Transparency in Long-Term Electric Demand Forecast: A Perspective on Regional Load Forecasting[1]

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Forecasting is an essential tool for planning and decision-making in the energy industry and various forecasting methods have been used for by electric utilities and resource planners (Taylor et al, 2007; Hahn et al, 2009). Electric utilities independently choose one or multiple methods to conduct their long-term forecasting to determine their revenue requirements and rate design for each customer segment. They also provide this information to the regional transmission and system planners for regional load forecasting.

With the modernization of the electric grid, electric utilities have been facing challenges to accurately forecast demand, particularly with fast integration of distributed energy resources (DERs) and energy efficiency (EE). Changes in the customer electricity demand with the integration of these technologies have affected the demand-side of the energy markets significantly and have led to more regional diversity in customer electricity demand. This increases the need for better understanding of load foresting conducted at the utility and regional level to achieve transparent and accurate electric load forecasting. At the regional level, this is particularly important for transmission planning because it requires highly expensive and irreversible investments and long-term regional load forecasting is an important factor for transmission planning.

In this article, we discuss the importance of incorporating energy efficiency and distributed energy resources in load forecasting methods commonly adopted by utility companies. Specifically, we illustrate the incremental effects of considering energy efficiency and distributed solar on load forecasting accuracy. In addition, we examine the implications of future solar photovoltaic (PV) integration and EE adoption on long term forecasts. Overall, we conclude the following: First, considering EE and DERs in electricity use forecasting generates different results from the scenario without these considerations. Second, different methodologies have different levels of accuracy performance, which can also vary by customer segment. This shows the importance of accuracy and transparency in regional load forecasting methods used by utilities. Third, forecasted peak demand is different in these EE and DER integration scenarios from the scenarios without these considerations, and the differences widen over time. Finally, the discrepancy between the peak demand forecasts increases with higher levels of solar integration scenarios and the difference is not negligible, especially for forecasts far in the future.

Load forecasting in regional markets

Recent changes in the energy industry stimulate greener and more sustainable energy. However, they also create several challenges for electric utilities, resource planners and policy makers with respect to forecasting demand for the system. Currently, electric utilities independently choose methods to forecast their long-term demand and use the forecasts to plan for energy delivery to end-use customers, revenue requirements and rate design for each customer segment - namely residential, commercial and industrial. Typically, customer-specific demand forecasts are estimated separately and then aggregated to represent the total customer demand. Electric utilities provide their long-term forecasts to the regional transmission and system planners for regional load planning. However, electric utilities are not required by the regulators to use a uniform approach for their load forecasts, so they can decide the most suitable forecasting approach for their own business. Figure 1 illustrates the parties that use electric load forecasting, the information flow among the utilities and the regional operator.

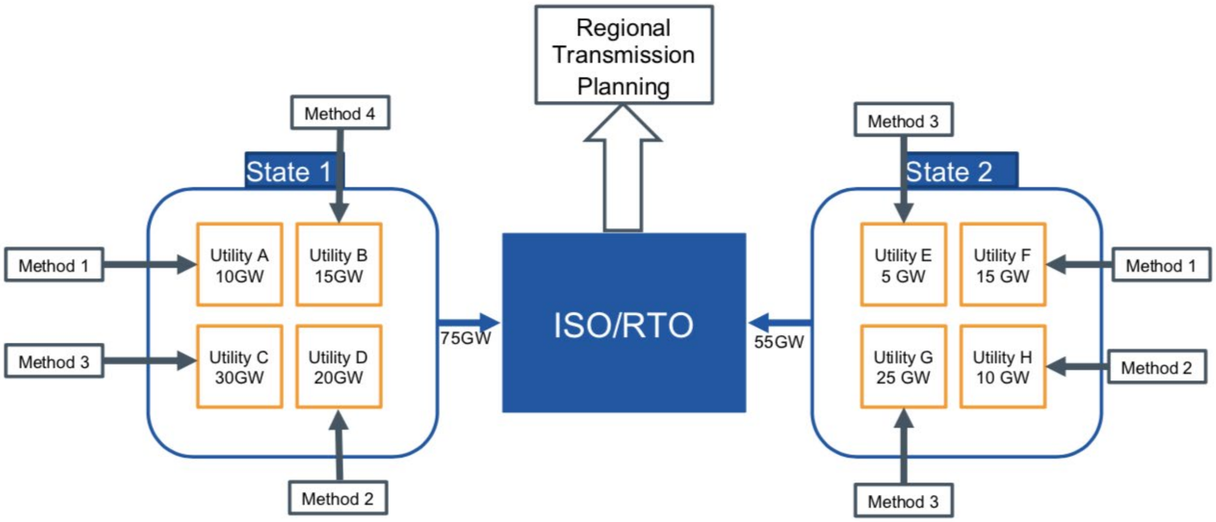


Figure 1: Illustration of the Use of Load Forecasting

Since each utility has their unique business models, service territories and customer profiles, it leads to load forecasting results being obtained by different methods. Further, there is often no transparency in the granularity of forecasting approaches employed across utilities, thus begging the question of whether the aggregation of different forecast outcomes is appropriate given the different forecasting approaches employed by utilities. In addition, there is no uniform approach on how to account for EE and the integration of DERs in long-term load forecasting for different customer segments. Although it is not common practice for all utilities for now, some of them have made adjustments to account for demand side energy resources including demand response, distributed solar and energy efficiency savings in their load forecasts for different end-use costumer sectors. However, these adjustments are based on strong assumptions, which may introduce inaccuracies to the projected distributed solar generation and energy efficiency savings.

Methodology

We employ two empirical methods to predict regional electricity demand for residential and commercial customer segments, and illustrate the results using the example of the Midcontinent Independent System Operator (MISO) service territory, including Minnesota, Iowa, Wisconsin, North Dakota, Illinois, Michigan, Indiana and Louisiana. State level energy efficiency is measured using the American Council for an Energy Efficient Economy (ACEEE) rating. The level of distributed energy resource integration is measured by the Freeing the Grid rating on net metering standards. The analysis focuses on forecasting monthly electricity sales by customer segment.

The following scenarios are analyzed and compared to show the differences in electric forecasts:

Scenario 1 Traditional model vs Updated model: forecasting residential and commercial electricity demand using the same empirical method with and without EE and DERs adjustments.

Scenario 2 Different methods: forecasting residential and commercial electricity demand using different empirical methods. Specifically, we employed Ordinary Least Squares (OLS-Method 1) estimation and time-series (TS-Method 2) estimation methods. The fundamental difference between two methods is the statistical estimation procedures. Time series model takes into account the time trend and correlations among past electricity consumptions, while OLS model treats each months of consumption as independent.

Scenario 3 Different methods and regions: forecasting residential electricity demand in two different states with different methods.

Our empirical specifications for residential and commercial demand estimation are widely used in academic and industry literature (Hagen and Behr 1987, Kyriakides & Polycarpou, 2007; Hahn et al. 2009) as well as are widely used by the electric and gas utilities to conduct short-term and long-term forecasting for their customer segments (Hahn et al., 2009). Data from 2007 to 2015 are used to estimate the model, and data from 2016 to 2017 are used for forecasting. Note that electricity demand forecast is estimated controlling for weather and state-specific economics factors in addition to price of electricity and price of substitutes (i.e., natural gas).

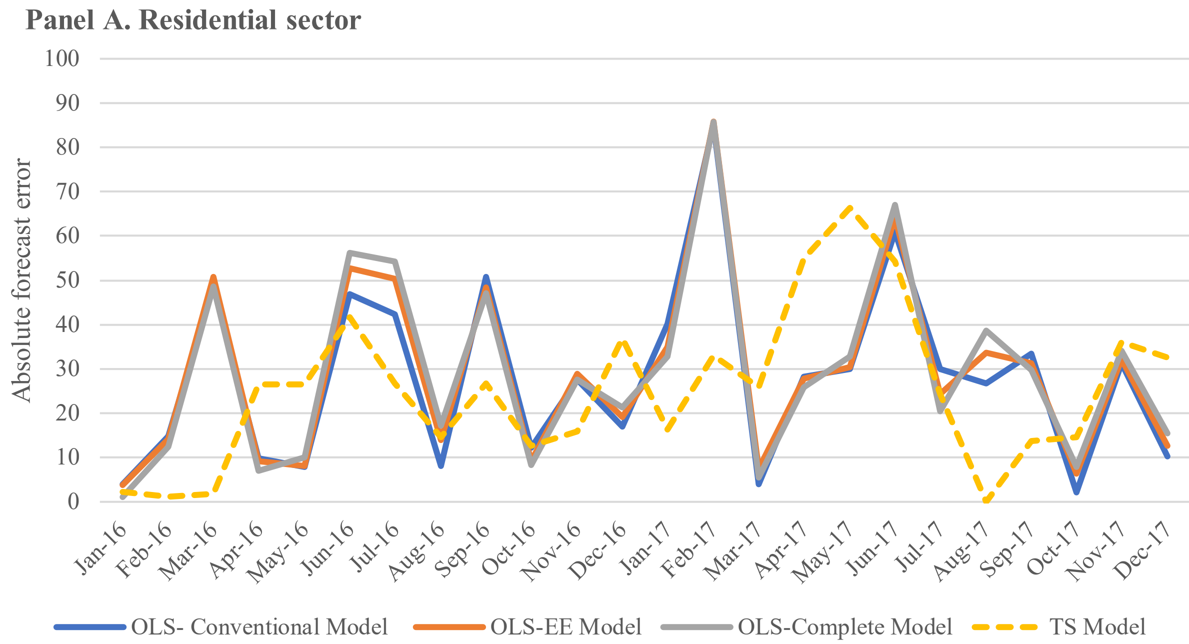
Results

Absolute forecast error, which is the absolute difference between actual and forecasted values, is often used to evaluate the accuracy of forecasts and enables comparison of different forecasting methods. Forecast error increases for several reasons including incorrect forecast approaches, model misspecification and data limitations.

Figure 3 shows how the models perform differently in predicting the average monthly electricity sales per customer across the 7 states in MISO territory by plotting the absolute forecast error in each month of 2016 and 2017. OLS method with EE and DER adjustments do not seem to improve forecast accuracy in residential sector significantly (Figure 3, Panel A), but makes a significant difference in reducing forecast errors in commercial sector (Figure 3, Panel B). Overall, TS models perform best in terms of reducing forecast errors in both sectors because they take into account the seasonal and cyclical nature of electricity demand, in addition to EE and DER adjustments.

Next, we forecast residential electricity sales per customer for two states within the MISO territory, Minnesota (MN) and North Dakota (ND) for the months of 2016 and 2017. After estimating state-specific forecasts, we aggregate electric load forecasts and compare forecasted loads using the same econometric approach versus different approaches. Figure 4 shows that forecasted load using the same method has different prediction than forecasted load using different methods. We also calculate the forecast error for forecasting using same vs. different methods for MN and ND. There is a significant difference in forecast accuracy between the forecasts using the same method and the ones using different methods.

Figure 1. Prediction Errors of Different Methods (Residential and Commercial Sectors)



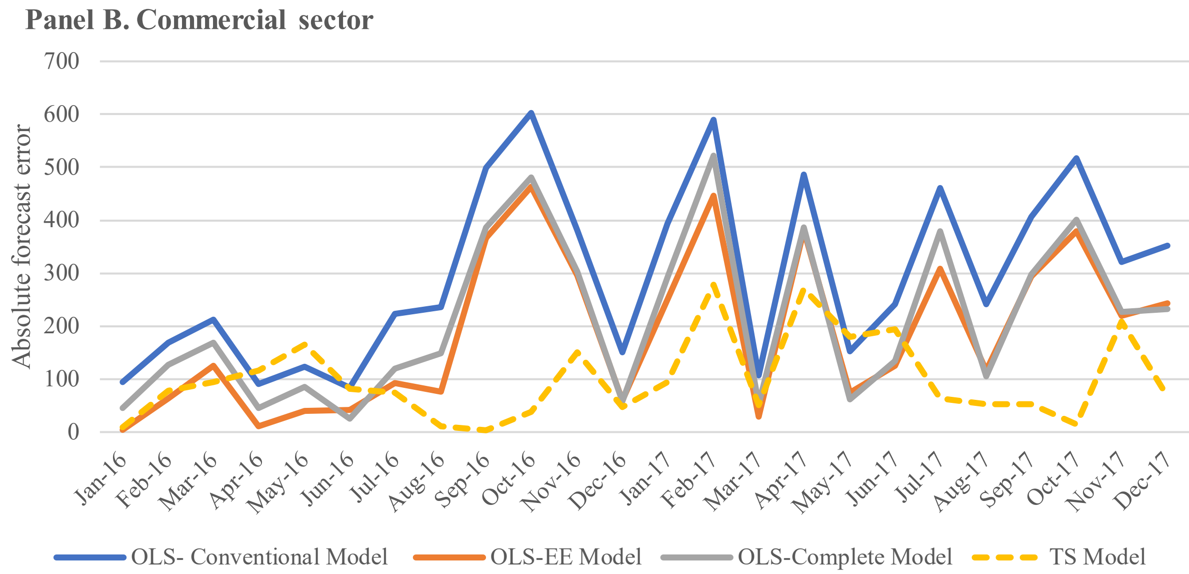
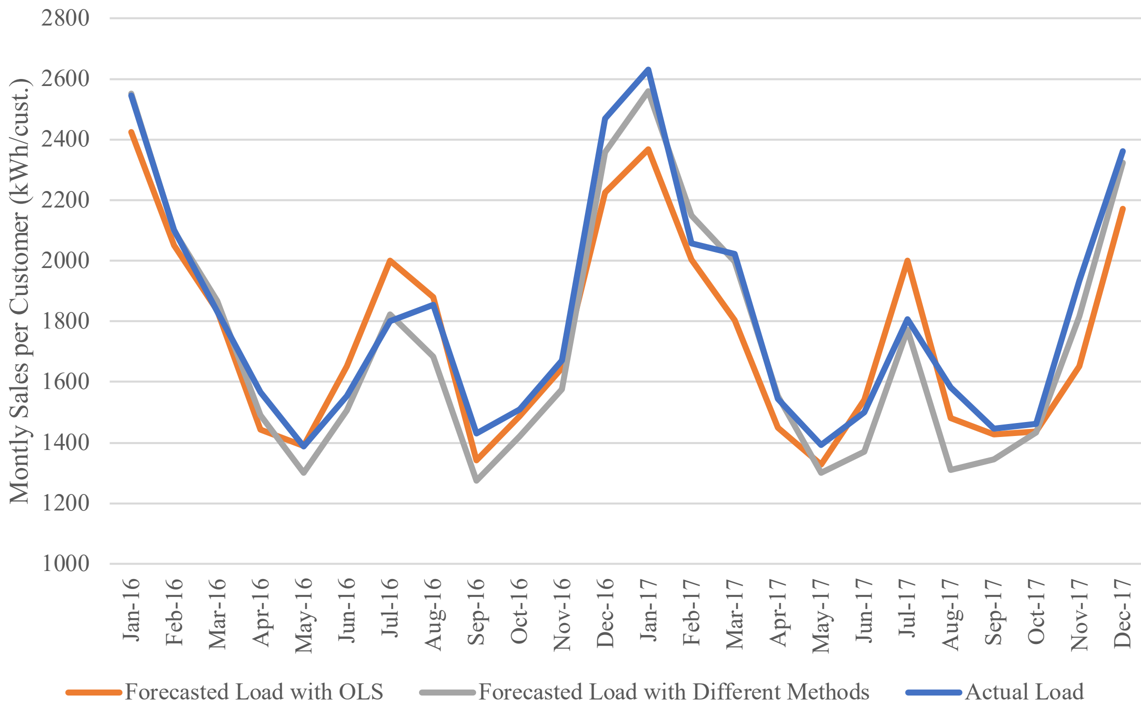


Figure 2. Predicted Load for Different States and Methods (Residential Load in MN and ND)

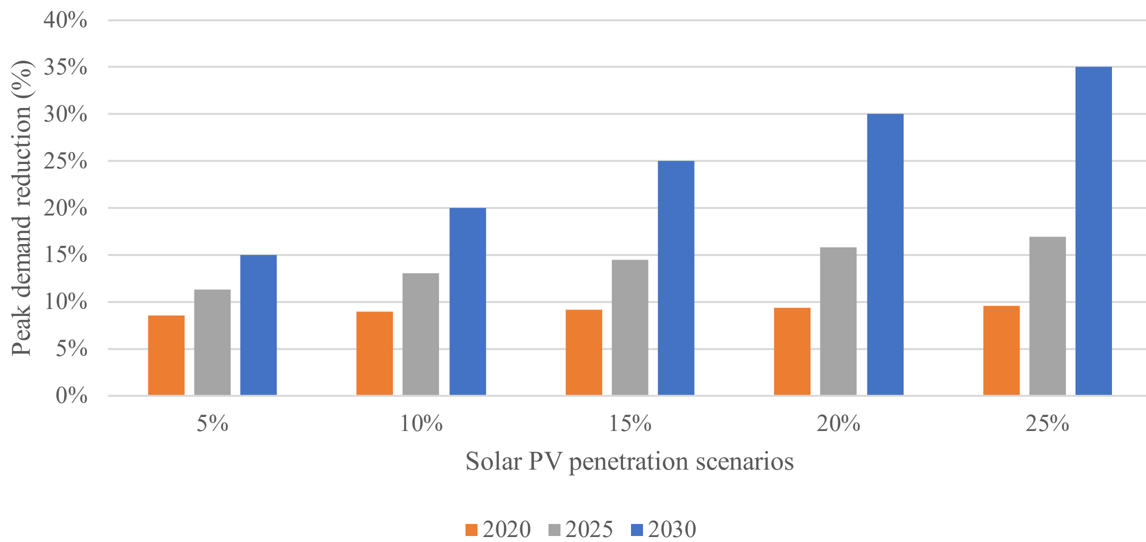


Simulation

To further illustrate the long-term implications of not including DER and EE savings on peak demand forecasting in longer term, we developed a simulation model to project residential summer peak demand through 2030 in Minnesota considering different solar PV integration and EE scenarios, and show the differences in forecasting outcomes widen over longer time horizon and with increasing uptake of solar PV. Figure 5 shows the percentage of residential peak demand reduction per customer achieved by five solar PV penetration scenarios in 2020, 2025 and 2030, while holding the peak demand reduction from EE at 10%.

Based on our peak demand simulations, we conclude the following: First, considering residential distributed solar and energy efficiency in peak demand generates different forecasting results from the scenario without these considerations. Second, the forecasted peak demand is different in these DER and EE integration scenarios, and the differences widen over time. Finally, the discrepancy between the peak demand forecasts increases with higher levels of solar integration scenarios and the difference is not negligible, especially for forecasts far in the future.

Figure 5. Peak Demand Reduction under Different Distributed PV integration Scenarios



Conclusion and Discussion

Transitioning to a cleaner and more sustainable electric power system by adopting EE and DERs has raised certain complications in using the existing load forecasting tools for policymaking and resource planning. Energy efficiency measures, especially utility sector energy efficiency programs, can substantially reduce peak energy demand and energy use, and improve system reliability (Berg, 2016). Distributed generation, especially distributed solar PV generation, brings opportunities and challenges to electricity load management. The PV generation at the hottest hours of the day can bring electricity demand to extremely low levels, and in the evening when people return home to turn on their appliances, PV generation also declines, which requires flexible generation capacity to come online quickly. The intermittent nature of distributed sources, as well as the timing mismatch between generation and demand, lead to increase in cycling-related costs (Perez-Arriaga and Batlle, 2012).

One of the complications is that traditional forecasting tools do not necessarily consider the impacts of EE and DERs on load forecasting. A survey conducted by Carvallo et al. (2016) shows that the sets of variables used for load forecasting by LSEs have not changed for a long time, and only a few of them adopted new forecasting techniques. Utilities and agencies can make inefficient and suboptimal procurement decisions based on these inaccurate load forecasts. This analysis shows that the inclusion of EE and DER adjustments is important by showing improved forecasting results once these adjustments are included into the electric load forecasting analysis.

Further, every forecasting method relies on assumptions, such as GDP growth, demographic changes, electricity substitutes and fuel price changes. In many cases, the assumptions used for forecasting have not been changed for a long time either (Caravallo et al, 2016), and utilities often do not disclose the assumptions used for their forecasts. In addition, long term forecasts often have larger forecast errors due to greater uncertainty. Our analysis demonstrated that a method with good forecast accuracy in one sector (e.g. residential) might not perform as well in another sector (e.g. commercial). Therefore, aggregated loads forecasts from multiple electric utilities without knowing their approaches can introduce bias to load forecasting for regional operators. Regional system operators, such as MISO, have limited authority to check long term load forecasts. Specifically, MISO can only audit load forecast one year into the future for its voluntary annual capacity auction. The remaining years are not audited by MISO because individual utilities do not need capacity auction more than one year into the future. This introduces additional challenges when it comes to verifying long-term regional load forecasting accuracy. Transparency across utilities in terms of their load forecasting methods are important to inform regional forecasts.

Another implication of load forecasting is resource planning related. Transmission planning load forecasts are “point” forecasts, which represents forecast load at a snapshot in time, while the wholesale market load forecast is predicted in real-time. The former is submitted to meet the North American Electric Reliability Corporation (NERC) reliability obligations under functional model, while the latter is submitted to adhere to Federal Energy Regulatory Commission (FERC) tariff. Therefore, inaccurate load forecasts aggregated by regional regulators can potentially impact both transmission and wholesale operational planning. Although some utilities make adjustments to their load forecasts to account for solar and energy efficiency savings, these savings are usually netted out from the forecasts instead of being included in the forecasting models. This study serves as an applied demonstration of these potential issues using basic econometrics methods and further research in this area is essential for the US power industry.