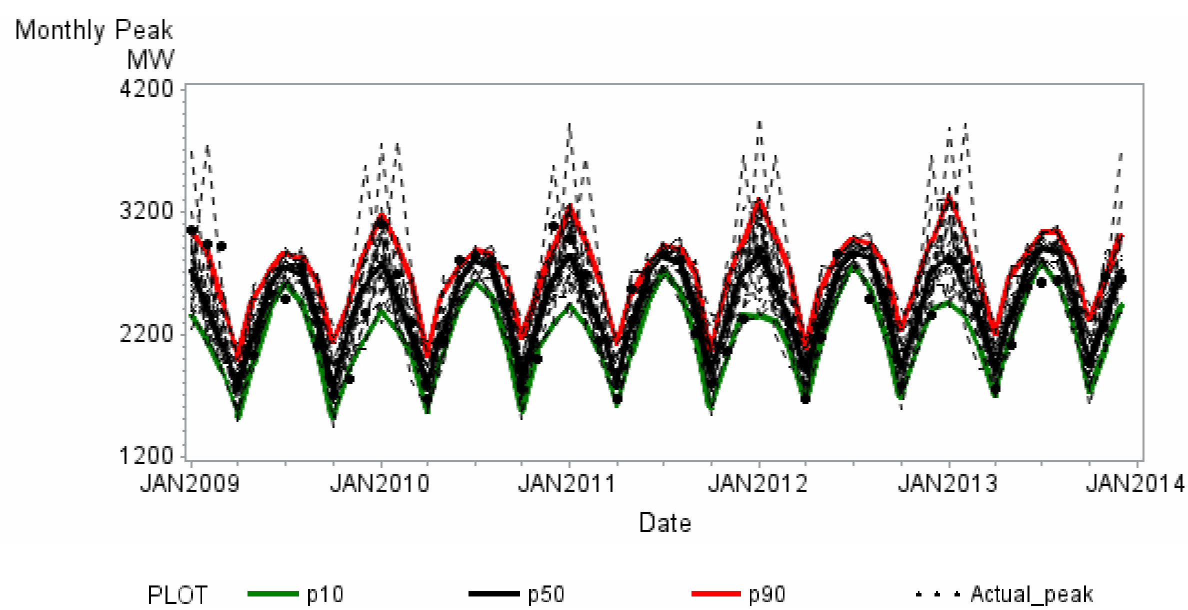

Figure 7-44: Ex ante probabilistic forecasts of NCEMC monthly peak demand (2009 – 2013)

B. NCEMC Zone 1

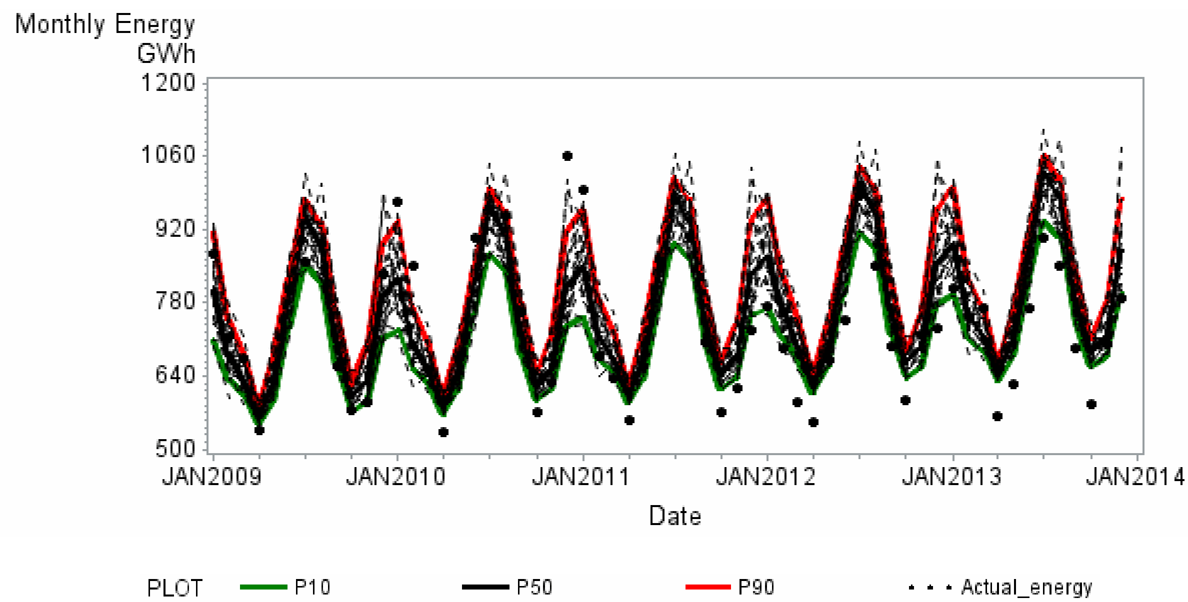

Figure 7-45: Ex ante probabilistic forecasts of NCEMC SA1 monthly energy (2009 – 2013)

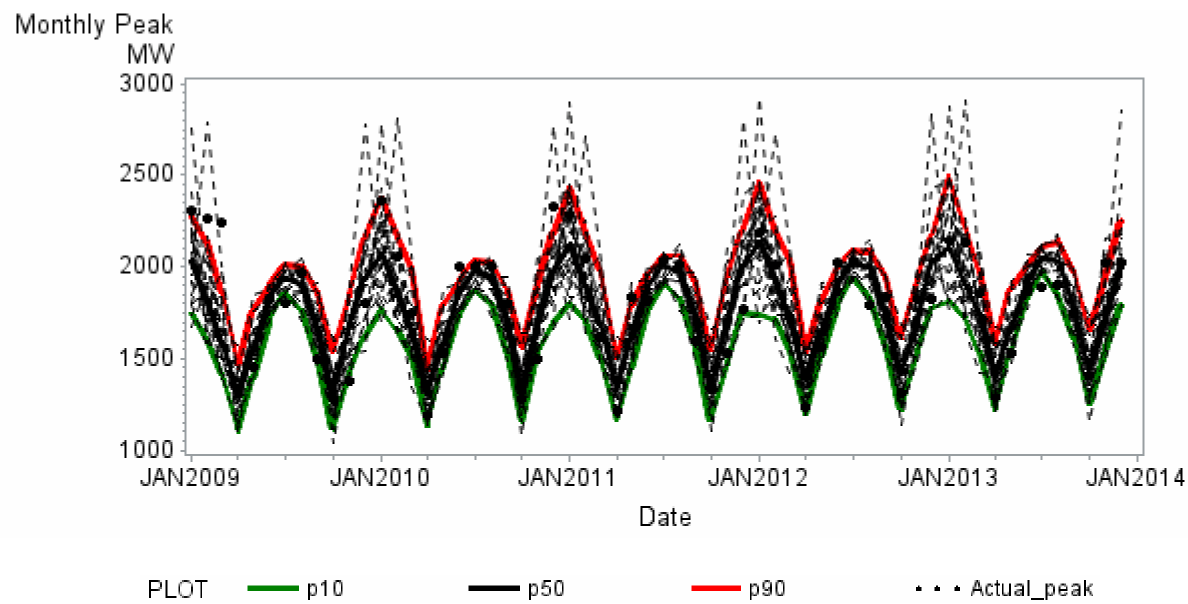

Figure 7-46: Ex ante probabilistic forecasts of NCEMC SA1 monthly peak (2009 – 2013)

C. NCEMC Zone 2

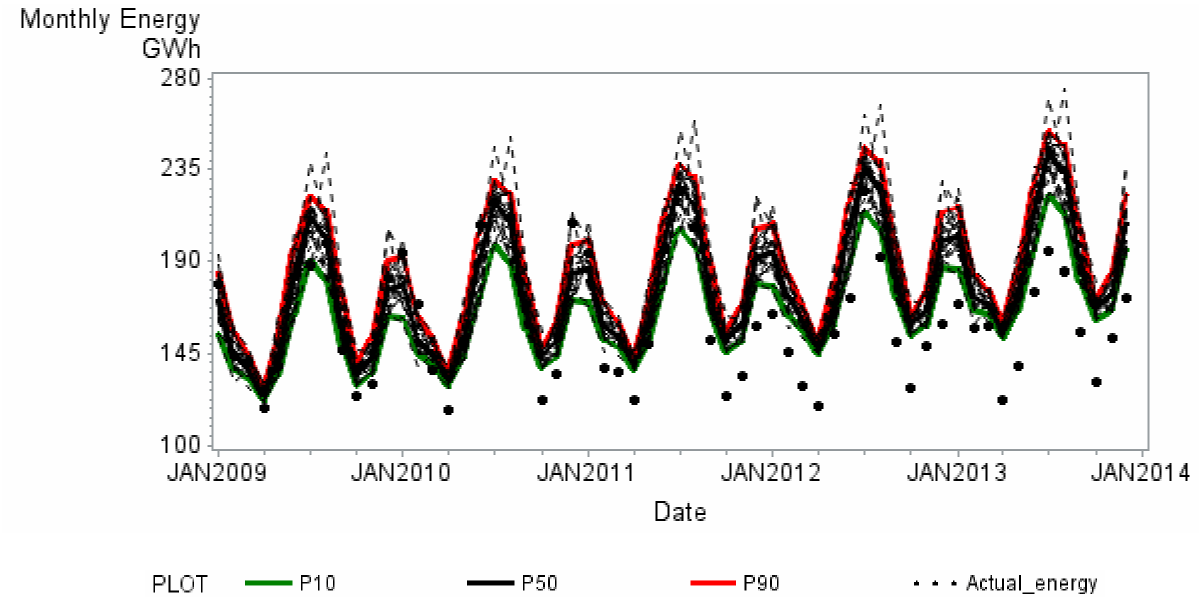

Figure 7-47: Ex ante probabilistic forecasts of NCEMC SA2 monthly energy (2009 – 2013)

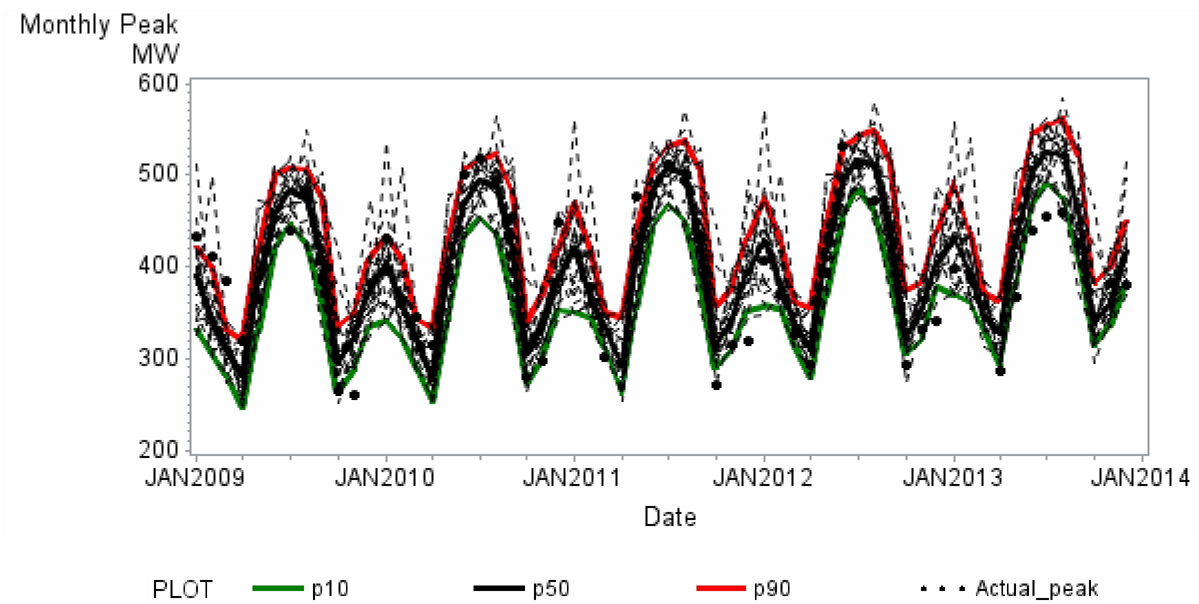

Figure 7-48: Ex ante probabilistic forecasts of NCEMC SA2 monthly peak (2009 – 2013)

D. NCEMC Zone 3

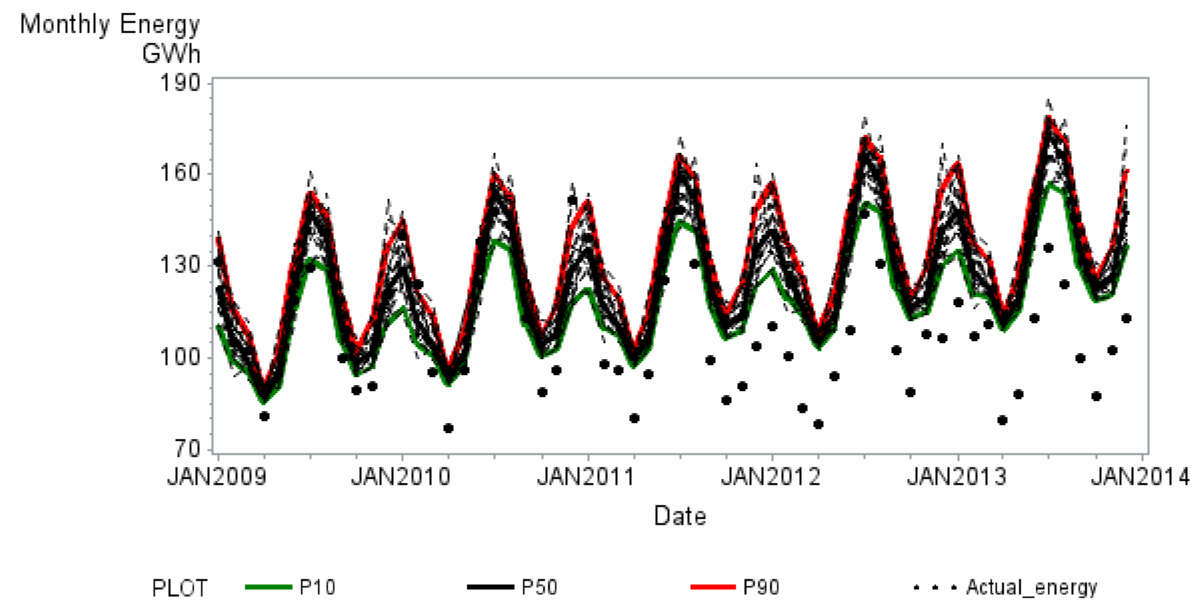

Figure 7-49: Ex ante probabilistic forecasts of NCEMC SA3 monthly energy (2009 – 2013)

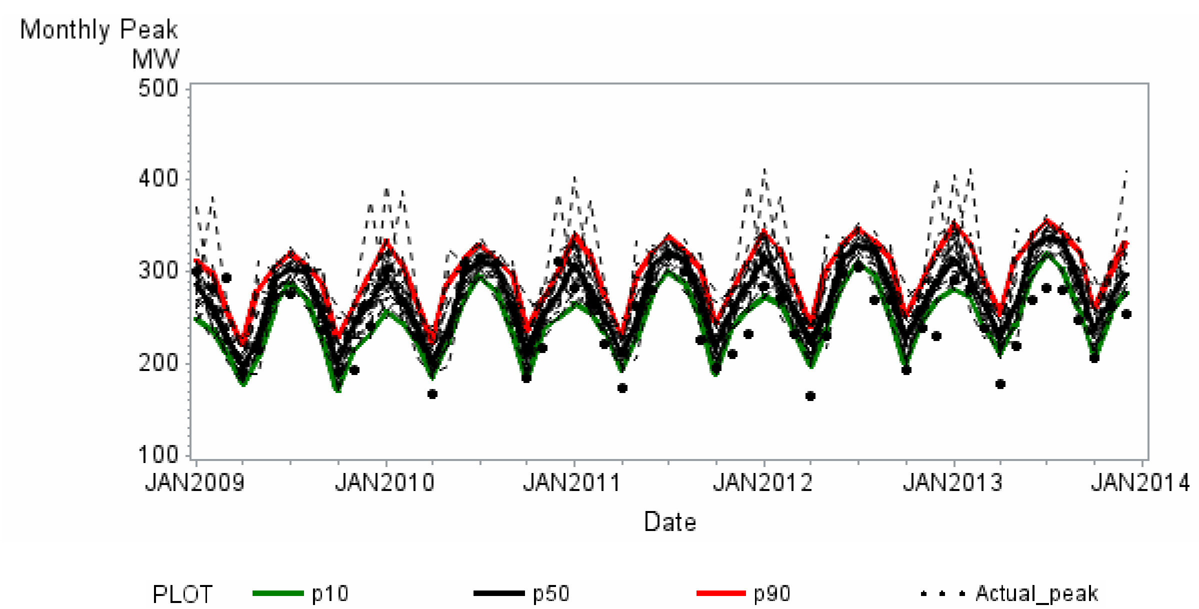

Figure 7-50: Ex ante probabilistic forecasts of NCEMC SA3 monthly peak (2009 – 2013)

7.4.5 Ex post Point Forecasting Results

In this section, we will show two ex post forecasts for NCEMC and its three power supply areas. The blue line is generated with actual observations of temperature and economy observation. The red line is generated with actual observations of temperature and forecasted economy.

A. NCEMC Total

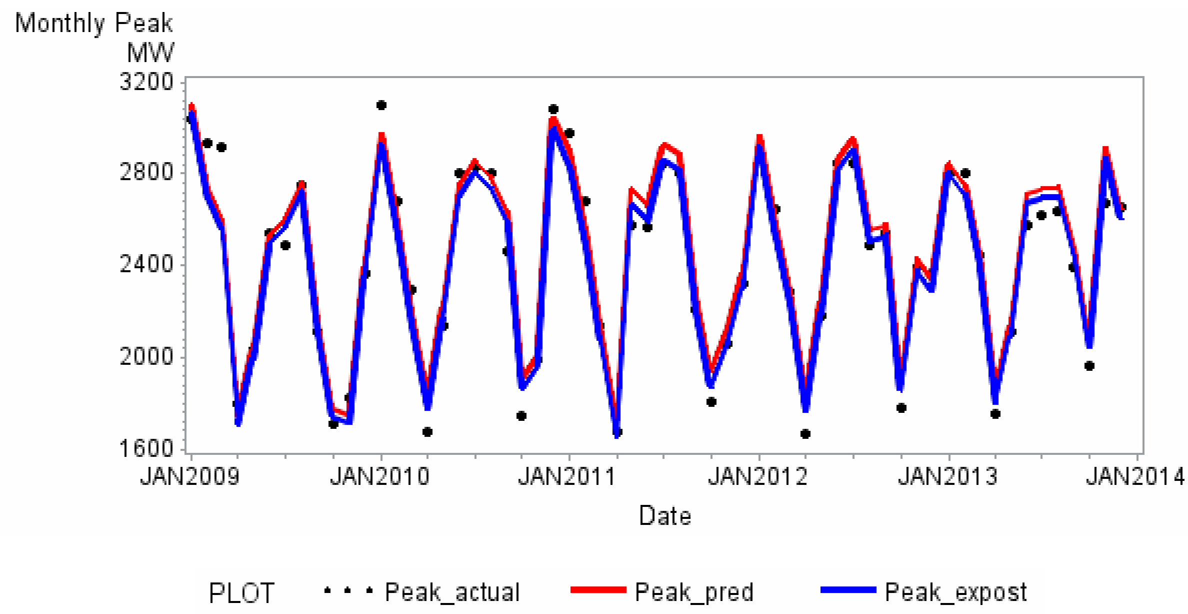

Figure 7-51: Ex post point forecasts of NCEMC monthly peak (2009 – 2013)

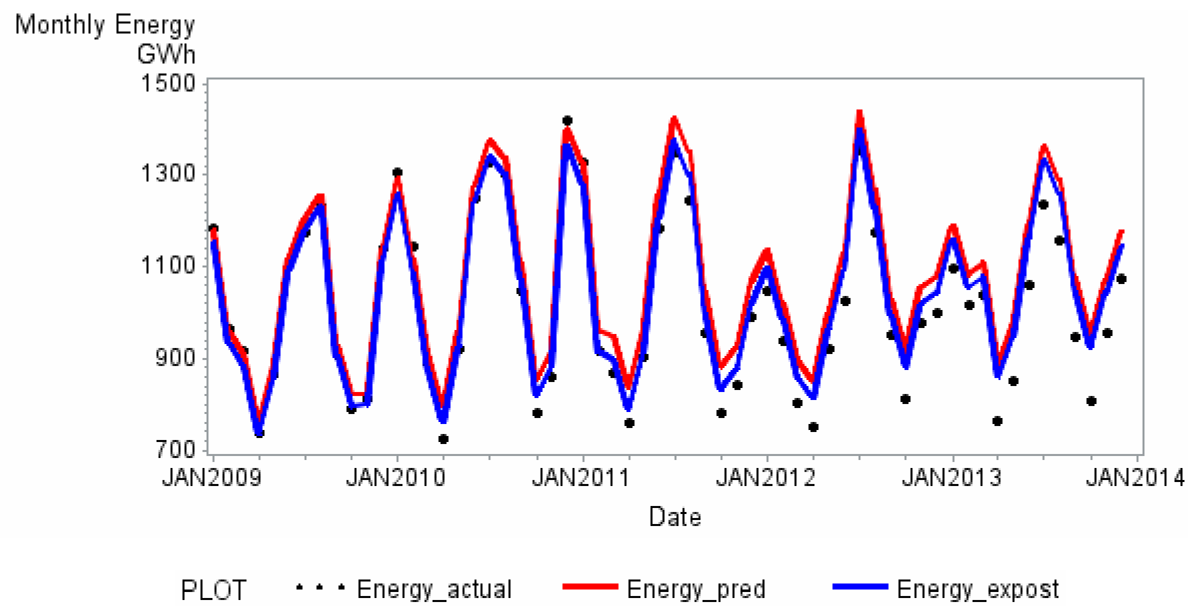

Figure 7-52: Ex post point forecasts of NCEMC monthly energy (2009 – 2013)

B. NCEMC Zone 1

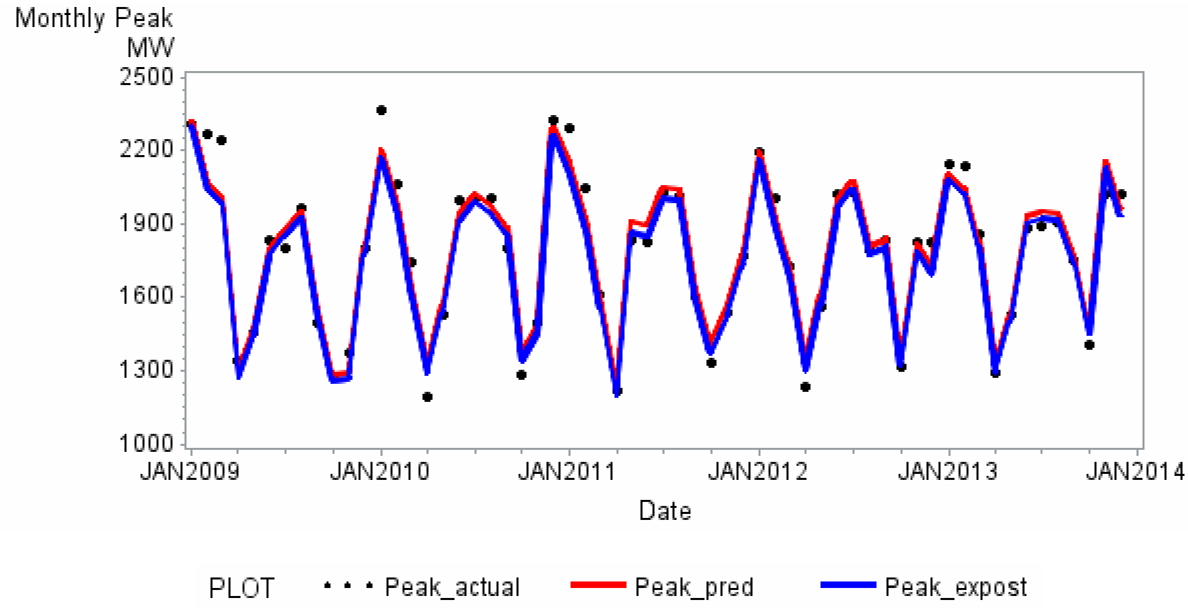

Figure 7-53: Ex post point forecasts of NCEMC SA1 monthly peak (2009 – 2013)

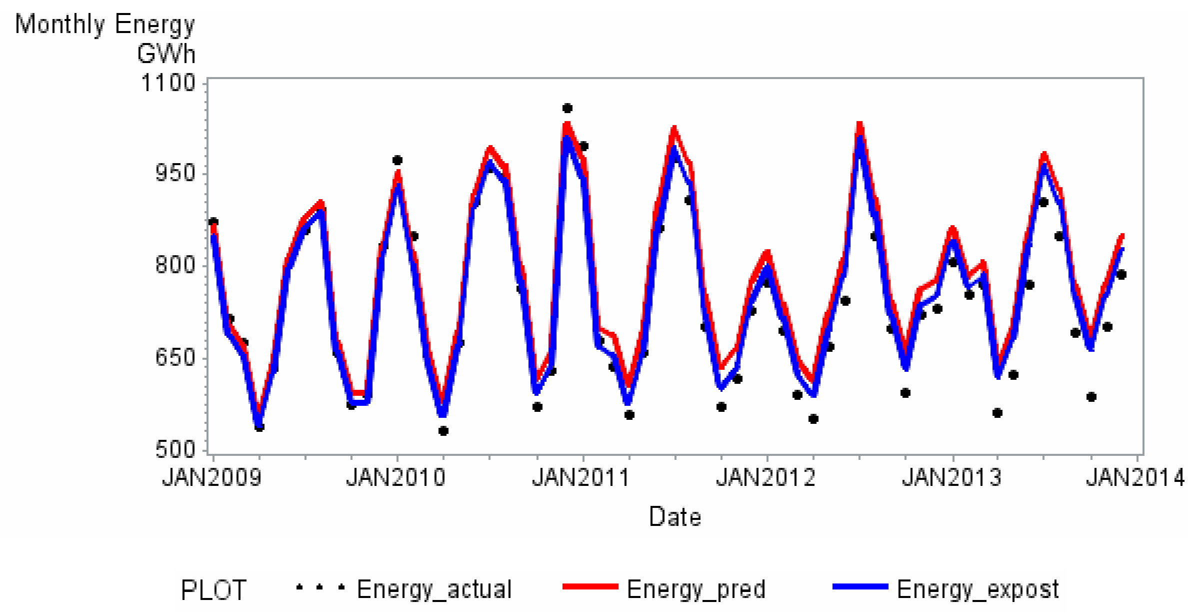

Figure 7-54: Ex post point forecasts of NCEMC SA1 monthly energy (2009 – 2013)

C. NCEMC Zone 2

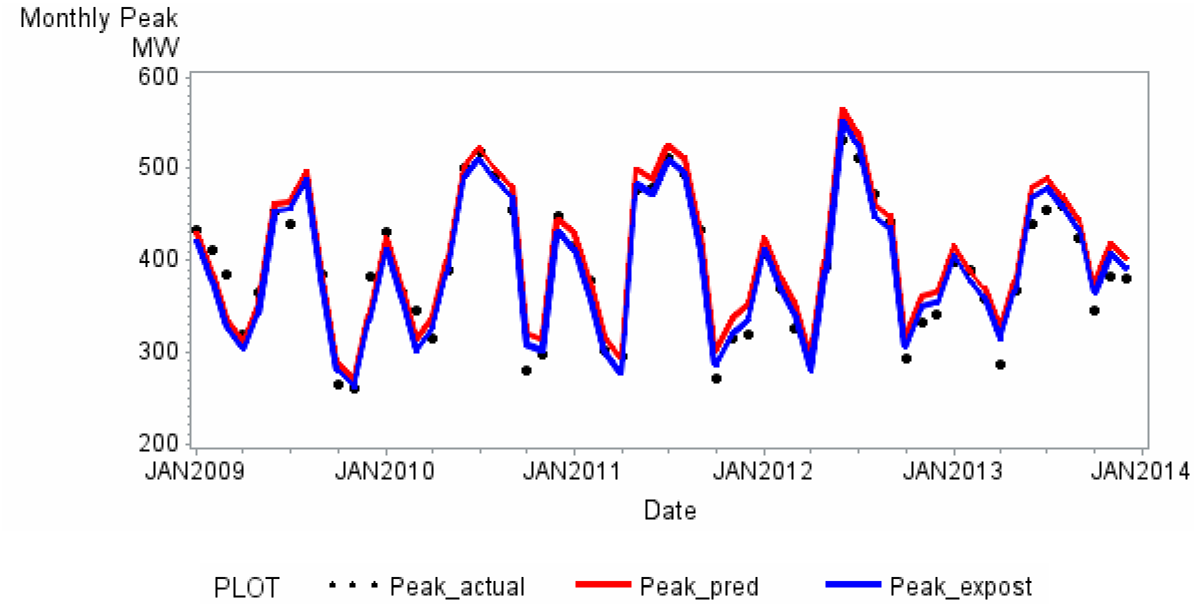

Figure 7-55: Ex post point forecasts of NCEMC SA2 monthly peak (2009 – 2013)

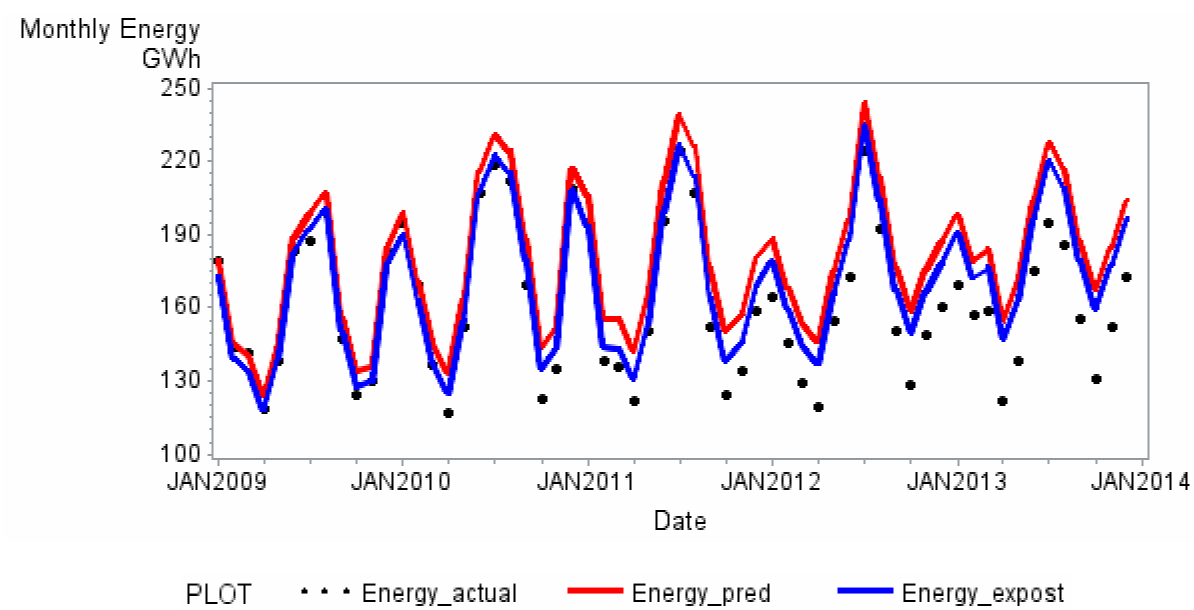

Figure 7-56: Ex post point forecasts of NCEMC SA2 monthly energy (2009 – 2013)

D. NCEMC Zone 3

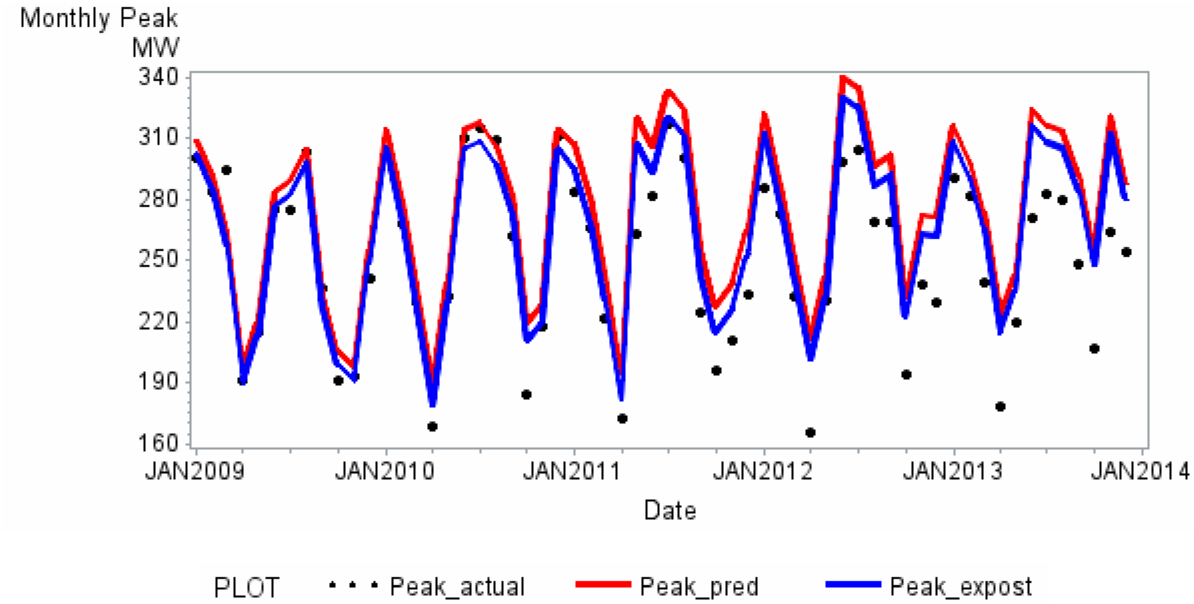

Figure 7-57: Ex post point forecasts of NCEMC SA3 monthly peak (2009 – 2013)

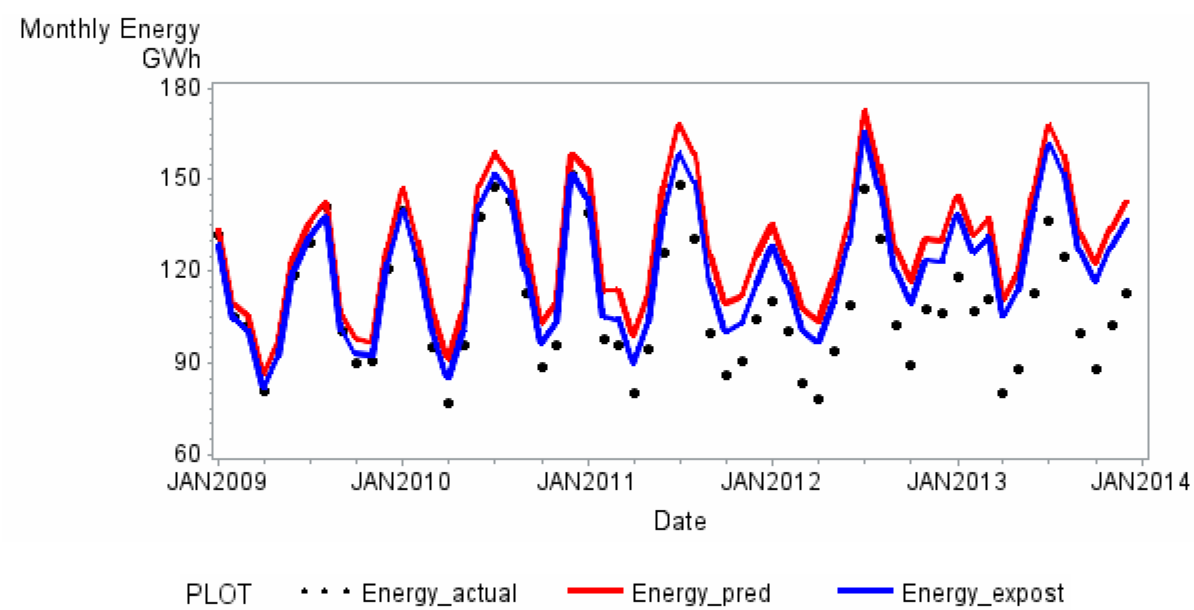

Figure 7-58: Ex post point forecasts of NCEMC SA3 monthly energy (2009 – 2013)

8. Assessment and Recommendations of Actions

8.1 Always Look for Improvements

All forecasts are wrong. Expecting perfect forecasts is unrealistic and one of the worst practices in forecasting. A best practice would be to set a realistic target with the understanding that accuracy can be affected by many factors: magnitude of the load, customer segmentation, and timing and predictability of those dependent variables. A bad model may have some lucky moments (and vice versa), but a good forecaster should always be able to analyze the situation with a cool mind regardless.

For many decades, researchers and practitioners have been working hard to reduce forecasting errors. As a result, various techniques have been tried for load forecasting. However, a forecast is just the output of the entire forecasting process. Accuracy is just one measure of the quality of the forecast. When evaluating the forecasting process (including the forecast itself), there are many other things we should consider, such as the output format, computational complexity, interpretability, reproducibility, traceability, defensibility, and so forth.

8.2 Develop Probabilistic Load Forecasts

Forecasting, by nature, is a stochastic problem rather than deterministic. There is no "certain" in forecasting. Things like "the sun will rise tomorrow" are not forecasts.

Since we forecasters are dealing with randomness, the output of a forecasting process is supposed to be in a probabilistic form, such as a forecast under this or that scenario, a probability density function, a prediction interval, or some quantiles of interest. In practice, a lot of decision making processes today cannot yet take probabilistic inputs, so the most commonly used forecasting output form is still point forecast, e.g., the future expected value of a random variable.

Note that evaluation of probabilistic load forecasts is different from that of point load forecasts. It is unfair and improper to evaluate long term probabilistic load forecasts based on the ex ante point forecasting accuracy. A recommended error measure for evaluating probabilistic load forecasts is pinball loss function, which was used as the error measure for the Global Energy Forecasting Competition 2014:

For a quantile forecast q_a with $a/100$ as the target quantile, this score L is defined as:

$$L(q_a, y) = \begin{cases} (1 - a/100) * (q_a - y), & \text{if } y < q_a; \\ a/100 * (y - q_a), & \text{if } y >= q_a \end{cases}$$

where y is the observation used for verification, $a = 1, 2, ..., 99$.

8.3 Select Models Based on Out-of-sample Tests, not R-square

Let's look at the two figures below. Both figures show 6 years of annual peak loads for a small area. In each case, we fit the 6 observations using a regression model, and then derive a one step ahead forecast. A simple linear regression model is used in Figure 8-1, which results in an R-square value of 0.7955. A polynomial regression model is used in Figure 8-2, which results in an R-square value of 1. Although we got a "perfect" R-square in Figure 8-2 with a 5th ordered polynomial regression model, its forecast does not seem to be as reasonable as the one in Figure 8-1.

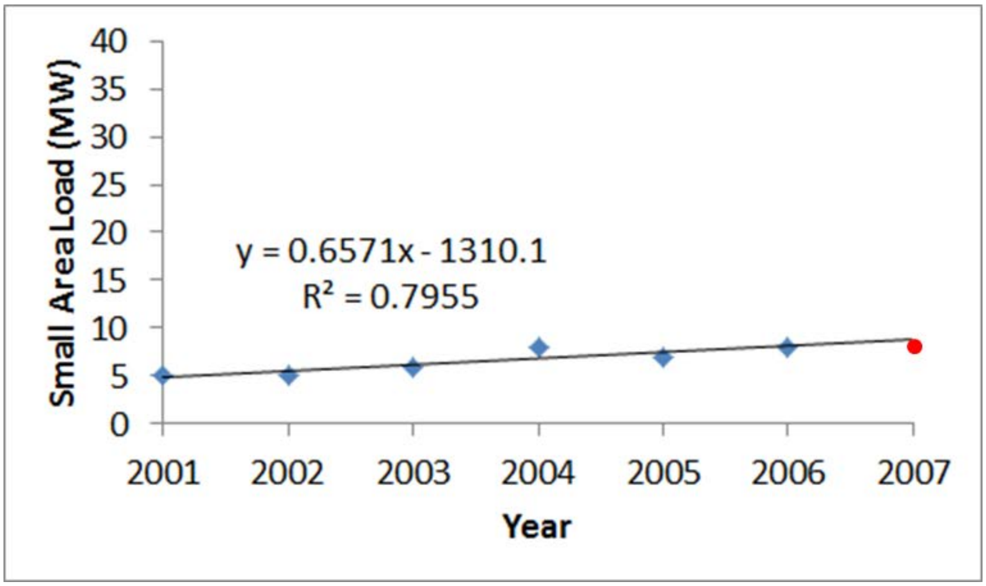

Figure 8-1: A simple linear regression model

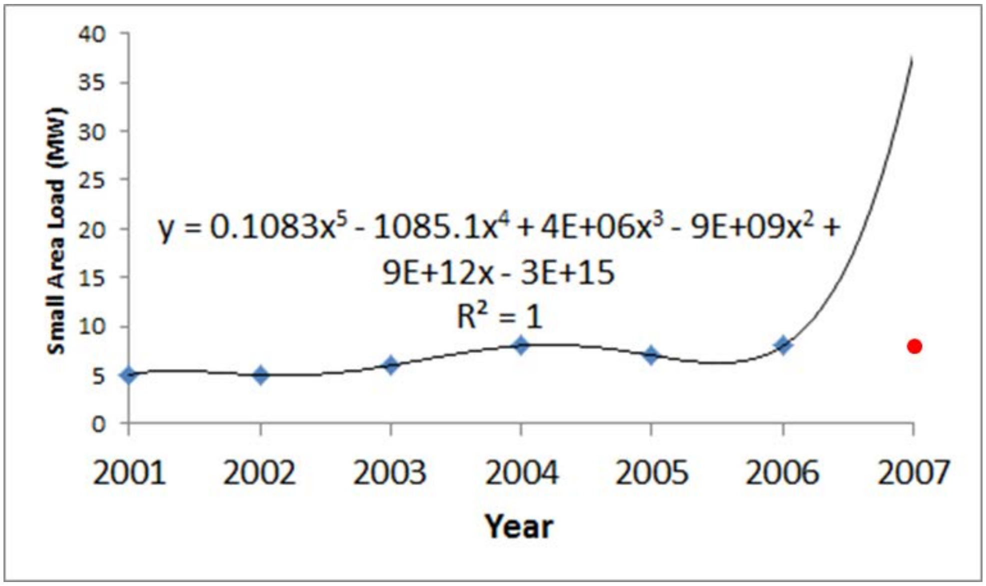

Figure 8-2: A polynomial regression model

8.4 Ex-post Forecasting Analysis

Forecasters enjoy predicting the future more than looking back to the past. Ex post forecasting analysis refers to after-the-event forecasting, or forecasting with actual information of the independent variables in the forecasted period. The ex post forecasting error can be treated as the modeling error. Very often the modeling error is way higher than the errors from the predicted independent variables, such as temperature and macroeconomic indicators. Such analysis can help improve the forecasting process. It is not a trivial task to evaluate long term load forecasts.

8.5 Establish Process to Update Weather Normalization Results

In a given year, a typical weather normalization process generates the normalized load for the previous year. Then this number will be locked with no changes going forward, unless some serious error is found in the data. There is a problem with such a process. No matter the weather normalization methodology is based on a normal weather profile or a simulation over a period of weather history, there is a time window associated with the weather. In other words, "normal" is defined based on human's understanding to the climate over a period of time. As time goes by, this understanding would change given more experience with the recent weather. For instance, at the year Y, normalizing load of the year Y-1 has to be based on weather information on or before the year Y-1. At the year Y+5, given the additional weather history from Y to Y+5, the normalized load of Year Y-1 may need to be revised accordingly. This requires a regular revision process added to the typical weather normalization process.

8.6 Stop Abusing Dummy Variables

In long term load forecasting, dummy variables are very good at helping capture the various seasonal patterns, such as month of a year, day of a week, and hour of a day. On the other hand, over-use of ad-hoc dummy variables can do great harm to the forecasts.

There is a lucky factor in forecasting. A good model may result in a large error sometimes, while a bad model may lead to very small error sometimes. The forecasters have to keep the mind cool in front of significant errors. More often than not, instead of following forecasting principles to figure out the cause of large errors, forecasters would assign dummy variables to the years with large errors. These dummy variables can help reduce the model fitting errors of the corresponding years to zero. In other words, the newly revised model with additional dummy variables can have perfect fits to those originally bad years. However, this usually does not add any predictive power to the model.

8.7 Avoid Undocumented Judgmental Changes

Since all forecasts are wrong, people often have different opinions about the future. Very often, after a forecaster turns the forecasts to business users, s/he would get various comments about the forecasting results. In many situations, these comments are based on the business sense instead of what the data says. The formal process is to include business rules to the forecasting process as much as possible, so that people do not have to manipulate the forecasting results directly. Sometimes, there is not enough data to support analytical models. In this case, if forecasting results have to be altered, there has to be thorough documentation showing the how the forecasts are being revised, reasons to support the changes, and the responsible parties involved in the changes.

8.8 Data Cleansing

There are many quality issues with real-world data. The most common data quality issue is missing values, which may be due to a temporary shutdown of the system—i.e., meter, SCADA or weather station. These missing observations can be technically "fixed" by imputing the missing values based on some linear extrapolation or regression splines. However, depending upon where these observations are, the technical fixes may create severe problems in the forecasting process. For instance, if the loads during daily peak hours were missing, those technical fixes most likely would result in a lower peak than actual.

These faked historical values often lead to underestimation of the future peaks. Instead of having the IT department do the data cleansing, forecasters should look into the data quality issue analytically through a modeling approach—developing a model based on available historical data to fill in the blanks.

8.9 Take Advantage of High-resolution Data

Utilities are having access to large amount of data with high resolution, both temporally and spatially. These data have been proven to be quite valuable to load forecasting. In long term load forecasting, load forecasting models based on hourly data are shown to be more accurate than the traditional monthly or daily models. There are also studies showing that grouping high-spatial-resolution data helps improves forecasting accuracy. It is recommended that utilities look into the usage of high-resolution in load forecasting processes. During the transition period, utilities may not get all the required data in high resolution. Therefore, to upgrade the load forecasting data source from low-resolution to high-resolution, utilities may have to first spend some efforts reconciling traditional monthly forecasts with the new hourly forecasts.

8.10 Keep It Simple, Stupid

Simple is not trivial. A simple model or methodology can be quite powerful. In fact, in the load forecasting arena, most models that offer significant practical value to the industry are developed from simple ideas. Always start with those simple models. Avoid adding new elements (i.e., techniques and variables), unless the additional complexity can be justified by significant performance improvement.

8.11 Gather a Second Opinion

All models are wrong. If only one model is being used, "bad" forecasts may occur very often. If multiple models are available, the situation can be completely different. Have confidence when the models agree with each other. Focus on the periods when these models disagree with each other significantly. Empirically, combining forecasting techniques usually does a better job than each individual by offering more robust and accurate forecasts. We would recommend utilities to try different vendors and/or methodologies to develop load forecasts.

8.12 Keep Knowledge and Infrastructure Up to Date

The forecasting community is advancing methodologies and techniques every day. Many of these new findings are applicable to energy forecasting. For instance, the hierarchal time series forecasting techniques used in retail and the consumer packaged goods industry can be adopted to household-level load forecasting. Probabilistic forecasting techniques used in meteorological forecasting have been applied to wind power forecasting. To keep the forecasts competitive in the market, energy forecasters have to follow the recent findings in the field. Getting involved in professional groups, such as the IEEE Working Group on Energy Forecasting, is an effective way to learn ideas from and share experience with other energy-forecasting experts.

8.13 Take an Interdisciplinary Approach to Integrated Load Forecasting

An integrated load forecasting methodology is shown in Figure 8-3. The mechanism consists of three components:

- ***An STLF model***: The STLF model captures the relationship between load and its primary driving factors, such as weather variables, calendar variables, and the cross effects. The model is developed to minimize the error in the short term, i.e., one day to two weeks ahead.
- ***STLF to VSTLF***: A STLF model can be transformed into a VSTLF model by adding the loads of some preceding hours as part of the inputs to the STLF model, which captures the autocorrelation of the current hour load and the preceding hour loads. Alternatively, with the STLF as a base, residuals of historical load can be collected and form a new series. Then by forecasting the future residuals and adding them back to the short term forecast, a very short term forecast can be obtained.
- ***STLF to M/LTLF***: by adding macroeconomic indicator variables to the STLF model and extrapolating the model to the longer horizon, the system-level MTLF and LTLF can be obtained. Consequently, this long term system level load forecast can be used as an input to spatial load forecasting.

The implementation of such an integrated forecasting methodology helps utilities apply consistent data to forecasting practices. The data cleansing efforts can be leveraged throughout the organization.

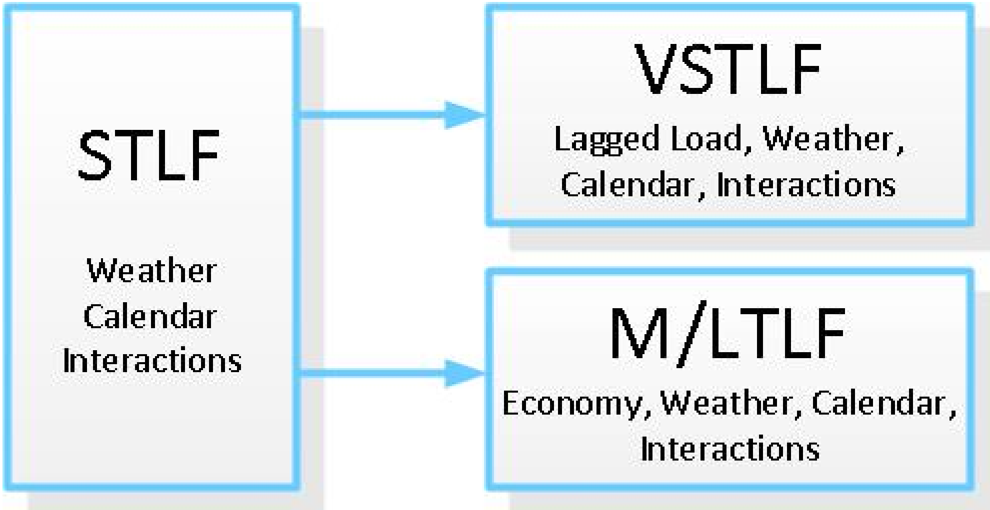

Figure 8-3: Integrated load forecasting methodology

Developing the load forecasts (at high voltage level) without using temperature forecasts does not offer much practical value in the modern world. Load forecasting is an interdisciplinary field. To further advance our knowledge, we have to take an interdisciplinary approach by involving various communities, such as statistical forecasting, artificial intelligence, meteorological science, and power engineering. Therefore, it is recommended to build an in-house analytics center of excellence where statisticians, data miners, meteorologists, business liaisons, IT analysts, and software developers can work together to tackle the emerging challenges of energy forecasting.

9. Glossary of Terms

This chapter lists over a dozen groups of terms that are frequently used in the load forecasting area, but often confusing to people. The original list[20] and the associated articles were posted on the blog *Energy Forecasting*, where the list serves as a living document and will be updated from time to time.

9.1 Load, Demand, Energy, and Power

In general, power is the amount of energy consumed or supplied per unit time or the rate at which energy is consumed or supplied. Energy is the integral of power over time. In the electric power industry, the most frequently used units of power are kW (kilowatt) and MW (megawatt). The conversion between units of power is as follows:

$$1 \text{ MW} = 1000 \text{ kW} = 1{,}000{,}000 \text{ W}.$$

Consequently, the common units of energy are kWh (kilowatt hour) and MWh (megawatt hour).

In an alternating current (AC) power system, there are three types of power; active power or real power (with unit of watt, W), reactive power (with unit of volt-ampere reactive, Var), and complex power (with unit of volt-ampere, VA). Apparent power is the magnitude of complex power. The power triangle describes the relationship of the three types of power. An equation of this triangle is as follows:

$$(\text{active power})^2 + (\text{reactive power})^2 = (\text{apparent power})^2.$$

A commonly made mistake is to treat apparent power as the sum of active power and reactive power. Active power and reactive power are perpendicular to each other in this triangle, and apparent power is always larger than or equal to the magnitude of active power and reactive power.

Power can also be used to describe generation (i.e. a 5 MW solar farm). When it is used to describe delivery (i.e. a 13 W CFL light bulb), "demand" is usually used to refer to the power on the delivery side. Therefore, the units of demand are the same as the units of power, which are kW and MW. Peak demand is the word frequently used in the electric power industry. It refers to the maximum power consumed by a utility, state, city, small area, community, factory, house, or end-use appliances.

On the consumption (or delivery) side, demand is the antonym of energy in some sense. For example, among many charges in an electricity bill, very often there are two charges: demand charge and energy charge. These two charges are often a source of confusion for customers. In a given billing period (the billing period will be explained in later chapters), the demand charge is based on the peak demand (in kW), while the energy charge is based on the total consumption over time (in kWh).

[20] http://blog.drhongtao.com/2014/09/load-forecasting-terminology.html

Load is a very ambiguous term. To different people in different departments of a utility, load may mean different things; such as active power (in kW), apparent power (in kVA), energy (in kWh), current (in ampere), voltage (in volt), and even resistance (in ohm). In load forecasting, load usually refers to demand (in kW) or energy (in kWh). On hourly data, the magnitude of energy is equal to that of the average power. As a result, there is no need to emphasize whether it is demand or energy. However, the magnitude of hourly peak demand can be greater than the magnitude of hourly energy. The reason for this is peak demand is typically defined on a 15-minute interval.

The term energy forecasting also has two definitions. A narrow definition is as follows: "forecasting the energy (in kWh)", which is heavily used in financial planning and rate design. A broader one is "forecasting in the energy industry", which can be used for many subjects, such as gas and electric load forecasting, renewable generation forecasting, price forecasting, demand response forecasting, outage forecasting, and so forth. The broader definition has been used for several recent initiatives, such as the IEEE Working Group on Energy Forecasting, Global Energy Forecasting Competitions, IEEE Transactions on Smart Grid Special Section on Analytics for Energy Forecasting with Applications to Smart Grid, International Journal of Forecasting Special Issue on Probabilistic Energy Forecasting, as well as others.

9.2 Forecasting and Backcasting

Forecasting is the process of exploring the future events that have not been observed or determined. Backcasting typically refers to the process of exploring the past events given the information known to date. The two terms seem to be mutually exclusive, but are often used in an ambiguous way. Before discussing the two terms in details, there are some basic terminologies which should be explained first.

- Forecast origin: the last available point in the historical data.
- Forecast horizon: the distance between the forecast origin and the furthest point a forecaster is forecasting.
- Step: the distance between the two adjacent observations.

Take day-ahead hourly load forecasting as an example. Usually, the load forecaster need to provide the forecast in the morning, such as for the 24 hours of the next day through hour ending 12am. If the forecaster starts developing the forecast at 5:10am with hourly weather data and load data through hour ending 5am, then the forecast origin is 5am of the day. Each step is 1 hour. The forecast horizon is 43 hours or 43 steps. One thing which should be aware of is that in practice day-ahead load forecasting is different from 24-hour ahead load forecasting. For instance, 24-hour ahead load forecasting means a forecaster provides forecasts of the next day's 24-hour demand which starts at 0:00 and ends at 24:00. The forecaster has had the data of today's 24-hour demand data at the time of doing forecasting. Day-ahead load forecasting means a forecaster could only have today's demand data until 6:00 (or other time), but need to forecast the next day's 24-hour demand which starts at 0:00 and ends at 24:00, so there is a

18-hour blank between today's 6:00 to the next day's 0:00. In general, day-ahead load forecasting is more challenging for a load forecaster than 24-hour ahead load forecasting.

Ex-ante forecasting and ex-post forecasting are two types of forecasting. Ex-ante forecasting means forecasting with information known through the forecast origin. So it is also called "before the event" forecasting and this is the only way to produce genuine forecasts. Ex-post forecasting is referred as "after the event" forecasting. In other words, the information of explanatory variables is assumed to be known when producing the forecasts. Back to the day-ahead load forecasting example, if day-ahead temperature forecasts are used to produce the day-ahead load forecasts, the results are ex-ante forecasts. If actual temperatures of the next day are used, the results are ex-post forecasts. Now we can see an overlap between forecasting and backcasting: ex-post forecasting is a subset of backcasting.

There are several other types of backcasting. One is to fit a model on historical data, which is also called model fitting. Another one is to first take one or several historical data out, and then use the rest of the history to estimate these observations assuming the actual temperatures are known for the entire history. This is similar to cross validation, though cross validation is usually conducted iteratively (training, validation, and test will be explained in the later chapters). When the observations are taken out at the end of the history, this cross validation becomes ex-post forecasting. Here it comes another overlap between backcasting and forecasting: backcasting is part of the entire forecasting process. To build a model for load forecasting, the processes like model fitting, ex-post forecasting, and sometimes, cross validation usually need to be done.

To avoid confusion, term backcasting is seldom used unless in the situation of a one-time cross validation. In the load forecasting track of Global Energy Forecasting Competition 2012, the topic was named as "forecasting and backcasting electricity demand". The "forecasting" was ex-ante forecasting because temperature data for the forecasted week was not provided. The "backcasting" here was cross validation because the historical data of eight nonadjacent weeks were taken out and the actual temperatures were provided for these observations.

9.3 Forecasting and Planning

Forecasting is to tell what the future would look like given one or more scenarios. Planning is to develop actions in order to reach a desirable stage in the future. Although the forecasting and planning functions often reside in one department of a utility, conceptually mixing the two often results in bad or even fraudulent forecasts and plans. The following examples will illustrate the relationship between the two.

9.3.1 Background

The planning department of the Big City Power & Light (a distribution company) was asked to make a 5 year plan for system maintenance and upgrade. The forecasting team developed a 10-year ahead forecast showing an increasing trend of peak demand at about 2% per year. Majority of the load growth was due to the new tax incentives for attracting high tech companies to a technology park near downtown area. The technology park was expected to add 10,000 high tech jobs over the next 5 years. These jobs would help with the local economy growth.

9.3.2 Example 1: A Legitimate Case

Based on the forecast, the planning team developed a plan to upgrade the existing infrastructure of the areas near the technology park to serve the load growth due to the newly added jobs.

9.3.3 Example 2: Another Legitimate Case with Iterations

After analyzing the power systems near downtown, the planning team concluded that reasonable system upgrade can support up to 1.5% annual growth. It is not economically justifiable to feed the projected demand at 2% annual growth by only upgrading the system. One possible solution was to launch several demand response (DR) and energy efficiency (EE) programs together with the system upgrade. The planning team need to understand what the load growth would look like given different options of the DR and EE programs. Based on the new scenarios provided by the planning team, the forecasting team then developed several new forecasts with different combinations of DR and EE programs. The new forecasts showed annual load growth at 1-1.5% per year. The planning team then developed a plan that included both system upgrade and selected DR and EE programs.

9.3.4 Example 3: A Fraudulent Case

One of the high tech companies asked the utility for a new distribution substation to ensure a highly reliable system to serve the data centers. After analyzing the power systems near downtown, the planning team concluded that the annual load growth has to be as high as 3% to justify the addition of the substation. This high tech company lobbied the executives of the utility, who then put a big pressure on the forecasting team. Under the pressure, the forecasting team added two dummy variables to the recent two years with low peak demand to create the 3% annual growth.

9.3.5 Remark

An easy way to spot the fraudulent forecast and plan is to check which one of them comes first. In a legitimate case, the plan should always come after the forecast. Otherwise, it is a fraudulent case.

9.4 Forecasting, Forecast, and Forecaster

In the electric power industry, many times people are confused about the meaning of forecasting, forecast, and forecaster, and it is easy to mix them up while using the three terms. In the former chapters, the meaning of forecasting has been elaborated, but here the emphasized part of forecasting is that it refers to the process of figuring out how data looks like in the future. Forecast is the result of a forecasting process. The person who develops the forecast is the forecaster, or forecasting analyst. The solution used by the forecaster is a forecasting system. The forecasting system may include a set of forecasting models, an algorithm to build and/or select the best model, and other functions such as ETL (extraction, transformation, and loading) and BI (business intelligence). An example of putting these terms into one sentence: the forecasters (forecasting analysts) at a utility are using a state-of-the-art forecasting system to build forecasting models and to produce forecasts in their short and long term load forecasting processes.

Most of time the three terms should be used as explained above, but there are several exceptions. Some papers in the load forecasting literature used the term "load forecaster" to represent a load forecasting system. For instance, ANNSTLF, a system developed 15 years ago by EPRI (Electric Power Research Institute), is the acronym of "Artificial Neural Network Short Term Load Forecaster".

9.5 Very Short, Short, Medium, and Long Term Load Forecasting

Load forecasting is so fundamental that it is being used across all sectors in electric power industry for various business applications. Because of its applications, there are many ways to classify the various load forecasts:

- Based on forecast horizon: very short, short, medium, and long term load forecasts;
- Based on resolution of the data or updating frequency (these two concepts are different!): hourly, daily, monthly, seasonal, and annual load forecasts;
- Based on business needs: operational, planning, and retail load forecasts.

The focus of this chapter is on the first group, load forecasting with different forecast horizons. Note that there are other terminologies based on the specific forecasting horizons, such as intraday forecasting and day ahead forecasting.

Anyone can have his/her own definition of very short, short, medium, and long term forecasting to separate the detailed tasks under the corresponding jurisdictions. Here are a few examples:

- The forecasting group in a distribution company that supports rate making and revenue projection may refer short term as one to five years ahead, and long term as 10 to 20 years ahead.
- The operations group in an Independent System Operator may use very short term for 5 -15 minutes ahead, short term for a few hours to one day ahead, medium term for 5 days ahead and long term for two weeks ahead.
- The policy makers may treat 30 to 50 years ahead forecasting as long term forecasting, and anything below 30 years as short or medium term.
- A retailer may consider short term as one week ahead, medium term as one week to a few months ahead, and long term as up to two years ahead.

In (Hong, 2010), a classification of the load forecasts is proposed by dividing the load forecasting problem into four sub-problems, very short, short, medium, and long term forecasting with the cutoff points 1 day, 2 weeks, and 3 years. Under different circumstances, short and very short term can be grouped together into short term load forecasting, and medium and long term can be grouped together into long term load forecasting. This classification is primarily based on the information being used to create the forecasts. The longer the forecasting horizon goes, the more information the forecasting process needs:

- Very short term load forecasting only requires past loads.
- Short term load forecasting usually requires past loads and weather information.
- Medium term load forecasting requires weather and economy information.
- Long term load forecasting needs weather, economy, demographic, and sometimes land use information.

There are overlaps among these classifications. For instance, short term load forecasting can also be generated without weather information though it is not a best practice for many utilities.

Besides knowing the definitions of these terms, it is also necessary to discuss how to use these terms. There are four principles related to using the terms:

1) *Respect the business audience*. When communicating with business users, first figure out what their terms mean, and then use their terms. Most importantly, do not try to change their terminology.
2) *Pay attention to the word(s) between "term" and "forecasting"*. Long term operational forecasting means one to two weeks ahead load forecasting, which can be referred as "short term load forecasting" in the aforementioned framework. When putting "operational" before forecasting, the horizon of interest is being limited to the lead time for operational purposes right away.

3) *Use the narrow definition if the methodology is specifically developed for a small category.* If a forecasting system is based on a univariate technique that does not give a good forecast beyond 6 hours, then name it very short term load forecasting system.

4) *Use the broad definition when the narrow definition is not suitable.* If a regression-based forecasting system is applicable to both hour-ahead and week-ahead forecasting, then it can be named as short term load forecasting system.

In retail business, due to the dynamic nature of the business, most companies don't plan for 10 years ahead. For example, long term retail energy forecasting actually is medium term load forecasting for electricity retailers. As a result, for the retailers, the former term is much more precise and professional than the latter one.

9.6 Model, Variable, Function, and Parameter

9.6.1 Model

What is model and how to build a model? One hundred engineers could provide one hundred answers. One engineer probably thinks about developing circuit models, which requires drawing lines, fuses, switches, and transformers on a distribution engineering software platform, while another thinks about building statistical models on analysis software.

In energy forecasting, the predictive models are different from physical models. A regression-based load forecasting model, for example, describes the relationship between load and the factors that drive the load. The following sections explain three components in such a model.

9.6.2 Variables

Load (or some transformation of the load) is the response variable. Hour of the day, temperature, and other driving factors are explanatory variables.

Energy forecasters may come from different disciplines. Depending upon their education background, the terms may be called differently. For instance, response variable is also known as dependent variable, output variable, and regressand (for regression models). The corresponding alternatives of explanatory variable are independent variable, input variable, and regressor.

Another way of naming variables is based on their contents. Temperature variables are often used to represent the variables made of temperatures and their augmented forms. Calendar variables are used to represent hour of the day, day of the week, month of the year, and holidays.

9.6.3 Function

Most load forecasters know that load is driven by calendar variables and weather variables and sometimes they share their models. The conversation often ends at confirming the usage of calendar and weather variables. All forecasters think they have a good model and are very pleased with the conversation.

However, the quality of their models and forecasts may vary significantly. For instance, in GEFCom2012 (Global Energy Forecasting Competition 2012), most contestants used calendar and temperature variables, but the range of their error scores are fairly large. This means that only communicating the variables is far from fully specifying a model.

Function is the formula describing the relationship between the response variable and explanatory variables. Taking load and temperature for example, their relationship can be modeled by using a piece wise linear function, a second order polynomial or third polynomial. The results may be quite different. Another meaning of function is at the algorithmic level. For instance, a function (algorithm) can be developed to automatically select variables to build a load forecasting model.

9.6.4 Parameters

Parameters, also known as coefficients, are used to quantify the relationship between the response variable and explanatory variables. Although many people believe the variables and their functional form is enough to specify a model, there should be one step further on parameter estimation. The reason is that parameter estimation methods and their associated assumptions may affect the parameter estimation results.

Parameters are often used in algorithm design as well. When performing outlier detection, for instance, a threshold is needed to tell whether an observation is an outlier or not. This threshold is called a parameter for this outlier detection algorithm.

This chapter is only about model and its three components. There are many other things in the forecasting process that affect the quality of forecasts. This is also why it usually takes a consultant (or consulting firm) a long time to audit the forecasting process of any utility.

9.7 Training, Validation, and Test

When developing models for forecasting or data mining (these two terms will be explained in the later chapters), forecasters usually slice the data into three pieces: training, validation, and test. Training data is used to estimate parameters. Validation data is used to select models. Test data is used to confirm the model performance.

This section will focus on two representative forecasting techniques, regression analysis and Artificial Neural Networks (ANN) to illustrate how the process works.

In regression analysis, parameters can be estimated by applying the ordinary least square method to the training data, which leads to a closed-form solution. The regression model is then used to calculate the errors on the validation data. After trying several regression models, the one with the lowest validation error is selected as the final model. This final regression model is used upon the test data to report the forecasting accuracy.

In ANN modeling, the parameters (weights and biases) are estimated iteratively with the objective to enhance the goodness of fit on the training data. Without any stopping criteria, such a training process may go on and on until the ANN perfectly fits the training data (assuming the ANN is large enough). Validation data is used to tell the algorithm when to stop updating the parameters. After each aforementioned update, the ANN is used to predict the validation data. The training stops when the prediction error starts increasing. The parameters corresponding to the lowest prediction error on the validation data are locked as the final ones for the ANN structure being tried. There are several factors that may affect the structure of an ANN model, such as the input variables, number of hidden neurons and hidden layers, interconnections, activation functions, and so forth. Forecasters can try multiple ANN structures using training and validation data, and then pick the one with the lowest validation error and report its performance on the test data.

There is, however, one way to cheat in this training-validation-testing process. It is common to see high forecasting accuracy from ANN based models in some papers. After looking at the performance on the test data, some of these authors may find that the results are not satisfying. They will then alter the models again and again so that the testing error is reduced. This is called "peeking the future" in forecasting. In other words, although the test data is not used for parameter estimation, it is being used for model selection. This is a popular and false practice especially in applying ANN to load forecasting. As a result, many ANN based models fail miserably in practice though they provide very high accuracy in the literature. The accuracy obtained this way is neither ex-post nor ex-ante forecasting accuracy, because the actual values of dependent variables are being used in model selection.

9.8 Linear Models and Linear Relationship

Many are probably familiar with the statements similar to the one below:

Because linear models can hardly capture the nonlinear relationship between load and temperature, we use Artificial Neural Networks (or other black-box models) in this paper.

The major conceptual error of the above statement is due to a common misunderstanding that linear models cannot capture nonlinear relationship. This section will use several examples to explain why this is a misunderstanding. Figure 9-1 shows a nonlinear curve, which is from a 3rd order polynomial function.

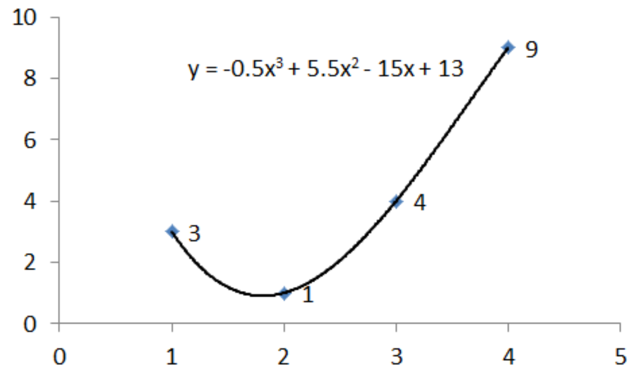

Figure 9-1: Illustration of a nonlinear curve

Some readers may doubt that the model in the Figure 1 is a linear model, but it actually is. Polynomial regression models in general are linear models. The reason is that the "linear" in linear models refers to the equations used to solve the parameters. By definition, a regression model is linear if it can be written as the form of Y = XB + E, where Y is a vector of values of the response variable; B is a vector of parameters to be solved; X is a matrix of values of explanatory variables; E is a vector of independent normally distributed errors.

To be more specific, an example of parameter estimation for a 3rd order polynomial regression model is:

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + e,$$

where x_2 is the square of x_1, and x_3 is the cube of x_1, and there are 4 parameters to be estimated. The following table provides 6 observations to explain how to estimate parameters.

obs	x_1	x_2	x_3	y
1	1	1	1	3
2	2	4	8	1
3	3	9	27	4
4	4	16	64	9
5	1	1	1	5
6	3	9	27	2

Six linear equations can be written from Table 1:

$$3 = b_0 + b_1 + b_2 + b_3 + e_1;$$
$$1 = b_0 + 2b_1 + 4b_2 + 8b_3 + e_2;$$

$$4 = b_0 + 3b_1 + 9b_2 + 27b_3 + e_3;$$
$$9 = b_0 + 4b_1 + 16b_2 + 64b_3 + e_4;$$
$$5 = b_0 + b_1 + b_2 + b_3 + e_5;$$
$$2 = b_0 + 3b_1 + 9b_2 + 27b_3 + e_6;$$

These equations can be written in the following form:

$$\begin{bmatrix} 3 \\ 1 \\ 4 \\ 9 \\ 5 \\ 2 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 4 & 8 \\ 1 & 3 & 9 & 27 \\ 1 & 4 & 16 & 64 \\ 1 & 1 & 1 & 1 \\ 1 & 3 & 9 & 27 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} + e$$

Therefore, a 3rd order polynomial regression mode is a linear model. The values of b_0, b_1, b_2 and b_3 can be obtained by minimizing the summation of squared errors:

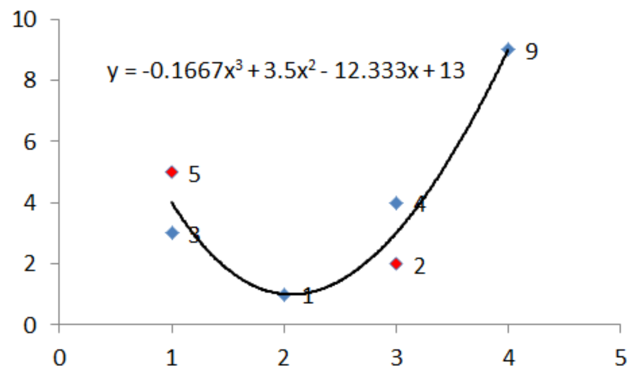

Figure 9-2: Illustration of a linear model for a nonlinear curve

To further clarify the concept of linear model versus nonlinear model, here are a few examples of nonlinear regression models:

$$y = b_0 + b_1x_1/(b_2x_2 + b_3) + e$$

$$y = b_0(exp(b_1x))U$$

Some nonlinear regression problems can be solved in a linear domain which makes the solving process less complicated. For instance, the second example can be transformed to a linear model by taking the logarithm on both sides:

$$\text{Ln}(y) = \text{Ln}(b_0) + b_1x + u$$

Linear models have been widely used by forecasters on load forecasting. Some good and successful examples of linear regression models can be found from (Hong, Pinson, et al., 2014; Hong, Wilson, et al., 2014; Hong, 2010). The models and methodologies developed in the (Hong, Wilson, et al., 2014; Hong, 2010) are already commercialized and deployed to utilities worldwide.

9.9 Weather Normalization and Load Normalization

In the electric power industry, there are two variables often associated with "weather normalization": reliability and load. More information of distribution reliability can be found in IEEE Working Group on Distribution Reliability. This section will focus on load.

9.9.1 Planning - the Business Driver of Weather Normalization

The electric power grid has significant effects on human beings' daily life. Electric utilities, the companies running the power grid and delivering electricity to our houses, have to conduct rigorous and comprehensive planning processes to ensure the financial stability of the company and system reliability of the grid. This is because a major driving factor of the load is weather, which is quite unpredictable beyond couple of weeks, so that utilities can hardly predict the load in the medium and long terms with high accuracy. Consequently, utilities would like to estimate the typical load first, and then try to understand the range of extreme loads. In other words, most planning decisions have to rely on the typical load and the margin on top of it. Although there is not a formal definition of weather normalization, the process of estimating the typical load is in fact weather normalization.

9.9.2 Traditional Practices of Weather Normalization

At a high level, the traditional weather normalization process includes two steps:

1) Develop a model based on actual observations of historical load and weather
2) Apply the model to a normal weather to obtain the load under normal weather

Many parameters in this process could affect the results of weather normalization, such as the frequency of the input data to model the relationship between load and temperature, cross-validation in the modeling stage, selection of normal weather, and so forth.

Over the past decades, utilities have been using monthly or annual data to develop predictive models for weather normalization. The models have been selected primarily based on the goodness of fit on the historical data. The normal weather published by NOAA (National Oceanic and Atmospheric Administration) is often used as the scenario for typical load.

9.9.3 Load Normalization against Weather

There are many issues with the traditional practices mentioned above: monthly or annual data does not provide detailed load and temperature profiles nor enough observations for comprehensive analysis; goodness of fit does not imply predictive power; load under normal weather may not lead to normal load.

To address these issues together with many other problems around weather normalization, Dr. Tao Hong has proposed the concept of load normalization in (Hong, Wilson, & Xie 2014). Then weather normalization can be interpreted as load normalization against weather. His proposed process includes three steps:

1) Develop a model based on actual observations of historical load and weather
2) Apply the model to a set of simulated weather profiles to obtain scenario based load forecasts
3) Derive median of monthly peak or monthly energy or other load of interest as the normalized load

There are many other factors driving the load in the long term, such as economy, demographics, etc. The similar load normalization concept can be applied to come up with load normalization against these factors.

9.10 Probability Forecasting and Probabilistic Forecasting

Probabilistic energy forecasting is an emerging branch of energy forecasting. It's very important to clarify some concepts in the early stage, so that the forecasters don't have to run into troubles arguing what the terms mean 10 years later. This section is about probability forecasting and probabilistic forecasting.

The definition of probability forecasting and probabilistic forecasting from Gneiting and Katzfuss (2014):

A probabilistic forecast takes the form of a predictive probability distribution over future quantities or events of interest…Although probability forecasts for binary events (e.g. an 80% chance of rain today, a 10% chance of a financial meltdown by the end of the year) have been commonly issued for the past several decades, attention has been shifting toward probabilistic forecasts for more general types of variables and event.

Probability forecasting mainly refers to assigning probabilities to binary events in the future, while probabilistic forecasting has a more general coverage beyond just binary events. Here are some examples in load forecasting:

9.10.1 Probability Load Forecasting

- The probability that the monthly peak will occur next Thursday.
- The probability that the annual peak of next year will be higher than the annual peak of this year.
- The probability that tomorrow's daily peak will be lower than 5.5 GW if the A/C cycling program is on.

9.10.2 Probabilistic Load Forecasting

- The probability distribution of the monthly peak this December
- The 1 in 10 year high load of next year
- The probability distribution of tomorrow's daily peak if the A/C cycling program is on

In general, probabilistic load forecasts can be in the form of probability distribution functions, quantiles, and intervals. Sometimes a probability forecast can be derived from a probabilistic forecast. For instance, forecasters can first figure out the probability distribution of tomorrow's daily peak under the scenario that the A/C cycling program is on, then they can calculate the probability that the daily peak is lower than 5.5 GW.

Although probabilistic forecasts are often generated based on scenarios, scenario-based forecasts may not be probabilistic forecasts. For instance, a forecaster can generate three long term load forecasts based on three scenarios of 0%, 1%, and 2% annual GDP growth. These three load forecasts are not probabilistic forecasts unless there are probabilities associated with each GDP growth scenario.

Note that interval forecasts may not be probabilistic forecasts. For instance, a forecaster transforms an hourly load series to an interval time series of daily max and min. Directly applying interval time series analysis to this transformed daily interval load data can result in an interval forecast of daily max and min load. Since the forecast does not have any probabilistic meaning, it is not a probabilistic forecast.

The theme of the Global Energy Forecasting Competition 2014 is probabilistic energy forecasting, not probability energy forecasting, because it requires the participants to provide probability distribution in 99 quantiles (quantiles, quartile, and percentile will be explained in the later sections).

9.11 Reliability (for Planning) and Reliability (for Forecasting)

Reliability in the power distribution system typically means the ability the power system delivers power to the end users. There are frequently used reliability indices in distribution planning:

- System Average Interruption Duration Index (SAIDI)

  = Sum of all customer interruption durations / Total number of customers served
- System Average Interruption Frequency Index (SAIFI)

  = Total number of customer interruptions / Total number of customers served

- Customer Average Interruption Duration Index (CAIDI)

  = Sum of all customer interruption durations / Total number of customer interruptions

  = SAIDI/ SAIFI

There is also a rich literature on reliability planning, including developing other reliability indices, evaluating, benchmarking, and enhancing power system reliability. The concept of reliability spreads across generation, transmission, and distribution systems.

In load forecasting, or more specifically, probabilistic load forecasting, reliability has a completely different meaning. A probabilistic forecast is reliable (or calibrated) if the empirical coverage is exactly the same as the predicted probability. For instance, a predicted profile at 90^{th} percentile should be on or above 90% of the observations. In other words, we expect 10% of the observations above this predicted profile. The property of reliability in probabilistic forecasting is similar to bias in point forecasting.

There are a few other places where reliability and forecasting are used together:

- A forecasting system is reliable if it functions as specified.
- Load forecasts is a key driver of reliability planning.
- Forecasters can forecast future value of reliability indices based on the weather conditions and investment in vegetarian management, etc.

9.12 Quantile, Quartile, and Percentile

Suppose a forecaster has a set of data sorted in ascending order. By dividing the data into q equal-sized pieces, the forecaster can get q-quantiles. The quantiles are the values marking the boundaries between two adjacent subsets.

Here is an example: Using 15 years of historical weather data to forecast next year's annual peak, a forecaster can create 15 scenarios, which lead to 15 forecasted annual peaks for the next year. Sorting these 15 annual peak forecasts in ascending order, he gets {810, 812, 813, 815, 815, 818, 820, 824, 827, 829, 832, 836, 839, 844, 848}. Below are the details of calculating the 4-quantiles.

- The rank of the first 4-quantile is 15 x (1/4) = 3.75, which rounds up to 4. The 4th smallest number is 815.
- The rank of the second 4-quantile is 15 x (2/4) = 7.5, which rounds up to 8. The 8th smallest number is 824.
- The rank of the third 4-quantile is 15 x (3/4) = 11.25, which rounds up to 12. The 12th smallest number is 836.
- The fourth 4-quantile is the largest number, which is 848.
- So the 4-quantiles are {815, 824, 836, 848}.

If 10 years of weather history is available instead of 15 years, the forecaster can get 10 annual peak forecasts in ascending order {810, 813, 815, 818, 824, 827, 829, 832, 839, 844}.

- The rank of the first 4-quantile is 10 x (1/4) = 2.5, which rounds up to 3. The 3rd smallest number is 815.
- The rank of the second 4-quantile is 10 x (2/4) = 5, which is an integer. Here the average of the 5th and 6th smallest numbers is used, which is (824 + 827)/2 = 825.5.
- The rank of the third 4-quantile is 10 x (3/4) = 7.5, which rounds up to 8. The 8th smallest number is 832.
- The fourth 4-quantile is the largest number, which is 844.

So the 4-quantiles are {815, 824, 832, 844}.

The 4-quantiles are called quartiles. The second 4-quantile (or the second quartile, Q_2) is median. The first (Q_1) and third (Q_3) quartiles are also called lower and upper quartiles respectively. The difference between upper and lower quartiles is interquartile range (IQR = Q_3 - Q_1).

The 100-quantiles are called percentiles. The commonly used percentiles in load forecasting are 50th, 90th, 95th, and 99th percentiles. The 50th percentile is median. In Global Energy Forecasting Competition 2014, the participants are required to provide the probabilistic forecasts of 99 percentiles, assuming the 100th percentile is infinity.

9.13 Resolution (for Hierarchical Load Forecasting) and Resolution (for Probabilistic Load Forecasting)

During the past several decades, utilities have been developing long term load forecasts mostly using monthly data aggregated up to revenue class level or higher. Deployment of smart grid technologies allows utilities to collect data with hourly or sub-hourly interval at household level. Using these high resolution data, forecasters can develop load forecasts at various levels in the system, which is called hierarchical load forecasting. There are two aspects of resolution in hierarchical load forecasting:

9.13.1 Spatial Resolution

Spatial resolution means how many points are being measured in a piece of land. In Dr. Tao Hong's paper, *Spatial Load Forecasting Using Human Machine Co-construct Intelligence Framework*, he divided the service territory of a medium sized utility into 3460 small areas, about 50 acres each. The data was from transformer load management system. In today's world, a "small area" can be 0.2 acre (the size of a typical single family home) or smaller. While short term load forecasts have been mostly developed based on hourly or half-hourly data, having load information at low levels can help enhance the forecasting accuracy (See the article: *One Size No Longer Fits All: Electric Load Forecasting with a Geographic Hierarchy*).

9.13.2 Temporal Resolution

Temporal resolution means the sampling frequency of the meters. In (Hong, Wilson, & Xie 2014), a major contribution was to demonstrate the additional forecasting accuracy gained by using high resolution data.

9.13.3 Resolution for Probabilistic Forecasting

In probabilistic load forecasting, resolution refers to how the size of prediction interval varies at different time periods. A high-resolution probabilistic forecast can properly quantify the uncertainties at different time periods by providing the prediction interval with variable size. For instance, in Figure 9-3 below, the prediction interval of summer months is much narrower than that of winter months, which tells that load is much more uncertain in winter than in summer.

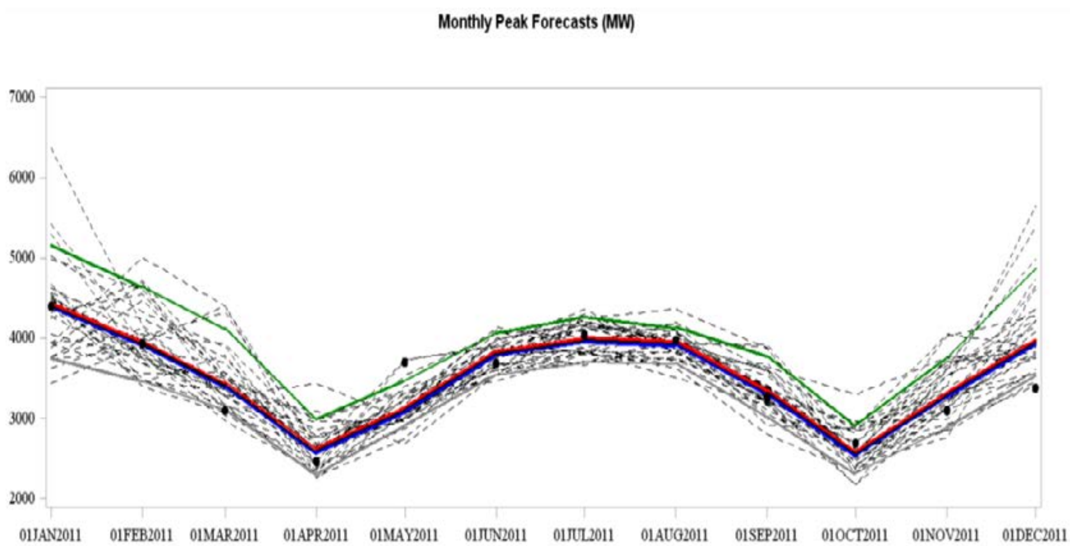

Figure 9-3: Sample month peak forecasts

9.14 Weather, Climate and Temperature

Weather is the condition of the atmosphere, such as temperature, humidity and rainfall, at a particular place over a short period of time, i.e., a few days. An example is that a weather forecast usually goes a few days ahead. Climate refers to the weather pattern of a place over a long period, i.e., a few decades or more. A well-known term is "climate change".

In load forecasting, the most frequently used weather variable is temperature. A temperature station is often called weather station, though a weather station may measure many variables beyond temperature.

Many utilities also include other weather variables as predictors in short term load forecasting models, such as humidity, wind speed and cloud cover. In reality, it is difficult to forecast these predictors with good accuracy, so there is a trade-off between the information gained by adding these additional variables and the noise introduced by their forecast errors. Under this condition, it is better to forecast with the principle of parsimony. Unless rigorous tests have been conducted showing the benefits of adding additional variables, forecasters are suggested to keep the model as lean as possible.

9.15 Prediction Interval and Confidence Interval

Prediction Interval and Confidence Interval are a pair of terms very difficult to distinguish, because statisticians and economists do not follow the same standard. Since load forecasting falls under the umbrella of forecasting, the terminology developed by the forecasting community is followed. In short, there is a simple rule that tells where to use confidence or prediction interval:

> *A confidence interval is associated with a parameter, while a prediction interval is associated with a prediction.*

The following three examples are used to illustrate how to apply these two terms in load forecasting.

9.15.1 Scenario Based Probabilistic Load Forecasting

Assume that 30 weather scenarios are created using 30 years of weather history. Based on each weather scenario, we can get a load forecast. Totally we get 30 load forecasts. The interval of 90/10 percentiles derived out of these 30 forecasts is a prediction interval.

9.15.2 Adding Error Distribution(s) to Point Forecast(s)

Assume that we develop a regression model for point load forecasting. We take out the residuals, and model them using a normal distribution. We then add this normal distribution back to the original point forecast to come up with a probabilistic forecast. An interval can be derived using the regression estimate +/- multiple standard deviations of the normal distribution. Many papers in the literature of load forecasting and its applications called this interval confidence interval, which is a typical misuse. It should have been called prediction interval.

9.15.3 Showing the Uncertainties around Estimated Parameters

In the old days, utility analysts generally worked on annual or monthly data with limited length of history. As a result, there were not many variables in the regression models. For instance, a typical model to forecast monthly energy can be:

$$Energy = b_0 + b_1 * CC + b_2 * CDD + b_3 * HDD + e$$

where CC represents customer count, and CDD/HDD represents cooling degree days and heating degree days.

After estimating the parameters, the analysts often reported the confidence interval and p value of each parameter. In this case, it is correct to call them confidence intervals. In today's world, to take advantage of the information from the large amount of data, we rarely use such a simple model. In a large model involving many variables, it is unrealistic and unnecessary to show the confidence intervals for all the parameters.

In conclusion, if one uses "prediction interval" consistently in load forecasting, one would be correct most of the time.

9.16 Load Factor, Coincidence Factor, Diversity Factor, and Responsibility Factor

9.16.1 Load Factor

Load factor is the average load of a system divided by its peak load. The higher the load factor is, the smoother the load profile is, and the more the infrastructure is being utilized. The highest possible load factor is 1, which indicates a flat load profile. In the old days, load factor was often used for long term peak demand forecasting. The forecasters first develop an energy forecast. They then calculate the average hourly load. Finally by dividing the forecasted average load by a predefined load factor, they can obtain the forecasted peak. However, one would avoid using this method for long term load forecasting in today's world where high resolution data is available for load forecasting.

9.16.2 Coincidence Factor and Diversity Factor

Coincidence factor is the peak of a system divided by the sum of peak loads of its individual components. It tells how likely the individual components are peaking at the same time. The highest possible coincidence factor is 1, when all of the individual components are peaking at the same time. Diversity factor is the sum of peak loads of all the components in a system divided by the peak of the entire system.

It is the reciprocal of coincidence factor. The higher the diversity factor, the more diverse the individual loads are in terms of peaking time. If the individual loads are peaking at the same time, the diversity factor is 1. Coincidence factor and diversity factor are often used for top-down forecasting in transmission and distribution planning. After the corporate level forecast is developed, the planning team would get a quota telling the sum of the peaks from various regions. This quota is usually calculated by dividing the forecasted system peak by coincidence factor. The regional peak load forecasts can then be developed subject to the constraint of this quota.

9.16.3 Responsibility Factor

Responsibility factor is the load of an individual component at the time of system peak divided by the peak load of this individual component. Responsibility factor tells how much of the component is contributing to the system peak. When a component peaks at the same time as the system, its responsibility factor is 100%. Responsibility factor is often used in guiding demand side management. Utilities often get charged for its contribution to the peak of the planning coordinator. To avoid a high charge, a utility has to reduce the responsibility factor. This can be done by implementing various programs that help shift the peak. Similarly, responsibility factor is also used in rate making. A customer with high peak demand may not get high demand charge if its peak occurs during off-peak period of the utility system load.

9.17 Standard Time, Daylight Saving Time, and Local Time

The Earth is round like a ball. When it is night in the U.S., it is morning in China. To do business beyond a local region, people need a common reference to communicate time. Standard time is the synchronization of clocks in different geographical locations within a time zone to a common time standard, usually based on the meridian at the center of the time zone.

Daylight saving time (DST) typically involves advancing clocks by an hour near the start of spring and adjusting clocks back in the fall. The primary purpose of daylight saving time is to adjust human activity schedule during daytime to take advantage of the daylight hours during summer time. Not every country has adopted DST. In U.S., Arizona and Hawaii are not observing DST. In the regions where DST is adopted, the term standard time typically refers to the time without the offset for the daylight saving time.

Local time means the time on the clock. In the regions not observing DST, local time is the same as standard time. In the regions observing DST, local time is standard time in winter and fall, daylight saving time in spring and summer. During the day when DST starts, there are 23 hours in local time. During the day when DST ends, there are 25 hours in local time.

In load forecasting, the load and weather data often comes from different sources. The misunderstanding of these terms often leads to data processing errors in load forecasting. Typical formats in load forecasting projects include 1) Greenwich Mean Time (GMT); 2) Standard time; and 3) Local time. While both GMT and standard time are observing 24-hour days, there are several variations of local time in load forecasting practice. During the first day of DST, some data sources observe a 23-hour day, while some use a 24-hour day with the 2nd (or 3rd) hour as zero or missing. During the last day of DST, some data sources observe a 25-hour day, while some observe a 24-hour day with the 2nd (or 3rd) hour as the sum of the two original readings of the same hour.

Regardless what format the raw data has, it is a general practice to convert the load and weather data to a 24-hour local time. At the beginning of the DST, the average between its adjacent two hours is used for the "missing" hour. At the end of DST, the average of the original two readings in the same hour is used. A list of DST start and end days in the U.S. from 1987 to 2020 is shown in Table 9-1 below.

Table 9-1: List of DST start and end days in the U.S. from 1987 to 2020

Year	DST Start	DST End
1987	4/5/1987	10/25/1987
1988	4/3/1988	10/30/1988
1989	4/2/1989	10/29/1989
1990	4/1/1990	10/28/1990
1991	4/7/1991	10/27/1991
1992	4/5/1992	10/25/1992
1993	4/4/1993	10/31/1993
1994	4/3/1994	10/30/1994
1995	4/2/1995	10/29/1995
1996	4/7/1996	10/27/1996
1997	4/6/1997	10/26/1997
1998	4/5/1998	10/25/1998
1999	4/4/1999	10/31/1999
2000	4/2/2000	10/29/2000
2001	4/1/2001	10/28/2001
2002	4/7/2002	10/27/2002
2003	4/6/2003	10/26/2003
2004	4/4/2004	10/31/2004
2005	4/3/2005	10/30/2005
2006	4/2/2006	10/29/2006
2007	3/11/2007	11/4/2007
2008	3/9/2008	11/2/2008
2009	3/8/2009	11/1/2009
2010	3/14/2010	11/7/2010
2011	3/13/2011	11/6/2011
2012	3/11/2012	11/4/2012
2013	3/10/2013	11/3/2013
2014	3/9/2014	11/2/2014
2015	3/8/2015	11/1/2015
2016	3/13/2016	11/6/2016
2017	3/12/2017	11/5/2017
2018	3/11/2018	11/4/2018
2019	3/10/2019	11/3/2019
2020	3/8/2020	11/1/2020

10. Bibliography

This section lists a selected group of load forecasting papers and reports, which we believe are useful for the audience who are interested in further exploring the area of load forecasting. The key references that this study is mainly based on and the recommended first-readings in load forecasting are highlighted in **bold**.

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