On the Impact of Demand Response: Load Shedding, Energy Conservation, and Further Implications to Load Forecasting

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***Abstract*— This paper discusses three aspects of demand response through a case study of a US utility: 1) how load profile changes due to demand response; 2) how much energy has been saved annually; 3) whether the load forecasts have been affected by demand response. A regression based approach is deployed to try to answer these questions. The results show that for this particular utility, the demand response programs on average help shave the peaks but do not significantly affect the annual sales. In addition, the forecasting accuracy can be improved by excluding the hours affected by demand response.**

***Index Terms*—demand response, load forecasting, multiple linear regression.**

I. Introduction

DEMAND response (DR) is receiving more and more attention today in the utility industry due to the wide deployment of the smart meters. While many utilities are mandated to set up demand response programs, there are still some fundamental issues to be fully addressed. This paper presents a case study for a medium sized utility to answer three questions: 1) Are the peaks really being shifted due to DR activities? 2) How much energy has been saved annually due to DR? 3) How does DR impact load forecasting processes? These three aspects directly or indirectly impact the key performance indices of a utility and are concerned by the utility executives, managers, analysts and engineers.

Over a 3-year period (2005 - 2007), there are in total 1297 hours being labeled as DR activities. These hours are spread into 290 periods or 252 days. Fig. 1 and Fig. 2 show the detailed spread by hour and month for an average year respectively. As shown in Fig. 1, there are two periods in a day when this utility may turn on DR programs: morning (Hour Ending 7:00 to 11:00), and late afternoon to evening (Hour Ending 15:00 to 23:00). Most DR activities occur in the latter period. This is consistent with the load profiles of this utility: evening peaks are usually higher than the morning peaks. As shown in Fig. 2, the highest bar is in March, when 55 hours per year are flagged by DR activities [1]. This is again consistent with the fact that the utility is summer peaking and most annual peaks occur in July.

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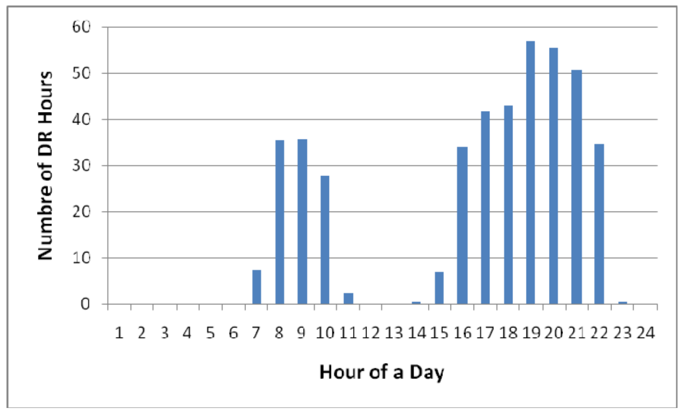

Fig. 1. Summary of DR activities by hour.

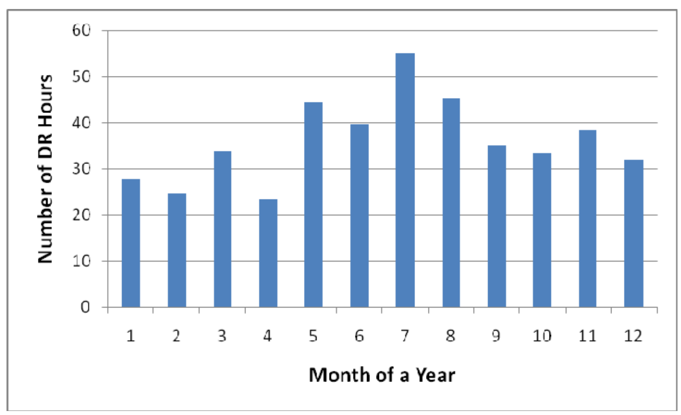

Fig. 2. Summary of DR activities by month.

II. Methodology

A. Data

The hourly load and temperature history from 2005 to 2008 has been used in this project. Other than labeling the hours with DR programs turned on as "DR", we also label the hour right after each DR period as "PostDR". This is used to incorporate the situation that extra electricity consumption may bounce back right after a DR period.

B. Model

The naïve multiple linear regression model proposed in [2] is used for analyzing the DR activities. The model can be written as:

$$E(Load) = \beta_0 + \beta_1 \times Trend + \beta_2 \times Day \times Hour + \beta_3 \times Month + \beta_4 \times Month \times TMP + \beta_5 \times Month \times TMP^2 + \beta_6 \times Month \times TMP^3 + \beta_7 \times Hour \times TMP + \beta_8 \times Hour \times TMP^2 + \beta_9 \times Hour \times TMP^3, \quad (1)$$

where *Trend* is a quantitative variable denoting a linear trend; *TMP* is a quantitative variable denoting the temperature; *Month*, *Day*, and *Hour* are class variables denoting 12 months of a year, 7 days of a week and 24 hours of a day, respectively.

III. Experiments and Results

A. Load Shedding

We divide the first three years of data into two groups: regular hours and the hours being labeled as either "DR" or "PostDR". From 2005 to 2007, there are totally 26280 hours, of which 1297 hours are labeled as "DR", 290 hours are labeled as "PostDR". We use the 24693 regular hours to predict the three years of hourly loads including the 1587 special hours ("DR" and "PostDR"). We then pick up individual days with DR program turned on to compare the actual load profile with the predicted one. As shown in Fig. 3, while the DR programs are on, the actual load is lower than the predicted load. This is reasonable and expected because we turn on DR programs for load shedding. During the "PostDR" hour, the actual load is still lower than predicted load. This is not consistent with our hypothesis: "extra electricity consumption may bounce back right after a DR period". This can be due to several reasons including:

1) The model is not accurate enough. We also observed some DR periods when the predicted loads are higher than the actual ones;
2) There is no significant "bounce-back" effect for this day.
3) Errors when recording the DR activities.

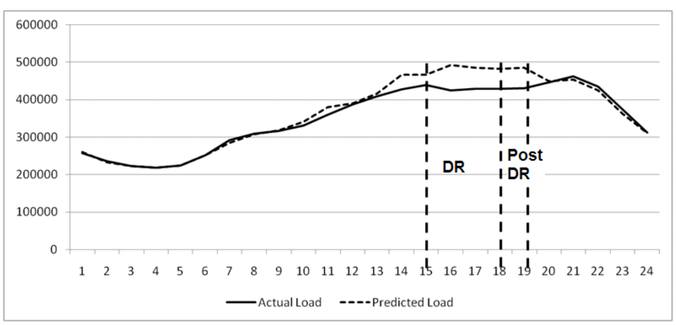

Fig. 3. A load shedding example.

B. Energy Conservation

We then look into the energy conserved (Predicted Load – Actual Load) during the DR hours and the energy bounced back (Actual Load – Predicted Load) during the PostDR hours. We get the total energy conserved during the DR hours as 4.86GWh, the total energy bounced back during the PostDR hours as 3.32GWh. Therefore, the total energy conserved due to DR activities over these three years is 1.54GWh, or 0.51GWh per year, which is about 0.016% of the total annual energy consumption of this utility.

C. Further Implications to Load Forecasting

From the forecasting process perspective, the utilities will have to forecast the loads without DR activities and the loads under different DR activity scenarios. In addition, the data used for constructing the model should be preprocessed to incorporate historical DR activities. For instance, we took out the special hours from model data to perform the day ahead and week ahead forecasting for 2008. The resulting MAPE together are shown in the Table I, where we can observe that the errors based on preprocessed data (w/o special hours) is smaller than the ones based on all data [3]. Considering that the DR hours of 2008 are also included in the error statistics, we expect more significant improvement on the regular hours.

TABLE I
Results (MAPE, %) Comparison

	One Day Ahead	One Week Ahead
w/o special hours	4.95	5.01
All hours	4.98	5.04

IV. Conclusion

In this paper, we discussed three aspects of DR impact: load shedding, energy conservation, and further implications to load forecasting. In the case study of a medium sized US utility, we make the following conclusions based on a naïve multiple linear regression model:

1) The utility successfully shift peaks as desired in most cases;
2) Minimal amount of energy (0.016% on annual basis) have been conserved due to DR activity. In other words, the revenue of this utility is not significantly hurt by the current DR practice;
3) Forecasting error can be reduced by excluding the special hours from the model data.

As discussed in Section III, the soundness of the conclusion can be affected by the accuracy of the model. Therefore, the future work includes using more accurate models to perform the analysis. We can also perform the similar analysis for each individual DR program and individual customer.

V. References

[1] Tao Hong, "From Load Forecasting to Demand Response", guest lecture at North Carolina State University, available online: http://courses.drhongtao.com

[2] Tao Hong, Pu Wang, and H. Lee Willis, "A Naive Multiple Linear Regression Benchmark for Short Term Load Forecasting," 2011 IEEE PES General Meeting, Detroit, MI Jul 24-29, 2011

[3] Tao Hong, "Short Term Electric Load Forecasting", PhD dissertation, North Carolina State University, 2010.

VI. Biographies

Tao Hong is an Industry Consultant at SAS Institute, where he leads the forecasting vertical of the utilities business unit. His major areas of expertise are in forecasting and optimization. He has applied various statistical and optimization techniques to the development of algorithms and tools for utility applications of analytics, such as energy forecasting, power system planning, renewable integration, reliability planning and risk management, etc. He has been providing consulting services to numerous large and medium utilities in Americas, EMEA and AP. The long term spatial load forecasting methodology implemented in his MS thesis and the short term forecasting methodology proposed in his PhD dissertation have been commercialized and deployed to many utilities worldwide. Dr. Hong currently serves as the Founding Chair of the IEEE Working Group on Energy Forecasting, where he leads the efforts of improving the forecasting practice of the utility industry. He has organized, chaired, and participated in many forecasting related sessions in several major conferences sponsored by IEEE Power and Energy Society and INFORMS. He is a reviewer of Fuzzy Optimization and Decision Making and several IEEE Transactions, such as Power Systems, Power Delivery, Sustainable Energy, and Smart Grid. Dr. Hong is an adjunct instructor at NC State University teaching load forecasting and demand response related topics at both Electrical & Computer Engineering department and the Institute for Advanced Analytics. He is also an instructor at SAS Institute teaching the Business Knowledge Series course "Electric Load Forecasting: Fundamentals and Best Practices", which is the first SAS course dedicated to the utility industry. Dr. Hong received his B.Eng. in Automation from Tsinghua University, Beijing, a M.S. in EE, a M.S. with co-majors in OR and IE, and a Ph.D. with co-majors in OR and EE from North Carolina State University. He is a member of Omega Rho International Honor Society.

Pu Wang is a research statistician developer at SAS Institute. She is specialized in operations research and statistical analysis with the applications in merchandise intelligence solutions. She has been doing research and development of emerging techniques in market response modeling and large scale demand forecasting for fashion goods retailers. She received her Bachelor of Engineering degree in Industrial Engineering from Tsinghua University, Beijing, where she was awarded with a first-class scholarship for the academic excellence. She received the Master and PhD degrees in Industrial Engineering from North Carolina State University.