Impact of Demand Response Contracts on Load Forecasting in a Smart Grid Environment

Qun Zhou, *Member*, *IEEE*, Wei Guan and Wei Sun, *Member*, *IEEE*

***Abstract*— Load forecasting is highly important for power system operation and planning. Demand response, as a valuable feature in smart grid, is growing dramatically as an effective demand management method. However, traditional load forecasting tools have limitations to reflect demand response customer behaviors into load predictions. The energy consumption by demand response customers is mostly guided by their signed contracts. Therefore, existing demand response contracts are reviewed in this study for both wholesale and retail markets. An illustrative example is provided to explore the impact of these contracts on load forecasting. A concept of proactive load forecasting considering contract types is then proposed and discussed for forecasting loads in a smart grid environment.**

***Index Terms*—Load forecasting, electricity prices, demand response, contract types, customer behaviors, smart grid**

I. Introduction

In restructured electricity industry, short-term load forecasting is very important in many application areas such as automatic generation control, load flow estimation, energy purchasing, and contract evaluation. The accuracy of short-term load forecast is an important factor for both economic and reliability benefits. Moreover, forecasting load in a longer-term assist operators for power system planning and also facilitate strategic decision making of market participants.

Over the last few decades, a variety of mathematical methods has been developed for load forecasting, including similar day approach, time series models, neural networks, expert systems, fuzzy logic, and statistical learning algorithms [1]-[3]. These common load forecast methods are based on the assumption that there are pre-specified functions, data structure or mapping between load and load affecting factors including time factors, weather data, and possible customers' classes [4].

There is no single model or algorithm that is superior for all utilities and several load forecasting methods sometimes are used in parallel or combination. It is hard to detect which forecasting method is more suitable for a given load area.

In the smart grid era, demand responses is enabled by advanced metering infrastructure, time-varying retail rates, and tools facilitating customer response to prices (e.g., smart appliances) [5]. It could be triggered by either reliability or price signals [6] and is expected to be a crucial mechanism to compensate system uncertainties and the associated risks including those related to intermittent renewable generation such as wind and solar. Thus load is no longer a function of weather, day of the week, or time of the day alone. Rather, it also depends on electricity prices as well as demand response actions.

Customer response to electricity price signals is the key to forecast loads in a smart grid environment. The link connecting prices and loads is the demand response contracts. Fig. 1 shows the market relationships among each entity, including end consumers, LSE/retailers, large industrial and commercial customers, generators and ISO. ISO or utilities often provide different types of demand response contracts to these energy end-consumers.

For a utility that needs to forecast loads for developing demand bidding strategies and a longer-term business strategy, customers' responses to retail prices need to be monitored. These behaviors are mostly determined by the contract types that customers have signed. For example, a customer with a flat rate contract is most likely indifferent about price changes, and his daily load profiles could only depend on time and weather data; in contrast, a customer with a real-time price contract could pay much attention to the price changes and adjust his daily energy consuming activities accordingly. Therefore, the way that customers respond to price signals, based on their signed contracts, needs to be considered in load forecasting.

The principle also applies to large industrial and commercial customers wholesale power markets. Ignoring this important factor will result in one-side load forecasting in a smart grid environment.

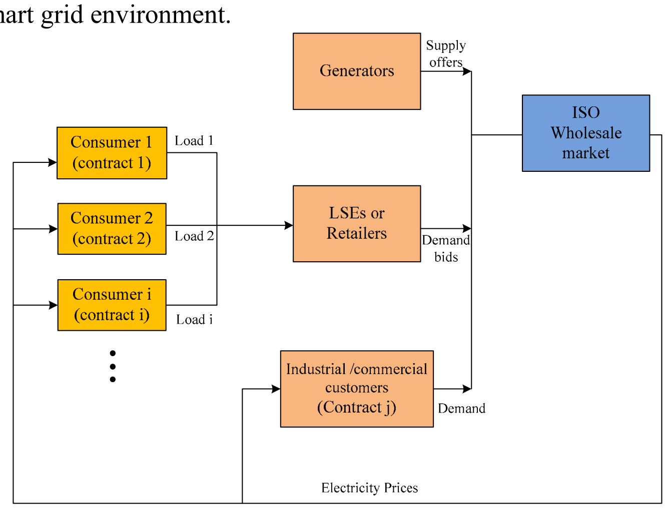

Fig 1. Market relationships via demand response contracts

Qun Zhou is with market operations team at Alstom Grid Inc., Redmond, WA 98052. Email: qunzhou@ieee.org

Wei Guan is with R&D at Alstom Grid Inc., Redmond, WA, 98052. Email: wei.guan1@alstom.com.

Wei Sun is with network applications team at Alstom Grid Inc., Redmond, WA 98052. Email: weisun@ieee.org.

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In this study, existing demand response contracts are carefully reviewed in Section II. An illustrative example is presented in Section III to examine how contract types and customer percentages affect load forecasting. Then a new concept of proactive load forecasting is then proposed to explicitly account for electricity prices, demand response contracts and customer behaviors.

II. Review of Existing Demand Response Contracts

Demand response brings great benefits to system operation, such as improving market efficiency, enhancing system reliability, and reducing green gas emissions. It has been introduced to power industry for many years, but mostly focused on large industrial and commercial customers. For instance, ERCOT has emergency interruptible load program for large customers [7]. SCE offers a variety of demand response programs, such as Automated Demand Response (Auto-DR), Permanent Load Shifting (PLS), and Scheduled Load Reduction Program (SLRP) [8].

Hogan [9] generalizes demand responses in wholesale power markets into three types: real-time pricing (RTP) demand response, explicit contract demand response, and imputed demand response. Customers pay real-time LMPs for their energy consumption in real-time pricing contracts. For the explicit contract demand response, customers can sell back the purchased but unconsumed energy to market. Customers that sign in imputed demand response contracts need to specify a consumption baseline and the difference between the actual consumption and baseline is the imputed demand response.

With smart meter technologies, utilities are now capable of recording the usage and prices of energy consumption by small commercial and residential customers more frequently. This enables the growths of time-varying pricing schemes for demand response. Many retail rate programs are developed in this regard.

Traditional flat retail rate requires customers to pay electricity at the same predetermined price regardless consuming times. Many time-based rate programs introduced to residential and small commercial customers. According to DOE report [10], time of use pricing (TOU) requires customers to pay different predetermined prices for peak and off-peak hours. Moreover, customers can be exposed to volatile prices through Real-time pricing (RTP). Variable peak pricing (VPP) is a combination of TOU and RTP in the sense that prices for peak and off-peak hours are different, but they are conditional on market situations. Critical peak pricing (CPP) is based on prices and time duration when a critical event is anticipated or observed by utilities. The prices in this case could be predetermined or based on system conditions.

Customers' responses to these variable pricing schemes are critical for determining electricity demand. The Department of Energy (DOE) has conducted consumer behavior studies to advance the electricity industry's understanding of demand response. To capture these characteristics, more advanced load forecasting tools are needed.

III. An Illustrative Example

This section gives an intuitive example to explore how different contract types and their percentages impact load profiles. Recognizing this important factor could be useful for developing advanced load forecasting tools.

Assume an electricity retailer has 2000 customer households signed in three contract types: flat-rate contract, TOU contract and RTP contract. These contracts reflect three types of customer behaviors: 1) using energy when needed; 2) concerned about time of the day; 3) concerned about electricity prices. For simplicity, these behaviors are expressed as functions of a baseline load profile given in Fig. 2. The base line reflects a typical electricity consumption of a household in a Summer day. All the parameters in the functions are chosen for the illustration purpose only.

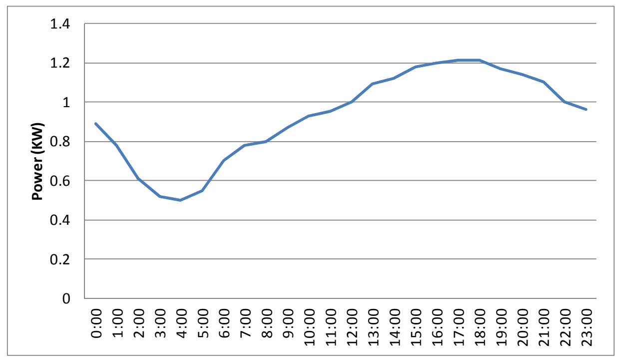

Fig.2 A typical daily load profile of a household in Summer

Let L_h^b denote the base line load at hour h and ε denote the deviation following a normal distribution $N(0, \sigma^2)$. The standard deviation σ is set to 0.1 in the example. The households with flat-rate contracts have electricity consumption L_h^{fr} as follows:

$$L_h^{fr} = L_h^b + \varepsilon \tag{1}$$

In contrast, TOU customers adjust their consumption behaviors based on hours in a day due to different predetermined rates. For example, these customers may shift their peak-hour consumption to off-peak hours for a lower payment rate.

The electricity consumption L_h^{tou} for TOU customers is assumed in the below function:

$$L_h^{tou} = \begin{cases} 0.9(L_h^b + \varepsilon), & h \text{ in peak hours} \\ 1.1(L_h^b + \varepsilon), & h \text{ in off-peak hours} \end{cases} \tag{2}$$

where daily peak hours are 10am to 9pm and off-peak hours are before 10am and after 9pm.

Unlike the above two types of customers, RTP customers adjust their behaviors based on time-varying electricity prices. Assume real-time Locational Marginal Price (LMP) signals are directly received by RTP customers and become the main driven factor for their consumption behaviors. Fig. 3 shows a daily Locational Marginal Price (LMP) profile in a typical summer day. The RTP load profile L_h^{rtp} is then assumed to be a downward-sloping curve with respect to LMP_h

$$L_h^{rtp} = 3 - 0.055LMP_h + L_n^b + \varepsilon \quad (3)$$

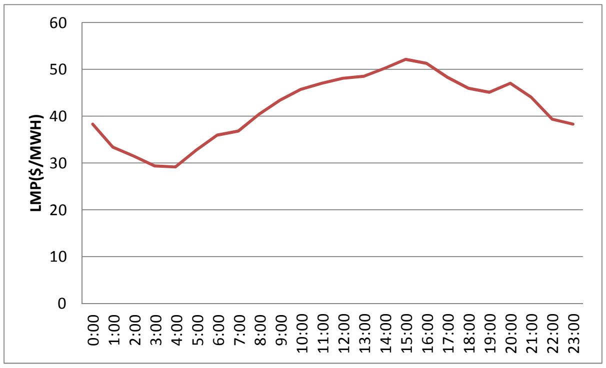

Fig. 3 A typical LMP profile in Summer

Now consider five scenarios with different percentage combinations of the three contract types. The load profiles aggregated by the retailer are depicted in Fig. 4. Each scenario is addressed below.

- Scenario 1: 100% flat-rate customers

Flat-rate customers use electricity when needed regardless of the hours or the prices. Hence, the aggregated load profile is similar to the baseline load profile.

- Scenario 2: 100% TOU customers

As can be seen, there is a slight peak load decrease and off-peak load increase. This reflects the load shifting behaviors for TOU customers.

- Scenario 3: 100% RTP customers

This scenario assumes 100% elastic load in response to electricity prices. It is seen that during hours 10am to 9pm, a tremendous decrease in load occur due to high LMPs. The curve gives an insight on RTP customers responding to electricity prices, but it might not reflect the real-life situations. Certainly in reality there are practical constraints in using electricity at certain time. Moreover, a large number of RTP customers reduce load in peak hours will also in turn lower the LMPs. This is an interactive process which needs advanced forecasting tools to model.

- Scenario 4: 50% TOU customers and 50% RTP customers

The load profile is flatten compared to the above four scenarios. This mixed feature is due to customers who are sensitive to both hours in a day and electricity prices.

- Scenario 5: 33.3% flat-rate customers, 33.3% TOU customers, and 33.4% RTP customers

The load profile is sharply flattened in this scenario. This phenomenon is derived from the customer contract diversity. Customer behaviors seem to be balanced out when forming the aggregated load.

Note that the curve shapes of load profile for different retailers may vary dramatically. However, studying the impact of contracts and knowing what the load profiles look like in different scenarios could help retailers in short-term forecasting and bidding, as well as longer-term planning.

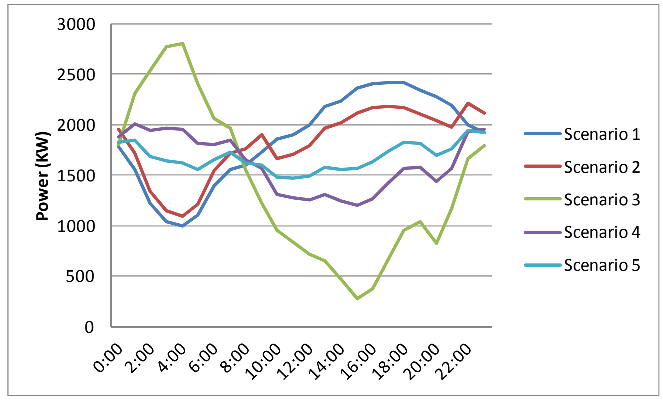

Fig. 4 Aggregated load profiles in five scenarios

IV. Proactive Load and Price Forecasting

Realizing the limitations of traditional forecasting tools, this study proposes a concept of proactive load forecasting that accounts for customer behaviors with different demand response contracts.

The proposed model in Fig. 5 contains two sub-models that physically mimic two interrelated events in electricity markets. Sub-model 1 models how customers with different contracts respond to prices in a given day or hour. Sub-model 2 mimics how electricity prices reflect load conditions through market-clearing process. Exogenous variables used in traditional forecasting tools (e.g. weather, day types) are still important inputs to sub-model 1. Electricity price and demand response contract types and percentages are additional but very critical inputs to more accurately capture customer behaviors. Sub-model 2 involves all the accessible information that is necessary for system operation to forecast prices, which are then fed back to sub-model 1 to forecast demand. For rational customers, they would predict the electricity prices, and then based on the prediction they modify their consuming behaviors. If the expectations of both load and prices are fulfilled, their behaviors and predictions are consistent. When this iterative process reaches demand-price equilibrium, the stable points can be used as a forecasting baseline that reflects rational customer behaviors.

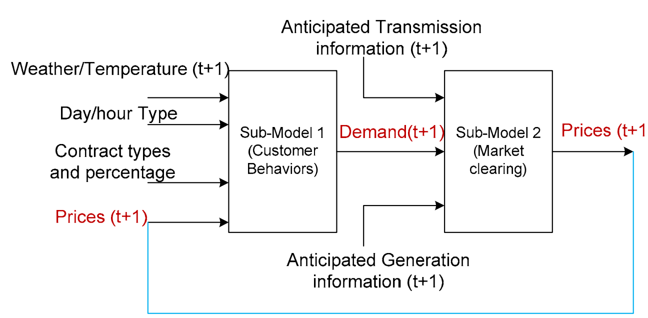

Fig. 5 Proactive load and price forecasting

V. Conclusion

The need of advanced load forecasting in a smart grid environment becomes more intense as demand response customers are increasing. Traditional load forecasting tools are limited in the sense that they don't take customer behaviors into account. Such customer behaviors are driven by the singed contract types. In this study, existing demand response contracts are reviewed. A illustrative example is provided to explore how these contracts affects load profiles so that they need to be included in load forecasting methods. A new concept of proactive demand and price forecasting is proposed. Future work will be focused on validating the proposed model through practical data.

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Qun Zhou (M'08) received her Ph. D degree from Iowa State University in 2011. She is currently with Alstom Grid as a power system engineer. Her research interests include economic analysis of power systems, load and price forecasting, and demand response in market operations.

Wei Guan received her Ph.D. degree from the University of Oklahoma in 2010. She is a power system engineer at Alstom Grid, Inc since 2011. Her interested research areas are energy finance and risk management, with a particular focus on energy portfolio management, marginal risk estimation and electricity derivative pricing.

Wei Sun (M'08) received his Ph.D. degree from Iowa State University, Ames, IA, U.S.A. He worked as a Regional Transmission Planning Engineer at California Independent System Operator (CAISO) in summer 2010. He was a Visiting Scholar at the University of Hong Kong in 2011. He is currently with Alstom Grid as a Power System Engineer. His research interests include power system restoration and self-healing, carbon dioxide emission regulation, generation scheduling, and optimization methodologies applied to power system problems.