Electric Customer Load Volatility and Its Impact on Electricity Costs, Prices, and Profits

3002005818

Electric Customer Load Volatility and Its Impact on Electricity Costs, Prices, and Profits

3002005818

Technical Update, December 2015

EPRI Project Manager

C. Holmes

ELECTRIC POWER RESEARCH INSTITUTE
3420 Hillview Avenue, Palo Alto, California 94304-1338 ▪ PO Box 10412, Palo Alto, California 94303-0813 ▪ USA
800.313.3774 ▪ 650.855.2121 ▪ askepri@epri.com ▪ www.epri.com

THE FOLLOWING ORGANIZATION, UNDER CONTRACT TO EPRI, PREPARED THIS REPORT:

Christensen Associates Energy Consulting

This is an EPRI Technical Update report. A Technical Update report is intended as an informal report of continuing research, a meeting, or a topical study. It is not a final EPRI technical report.

NOTE

For further information about EPRI, call the EPRI Customer Assistance Center at 800.313.3774 or e-mail askepri@epri.com.

ACKNOWLEDGMENTS

The following organization, under contract to the Electric Power Research Institute (EPRI), prepared this report:

Christensen Associates Energy Consulting, LLC
800 University Bay Drive, Suite 400
Madison, WI 53705-2299

Principal Investigators
L. Kirsch
B. Eakin
D. Hansen
M. Morey

This report describes research sponsored by EPRI.

This publication is a corporate document that should be cited in the literature in the following manner:

Electric Customer Load Volatility and Its Impact on Electricity Costs, Prices, and Profits. EPRI, Palo Alto, CA: 2015. 3002005818.

PRODUCT DESCRIPTION

Customer demand for electricity (i.e. load) varies from moment to moment. Electric load volatility impacts utility costs, and ultimately profits, of providing electricity. This report explains what electric load volatility is, why it matters to stakeholders, how it has likely changed in recent decades, how it might be measured, and how its adverse impacts might be mitigated.

Background

"Load volatility" is a standardized measure of the uncertainty of future customer electricity loads. Aggregated across customers, load volatility also affects the costs of maintaining reliable power systems. Due to the growth of distributed resources, and because of changes in the technical and institutional bases for controlling power systems, load volatility issues have evolved over the past two decades. This report investigates electric load volatility.

Objectives

To survey existing methods to describe and explain the concept of electric load volatility.

Approach

The report was developed based upon the authors' experience with the subject at hand, supplemented by appropriate references to the literature.

Results

This research explains concepts and surveys existing methods. It includes sections that define load volatility, why it matters, how load volatility might be changing, modeling and forecasting load and load volatility, and managing the impacts of load volatility. Further research into load modeling and forecasting, demand-side program database development, and production patterns of emerging distributed resource technologies is needed to investigate the measurement and mitigation of load volatility.

Applications, Value, and Use

This report is addressed to a general audience of electricity industry stakeholders, particularly those interested in issues pertaining to retail electricity pricing and electricity investment, including distributed resource investment.

Keywords

Demand response
Distributed resources
Electricity pricing
Load forecasting
Time-based pricing

ABSTRACT

This report explains what electric load volatility is, why it matters to stakeholders, how it has likely changed in recent decades, how it might be measured, and how its adverse impacts might be mitigated. "Electric load volatility" is a standardized measure of the uncertainty of future customer electricity loads. It is important because of the impact it has on the costs, and ultimately the profitability, of providing electrical energy. Aggregated across customers, load volatility also affects the costs of maintaining reliable power systems. Load volatility is changing over time because of ongoing changes in the ways that customers use electricity, and an ongoing proliferation of distributed resources throughout power systems. Load volatility is measurable through calculations derived from load forecasting models. Utilities can manage the impacts of load volatility by reducing load volatility itself, and by mitigating its financial impacts.

EXECUTIVE SUMMARY

"Load volatility" is a standardized measure of the uncertainty of future customer electricity loads due to random events such as changing business conditions and changing weather. It is a measure of the uncertainty of load outcomes around the expected load profile.

Because the factors underlying load uncertainty vary among customers, load volatilities will vary across customer classes and will sometimes be very customer-specific. Since these factors can differ by season, day of week, and time of day, load volatilities will generally change over time, even for a single customer.

Just as grid resilience is an important aspect of designing and maintaining an electric system, so too is load volatility. Load volatility is the customer analog, behind the meter, to grid resilience. In fact, one could postulate the creation of a resilience market, where the supply and demand for resilience and volatility could be established and priced based on customer demands, capacity assets and end-use technology.

Why Load Volatility Matters

Load volatility is important because of the impacts it has on the costs, and ultimately the profitability, of providing electrical energy. Aggregated across customers, load volatility also affects the costs of maintaining reliable power systems. By using load volatility to quantify load uncertainty, we can quantify load-related risks to electricity provider profits and power system reliability. This information can facilitate electricity providers' efforts to incorporate these risks into their pricing and investment policies.

In setting retail prices, the retailer faces financial risks due both to the uncertainties in loads and wholesale energy prices, and to the covariance between loads and wholesale energy prices. In other words, load volatility affects retail electrical energy prices through its interaction with wholesale price volatility. When load volatility and wholesale prices are positively correlated, load volatility raises the breakeven retail electricity prices above the expected wholesale energy price.

Aggregate load volatility reflects critical uncertainties that the supply of resources must address, raising the quantities of resources needed to meet load, and that must have the frequency control and fast-start capabilities needed to meet load changes. As aggregate load volatility rises, there are greater threats to reliability and higher resource costs to maintain reliability.

How Load Volatility May Be Changing

Load volatility is driven by factors that are common to many customers, as well as by factors that are idiosyncratic to particular customers. In the short run, weather affects many loads, while leisure and short-term economic factors affect different customers according to their particular circumstances. In the long term, broad changes in economic conditions and technology affect many loads similarly, while other economic and business circumstances affect different customers in different ways.

Because the drivers of load volatility are changing over time, load volatility itself – at both the individual customer level and in the aggregate – may be changing over time. Such volatility changes are likely to have occurred in recent years, and are likely to still be occurring, due to ongoing changes in the ways that customers use electricity, and to an ongoing proliferation of distributed resources throughout power systems. Customers' uses of electricity are changing as technologies advance, as consumer tastes evolve, and as the national economy continues moving away from heavy industry and toward services. Because network resources need to cover the portion of consumption that is not covered by distributed resources, the need for and cost of network resources is significantly influenced by the power provided by and reliability of distributed resources.

Modeling and Forecasting Load and Load Volatility

Because load volatility measures the uncertainty of load outcomes around the expected load profile, a key conceptual and practical challenge is to distinguish between *expected changes in load* and *unexpected deviations in load*. In the load data, expected changes and unexpected deviations are intertwined. The analytic objective is to separate these two strands, using statistical analysis to peel off the uncertainty strand and then use that strand to calculate and analyze volatility.

Many different types of models can be used to estimate expected loads. All models nonetheless reveal deviations between expected loads and actual loads. These deviations serve as the error terms from which load volatility can be quantified.

Managing the Impacts of Load Volatility

Utilities can manage the impacts of load volatility in two basic ways. The first is by reducing load volatility itself. The second is by mitigating the financial impacts of load volatility.

Reducing the volatility of load itself requires that the utility have some means of reducing load uncertainty, which means somehow placing limits on customers' loads. In the U.S., this can be achieved through direct load control programs, price signals that influence loads (such as through real-time pricing, critical peak pricing, and peak-time rebate programs, or through demand charges), and technology fixes (like smart energy systems, storage technologies, and Internet-connected devices).

The financial impacts of load volatility can be mitigated by reducing load volatility or by pricing retail products to incorporate costs associated with load and wholesale price volatilities. The retail design problem is partly a matter of setting retail prices at the appropriate levels and partly a matter of differentiating electricity products and customers. To achieve an expected breakeven price, the level and structure of retail prices must reflect the costs of providing customers with the energy, ancillary, transmission, and distribution services that they use. Because load volatility is not a service *per se*, there should not be any price on load volatility itself. Instead, the costs of load volatility should be recovered through the prices of the services that are made more costly by load volatility. The costs of load volatility may also be reduced by differentiating retail prices by time, location, and customer.

Directions for Further Research

There are a few lines of research that may shed light on the measurement and mitigation of load volatility. First, because the quantification of load volatility is a derivative of load forecasting, future research may profitably engage in a detailed examination and synthesis of the econometric literature on load modeling and forecasting. Second, because system operators can mitigate load volatility through demand-side management programs, it would be helpful to develop a database that indicates the extent to which such programs result in actual demand reductions. Third, future research could explore in detail the effects on net load volatility of emerging distributed technologies.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1
INTRODUCTION

Load volatility is important because of the impacts that it has on the costs, and ultimately the profitability, of providing electrical energy. Aggregated across customers, load volatility also affects the costs of maintaining reliable power systems. Load volatility issues have evolved over the past two decades because of the growth of distributed resources and because of changes in the technical and institutional bases for controlling power systems.

This report explains what electric load volatility is, why it matters to stakeholders, how it has likely changed in recent decades, how it might be measured, and how its adverse impacts might be mitigated. It is organized accordingly.

2
WHAT IS ELECTRIC LOAD VOLATILITY?

Customers' electricity demands – called "loads" – vary from moment to moment. A customer's *historical load profile* indicates the past experience of what the customer's loads have been, usually on an hourly basis. The historical load profile depends partly on the customer's usual routine but also depends upon random events that affect the customer's electricity-using activities. Forecasts of a customer's *future load profile* reflect the expectation of what the customer's loads will be based upon the customer's usual routine but do not reflect uncertain random events. A customer's actual future loads can therefore be regarded as consisting of two components, an expected future load profile plus unexpected loads that depend upon uncertain future events.

Different customers have very different load profiles. For example, a three-shift industrial customer with around-the-clock operations might have a load that is nearly constant every hour of the year, yielding a flat load shape. An agricultural goods processor might have higher loads around harvest time than at other times of the year. A commercial customer might have high loads during weekday business hours and low loads otherwise. A residential customer might have loads that are highest during evening and weekend hours, and highest during the summer cooling season.

Figure 2-1 presents the actual historical loads of a hypothetical residential customer along with the expected loads that would have been statistically forecast based upon the customer's past behavior. The horizontal axis indicates the hour of the day, while the vertical axis shows the customer's load in MW. In this example, the customer's actual loads (represented by the solid blue line) are lower than the forecast loads (represented by the dashed red line), possibly because this particular summer day may have had cooler weather, and therefore lower cooling needs, than usual.

Statistical analysis enables us to identify the uncertain component of the customer's load as the difference between the actual and expected loads. This uncertain component provides the data with which load volatility may be quantified.

Load volatility is a standardized measure of the uncertainty of future customer electricity loads due to random events such as changing business conditions and changing weather. It is a measure of the uncertainty of load outcomes around the expected load profile. This uncertainty is illustrated, for example, by the differences between the two lines in Figure 2-1. The quantification of this measure depends upon the plausible assumption that the range of future load outcomes is bounded by our knowledge of the past history of loads, so that the load-related risks to electricity provider profits and power system reliability can also be bounded.

Because the factors underlying load uncertainty vary among customers, load volatilities will vary across customer classes and will sometimes be very customer-specific. Because the factors underlying load uncertainty can vary by season, day of week, and time of day, load volatilities will generally vary over time even for a single customer.

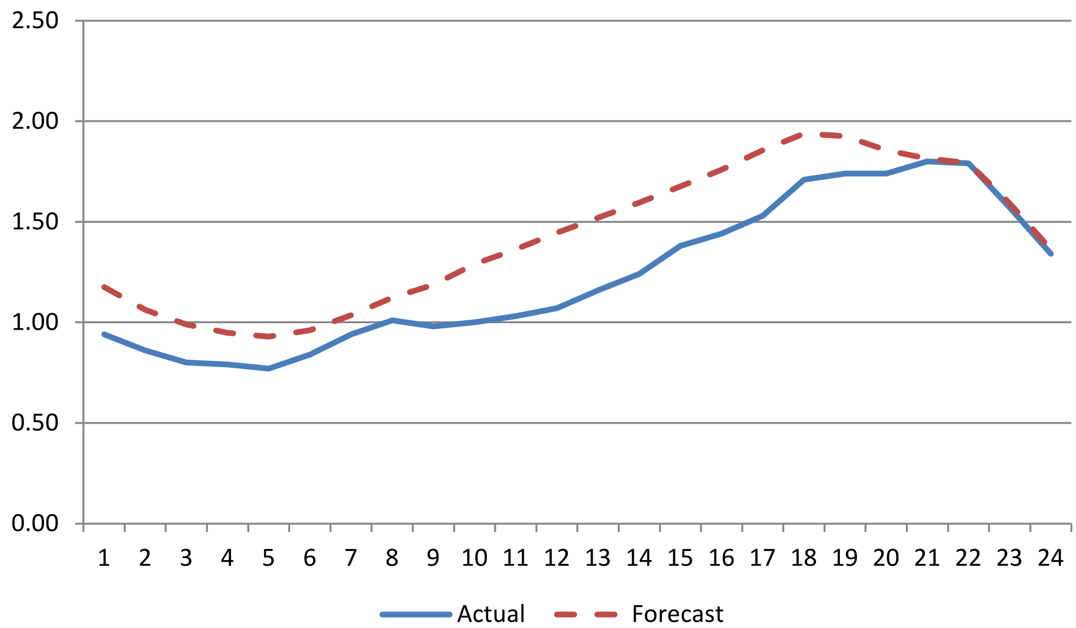

Figure 2-1
Actual Versus Expected Loads for a Hypothetical Customer

Load volatility is *not* a measure of the amount by which load changes from hour to hour because such changes are *expected* due to customers' routinely changing electricity needs over the course of a day, a week, or a year. Instead, load volatility is a measure of the *uncertainty* in how much electricity that customers will consume in each time period. In other words, load volatility can be defined as the deviation of load from an expected reference level in some specified period of time, usually an hour.

Consequently, the term *load volatility* refers to an entirely different phenomenon than the *price volatility* associated with stock market equities. For a particular common stock, for example, price volatility measures the amount by which the price of the stock bounces around from hour to hour or day to day. The key fact is that the stock price is for a single good, namely a share of some corporation. Load volatility, by contrast, does not refer to the amount by which load bounces around from hour to hour because, among other things, electricity at noon on Thursday is *not* the same good as electricity at midnight on Saturday. Instead, load volatility measures how *actual* load at noon on Thursday deviates from *expected* load at noon on Thursday. While price volatility for equities reflects the speed with which investors' perceptions of a stock's value changes over time, electricity load volatility reflects the uncertainty in loads at each particular moment in time.

Electricity load volatility can reflect uncertainties in future electricity prices to the extent that customers who face time-differentiated prices respond to those prices. For such customers, uncertain prices are among the random events that affect load. If future time-differentiated prices were known with certainty, then these prices might affect the customer's load *profile* but would not affect the customer's load *volatility*.

Consequently, a key conceptual and practical challenge is to distinguish between *expected changes in load* and *unexpected deviations in load*. In the load data, expected changes and unexpected deviations are intertwined. The analytic objective is to separate these two strands, using statistical analysis to peel off the uncertainty strand and then use that strand to calculate and analyze volatility. In other words, the challenge is to distinguish the signal and the noise, discerning whether there is information in the noise that can explain some part of the noise and how it might be changing over time. Volatility is a way of measuring the noise.

3 WHY LOAD VOLATILITY MATTERS

Load volatility affects the costs, and ultimately the profitability, of providing electrical energy. Aggregated across customers, load volatility also affects the costs of maintaining reliable power systems. By using load volatility to quantify load uncertainty, we can quantify load-related risks to electricity provider profits and power system reliability. This information can facilitate electricity providers' efforts to incorporate these risks into their pricing and investment policies.

Impacts on the Profitability of Providing Electrical Energy

In each hour, a retailer's gross profit from the sale of electrical energy to a particular customer equals that customer's load times the amount by which the retail price exceeds the wholesale energy price of energy. For any hour h and customer j, this can be expressed as:

$$\boldsymbol{Gross\ Profit_{hj} = L_{hj} * (P_{hj} - WEP_h)} \qquad \textbf{Eq. 3-1}$$

where $Gross\ Profit_{hj}$ is the gross profit from selling power to customer j in hour h, L_{hj} is the load of customer j in hour h, P_{hj} is the retail price charged to customer j in hour h, and WEP_h is the wholesale energy price in hour h. When the retail price must be set in advance, as is usually the case, this gross profit is uncertain because both the customer's load and the wholesale energy price are uncertain.

While an individual customer's load rarely affects wholesale energy prices, individual customers' loads will often be correlated with wholesale energy prices. For example, on hot summer days, high customer loads will need to be served, at the margin, by relatively costly power plants; so high customer loads will cause, and be correlated with, high wholesale energy prices.

Given a preset retail price, the variance of the gross profit depends upon the variances and covariance of load and wholesale energy price:

$$\begin{aligned} var(Gross\ Profit_{hj}) = {} & (P_{hj} - E\{WEP_h\})^2 * var(L_{hj}) + E\{L_{hj}\}^2 * var(WEP_h) \\ & -2 * E\{L_{hj}\} * (P_{hj} - E\{WEP_h\}) * cov(L_{hj}, WEP_h) \\ & + \boldsymbol{var(L_{hj}) * var(WEP_h) + cov(L_{hj}, WEP_h)^2} \end{aligned} \qquad \textbf{Eq. 3-2}$$

This equation shows that, in setting retail prices, the retailer faces financial risks due both to the uncertainties in loads and wholesale energy prices and to the covariance between loads and wholesale energy prices.

In general, retailers should set retail prices according to an expected load-weighted average of wholesale energy prices. This is not the same as setting retail prices according to the wholesale energy prices associated with expected loads, however. Because loads are correlated with wholesale energy prices, pricing according to expected loads would *not* be sufficient to give the retailer an expected profit. This can be seen in Figure 3-1, which provides a simplistic illustration of the problems created by the correlation between loads and wholesale energy prices. The figure shows wholesale energy prices as a function of total power system load. Because it is common for wholesale energy prices to rise more rapidly at high load levels than at low load levels, the figure shows a wholesale energy price curve that has a slope that rises with load.

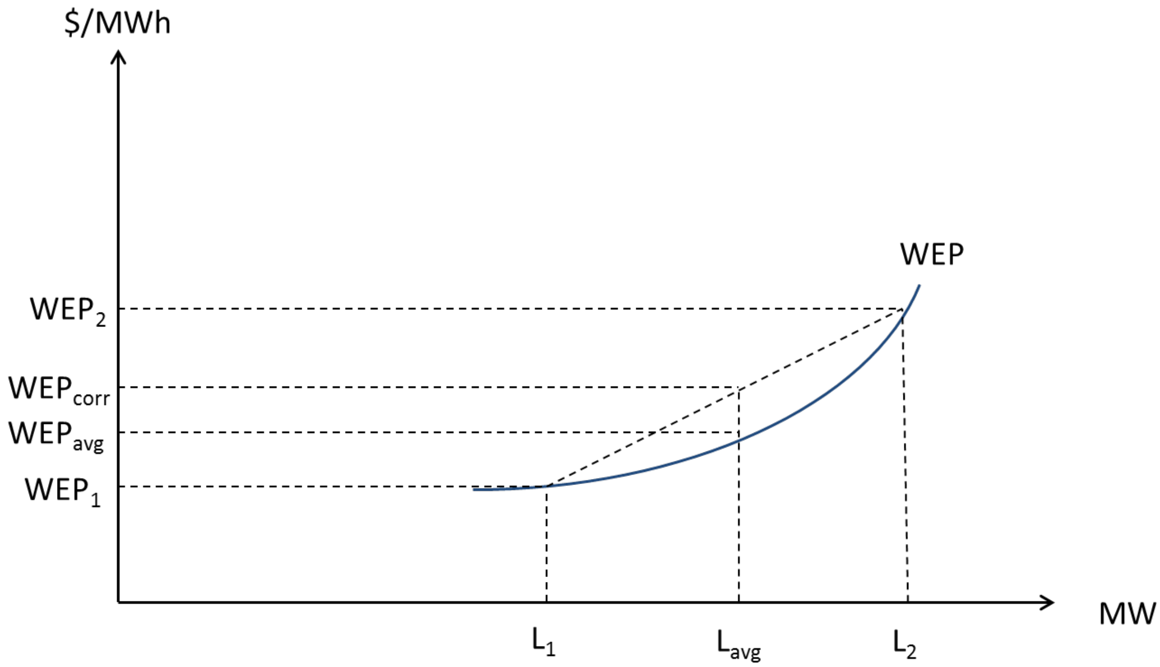

Figure 3-1
Loads, Wholesale Energy Prices, and Profitable Pricing

Suppose that system load has a 50% chance of being at level L_1 and a 50% chance of being at level L_2. The wholesale energy price associated with average load L_{avg} is WEP_{avg}. But the average of the wholesale energy prices associated with L_1 and L_2 – that is, the average of WEP_1 and WEP_2 – is WEP_{corr}, which is higher than WEP_{avg}. To operate profitably, the retailer needs to base retail prices on WEP_{corr}, and would lose money by basing its prices on WEP_{avg}. In other words, load uncertainty, as measured by a metric such as load volatility, is critical for determining competitive retail electricity prices.

Load volatility tends to raise expected marginal costs, particularly at high load levels. Although the load volatility of *individual* customers does not impact wholesale energy prices and the consequent competitive retail prices, *aggregate* load volatility does impact these costs and prices. Nonetheless, for retail pricing purposes, the uncertainties that matter are those of the individual customers or groups of customers for whom particular retail rates are being developed.

Impacts on Resource Investment and Power System Reliability

Power systems must incur significant capital and operating costs to address the reliability issues created by load volatility. Because the demand and supply of electricity must be equal at all times within each electric power system, power resources must be sufficient to meet the system's peak demand with a margin of error sufficient to cover resources' forced outages and to cover the uncertainties in exactly what peak demand will be. Furthermore, more volatile loads are more difficult to follow, generally requiring more capital equipment (at the generation, transmission, and distribution levels) to meet uncertain peak loads, and generally requiring both more capital equipment and higher operating costs to provide regulating and operating reserves (ancillary services) than do less volatile loads. Resource costs depend upon the quantity of capacity that is needed to meet peak load, and upon the types of resources that are needed to meet the system load pattern at least cost, considering not only the durations of load levels but also the speeds at which loads ramp up and down and the uncertainties in the required ramp rates.

Load is thus a key determinant of the quantity, mix, and costs of the resources that are needed to reliably operate power systems. Load volatility reflects critical uncertainties that the supply of resources must address, raising the quantity of resources that is needed to meet load and raising the quantity of resources that must have the frequency control and fast-start capabilities that are needed to meet unexpected load changes. Higher load volatility poses a greater threat to reliability and requires greater resource costs to maintain reliability than does lower load volatility.

For reliability and planning purposes, aggregate load volatility, not individual customers' load volatilities, is critical. This aggregate load volatility can be measured over the several time frames that are important in maintaining reliability. These include the planning time frames (in years) required for resource investments as well as the operating time frames (in days or hours) required for power system commitment and dispatch.

Implications of Volatility for Retail Electricity Pricing

Load volatility affects retail electrical energy prices through its interaction with wholesale price volatility. For example, a "flip-the-switch" retail product with a fixed price set at time 0 for some future hour h would have the following breakeven price:[1]

$$P_{FTS} = F_{0,h} e^{\rho \sigma_P \sigma_L h} \qquad \textbf{Eq. 3-3}$$

where $F_{0,h}$ is the forward price or expected spot price at time 0 for future hour h, e is the exponential operator (2.71828), ρ is the correlation between load and wholesale spot price volatilities, σ_P is wholesale spot price volatility, and σ_L is load volatility. Equation 3-3 says that the flip-the-switch price equals the expected spot price with an adjustment for price and load volatility. Because the exponential operator, the volatilities, and future hour are all positive numbers, the direction of the adjustment – positive or negative – depends entirely on the sign of ρ, the correlation between loads and spot prices:

- If $\rho < 0$, $P_{FTS} < F_{0,h}$, so if loads and spot prices tend to move in opposite directions, the flip-the-switch price will be lower than the expected spot price.
- If $\rho = 0$, $P_{FTS} = F_{0,h}$, so if loads and spot prices are uncorrelated, the flip-the-switch price will be the same as the expected spot price.
- If $\rho > 0$, $P_{FTS} > F_{0,h}$, so if loads and spot prices tend to move in the same direction, the flip-the-switch price will be higher than the expected spot price.

[1] This equation is from [20, p. 12-11].

Because the correlation is generally positive (i.e., when loads are unexpectedly high, prices tend to be unexpectedly high), the flip-the-switch price will generally exceed the expected spot price. Note, however, that high load volatility is important only when the correlation and wholesale price volatility are both significant.

Load volatility has the similar impacts on breakeven retail electricity prices in general as it does on breakeven flip-the-switch prices in particular: it affects breakeven prices according to load volatility, wholesale spot price volatility, and the correlation between loads and wholesale spot prices. Because this correlation is usually positive, load volatility usually raises breakeven retail prices above expected wholesale energy prices. On the other hand, because the volatilities and correlation can differ by season and time of day, the impacts of load volatility upon price can vary by time of use, being larger in some time periods (particularly peak periods, when small load changes can cause large spot price changes) than in other time periods.

In principle, prices could be set so that each customer bears the costs of the risks created by their individual load volatility. For administrative reasons, however, it would usually be practical to apply such individual treatment only to the largest customers. For most customers, prices would usually be set so that each customer group bears the costs of the risks created by their aggregate load volatility.

4

HOW LOAD VOLATILITY MAY BE CHANGING

Load volatility is driven by factors that are common to many customers as well as by factors that are idiosyncratic to particular customers. Load volatility is also driven by factors that can be distinguished by the duration of their impacts.

Table 4-1 presents a partial list of the drivers of load volatility, distinguished by commonality and duration. In the short run, weather affects many loads, while leisure and short-term economic factors affect different customers according to their particular circumstances. In the long term, broad changes in economic conditions and technology affect many loads, while other economic and business circumstances affect different customers in different ways.

Table 4-1
Some Drivers of Load Volatility

Duration	Common Drivers	Idiosyncratic Drivers
Short-Term (hours or days)	weather	For residences: • Vacations For businesses: • Sales • Operational circumstances
Long-Term (months or years)	• Overall economic conditions • Changing electricity uses • Advances in distributed resource technologies	For residences: • Economic circumstances For businesses: • Competition • Applicable technological progress

Because the drivers of load volatility are changing over time, load volatility itself – at both the individual customer level and in the aggregate – may be changing over time. Such volatility changes are likely to have occurred in recent years, and are likely to still be occurring, due to ongoing changes in the ways that customers use electricity and to an ongoing proliferation of distributed resources throughout power systems.

Uses of Electricity Are Changing

Customers' uses of electricity are changing as technologies advance and as consumer tastes evolve. Aggregate loads on power systems are changing as the national economy continues moving away from heavy industry and toward services.

Evolving Consumer and Industrial Technologies

In the period 1998-2005, total U.S. residential electricity use doubled for lighting; increased by more than 50% for home entertainment systems and space cooling; increased by about 10% for dishwashers, clothes dryers, and personal computers; and dropped by more than 10% for freezers, space heating, and refrigeration.[2] Figure 4-1 shows that, between 1978 and 2005, residential use of energy (including gas and oil) dramatically shifted from space heating toward relatively electric-intensive uses for appliances, electronics, and air-conditioning. Figure 4-2 shows that the percentages of households having various types of appliances changes over time, sometimes rising and sometimes falling, with occasional dramatic increases in market penetration of new technologies (microwave ovens in this figure). Figure 4-3 shows that the percentage of homes with air conditioning has risen substantially throughout the U.S. in recent decades. These figures together illustrate the unsurprising fact that residential uses of electricity have changed significantly during past decades.

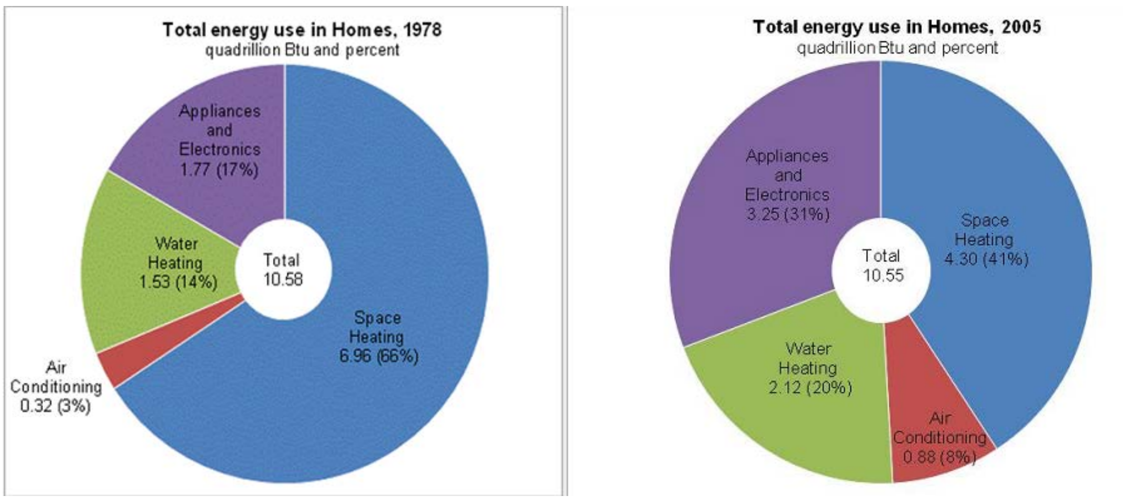

Figure 4-1
U.S. Total Residential Energy Uses, 1978 and 2005[3]

[2] See [10, p. 138].

[3] The figure is from [13, Figure 1].

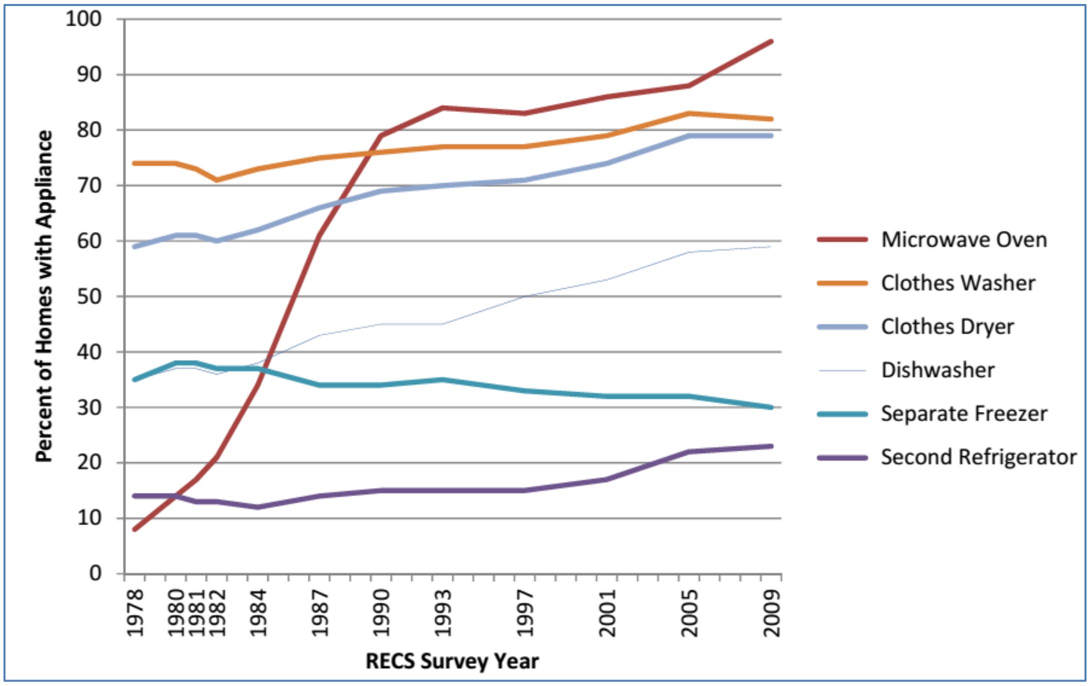

Figure 4-2
Penetration of Select Household Appliances in the U.S., 1978-2009[4]

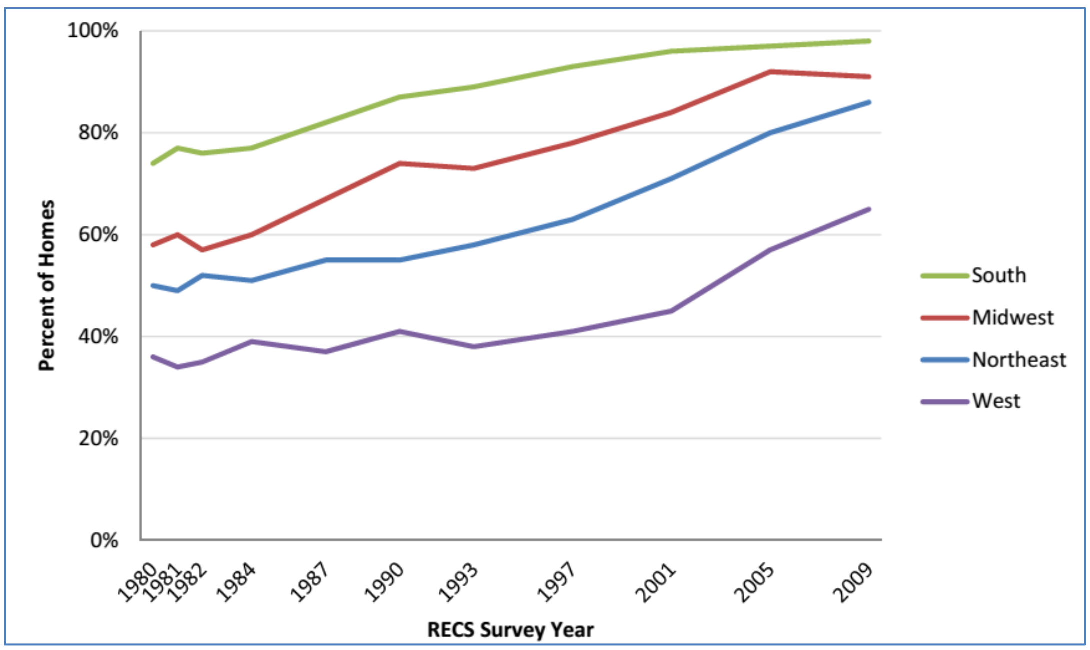

Figure 4-3
Percent of U.S. Homes with Air Conditioning, by Region, 1980-2009[5]

---

[4] The figure is from [13, Figure 1]. RECS is the Residential Energy Consumption Survey (RECS) administered by the U.S. Energy Information Administration.

[5] The figure is from [13, Figure 6].

Figure 4-4 shows how major residential uses of electricity, excluding electric vehicles, are forecast to evolve over the next three decades.[6] Each curve indicates the share of each of the seven largest uses as a percentage of total residential electricity consumption. The significant trends shown in the figure are a substantial drop in the share of lighting load, a small drop in the share of refrigeration load, an erratic drop in the share of space heating load, and a correspondingly erratic increase in the share of space cooling load. Not shown in the figure is an increase in the aggregate share of electric vehicle and other loads.

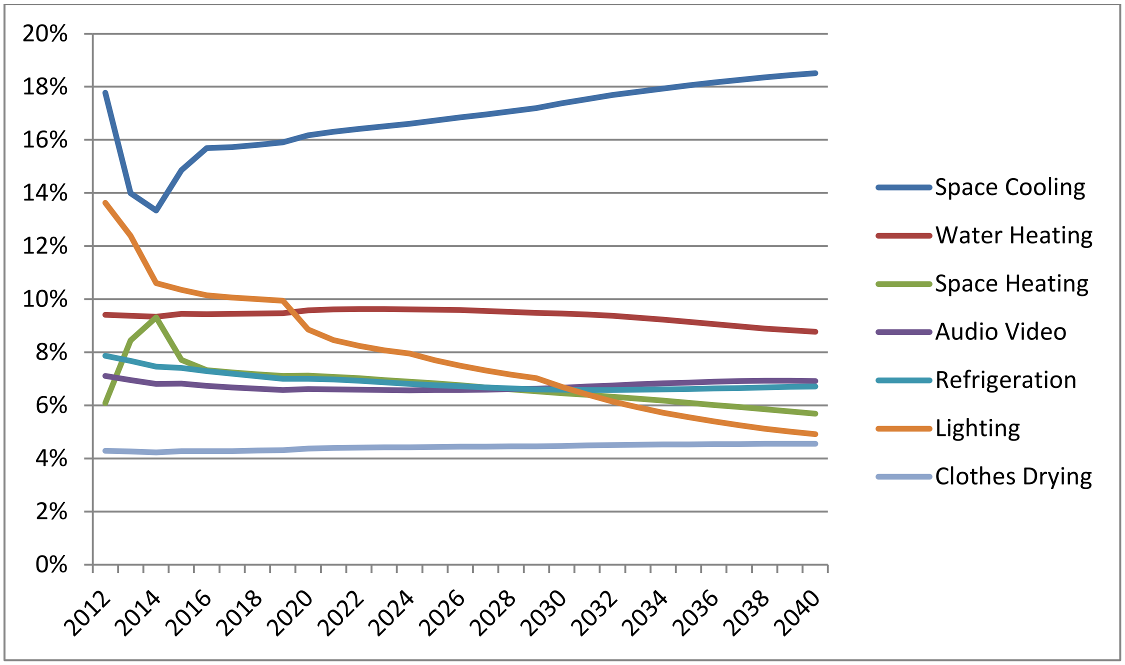

Figure 4-4
U.S. Residential Customer End-Use Shares of Electricity, 2012-2040[7]

Figure 4-5 shows how major commercial uses of electricity, excluding electric vehicles, are forecast to evolve over the next three decades. Each curve indicates the share of each of the five largest uses as a percentage of total commercial electricity consumption. An upward trend is forecast only for non-computer office equipment. Downward trends are forecast for the other four major uses, with particularly significant decreases in lighting and refrigeration loads. There is a significant forecast increase in the aggregate share of other loads not shown in the figure.

[6] Unfortunately, the forecasts of residential and commercial uses exclude electric vehicle use, the data for which are buried in a forecast of fuel requirements for the transportation sector.

[7] Data are from [24, Table A4].

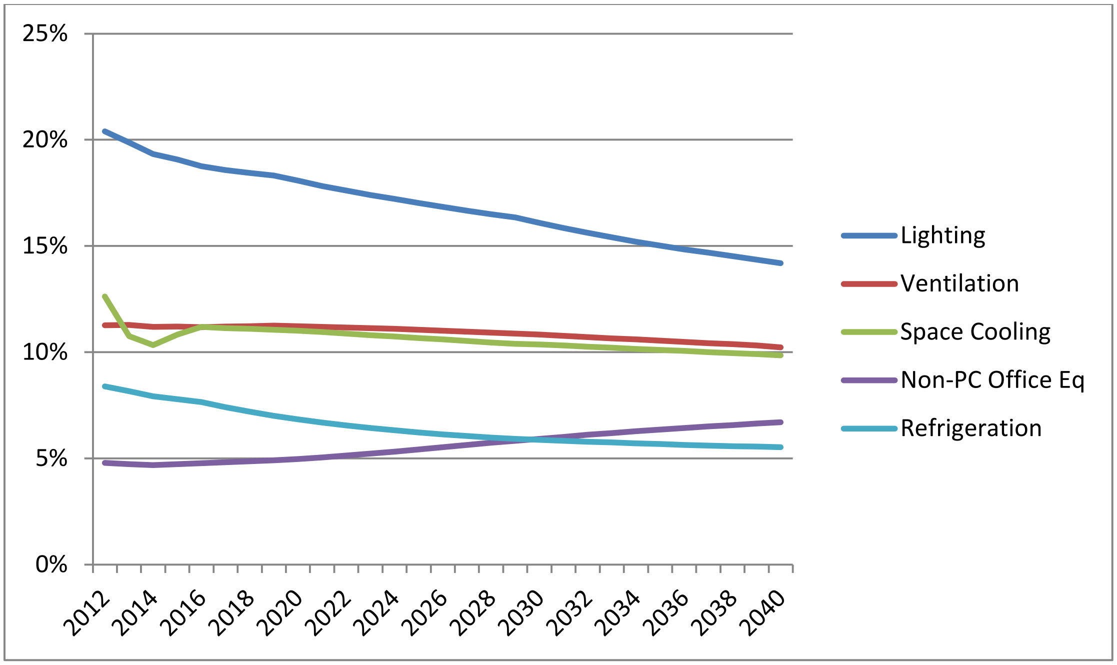

Figure 4-5
U.S. Commercial Customer End-Use Shares of Electricity, 2012-2040[8]

Evolving Customer Mix

Figure 4-6 shows how, for the U.S. as a whole, the relative consumption of electrical energy has shifted among customer classes over the past quarter century and is forecast to shift over the next two decades. The residential share of consumption, represented by the short-dashed blue line, has risen modestly from 35% of total electrical energy consumption in 1990 to 38% in 2015, with a modest drop to 36% forecast for 2035. The changes in the commercial and industrial shares, by contrast, have been more dramatic, as the U.S. economy has shifted away from manufacturing and toward services. Between 1990 and 2015, the commercial share, represented by the long-dashed red line, has moved upward from 29% to 36%, while the industrial share, represented by the solid green line, has moved downward from 36% to 26%. Between now and 2035, both the commercial and industrial shares are forecast to rise slightly, to 37% for the commercial class and 28% for the industrial class.

---

[8] [24, Table A4].

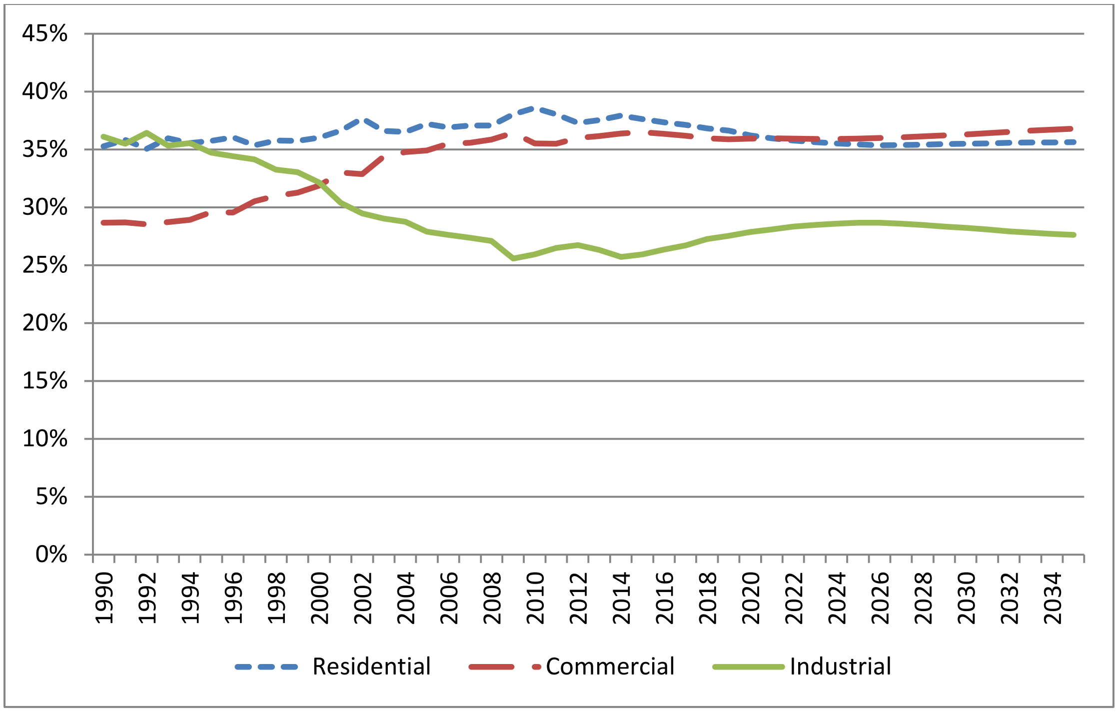

Figure 4-6
Shares of U.S. Electrical Energy Consumption, by Major Class, 1990-2034[9]

The de-industrialization implied by Figure 4-6 would have increased overall load volatility if residential and commercial customers, having relatively weather-sensitive loads, have higher volatility than the industrial class.

Distributed Resources Are Changing Needs for Network Resources

Distributed resources are gaining larger shares of total power production, a trend that is widely forecast to continue into the future. Network resources need to cover the portion of consumption that is not covered by distributed resources. For example, a residential customer with rooftop solar panels has a net load equal to their gross consumption of electricity minus their solar output; and network resources must serve that net load. Consequently, the need for and cost of network resources is significantly influenced by the power produced by distributed resources.

In mathematical terms, the power system needs to serve customers' net loads, which are equal to the amounts by which gross loads differ from own-generation:

$$NetL_{hj} = GrossL_{hj} - GEN_{hj} \qquad \textbf{Eq. 4-1}$$

where $NetL_{hj}$ and $GrossL_{hj}$ are respectively the net and gross loads of customer j in hour h, and GEN_{hj} is the own-generation of customer j in hour h. The uncertainty in customers' loads, as represented by variance, therefore depends upon own-generation as follows:

$$var(NetL_{hj}) = var(GrossL_{hj}) + var(GEN_{hj}) - 2 * cov(GrossL_{hj}, GEN_{hj}) \qquad \textbf{Eq. 4-2}$$

---

[9] Data through 2013 are from [23]. Forecasts beginning 2014 are from [24, Table A8].

The volatility of net loads thus depends upon the volatility of gross loads, the volatility of self-generation, and the covariance between gross loads and self-generation. If the customer's gross load and self-generation tend to move up and down together, net load volatility will be less than gross load volatility. If the customer's gross load and self-generation tend to move in opposite directions, net load volatility will be greater than gross load volatility.

In addition to impacting the time patterns of customers' net loads, distributed resources also affect the wholesale energy prices that underlie competitive retail prices. Under net metering schemes similar to those presently in place in most states, the relevant gross profit is found by inserting equation (4-1) into equation (3-1):

$$Gross\ Profit_{hj} = \left(GrossL_{hj} - GEN_{hj}\right) * \left(P_{hj} - WMC_h\right) \qquad \textbf{Eq. 4-3}$$

The variance in the gross profit of equation 4-3 is even messier than the variance shown in equation 3-2, and is therefore not spelled out here in mathematical terms. In words, the variance of the gross profit of equation 4-3 depends upon the variances of loads, own-generation, and wholesale energy prices, as well as upon the covariances among these three variables. The determination of profitable retail prices is affected by these variances and covariances.

Supply-Side Resources

Power system stability and reliability can be improved by supply-side distributed resources that are dispatchable, because such resources can respond to market prices and operator control signals in ways that increase supply when supply is needed most and reduce supply when supply is needed least. For example, customers with their own gas or diesel generators can produce power when the power system needs it most, thereby responding to fluctuations in market conditions, reducing the need for network resources to meet peak load, and helping local networks maintain electricity service when there are transmission or distribution system outages. Such use of own-generation will tend to be positively correlated with the customer's gross load and will tend to reduce the utility's costs of serving the customer. In terms of equation 4-2, the covariance term will be positive, which will reduce the variance of net load.

Application of Concepts:
Increasing Residential Solar Penetration

As rooftop solar becomes more prevalent, the expected net load profile will change: net load will be lower in sunny hours. If solar penetration is high enough, wholesale energy prices in sunny hours will also be reduced. The effect on customer-level volatility will depend on the correlation between customers' consumption and generation. The effect on aggregate volatility may be pronounced if solar generation is highly correlated across customers, as will be the case if cloud cover affects everyone's solar panels at the same time.

Under net metering, the breakeven retail price depends upon the correlations between net loads and wholesale prices. Under a gross metering scheme, there could be different prices for electricity consumption and production, where the respective prices would be separately based upon consumption and production patterns, including the volatilities thereof. If solar production is sold to the utility under a feed-in tariff that guarantees a buy-back price, a breakeven version of that guaranteed price would be determined just like a long-term flip-the-switch price.

On the other hand, power system stability and reliability can be complicated by supply-side distributed resources that are not dispatchable. Such complications arise not only from the inability of such resources to respond to market prices and power system conditions, but also arise from these resources placing new stresses on power systems. For example, solar resources can have volatile production patterns as solar output goes up and down with the difficult-to-predict passage of clouds; and while solar power is likely to be available to meet summer afternoon peak loads, it is not available to meet winter evening peak loads.

The challenges that arise from solar resources are implied by Figure 4-7 and Figure 4-8. Figure 4-7 shows average hourly available solar energy – measured by global horizontal irradiance, in watt-hours per square meter – for six U.S. cities in July 2010. Of course, irradiance is highest midday and varies by city, with desert and southern cities tending to have higher irradiance than coastal or northern cities. Solar resources' output depends upon irradiance, among other factors, and will be higher as irradiance is higher.

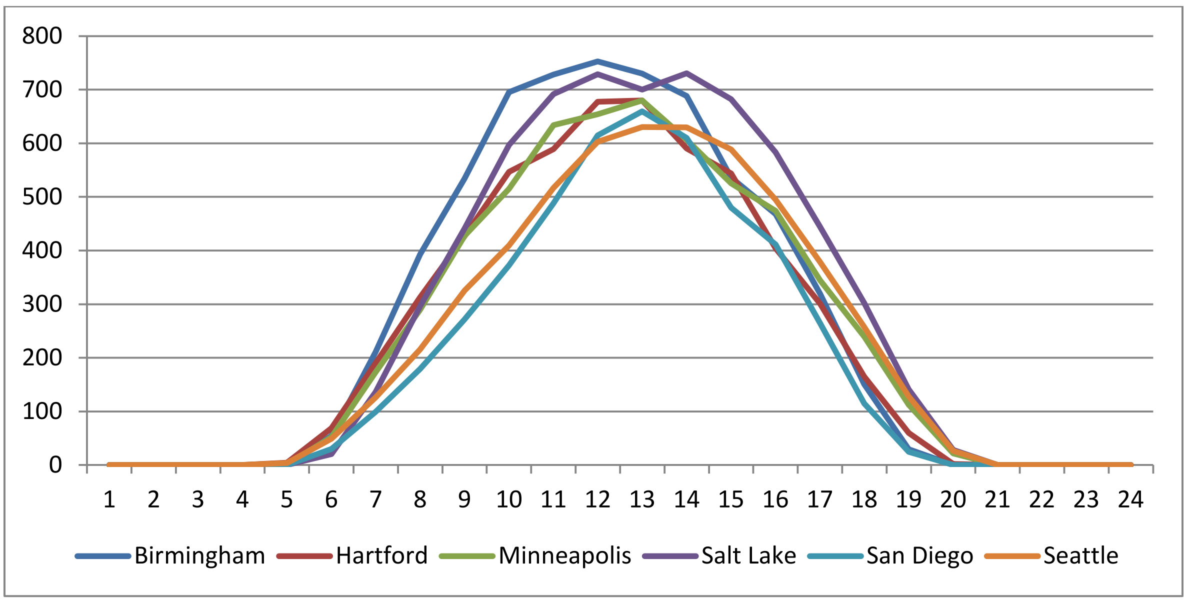

Figure 4-7
Average Hourly Global Horizontal Irradiance for Six U.S. Cities, July 2010[10]

A key commonality among the six cities is the uncertainty in their hourly outputs. For each of the cities, Figure 4-8 shows the range of irradiance for each hour of the day in July 2010, with the hourly averages from Figure 4-7 shown as diamonds. Each hourly maximum is typically triple or quadruple the respective hourly minimum, which implies that solar rooftop output in many cities will have a range of uncertainty characterized by a factor of three or four depending upon ambient weather conditions. The volatility of solar rooftop output will thus be quite high relative to average solar rooftop output. How that volatility affects the volatility of net loads will depend upon the relationship between gross loads and solar generation.

[10] Data are from [18].

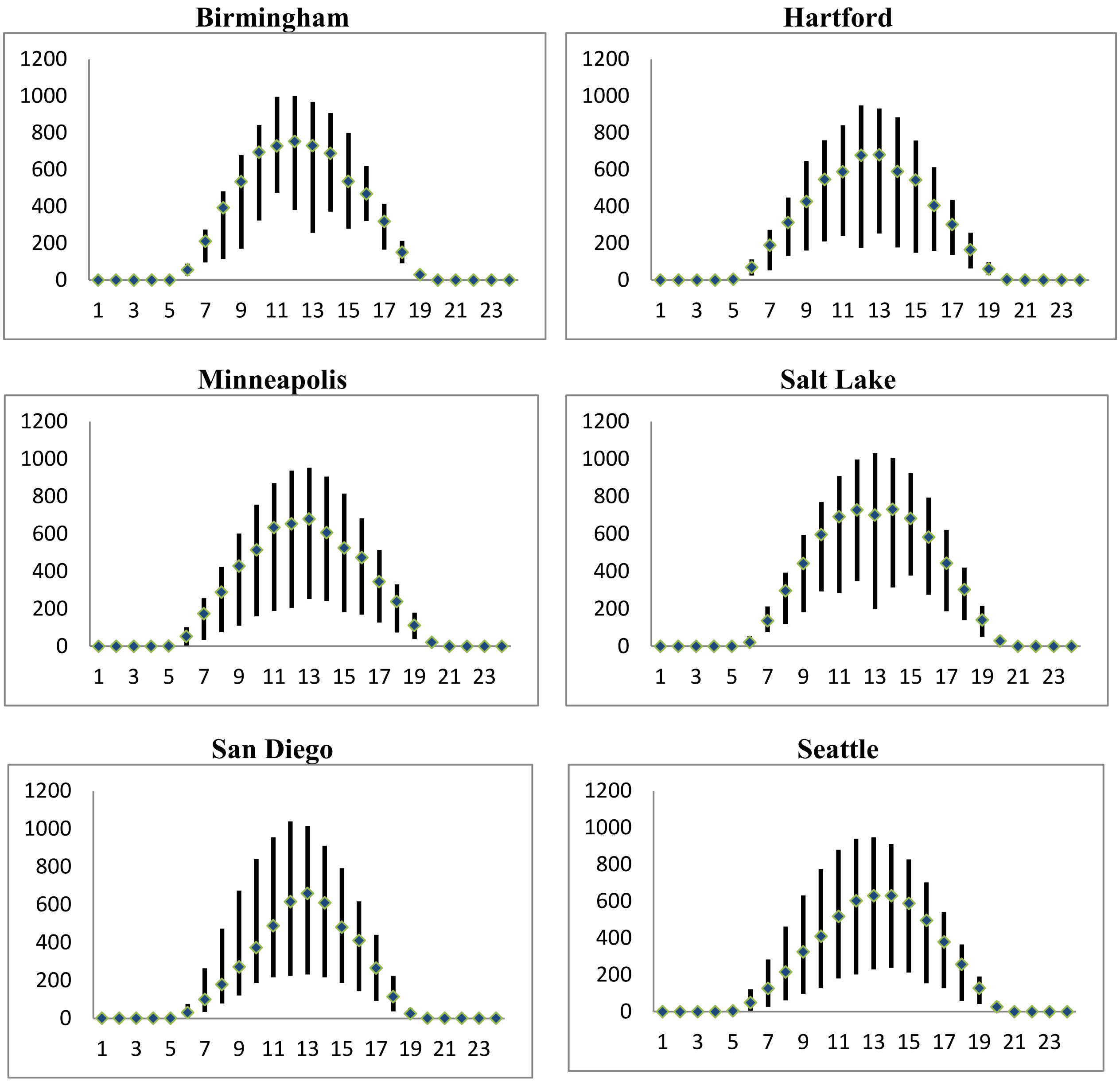

Figure 4-8
Minimum, Maximum, and Average Hourly Irradiance for Six U.S. Cities, July 2010[11]

Demand-Side Resources

As with supply-side resources, power system stability and reliability can be improved by demand-side distributed resources that are dispatchable. This improvement can arise from dispatchable resources' ability to respond to market prices and operator control signals in ways that reduce demand when supply is most scarce. Again, such resources can reduce the need for network resources to meet peak load and to respond to fluctuations in market conditions.

---

[11] *Id.*

A key empirical question is whether demand-side resources are, in the aggregate, becoming more reliable and dispatchable over time. Because the electric power industry traditionally measures the success of its demand-side programs according to the number of customers and MWs enrolled, publicly available reports say a great deal about such enrollment numbers; but they say relatively little about the extent to which demand-side resources are actually available when needed. Some tidbits of information that might cast light on the availability question are as follows:

- The market monitor for PJM finds that the observed average load reduction of emergency events implies demand response compliance rates of 97.6% in 2012,[12] 81.8% in 2013,[13] and 29.2% in 2014.[14]
- The New York Independent System Operator has an Emergency Demand Response Program (EDRP) in which "EDRP resources are not obligated to curtail their load during an EDRP event."[15] It has a Day-Ahead Demand Response Program that did not call upon demand-side resources at any time during the most recent analysis period of August 2013 through July 2014.[16] It has a Demand-Side Ancillary Service Program in which its only demand-side resources, namely three resources with 126.5 MW of capability, had "an average performance of 154% during the analysis period of May 2014 through October 2014."[17] It has an Installed Capacity – Special Case Resource program in which responses from demand-side resources were "voluntary" at the height of the January 2014 polar vortex power shortage, on which occasion such resources and EDRP resources had a 26.3% response rate.[18]

In other words, compliance rates can vary substantially over time and by program; and some demand response programs do not even impose upon demand-side resources an obligation to perform, even in emergencies. Without substantial research that is outside the scope of this report, we are unable to identify significant evidence about the extent to which demand response might be relied upon to reduce load volatility, or the extent to which it may have already done so. It is clear, however, that the impacts of demand response programs upon volatility will be idiosyncratic to the characteristics of each demand-side program.

---

[12] [15].

[13] [16].

[14] [17].

[15] [19, p. 1].

[16] [19, p. 5].

[17] *Id*.

[18] [19, p. 15]. The 26.3% response rate is an aggregate of the 27.5% and 4.3% rates reported in the source document.

5
MODELING AND FORECASTING LOAD AND LOAD VOLATILITY

To understand how load volatility can be measured and addressed for purposes of managing electricity pricing and investment risk, it is necessary to first understand how load itself is modeled and forecast. With load volatility defined generally as the deviations of load from some expected level, it is vital to do as good a job of modeling the expected load profile in order to grasp how deviations from the expectation can be characterized, modeled, and used to manage risk.

There is no general agreement among analysts about the "best" way to model load; so there is no general agreement about the "best" way to model the error terms (noise) in the load profile. Consequently, we do not propose a single method for measuring load volatility, but instead provide an overview of various approaches to modeling electricity load that lead to corresponding characterizations of load volatility based upon the error terms of various load forecasting models.

The discussion begins with a mathematical definition of load volatility. It then provides an overview of load modeling, particularly modeling the error term to get at volatility. Along the way, there is a high-level discussion of the pros and cons of the various models and estimators.

The Mathematics of Load Volatility

The load volatility at some future time *T* periods in the future is defined as percentage standard deviation of potential loads L_T at that time divided by the square root of *T*:

$$\sigma_T \equiv \frac{std[ln(L_T)]}{\sqrt{T}} = \sqrt{\frac{1}{T}\sum_{h=1}^{T}[ln(L_h) - \mu]^2} \qquad \textbf{Eq. 5-1}$$

where $ln(L_h)$ is the natural logarithm of load in hour h, μ is the expected value of $ln(L_h)$, and the summation is over the relevant hours. For example, to determine the load volatility on spring non-holiday weekdays at noon, the summation would be over spring non-holiday weekdays at noon. This formulation assumes that, for any particular hour (like a Tuesday noon), $ln(L_h)$ has constant mean μ and constant variance $var\{ln(L_h)\}$. Because the standard deviation measures load uncertainty, load volatility is thus a time-normalized measure of the uncertainty in the potential values of future load.

Load volatility changes over time. As measured by the standard deviation in the numerator of equation 5-1, load uncertainty is greater in some time periods (like summer weekday afternoons) than in other time periods. Meanwhile, the time-normalization in the denominator in equation 5-1 tends to cause load volatility to fall over time. Thus, if uncertainty is constant over time, volatility will decay to zero as T becomes very large. In practice, load uncertainty is likely to increase over time, though not as quickly as the square root of T; so volatility will tend to fall over time, but not to zero.

Modeling and Forecasting Load

Because the costs of over- or under-contracting for power can lead to financial distress for an electricity provider, there are substantial financial rewards to electric service providers for minimizing their volumetric risks. Consequently, load forecasting is an integral part of the process of setting retail electricity prices, determining the terms of electricity trades, and planning and operating electric power systems. Short-term load forecasts are important for resource commitment and dispatch decisions as well as for short-term trading. Short- and medium-term load forecasts are important for forecasting market prices and valuing short- and medium-term contracts. Long-term load forecasts are important for resource investment valuation and for valuing long-term contracts.

Load forecasting involves accurately predicting the magnitude, geographical locations, and timing of loads over a well-defined future period. The bulk of the modeling attention concerns forecasting hourly total system load, though models are also concerned with predicting daily, weekly, monthly, and annual values of total and peak system loads. In general, shorter-term forecasts are more accurate than longer-term forecasts; and longer-term forecasts tend to be weather-normalized so that expected loads reflect “normal” weather conditions. In all cases, given a forecast of the expected load, it is possible to define and develop measures of volatility in terms of deviations from the expectation.

Load forecasting for any time horizon is challenging because time series of measured load exhibit “seasonality” at the daily, weekly, and annual time scales. Furthermore, loads depend upon many exogenous variables, such as weather conditions, economic events, and even social events, all of which must be considered in developing a picture of the expected load.

A wide variety of methods have been applied to the task of load forecasting. These fall into two major categories:

- statistical (parametric) methods, including simplistic similar-day methods, various smoothing techniques, regression models, and Box-Jenkins-style time-series models; and
- artificial intelligence-based (non-parametric) methods, including neural networks, fuzzy logic, expert systems, and support vector machines.

Almost all of these methods can be adapted to analyze load volatility at any level of time, spatial, and customer granularity. For example, if data series are available at the customer level, these techniques can be applied to estimate and to predict load volatility and to form a basis for risk management at the customer level.

Statistical Methods

Statistical methods forecast loads by analyzing relationships between historical loads and exogenous variables such as weather and economic measures, and may also include previous load values as explanatory measures. These types of models can be appealing because relatively intuitive physical or economic explanations may be given to the estimated relationships, thus helping convey an understanding of consumer behavior. Such models are often criticized, however, for their limited ability to model the usually non-linear relationships between loads and their underlying variables. Nonetheless, in practical applications, linear models appear to perform as well as the non-linear alternatives, which also have limitations.

A large variety of statistical techniques have been developed for short-term load forecasting. Statistical approaches begin with mathematical models that express load as a function of various explanatory factors. Statistical models can be classified as additive or multiplicative. The two types differ in that the additive model expresses the forecasted load as the sum of a set of predictor variables while the multiplicative model expresses the forecast as a product of a set of factors. Additive models tend to be more popular than multiplicative models because they lend themselves to more intuitive explanations.

An additive model for predicting total load in hour h may take the form:

$$L_h = L_h^b + L_h^w + L_h^s + \varepsilon_h \qquad \textbf{Eq. 5-2}$$

where L_h is the load in hour h, L_h^b is the weather-normalized base load that represents standardized load shapes for each day-type throughout the year, L_h^w is the weather-sensitive load component, L_h^s is a component that represents special events such as vacations or holidays, and ε_h is the error term that accounts for noise and remaining unexplained deviations from the expected load pattern. Equation 5-2 says that each hour's load is the sum of the latter four components.[19]

The load forecasts and error terms of the additive model structure are estimated in a variety of ways.

The similar-day approach bases load forecasts on historical data from days in recent years that exhibit profiles or characteristics similar to those of the forecast day. Days may be grouped according to similarities that include weather, day of the week, and the date. Often, similar days or groups of days are identified through statistical clustering techniques. The forecast can be based on a linear combination or regression procedure that can include several similar historical days, perhaps with trend coefficients.

Regression methods are widely used to construct short-, medium-, and long-term load forecasts.[20] These methods use statistical techniques to model the relationship of load to factors such as weather, day type, and customer class. The typical regression model expresses the load as a linear function of one or more explanatory variables and an error term that can be subject to further modeling to address load volatility, as follows:

$$L_h = \beta_0 + \beta_1 X_{1h} + \beta_2 X_{2h} + \cdots + \beta_k X_{kh} + \varepsilon_h \qquad \textbf{Eq. 5-3}$$

where $X_{1h},\ldots,X_{kh}$ are explanatory variables believed to influence load, and $\beta_0, \beta_2, \ldots, \beta_k$ are regression coefficients that are estimated by the regression analysis.[21] The explanatory variables

---

[19] A multiplicative model may take the form $L_h = L_h^b \times L_h^w \times L_h^s \times \varepsilon_h$, where L_h^b is base load, L_h^w is the weather-sensitive component, L_h^s is the special events component, and ε_h is the error term.

[20] For examples of such models, see [2], [5], [7], [9], and [22].

[21] Typically the statistical method used to estimate the parameters is the method of least squares or, alternatively, the maximum likelihood technique. However, there are a wide variety of other optimization methods that have been applied, such as robust regression methods that are less influenced by skewed distributions and outliers in the time series data.

can be simple, like maximum daily temperature, or complex functions of simple variables, such as the squared difference between maximum and minimum daily temperatures. Regression models are capable of accommodating non-linear relationships to some degree.

Time series methods assume that the load data and other relevant explanatory factors follow structural patterns that may be characterized by autocorrelation, trend, or seasonal variation. Time series forecasting methods estimate such structural patterns. Time series have been used broadly for decades in economics and physics, as well as for electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods. ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non-stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends (at the very least) on the weather and time of day, ARIMAX is the most obvious adaptation of the simpler classical ARMA and ARIMA models for load forecasting; and there is a large body of literature reporting on the ARIMAX modeling approach.[22] The typical ARMA model for load forecasting takes the form of the following equation:

$$L_h = \sum_{j=1}^{p} \gamma_j L_{h-j} + \sum_{=1}^{q} \theta_j \varepsilon_j \qquad \textbf{Eq. 5-4}$$

where L_{h-j} is the value of load j periods in the past, ε_j is a random load disturbance (volatility) term, and $\gamma_1,\ldots,\gamma_p$ and $\theta_1,\ldots,\theta_q$ are model parameters to be estimated.

The random disturbance term in traditional ARMA and ARIMA models is assumed to have a Gaussian (i.e., normal) distribution with zero mean and finite constant variance and covariance functions, though a wide variety of time series models depart from these assumptions. These models address various forms of non-linear dynamics of the load time series, including the strong dependence of the variability of the series on its own past, non-constant conditional variance, and the tendency of the underlying distribution to exhibit fat tails.

Other time series models are referred to as Autoregressive Conditional Heteroskedastic (ARCH) models, as generalized ARCH (GARCH) models, and variants of these that incorporate exogenous variables (ARCHX and GARCHX). The key feature that distinguishes these models from the traditional time series models is the characterization of the error structure as follows:

$$k_h = \varepsilon_h \sigma_h \quad \text{with} \quad \sigma_h^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i k_{h-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{h-j}^2 \qquad \textbf{Eq. 5-5}$$

where ε_h is assumed to be independently and identically distributed as a normal random variable with mean zero and variance one, and $\alpha_0,\ldots,\alpha_q$ and $\beta_1,\ldots,\beta_p$ are parameters to be estimated.

[22] See [4] and [6].

Artificial Intelligence-Based Methods

Artificial intelligence-based (AI-based) methods tend to be more flexible than statistical methods and can handle complexity and non-linearity. Unfortunately, AI-based methods are generally "black box" tools, making it difficult or impossible to incorporate specific relationships such as those that can be tested by a statistical method. Furthermore, the performance of AI-based methods has received mixed reviews when applied to load forecasting.

Artificial neural networks (ANNs) are prominent among AI-based methods because their application requires no prior modeling experience to obtain reasonable load forecasts. ANNs were developed to perform "intelligent" tasks similar to those performed by the human brain in that an ANN acquires knowledge through learning and stores this knowledge within inter-neuron connection strengths known as synaptic weights. ANNs employ algorithms that automatically classify the input data and associate it with the respective output values, eliminating the need for human judgment regarding model structure and development. There is no need to make *a priori* assumptions about model structure or underlying population distributions. Relative to traditional linear statistical models, ANNs are inherently non-linear and have the advantage of being able to represent both linear and non-linear relationships and to learn these relationships directly from the data being modeled.

ANN models can be classified by their architecture, processing, and learning. The architecture defines the neural connections. The network elements are arranged in a relatively small number of layers of elements between network inputs and outputs. The outputs are linear or non-linear functions of the inputs. The inputs can be the outputs of other network elements as well as actual network inputs.

The most widely used ANNs in forecasting problems are referred to as multi-layer perceptrons (MLPs), which use a single hidden layer feed forward network. The model is characterized by a network of three layers – input layer, hidden layer, and output layer. There may be more than one hidden layer. The nodes in various layers are also known as processing elements. The three-layer feed forward architecture of ANN models can be illustrated as in Figure 5-1, which shows various inputs entering the Input Layer and following a weighting process are passed to the Hidden Layer(s), followed by another weighting process before passing to the Output Layer for final processing to produce outputs.

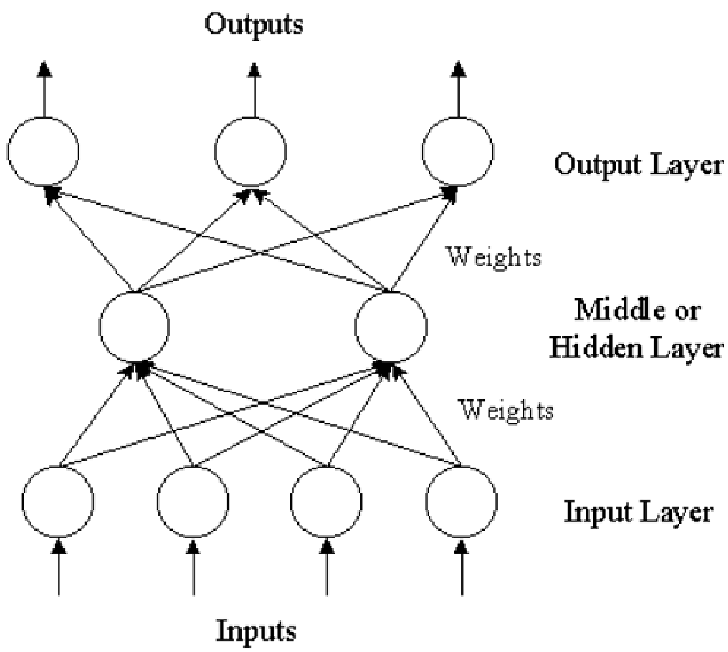

Figure 5-1
The Three-Layer Feed Forward ANN Architecture[23]

The output of the ANN model is computed using an expression similar to the following equation:[24]

$$L_h = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} L_{h-i}\right) + \varepsilon_h \qquad \textbf{Eq. 5-6}$$

where L_{h-i} are the hourly inputs and L_h is the output. The integers p and q are the numbers of input and hidden nodes, respectively. The α_j and β_{ij} are the connection weights, and ε_h is the random disturbance (noise) term. The function g(.) is often assumed to take the logistic sigmoid form $g(x) = \frac{1}{1+e^{-x}}$, which is known as the activation function.[25]

The feed forward ANN model in equation 5-6 performs a non-linear functional mapping from the past load observations to the future load values, with the mappings determined by the network structure and the connection weights. The connection weights are typically estimated using non-linear least squares or maximum likelihood procedures. ANN models can accommodate seasonality in the load data as well as model specific days – weekdays versus weekends, for example – using a time-lagged variation of the standard ANN model structure.

[23] See [1].

[24] The ANN model can be adapted to forecast the next day's peak load or total load. Multiple output ANN models can be used to forecast a series of loads, such as 24 hourly loads that define the next day's load profile, or 7 daily peak loads.

[25] The activation function can take other forms such as linear, hyperbolic tangent, and Gaussian.

In some applications, ANN models have out-performed other methods; but in other instances, ANN models have not performed as well as regression methods or exponential smoothing techniques.

Expert systems produce forecasts based upon rules and procedures that are similar to those used by human experts in the field of interest. The incorporation of such rules and procedures into the expert system software enables forecasts to be automatically produced without additional human inputs. Nonetheless, expert systems forecasting ability is strengthened when software development is closely guided by human experts so that they accurately and fully incorporate the experts' knowledge. This can result in the expert system incorporating thousands of decision rules. As applied to electric power systems, a system operator's historical knowledge of load and its determinants can be represented in a parameterized rule base that is complemented by a location-specific parameter database.[26] Expert system forecasts are frequently combined with forecasts from other methods.

Support vector machines (SVMs) have a system of classification and regression that was originally developed in the context of statistical learning theory.[27] Initially, SVMs were designed to solve pattern classification problems, such as optimal character recognition, face identification, and text classification. They quickly found wide applications in other domains, such as function approximation, regression estimation, and time series prediction problems. The objective of SVM is to find a decision rule with good generalization ability through selecting some particular subset of the training data, called support vectors. In this method, the input data are classified (separated) by a separating hyperplane (i.e., a rule that determines whether the data belong in one group or another group). The process can be repeated to refine the classification system and to arrive at an optimal separating hyperplane (i.e., classification of the data into two or more classes without error).

There has not been extensive application of SVM methods to load forecasting. Several studies of SVM methods have found them to be as good as or better than other methods.[28]

---

[26] See [8] and [21].

[27] See [25].

[28] See [3], [11], [12], and [14].

6
MANAGING THE IMPACTS OF LOAD VOLATILITY

Utilities can manage the impacts of load volatility in two basic ways. The first is by reducing load volatility itself. The second is by mitigating the financial impacts of load volatility. Either way, the estimation of volatility needs to be consistent with its application.

Reducing Load Volatility

Reducing the volatility of load itself requires that the utility have some means of reducing load uncertainty, which means somehow placing limits on customers' loads. In some times and places other than the United States of the present, customers could subscribe to minimum or maximum quantities of electricity service. More practical for present purposes are the following sorts of programs and technical approaches:

- The utility can have some control over customers' loads, particularly peak loads. This approach is used in myriad direct load control programs.
- The utility can send customers price signals that influence loads. This approach is used, for example, in real-time pricing, critical peak pricing, and peak-time rebate programs. This approach is also implicit in demand charges, which can induce customers to hold down their peak loads and improve loads factors, both of which make loads less variable and probably make them less volatile.
- Smart energy systems, storage technologies (like batteries), and Internet-connected devices can help customers better manage the net power flows that customers impose on the power system. Such technology fixes can mitigate load volatility if retail electricity prices are structured in ways that reduce customer bills for customers with less variable net loads.

Mitigating the Financial Impacts of Load Volatility

The financial impacts of load volatility can be mitigated by reducing load volatility as just described or by pricing retail products to incorporate costs associated with load and wholesale price volatilities. The retail design problem is partly a matter of setting retail prices at the appropriate levels and partly a matter of differentiating electricity products and customers.

To achieve an expected breakeven price, the level and structure of retail prices must reflect the costs of providing customers with the energy, ancillary, transmission, and distribution services that they use. Because load volatility is not a service *per se*, there should not be any price on load volatility itself. Instead, the costs of load volatility should be recovered through the prices of the services that are made more costly by load volatility:

- The expected costs of energy and ancillary services are increased by volatility in two ways. First, it is necessary to have more generation capacity to serve potentially high loads. Second, it is necessary to have costly resources that can rapidly respond to the load uncertainties associated with volatility. These two types of costs can materialize in the forms of both capital costs and operating costs.

- For some transmission and distribution systems, costs will be increased by volatility because of the need to have greater transmission and distribution capacity to serve potentially high local loads. The cost increase will mostly be capital costs, though restricting transmission flows in anticipation of uncertain load changes can increase the operating costs associated with transmission congestion.

The costs of load volatility may also be reduced by differentiating retail prices by time, location, and customer. Such differentiation can mitigate cost uncertainties associated with load volatility by allowing closer matches between prices on the one hand and expected costs on the other. Such differentiation improves economic efficiency by sending more accurate price signals to customers, and improves fairness by having customers pay prices closer to the costs that they are expected to impose on the power system. The practicalities that limit differentiation include the following:

- Forecasts of customer loads are inevitably imperfect, and are subject to greater error at the individual customer level than at the customer group level.
- Price forecasts are inevitably imperfect.
- Price differentiation over time is less simple than a flat rate.
- Price differentiation *by location* is sometimes regarded as unfair because it seems to treat similar customers differently, even if, in fact, the costs that differently located customers impose on the power system are materially different.
- Price differentiation *by customer* is sometimes regarded as unfair because it seems to treat similar customers differently, even if, in fact, customers' uses of the power system are materially different.

7 DIRECTIONS FOR FURTHER RESEARCH

There are a few lines of research that may shed light on the measurement and mitigation of load volatility.

First, because the quantification of load volatility is a derivative of load forecasting, future research may profitably engage in a detailed examination and synthesis of the econometric literature on load modeling and forecasting. As implied by Chapter 5 of this report, that literature is extensive.

Second, because system operators can mitigate load volatility through demand-side management programs, it would be helpful to develop a database that indicates the extent to which such programs result in actual demand reductions. The data required for such an effort would need to be gleaned from a plethora of utility filings on their demand-side programs. The results would need to recognize the several very different types of such programs. This information would be helpful not only for quantifying the impacts of these programs on load volatility but also for identifying the programs that are most effective.

Third, future research could explore in detail the effects on net load volatility of emerging distributed technologies such as rooftop solar, residential battery storage systems, programmable-controllable thermostats, electric vehicles, and smart appliances. Such research can be particularly useful for distribution planning.

8
REFERENCES

1. R. Adhikari and R.K. Agrawal, *An Introductory Study on Time Series Modeling and Forecasting*, Lambert Academic Publishing, January 29, 2013, Figure 4.1, p. 26.

2. W. Charytoniuk, M. S. Chen, and P. Van Olinda, "Nonparametric Regression Based Short-Term Load Forecasting," *IEEE Transactions on Power Systems*. Vol. 13, No. 3, pp. 725-730 (1998).

3. B. J. Chen, M. W. Chang, and C. J. Lin, "Load Forecasting Using Support Vector Machines: A Study on EUNITE Competition 2001", *IEEE Transactions on Power Systems*. Vol. 19, No. 4, pp. 1821-1830 (2004).

4. M. Y. Cho and J. C. Hwang "Customer Short-Term Load Forecasting by using ARIMA Transfer Function Model," *Proceedings of the International Conference on Energy Management and Power Delivery*. Vol. 1, pp. 317-322 (1995).

5. R. Engle, C. Mustafa, and J. Rice, "Modeling Peak Electricity Demand," *Journal of Forecasting*. Vol. 11, pp. 241-251 (1992).

6. J. Y. Fan and J. D. McDonald, "A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems," *IEEE Transactions on Power Systems*. Vol. 9, pp. 988-994 (1994).

7. T. Haida and S. Muto, "Regression Based Peak Load Forecasting using a Transformation Technique," *IEEE Transactions on Power Systems*. Vol. 9, pp. 1788-1794 (1994).

8. K. L. Ho, Y. Y. Hsu, F. F. Chen, T. E. Lee, C. C. Liang, T. S. Lai, and K. K. Chen, "Short-term Load Forecasting of Taiwan Power System Using a Knowledge Based Expert System," *IEEE Transactions on Power Systems*. Vol. 5, pp. 1214 – 1221 (1990).

9. O. Hyde and P.F. Hodnett, "An Adaptable Automated Procedure for Short-Term Electricity Load Forecasting," *IEEE Transactions on Power Systems*. Vol.12, 84-93 (1997).

10. International Energy Agency. *Gadgets and Gigawatts: Policies for Energy Efficient Electronics*. Paris. 2009.

11. Y. Li and T. Fang, "Application of Fuzzy Support Vector Machines in Short-term Load Forecasting," *Lecture Notes in Computer Science*. Vol. 2639, pp. 363 – 367 (2003). B

12. Y. Li and T. Fang, "Wavelet and Support Vector Machines for Short-term Electrical Load Forecasting," *Proceedings of the Third International Conference on Wavelet Analysis and Its Applications*. Vol. 1, pp. 399-404 (2003). A

13. B. McNary and C. Berry, "How Americans are Using Energy in Homes Today," *ACEEE Summer Study on Energy Efficiency in Buildings*, 2012.

14. M. Mohandes, "Support Vector Machines for Short-term Electrical Load Forecasting," *International Journal of Energy Research*. Vol. 26, pp. 335-345 (2002).

15. Monitoring Analytics, LLC, *2012 State of the Market Report*, Volume 2, March 14, 2013, p. 169.

16. Monitoring Analytics, LLC, *2013 State of the Market Report*, Volume 2, March 13, 2014, p. 197.

17. Monitoring Analytics, LLC, *2014 State of the Market Report*, Volume 2, March 12, 2015, p. 218.

18. National Renewable Energy Laboratory, *National Solar Radiation Data Base*, 1991 - 2010 Update, http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2010/hourly/list_by_state.html.

19. New York Independent System Operator, *NYISO 2014 Annual Report on Demand Response Programs*, January 15, 2015.

20. *Pricing Energy Using the Product Mix Model: A Primer for Retail Energy Companies*. EPRI, Palo Alto, CA: September 1999.

21. S. Rohman and O. Hazim, "Load Forecasting for Multiple Sites: Development of an Expert System-based Technique," *Electric Power Systems Research*. Vol. 39, pp. 161-169 (1996).

22. S. Ruzic, A. Vuckovic, and N. Nikolic, "Weather Sensitive Method for Short-Term Load Forecasting in Electric Power Utility of Serbia," *IEEE Transactions on Power Systems*, Vol. 18, 1581-1586 (2003).

23. U.S. Energy Information Administration. *Retail Sales of Electricity by State by Sector by Provider*. EIA-861. www.eia.gov/electricity/data/state, April 29, 2015.

24. U.S. Energy Information Administration, *Annual Energy Outlook 2015*, www.eia.gov/forecasts/aeo, April 2015.

25. V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer Verlag, 1995.

Export Control Restrictions

Access to and use of EPRI Intellectual Property is granted with the specific understanding and requirement that responsibility for ensuring full compliance with all applicable U.S. and foreign export laws and regulations is being undertaken by you and your company. This includes an obligation to ensure that any individual receiving access hereunder who is not a U.S. citizen or permanent U.S. resident is permitted access under applicable U.S. and foreign export laws and regulations. In the event you are uncertain whether you or your company may lawfully obtain access to this EPRI Intellectual Property, you acknowledge that it is your obligation to consult with your company's legal counsel to determine whether this access is lawful. Although EPRI may make available on a case-by-case basis an informal assessment of the applicable U.S. export classification for specific EPRI Intellectual Property, you and your company acknowledge that this assessment is solely for informational purposes and not for reliance purposes. You and your company acknowledge that it is still the obligation of you and your company to make your own assessment of the applicable U.S. export classification and ensure compliance accordingly. You and your company understand and acknowledge your obligations to make a prompt report to EPRI and the appropriate authorities regarding any access to or use of EPRI Intellectual Property hereunder that may be in violation of applicable U.S. or foreign export laws or regulations.

The Electric Power Research Institute, Inc. (EPRI, www.epri.com) conducts research and development relating to the generation, delivery and use of electricity for the benefit of the public. An independent, nonprofit organization, EPRI brings together its scientists and engineers as well as experts from academia and industry to help address challenges in electricity, including reliability, efficiency, affordability, health, safety and the environment. EPRI also provides technology, policy and economic analyses to drive long-range research and development planning, and supports research in emerging technologies. EPRI's members represent approximately 90 percent of the electricity generated and delivered in the United States, and international participation extends to more than 30 countries. EPRI's principal offices and laboratories are located in Palo Alto, Calif.; Charlotte, N.C.; Knoxville, Tenn.; and Lenox, Mass.

Together…Shaping the Future of Electricity

3002005818

Electric Power Research Institute
3420 Hillview Avenue, Palo Alto, California 94304-1338 • PO Box 10412, Palo Alto, California 94303-0813 • USA
800.313.3774 • 650.855.2121 • askepri@epri.com • www.epri.com