Solving the Utility Load Forecasting Conundrum

A New Framework

BY KEN SEIDEN AND BRIAN EAKIN

Load forecasting errors have grown to an unprecedented level, and the corresponding risks are astounding. Flat or declining loads, downward pressure on earnings, customer-owned distributed generation, energy efficiency programs, and new codes and standards are the new normal. Casting blame on the weather is a common refrain.

The time has come for a more comprehensive approach to load forecasting that can address the increasing complexities of the Energy Cloud. If you are a utility executive concerned about suffering significant forecast misses and want guidance on how to fix the problem, keep reading.

See Figure One.

The focus of this article is on long-term forecasting, which we define as anything a year or more in the future. In the 1970s, utilities started using econometric and mixed end-use econometric models to produce long-term forecasts. Out went twelve-inch rulers, a previously powerful tool, as OPEC, inflation, industrial productivity, and energy efficiency entered our vocabulary and were directly addressed by the new methodology.

This econometric forecasting paradigm has since enjoyed a forty-year run as the predominant long-term load forecasting approach. But, as any well-trained econometrician will tell you, the underlying causal modeling structure leads to spectacular failures when its foundation changes.

And, like it or not, that is where we are in the electric power industry of 2017. Solving the load forecasting conundrum does not require unattainable data or the invention of new analytical techniques.

In this article, we lay out a new bottom-up load forecasting framework that combines strategic customer segmentation, customer choice modeling, and granular load analytics to deliver load forecasts that decision makers can trust.

See Figure Two.

The Emerging Energy Cloud

Long-term load forecasting errors are not new. We have seen them before: in the recession of the 1980s after widespread appliance energy efficiency standards were first enacted, during the power crises and price shocks of the late 1990s, and during the recessions of the early 1990s and 2000s.

The most adept utility forecasters adjusted their models frequently by obtaining more accurate economic forecasts, re-estimating the econometric model relationships between loads, economic activity, and prices, and augmenting the basic econometric modeling paradigm with end-use components that captured early energy efficiency standards and utility program activities.

The Great Recession marked the beginning of the end of econometric load forecasts. For utilities, a hat trick of effects such as enormous increases in energy efficiency standards and utility programs, double-digit rate increases necessary for infrastructure investment, and the recession itself rendered the econometric models incapable of distinguishing or weighting these effects. All of which put downward pressure on sales, revenue, and earnings.

A more comprehensive approach to load forecasting can address the increasing complexities of the Energy Cloud.

As the econometricians waited for the dust to settle and the underlying post-recession data to arrive, the final nail in the coffin of utility econometric forecasting hit the industry: the Energy Cloud.

As noted by our colleagues, Mackinnon Lawrence and Jan Vrins, "The prolific rise of renewables and distributed energy resources, behind-the-meter smart devices, digital infrastructure, advanced controls and analytics, and changing customer demands are ushering in a new era of highly networked power…we call this the Energy Cloud."

The concept of changing customer demands and the proliferation of energy-consuming and producing alternatives is at the heart of the load forecasting conundrum. For example, econometric and end-use load forecasts have long recognized that residential customers respond to price signals and energy efficiency choices.

However, most existing forecasting models focus on the margins, with households choosing alternative fuels or energy efficiency options when replacements are needed. Or when

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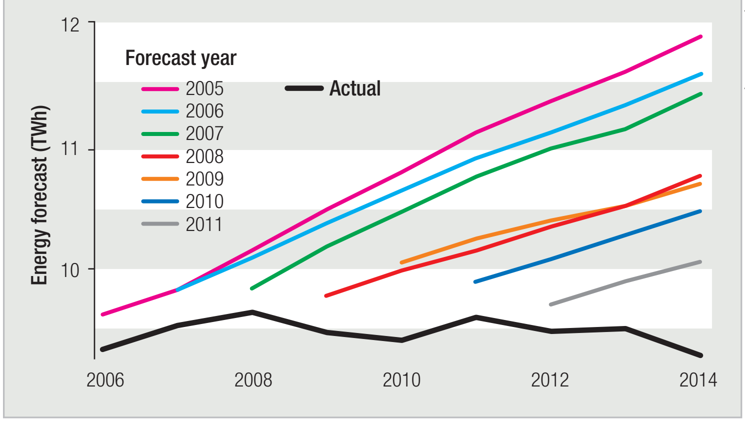
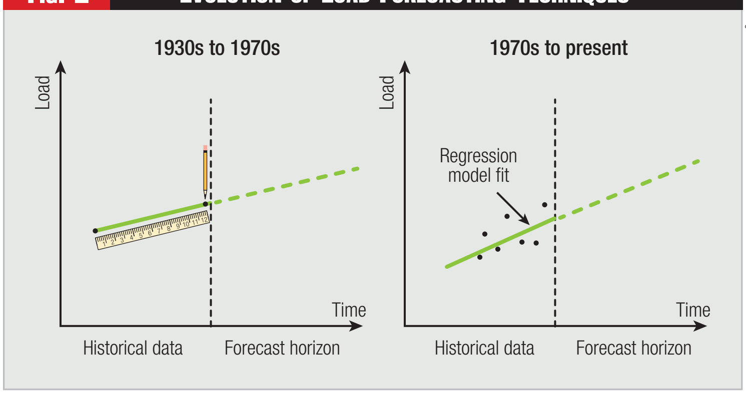
FIG. 1 LOAD FORECASTS VERSUS ACTUAL LOADS

Seven consecutive load forecasts versus actual loads for a US utility



Source: Lawrence Berkeley National Laboratory

FIG. 2 EVOLUTION OF LOAD FORECASTING TECHNIQUES



Source: Navigant

customers engage in modest changes in energy consumption behaviors such as turning down lights or thermostats in response to higher electricity prices.

We are aware that many utilities have recently missed near-term forecasts and expected earnings due to mild weather. These weather effects can swamp the transformational effects of the Energy Cloud in forecasting energy sales next year.

Therefore, it is important to separate the weather and Energy Cloud effects on forecasted loads. Although this article is focused on long-term, transformational load forecasting issues associated with the Energy Cloud, we will return to the topic of load forecasting with climate change in a future article.

Customer Segmentation

The choices faced by virtually every customer in our transformed energy market can be viewed as an extension of how we have been forecasting our largest customers. That is, the concept of merely segmenting customers into residential, commercial, and industrial classes needs a much finer resolution to appropriately handle the proliferation of choices customers enjoy today.

The key motivation is that the average customer's electricity usage in each class will quickly diverge relative to the recent past. If this is true, analysis and forecasting approaches that focus on the average customer will miss the mark. The only way to accurately forecast in such circumstances is to disaggregate or segment the customer base in each class.

There are many potential structural, demographic, and financial factors affecting the adoption of technologies and behaviors. Customers should be segmented by these characteristics to accurately project who can even be considered in the market for each technology and the likelihood of adoption.

Furthermore, utilities and other companies seeking to understand customer decision-making are already conducting predictive analytics. Those begin with establishing attribute-based clusters or groups of customers most likely to adopt the technology.

Of course, there are many technologies customers might choose throughout the Energy Cloud transformation. The utility industry understands this, making a more refined segmentation necessary to forecast new technology adoption among customers.

This begs a very simple question. If we think it is important to segment customers to better understand new product adoption, why would a load forecast that aggregates the entire residential, commercial, or industrial class into a single group accurately predict future loads?

The key motivation is that the average customer's electricity usage in each class will quickly diverge relative to the recent past.

Customer Choice

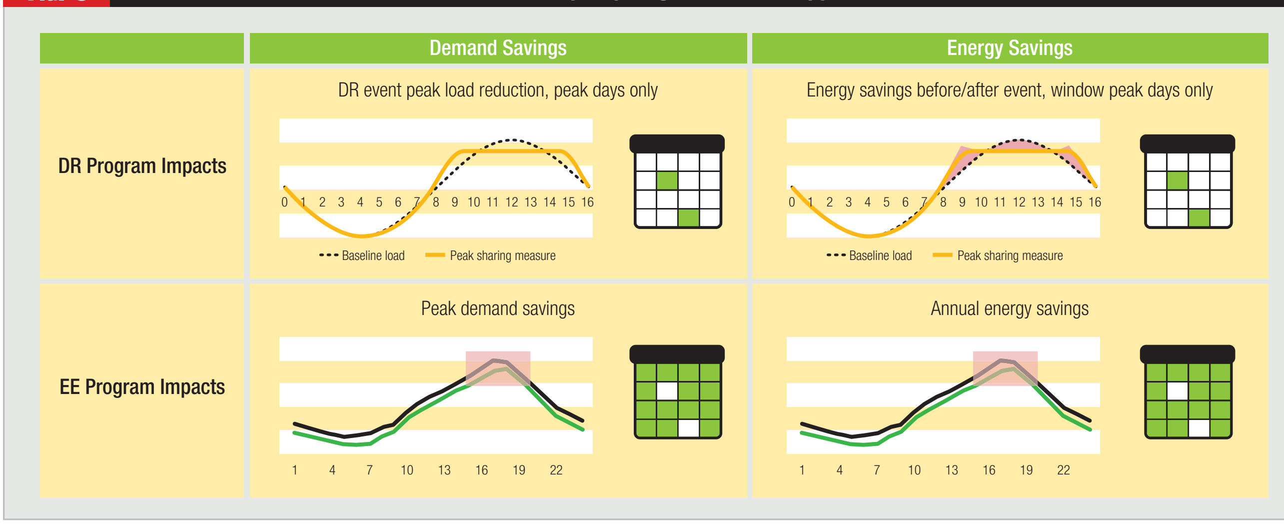
Utilities must recognize that competitive threats go well beyond large customers. The very nature of the technologies available to customers means that we need to account for competition in load forecasts.

That is, utility load forecasters need to begin thinking with a competitive mindset like our counterparts in telecom, financial services, retail trades, and most other industries.

The notion of modeling competitive behavior has a long, lost history in the utility industry. Discrete choice modeling, a branch of econometrics developed in the 1970s and still widely used across many industries today, was at the core of the end-use models developed by the Electric Power Research Institute and other organizations in the 1980s and 1990s.

The models were originally developed to handle customer choices between electricity, gas, and other fuels for heating, water heating, cooking, and other fuel-competitive loads. We have

Fig. 3 **Example of Load Shape Analytics**



Source: Navigant

been asked, "Why can't these end-use based models be used to forecast today?" The answer is simple: The focus of these models is an individual end use, with the emphasis on the equipment, not the customer.

For example, in the case of residential photovoltaic, these models in use at utilities suffer from the same segmentation problems we noted previously. Moreover, they cannot address customer choice and usage at the building level, which is precisely what customers are doing when they choose photovoltaic, automate their homes, participate in demand response, or select one of many other new product and service options.

"The industry now finds itself with a plethora of customers from which load shape analytics can be performed."

– Ken Seiden

Load forecasters can use the underlying competitive market forecasting approach from end-use models and from discrete choice analytics in new load forecasting models. In our view, discrete choice analytics enhance machine learning algorithms by providing causal indicators or weights to specific customers, buildings, and technology attributes. That allows utilities to incorporate what-if analytics directly into the load forecasting models.

For example, this approach allows the forecast to explicitly include the effects of utility incentives and marketing on the adoption of new technologies, which means alternative scenarios can be directly considered in the load forecasting process.

Load Shape Analytics

Beginning with smart grid pilots and continuing with utility-wide installations of advanced metering technology, the industry now finds itself with a plethora of customers, all customers in many cases, from which load shape analytics can be performed.

For example, we can isolate customers who participate in various energy efficiency and demand response programs to understand the effects on consumption and underlying load shapes. Interestingly, such comparisons are required by many regulatory commissions when evaluating energy efficiency and demand response programs.

Yet, we are unaware of a single utility that relies on these types of models as a primary component of its load forecasting system.

See Figure Three.

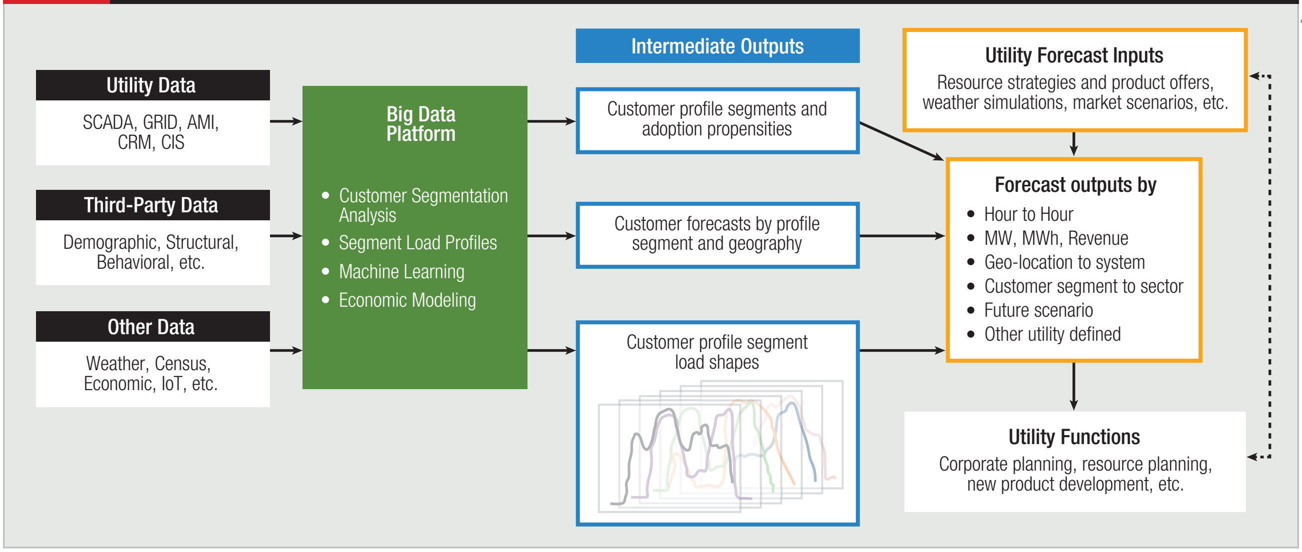
Utilities who do not yet have advanced metering infrastructure, net metering, or other hard data directly linked to individual customers can still benefit from load profile analytics. SCADA system data can be leveraged to collectively model groups of customers linked to SCADA measurement points.

This can enable analysis similar to what would eventually be done with AMI data and provide additional value from existing SCADA system investments. There are also many tried and true building simulation models calibrated to actual interval data from across the industry, that create synthetic load profile data.

Load Forecasting for a Transformed Utility Industry

The bottom-up load forecasting framework we have outlined

FIG. 4 LOAD FORECASTING FRAMEWORK FOR THE ENERGY CLOUD



Source: Navigant

takes advantage of existing grid modernization and information technology investments, along with advances in machine learning and structural analysis techniques.

Developing a comprehensive understanding of customer segmentation, customer choices, and load shape characteristics is the key to solving this challenge.

In this framework, the forecast represents a specific scenario where all customers are treated similarly from an analytical point of view. Each customer is associated with a segment and the choice of new technologies or behaviors are modeled with the corresponding loads.

> “It takes a strong quantitative aptitude to develop and implement the correct set of forecasting algorithms.”
>
> *– Brian Eakin*

There is no need to perform a subtraction of incremental distributed resource impacts, because net loads are built directly into the customer segment and technology-specific load profiles. Alternative policies, products and services, initiatives, incentives, and marketing efforts are reflected in alternative scenarios defined by function.

This approach to forecasting goes beyond the wide range of detailed scenarios. It allows for the forecast to be analyzed and reported in ways that have not been feasible in legacy forecasting solutions.

The addition of geo-location information to each measurement point allows for the forecast to be presented in a detailed spatial context, providing the bottom-up neighborhood and circuit-level load shape and growth information needed for advanced distribution planning.

See Figure Four.

The outcome of this capability is a deep insight into the locations that are affected by each scenario. That allows the utility to proactively develop targeted distribution system investments and customer solution offerings to address those cases.

For example, proactively identifying circuits associated with customers who are likely to adopt electric vehicles allows for transformers to be upgraded before the electric vehicle charging loads exceed the capacity of those assets.

Moving to this forecasting approach that is driven by big data is not a trivial undertaking. It takes a thoughtful and coordinated effort to make use of all information available to the utility. And a preparedness to respond to insights that are far more detailed and accurate than have been previously produced.

It takes an open mind to see the value in a broad range of data that may have never been used in a forecast. It takes a strong quantitative aptitude to develop and implement the correct set of forecasting algorithms.

But, most importantly, it takes an unwavering commitment to enhancing forecasting capabilities to catch up with other industries such as financial services and retail and deliver the insights necessary to function within the evolving Energy Cloud. PUF