Quantifying Benefits of Demand Response and Look-ahead Dispatch in Systems with Variable Resources

Final Project Report

Power Systems Engineering Research Center

Empowering Minds to Engineer
the Future Electric Energy System

Quantifying Benefits of Demand Response and Look-ahead Dispatch in Systems with Variable Resources

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Power Systems Engineering Research Center

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Executive Summary

Policies that require large expansions of renewable generation sources pose both technical and economic challenges for power systems. For example, over half the states have established Renewable Portfolio Standards, and many have very ambitious goals to generate substantial fractions of electricity with renewable sources. One of the primary obstacles is that renewable generation sources are intermittent and thus create challenges for both system operators and market designers. Due to the limited predictability and high inter-temporal variability of renewable generation, novel operation and market design methods are needed for a cost-effective approach to integrating these resources into the power system.

This project addresses these challenges by *quantifying the benefits of using price-responsive demand in conjunction with a dynamic look-ahead dispatch algorithm*. Importantly, our estimated benefits correspond to a real-world power system, as we use actual data on demand-response and wind generation by location, as well as a dispatch model calibrated to the actual network topology.

We evaluate the effect of integrating demand response with a dynamic look-ahead dispatch model on power system scheduling based on realistic data obtained from Electric Reliability Council of Texas (ERCOT). Measures of ERCOT demand response and site-specific wind generation data are used. The project has two major elements: (1) estimating demand-response by location on the grid, and (2) applying a look-ahead dispatch algorithm to a real-scale system such as ERCOT, using demand-response as input parameters. Figure 1 shows the schematic overview of the project activities.

The major outcome of this project is that (1) real-world price elasticity based on ERCOT data is quantified and analyzed. The estimation of own and cross elasticity is critically assessed; and (2) the economic benefits of combining look-ahead dispatch with price-responsive demand is quantified. Such benefits manifest themselves in both economic

savings during normal operating conditions, and the economic savings in avoiding infeasibilities.

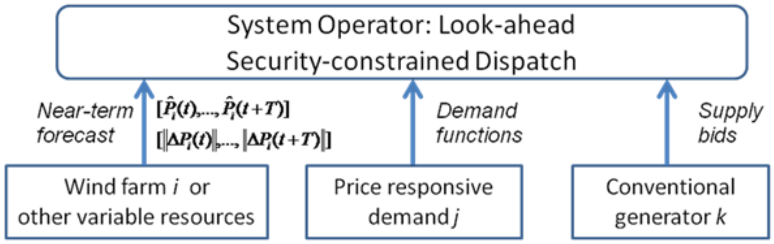

Figure 1: Implementation of look-ahead dispatch with price responsive demand

Figure 1 Implementation of look-ahead dispatch with price responsive demand

For the first part of estimating demand elasticity in ERCOT, econometric study is conducted based on wholesale level commercial and industrial loads. Both own and cross-elasticity is derived based on the commercial & industrial (C&I) load data in ERCOT which are subject to time-varying prices. The own elasticity is found to be relatively low compared with most literature suggest.

For the second part of the study, we estimate the benefits of introducing time-coupled look-ahead dispatch in a realistic system such as ERCOT. The economic benefit of introducing look-ahead as compared with static dispatch is the reduced overall system dispatch, because of the prepositioning of generation output in anticipation of future net load variations. The estimated saving for the ERCOT is approximately $10 million per year. In addition to the economic benefits during normal operating conditions, the introduction of look-ahead also benefit the system when potential insecurity occurs. Such savings can be quantified in avoided load shedding cost. We present the savings of this in Chapter 3.

By combining look-ahead dispatch with price responsive demand, the total system benefits include: (1) increased overall social welfare; (2) reduced wind-related curtailment; and (3) smoothed price performance. The detailed study is described in Chapter 4.

This project provides empirical study documenting the benefits of advanced dynamic look-ahead dispatch with price responsive demand. It could serve as a basis for policy and pricing discussions for the ongoing migration toward a clean energy portfolio. While all the empirical study is based on one particular region ERCOT (which has the highest wind penetration in the U.S. as a region), similar study methodologies can be applied in many other regions. Future work could investigate the implication on market price with time-coupled look-ahead dispatch. In addition, how to quantify temporal shifts in demand response is also another important theoretical and empirical challenge.

Project Publications:

- Y. Gu, and L. Xie, "Early Detection and Optimal Corrective Measures of Power System Insecurity in Enhanced Look-Ahead Dispatch," *IEEE Transactions on Power Systems*, vol.28, no.2, pp.1297-1307, May 2013.
- Y. Gu, and L. Xie, "Fast Sensitivity Analysis Approach to Assessing Congestion Induced Wind Curtailment," *IEEE Transactions on Power Systems*, (accepted, to appear).
- L. Xie, Y. Gu, A. Eskandari et al., "Fast MPC-Based Coordination of Wind Power and Battery Energy Storage Systems," *Journal of Energy Engineering*, vol. 138, no. 2, pp. 43-53, 2012/06/01, 2012.
- Y. Gu, and L. Xie, "Look-ahead Dispatch with Forecast Uncertainty and Infeasibility Management," in *Power & Energy Society General Meeting*, San Diego, 2012.
- Y. Gu, X. Wang and L. Xie, "Horizontal Decomposition-based Stochastic Day-ahead Reliability Unit Commitment," in *Power & Energy Society General Meeting*, Vancouver, 2013.
- L. Xie, Y. Gu, and M.D. Ilić, "Look-Ahead Model-Predictive Generation Dispatch Methods" in M.D. Ilić, L. Xie, and Q. Liu, editors, Engineering IT-Based Electricity Services of the Future: The Tale of Two Low-cost Green Azores Islands, Springer, 2013.

- J. Joo, Y. Gu, L. Xie, J. Donadee, and M.D. Ilić, "Look-ahead Model-Predictive Generation and Demand Dispatch for Managing Uncertainties" in M.D. Ilić, L. Xie, and Q. Liu, editors, Engineering IT-Based Electricity Services of the Future: The Tale of Two Low-cost Green Azores Islands, Springer, 2013.
- L. Xie, Y. Gu, X. Zhu and M. Genton, "Short-term Spatio-temporal Wind Power Forecast in Robust Look-ahead Power System Dispatch," *IEEE Transactions on Smart Grid*, (submitted).

Student Theses:

- Y. Gu, 2014 (expected). “Early Detection and Optimal Corrective Measures of Power System Insecurity in Enhanced Look-Ahead Dispatch,” PhD dissertation, Texas A&M University.
- C. Cancho, 2012. “Essays on Energy and Regulatory Compliance”, PhD dissertation, Texas A&M University.

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1. Introduction

1.1 Background

Huge technical and economic challenges are posed due to large expansion of renewable energy. In contrast to conventional thermal generation resources such as coal power plants and natural gas power plants, most renewable power resources (such as wind generation and solar generation) are intermittent and variable with limited predictability [1-4].

Because of the limited predictability and high inter-temporal variation of those renewable resources, existing market design and operational approach may not be sufficient to handle all the conditions. Therefore, innovative operation and market design methods are needed to cost-effectively integrate the renewable resources into the power system.

One of the major operational changes is that the industry is moving from a static near real-time economic dispatch to dynamic look-ahead economic dispatch to allow for more flexibility in support of higher penetration of variable renewable resources [5].

This technical report empirically studies the impact of implementing a look-ahead dynamic economic dispatch with price responsive demand in Electric Reliability Council of Texas (ERCOT) nodal market operations.

1.1.1 The Operational Challenge of Integrating Variable Generation

Due to the increasing penetration of renewable generation, new challenges are posed to power system operations [6-8].

During past two years, global demand for renewable energy continued to rise, despite the international economic crisis, ongoing trade disputes, and policy uncertainty and declining support in some key markets. Renewable energy supplied an estimated 19% of global final energy consumption by the end of 2011 [9].

Among the total renewable energy consumption, only approximately 9.3% came from traditional biomass while useful heat energy from modern renewable sources accounted for an estimated 4.1% of total final energy use;

Hydropower made up about 3.7%; and an estimated 1.9% was provided by power from wind, solar, geothermal, and biomass, and by biofuels.2 Renewables are a vital part of the global energy mix.

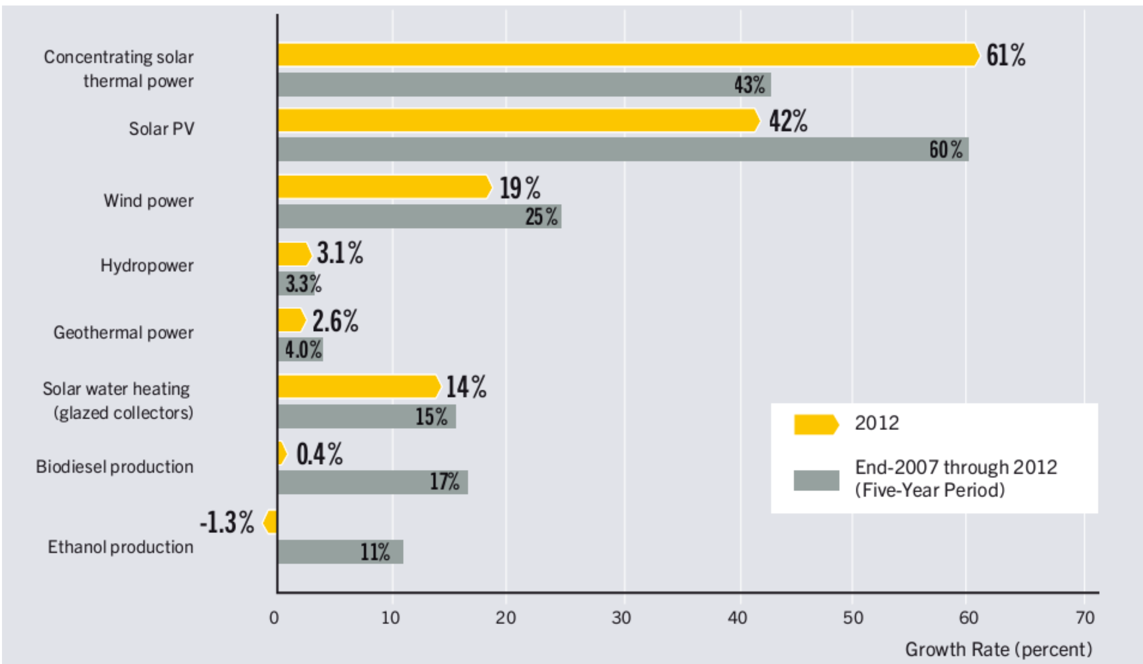

Figure 2 Average annual growth rates of renewable energy capacity

In Figure 2, the average annual growth rates of renewable energy capacity are presented [9].

Globally, total renewable power capacity exceeded 1,470 gigawatts (GW) in 2012, up about 8.5% from 2011. Hydropower rose to an estimated 990 GW, while other renewables grew 21.5% to exceed 480 GW. Globally, wind power accounted for about 39% of renewable power capacity added in 2012, followed by hydropower and solar PV, each accounting for approximately 26% [9].

Passing bio-power, solar PV capacity reached the 100 GW milestone and become the third largest renewable technology in terms of capacity (but not generation), after hydro and wind.

Having accounted for an ever-growing share of electric capacity added worldwide each year, renewables in 2012 made up just over half of net additions to electric generating capacity. By year's end, renewables comprised more than 26% of total global power generating capacity and supplied an estimated 21.7% of global electricity, with 16.5% of total electricity provided by hydropower. While renewable capacity rises at a rapid rate from year to year, renewable energy's share of total generation is increasing more slowly because many countries continue to add significant fossil fuel capacity, and much of the renewable capacity being added (wind and solar energy) operates at relatively low capacity factors [9].

In Figure 3, total renewable power capacity in various regions have been presented.

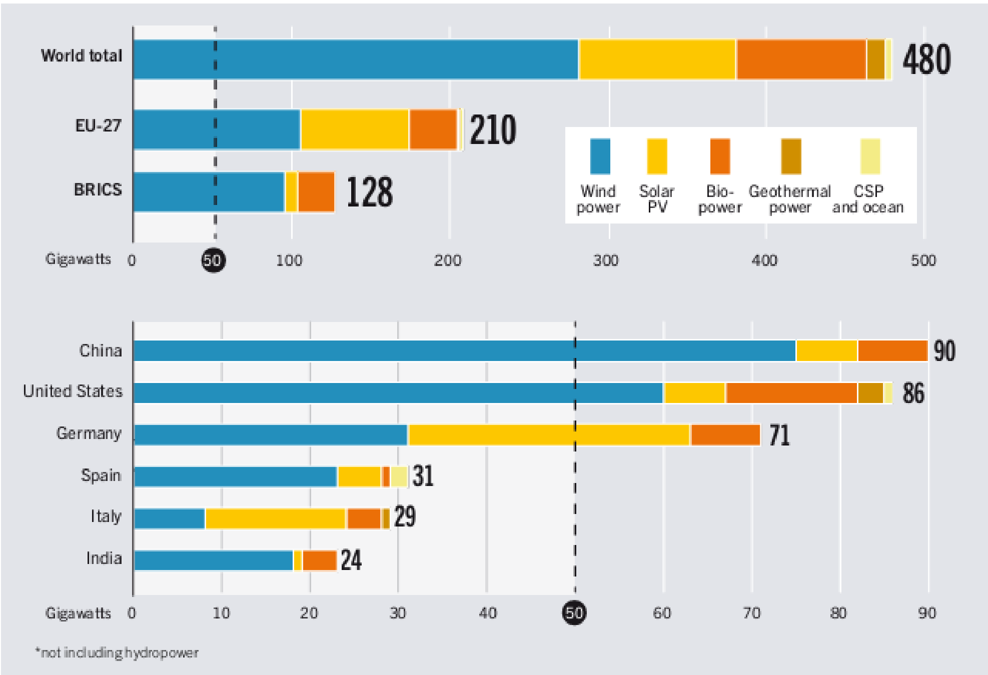

Figure 3 Renewable power capacity in world, EU-27, BRICS, and top six countries.

Because of such a rapid development in renewable resources especially for those intermittent resources such as wind and solar, a lot of challenges are posed to power system operations.

In conventional power system operation, the major uncertainty and variability come from the demand. Figure 4 present the day-ahead load forecast and 10 minutes ahead load prediction. As we can see, the existing power engineering did a pretty good job in load forecast. The difference between the day-ahead load forecast and real-time load forecast is small and manageable.

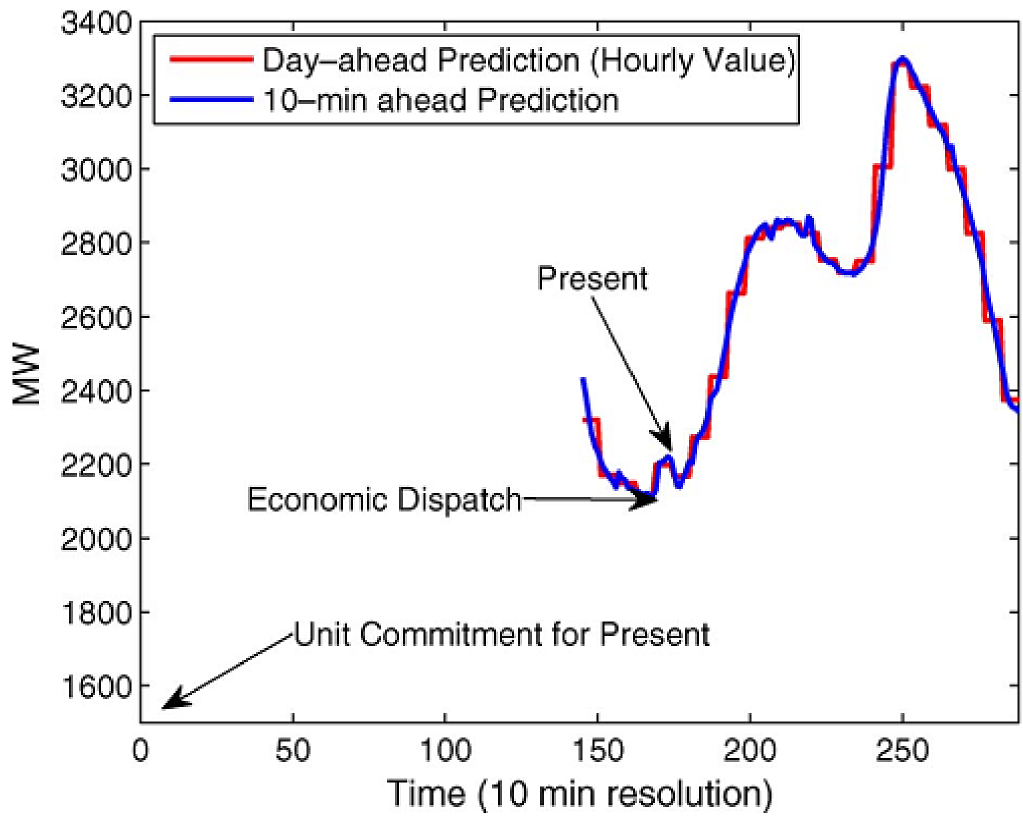

Figure 4 Day-ahead and 10-min-ahead load prediction, and timing of UC and ED functions.

In Figure 5, it presents the 10-minute ahead load forecast and second by second actual load [2]. As we can see, the 10-minute ahead forecast basically represents the expected value of the actual load. Those variations and deviations away from the 10-minutes load forecast are taken care by automatic generation control (AGC).

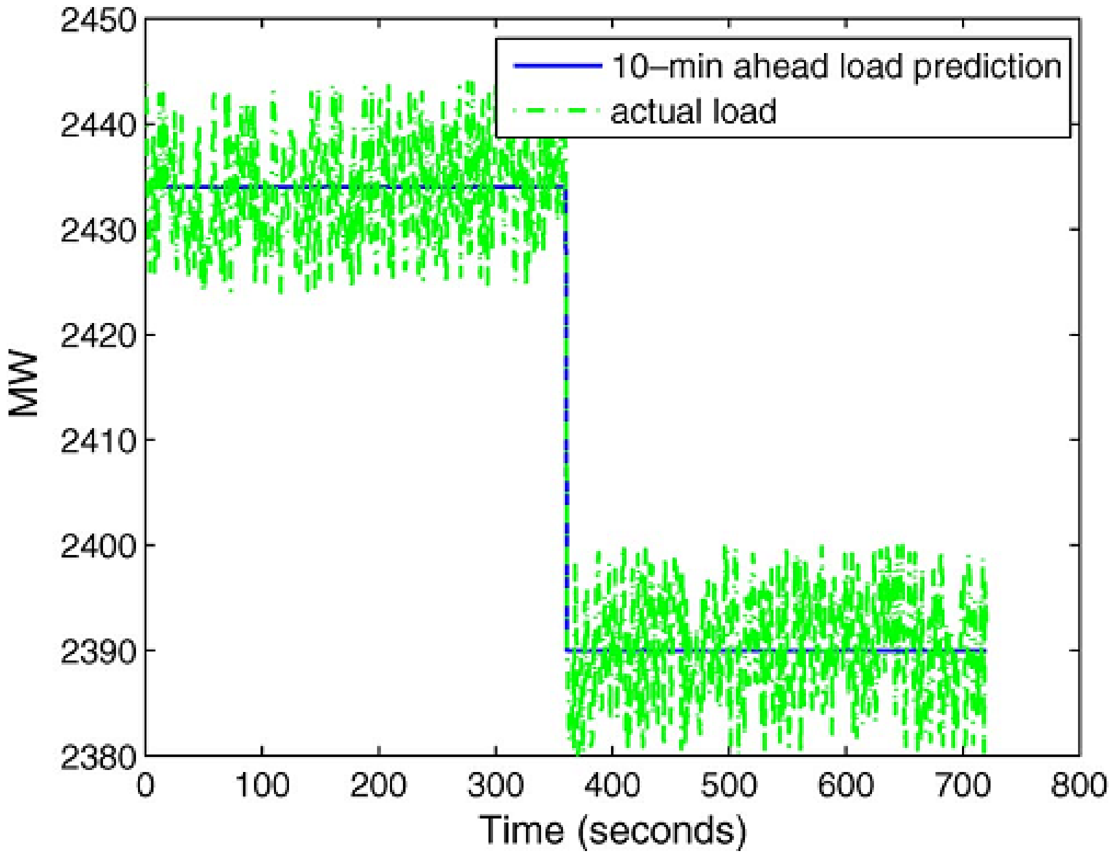

Figure 5 10-min-ahead load prediction and second-by-second actual load.

However, under high penetration of renewable generation, the forecast pattern of the deviations has changed. The day-ahead and 10 minutes wind prediction are presented in Figure 6 [2]. And the zoomed-in 10 minutes wind prediction and actual wind generation are presented in Figure 7. As we can observe the deviation and variation are much higher than Figure 4 and Figure 5. The conventional AGC system may not be fully responsible to the intermittency resulting from the renewable generations.

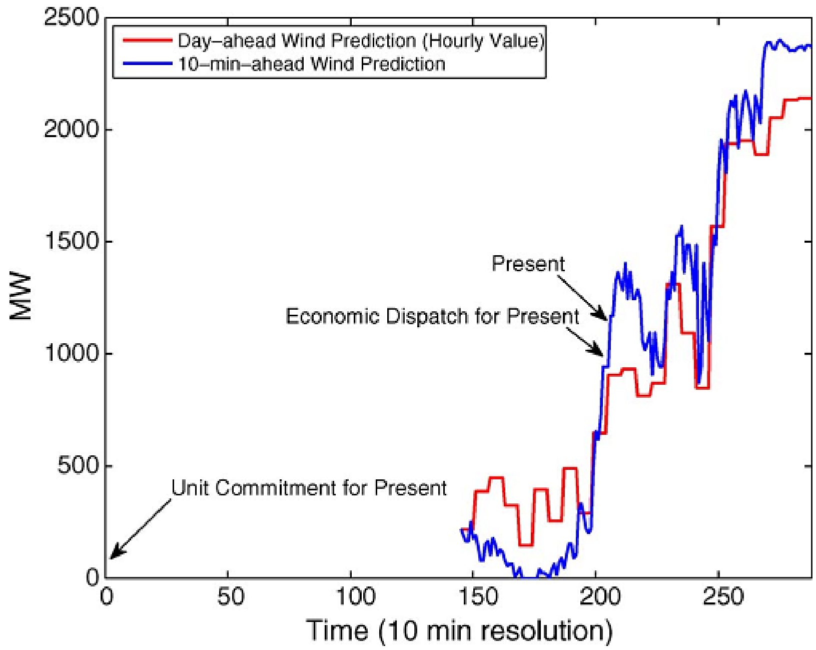

Figure 6 Day-ahead and 10-min-ahead wind prediction, timing of UC and ED functions.

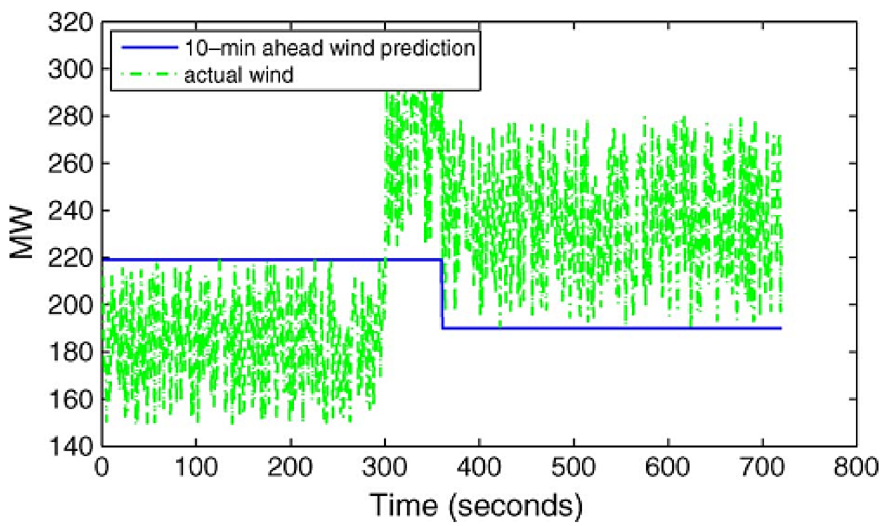

Figure 7 Schematic 10-min-ahead wind prediction and second-by-second actual wind.

1.2 Target of Research

The objective of this project is to address these challenges by *quantifying the benefits of using price-responsive demand in conjunction with a dynamic look-ahead dispatch* *algorithm.* Our estimated benefits correspond to a real-world power system, as we use actual data on demand-response and wind generation by location, as well as a dispatch model calibrated to the actual network topology.

In this project, we use ERCOT demand data and site-specific wind generation data. This project yields realistic estimates of the system benefits that such methods would yield in real-world power systems. As more system operators are incorporating towards time-coupled dispatch into Energy Management Systems (EMS) and Market Management System (MMS) [10], this project could provide quantifiable benefits in a specific system.

The project has two major elements:

- Estimating demand -response by location on the grid.
- Applying a look-ahead dispatch algorithm to a real -scale system such as ERCOT, using demand-response as input parameters.

1.2.1 Demand Response

Demand response offers many benefits to power systems, including the ability to integrate more intermittent renewable generation sources and to reduce the cost of ancillary services. Although many researchers and policymakers have discussed the role of demand response, very little empirical research has been done to quantify the level of demand response and benefit of demand response in an actual system. In particular, in ERCOT the market players do not have a solid grasp of how much demand response reliably exists, especially with new “enabling technologies” on the customer side of point of connection.

The first task of this project to quantify the demand elasticity of commercial and industrial (C&I) loads by location. We use customer-level data for C&I customers in ERCOT to econometrically estimate the own and cross elasticity of demand for specific types of customers in specific hours and seasons. This allows us to understand how demand elasticity varies by customer type (e.g. large retail store).

1.2.2 Look-ahead Dispatch with Price Responsive Demand

Another major task of this project is to quantify the economic benefits of conducting dynamic look-ahead dispatch with price responsive demand in ERCOT system. Starting from the look -ahead market operation procedures that have been implemented in several major RTOs [10], we developed a dynamic look-ahead simulation platform which includes price responsive demand. Such a simulation platform is based on the preliminary work done by the PIs [2, 11-14]. This platform enables quantification of the potential economic benefits from look-ahead dynamic dispatch and price responsive demand in support of integrating large-scale variable resources. The site-specific variable wind generation data and the substation-level elastic demand data obtained from ERCOT are the inputs to this simulation platform. In addition, development of look-ahead dispatch concepts is also tested in this real world-scale simulation platform.

1.3 Report Organization

This technical report is organized in five chapters. The first chapter gives a background of the whole research. Chapter 2 presents the price demand response model we used in this research. Chapter 3 discusses look-ahead economic dispatch and its advantages using ERCOT as an empirical example. Chapter 4 describes the economic benefits of implementing the look-ahead economic dispatch with price responsive demand in ERCOT market. Chapter 5 provides the concluding remarks and future work.

2. Quantifying Actual Demand Response in ERCOT

2.1 Institutional Background behind Demand Response in ERCOT

Texas is one of several U.S. states to allow retail competition in electricity. Retail firms procure power from generation owners and sell to commercial, industrial, and residential end-users. Since 2002, commercial and industrial (C&I) customers served by the Electric Reliability Council of Texas (ERCOT) have been able to purchase power from a competitive retailer rather than the former vertically integrated utility. Individual C&I customers and electric retailers bilaterally negotiate power contracts.

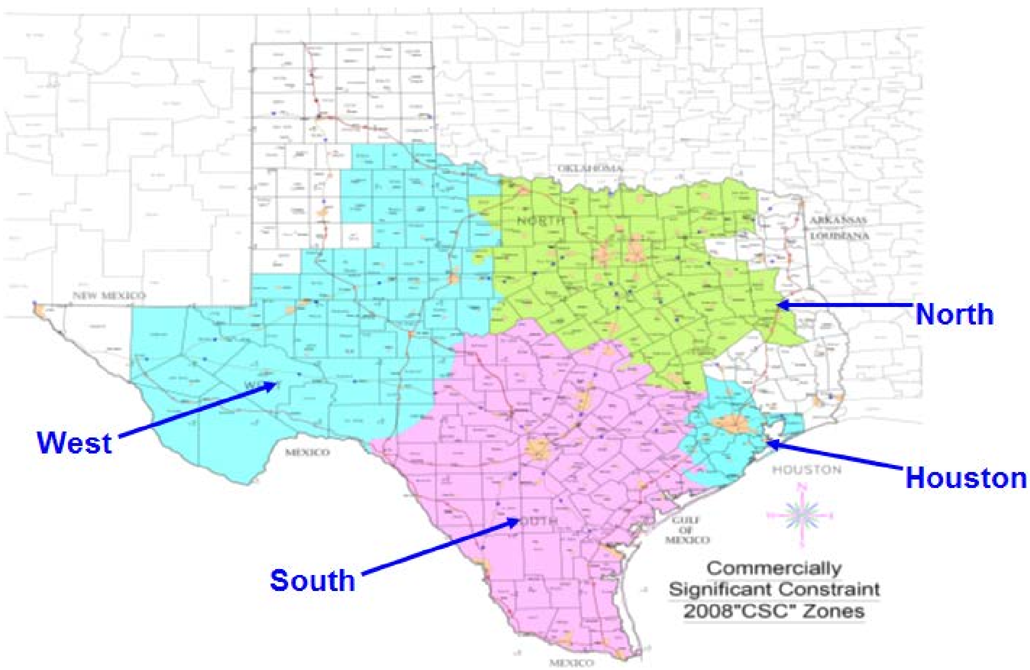

Figure 8 TVP zonal proxy for locations.

The agreements can vary along a variety of dimensions including how risk is shared and how much the customer is exposed to the wholesale spot price of power. For example, a contract could simply specify a fixed rate for all consumption -- a so-called requirements contract.

Other possible contracts could specify a price that varies in the time of day, week, or season of usage, and is often referred to as a time-of-use price. For these two types of contracts, the retail price is not directly tied to the wholesale spot price and thus does not reflect the short-run variation in supply and demand conditions of the system.

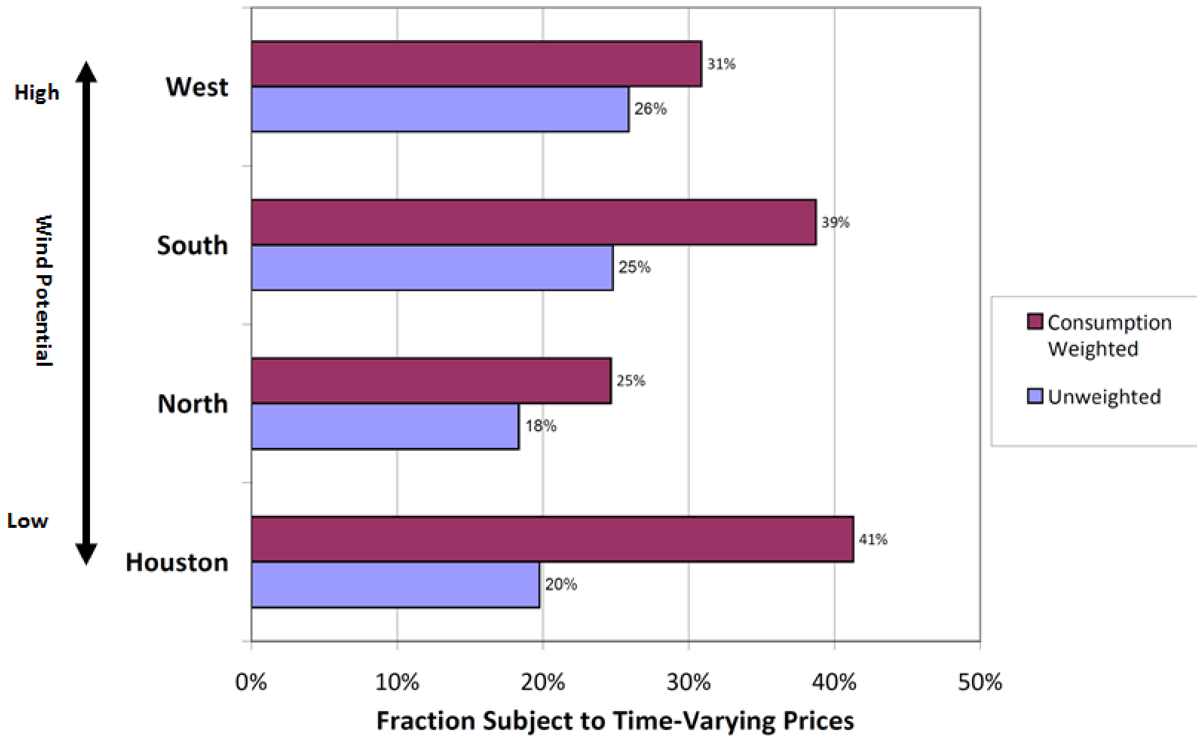

Figure 9 TVP take-up occurs in areas with current and future wind generation.

Besides electric consumption, customers also have to pay for transmission charges, a fee for the use of the electric grid. The design of transmission charges is based upon the consumer's contribution to demand during four peak times in summer months (Four Coincidental Peaks, 4 CP), thus providing consumers with an incentive to reduce their power purchases during the summer peaks [15].

This transmission charge introduces a complication for the empirical work because reductions in consumption during summer peak time may be partially driven by consumers trying to avoid the transmission fee. These reductions will not be distinguishable from reductions driven purely by a high wholesale market price. Thus, we may overestimate demand responsiveness to prices.

TVP typically take one of two forms. Critical peak pricing (CPP) allows prices to vary with short-run system conditions. Under CPP, the retailer/utility can declare a day or hour to be a critical peak period, and the price is contracted to be substantially higher during those episodes. In some cases, the critical peak price may be the wholesale spot price for that period. CPP contracts typically limit the number of times that the retailer/utility can declare critical peak periods. Real-time pricing (RTP) passes the wholesale spot price along to customers.

Either of the time-varying contracts could hedge a customer against price risk for a portion of the consumption but still expose the customer to the spot price on the margin. The existing literature has detailed descriptions of the types of retail pricing schemes (for example, see [16]). Retail prices under such bilaterally negotiated contracts will reflect factors such as wholesale prices, premia paid to avoid risk, and transmission and distribution charges by the distribution utility. For instance, a retailer offering a time-varying price contract to a particular customer will pass the risk involved in having unexpectedly high wholesale prices. At the same time, a customer entering into a time-varying price contract will have the opportunity to save costs by curtailing demand at peak times, or reallocating consumption within the day.

2.2 Data

We use a unique dataset of individual customer-level data for virtually all commercial and industrial (C&I) customers with interval data recorders (IDRs).[1] ERCOT provided us with data on the electricity consumption for 8,537 C&I customers that are metered with interval data recorders that allow the distribution utility to record consumption every 15 minute interval. These customers represent approximately 20% of the total energy load in ERCOT and the 33% of the C&I energy consumption in Texas. For each of these customers, our data include consumption for each 15 minute interval from October 2007 to September 2008.

[1] During the sample period, all customers with a peak demand higher than 700 kW were required by ERCOT to have an interval data recorder installed. The compliance rate for this requirement was almost universal. Customers were also allowed to request voluntarily the installation of these devices.

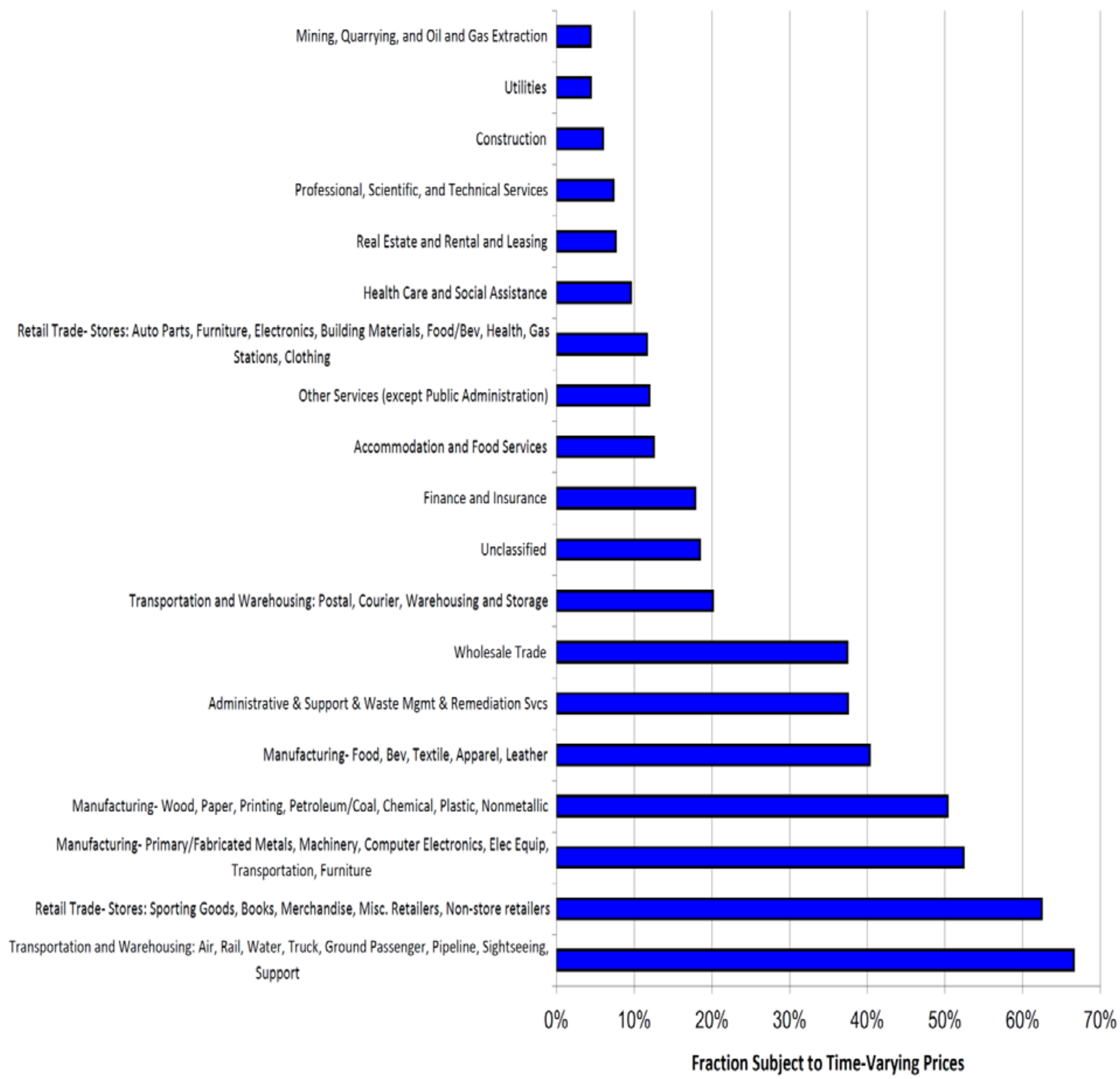

Figure 10 TVP take-up varies substantially by industry

For each customer, ERCOT provided us with information about the contract between the customer and its retailer. ERCOT requested that each retailer identify for each of the retailer's customers whether the contract provided "a financial incentive or requirement to reduce consumption in response to high wholesale spot prices." In particular, the retailers were asked to provide an indicator of whether the contract included either real-time pricing, critical peak pricing, or any other pricing structure that created incentives to reduce demand when balancing market prices rose.

This measure of exposure to time-varying prices (TVP) is for a single snapshot in time -- the survey response was due to ERCOT on April 1, 2009. We assume that the contract in place when the retailer responded to the survey had similar properties as the contracts governing our sample period of October 2007 to September 2008. According to this metric, approximately 15% of customers were on time-varying prices. However large customers are more likely to face time-varying prices; 30% of C&I load faces time-varying prices.

Customers may also sell curtailing capacity though agreements known as Loads Acting as Resources (LaaRs), either to ERCOT or directly to load-serving entities. As of the end of 2008, 144 firms were qualified to provide load curtailment capacity, with 5 of them concentrating about one-half of the total curtail capacity (more than 100MW)[15]. Typically, LaaRS are called to reduce load three times a year. Another alternative for selling curtailment capacity is the Emergency Interruptible Load Service (EILS). Under EILS, interruptible loads that are not providing an operating reserve receive a payment for curtailing consumption within a 30-minute of ERCOT declaring an emergency [15]. Both programs introduce a challenge for the empirical estimation, because during high-prices episodes non-TVP firms can reduce consumption because of their participation in these programs, and TVP firms could not reduce consumption or do it only marginally in order to preserve their curtailment capacity already under contract. Unfortunately, we do not have information on which firms participate in EILS. Therefore, the days when LaaRs episodes occurred are excluded from our sample.

The total amount of C&I consumption (metered with IDRs) subject to time-varying prices has a flatter daily load profile than the C&I consumption not facing TVP. This is illustrated in Figure 11 which shows the average daily aggregate consumption profile for customers on TVP and those not on TVP. Customers not facing TVP have a daily load shape that peaks later in the day and exhibits a higher peak to trough ratio than TVP customers.

2.3 Empirical Model and Estimation

To estimate the effect of prices on customer-level load, we estimate jointly the conditional input demands (CID) for the 96 intervals of the day, following and modifying Patrick and Wolak's (2001) methodology [17]. The CID used for the estimation are derived from a Generalized Mc Fadden (GMF) cost function. We opt for this cost function among many other used in the literature because of its consistency with the conditions imposed by the microeconomic theory. In addition to satisfy homogeneity of degree one in input prices, this specification can satisfy the concavity in input prices, which cannot be guaranteed using other common cost functions, such as the translog or Generalized Leontief functions [18].

These properties of the cost function are important for our setting. In intuitive terms, homogeneity of degree one implies that if all input prices increase by certain proportion, then total cost will increase by the same proportion. Concavity in input prices imply that if the price of one particular input increases, total cost will increase, but less than proportionally. In this case, the firm can substitute the use of that input for other cheaper inputs. This second condition is particularly relevant in this study, because we want to allow firms to shift consumption across intervals within the day for the production process.

For estimation, as in [17], we assume that firms choose production to minimize costs, and we use a modified Generalized McFadden cost function:

$$C_{kd}(p,y) = \left[\frac{1}{2}\sum_{i=1}^{96}\sum_{j=1}^{96} c_{ij}\, p_{id}\, p_{jd}\right] y_d + \sum_{i=1}^{96} b_{ii}\, p_{id}\, y_d + \sum_{i=1}^{96} b_i\, p_{id} + \sum_{i=1}^{96}\left[d_i f\left(W_{id}\right) + \theta F_k + U_{ikd}\right] p_{id} \tag{1}$$

From Shephard’s Lemma, the partial derivative of the cost function with respect to each input price yields the conditional input demand for input *i*:

$$E_{ikd}(p,y)=\left[\frac{1}{2}\sum_{i=1}^{96}c_{ij}p_{jd}+b_{ii}\right]y_d+b_i+d_i f\left(W_{id}\right)+\theta F_k+U_{ikd} \qquad (2)$$

In the most general specification, this model contains many parameters, so in order to make the model more parsimonious, we incorporate “smoothness” across the intervals’ substitution patterns by employing a Fourier series. Details are included in [19]. As a result, we are able to estimate a matrix of 96x96 own- and cross-price elasticities to capture substation among all intervals in a given day.

2.4 Results

To estimate the price elasticities, we focus on the intervals when there was potentially a strong incentive to curtail electricity consumption. Hence, we analyze only the days during the summer of 2008 when unusually high prices occurred. The criteria used for defining an unusually high price were 1.5 times the standard deviation above the mean price for the interval and congestion zone (Houston, North, West, South). Using this criteria, 50 days out of the 91 days were selected. Details on the selection process can be found in [19].

Next, we divided C&I firms into quartiles of consumption based upon the firm's consumption data from June 2008 to August 2008. This separation of firms by “size” generates more homogeneity and facilitates the model estimation.

We obtain some important conclusions from these results. First, the estimated magnitudes of elasticity are modest. All the reported median values are below 0.02 in absolute value, with most of them being below 0.01. This result is consistent with previous results in the literature. For instance, [20] find that aggregate own-price elasticity of demand in

ERCOT is -0.000008, while [21] find that the 20 largest customers in Houston have no significant response to prices.

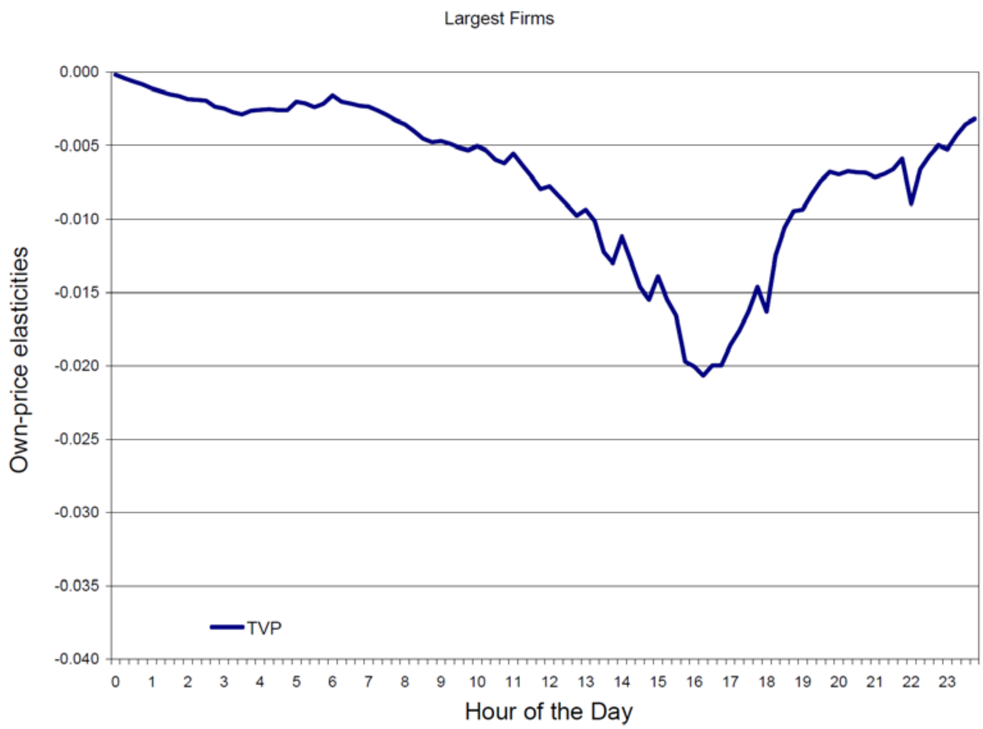

Figure 11 Quartile 4: own price elasticity for the Largest Firms on TVP

As an illustration of our results, the figure below reports the own-price elasticities by interval of the day for the firms in the highest quartile.

The figure above is an illustration of the own-price elasticities (e.g. the on-diagonal terms of the elasticity matrix). We generated the full matrix of 96x96 elasticities for each zone, and these matrices of substitution patterns are used as inputs into the look-ahead dispatch model described in the next chapter.

3. Look-ahead Dispatch with Price Responsive Demand

In this chapter, we formulate and apply look-ahead dispatch with price responsive demand in the ERCOT equivalent system. The benefits of both look-ahead dispatch and price responsive demand are quantified and analyzed.

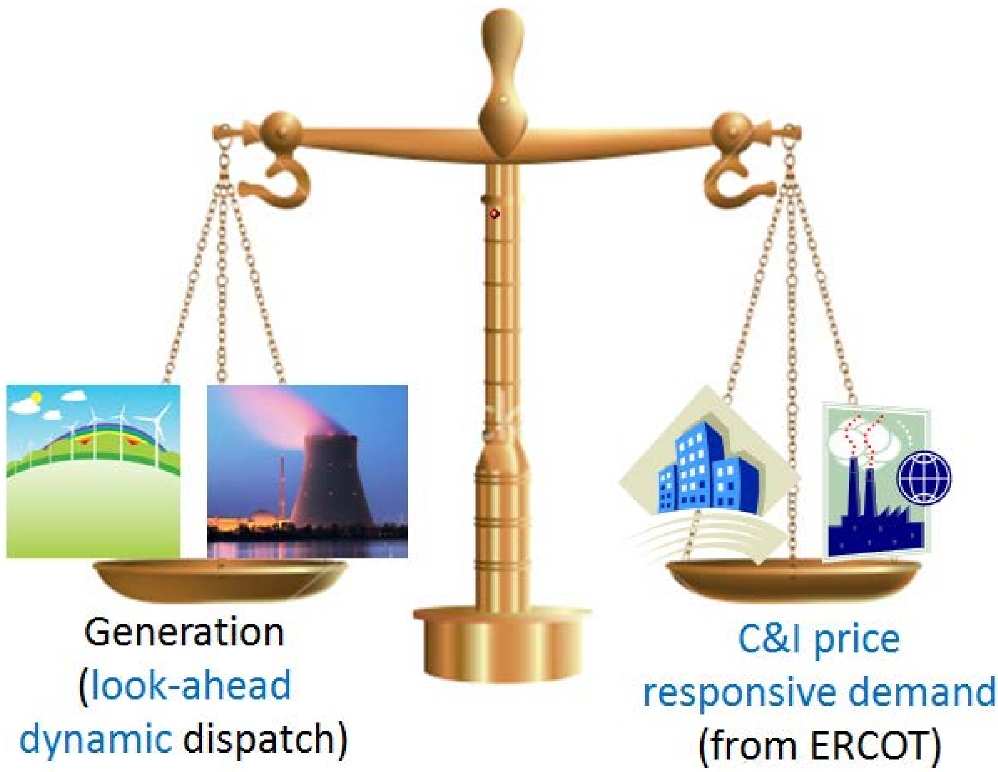

Figure 12 Quantifying system benefits using real-world data

3.1 Background

Dynamic look-ahead dispatch is motivated by the need for a more advanced dispatch algorithm with enhanced capability to manage the security risks (for much broader set of conditions [22-24]) due to the high variation and uncertainty introduced by intermittent resources and contingencies in electric power systems. In recent years, as an alternative to conventional static security constrained economic dispatch (SCED), look-ahead SCED has become a new industry standard in real-time energy market operations [5, 25]. In contrast with the single-stage optimization of static SCED, look-ahead SCED works out a scheduling plan for a future period (e.g., the next 2 hours). By (i) utilizing the accurate most recently updated load and intermittent generation forecasts (e.g., 10-minute ahead forecast) and (ii) incorporating the inter-temporal constraints (e.g., ramp rate), look-ahead SCED exhibits an improved economic performance over static SCED [2].

Although the efforts in industry for doing look-ahead dispatch are recent, the concept of the look-ahead (dynamic) dispatch originated to the 1980s [26, 27]. The major motivation behind conducting look-ahead (dynamic) economic dispatch was to incorporate the near-term variable load forecast and schedule the system resources cost-effectively. Our recent work extends and justifies the joint benefits when taking into account the environmental impacts (emission costs, primarily), intermittent resources, responsive demand resources and uncertainty management as well as security benefits [13, 14, 28-33].

3.1.1 Economic Benefits of Dynamic Look-ahead Dispatch

As is discussed in many valuable existing works [26, 27], one of the major advantages of dynamic look-ahead dispatch is the improvement in economic performance. Figure 13 presents an illustrative example. There is a three bus system with three generators. The wind generator (Wind farm) has a capacity of 80 MW at 3$/MWh marginal cost. The natural gas generator has a capacity of 120 MW at 40$/MWh. The coal generator has a capacity of 150 MW at 30$/MWh marginal cost. The ramping rates for the natural gas unit and for the coal unit are 20 MW/5 mins and 15 MW/5 mins respectively.

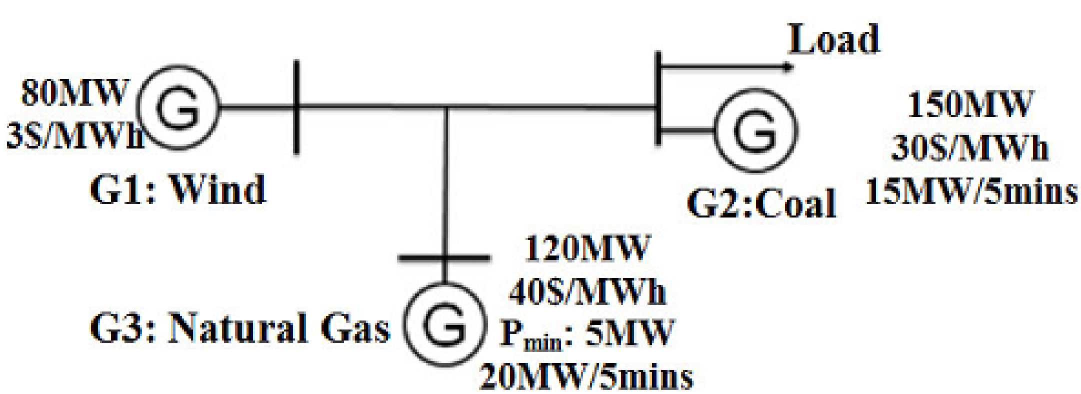

Figure 13 Illustrative example of look-ahead dispatch in economic performance:

In Table 1, it then shows the conventional static dispatch results, when it is applied to this system. For the first time interval, given the wind production potential of 65 MW and load of 110 MW, the coal unit is to be dispatched to 40 MW and the natural gas unit is to be dispatched to only 5 MW because of their marginal costs. However, at the second time interval, wind production potential increase to 80 MW and load decrease to 90 MW. Due to the ramping limit, the coal unit can only go down to 25 MW and the wind farm has to go down to 60 MW, which results in wind curtailment of 20 MW.

Table 1 Illustrative Example: Static Dispatch

	0:00	0:05
Ava. Wind	65MW	80MW
G1	65MW	60MW
G2	40MW	25MW
G3	5MW	5MW
Load	110MW	90MW

However, if the dynamic look-ahead dispatch is applied to this system, the economic benefits will change, as shown in Table 2. For the same first time interval, given the wind production potential of 65 MW and load of 110 MW, despite the low marginal cost, the coal unit is to be dispatched at 20 MW and the natural gas unit is to be dispatched at 25 MW. By doing this, it allows extra room reserved for wind ramping in the next time interval. At the second time interval, wind production potential increase to 80 MW and load decrease to 90 MW. This time the pre-reserved room allows the wind farm to go up to 80 MW and both coal and natural gas units go down to 5 MW. Therefore, the look-ahead dispatch avoids the potential wind curtailment and yields about 10% economic benefit improvement.

Table 2 Illustrative Example: Look-ahead Dispatch

	0:00	0:05
Ava. Wind	65MW	80MW
G1	65MW	**80MW**
G2	20MW	5MW
G3	25MW	5MW
Load	110MW	90MW

3.1.2 Security Benefits of Dynamic Look-ahead Dispatch

Another major advantage of dynamic look-ahead dispatch, besides the improvement in the economic benefits, is the improvement in operational security to the dispatch problem [33]. In Figure 14, an illustrative example is presented.

Figure 14 Illustrative example of look-ahead SCED security improvement

In the illustrative system, there are two power sources: a wind farm with a capacity of 40 MW and a coal power plant with a capacity of 80 MW and a ramping capability of 10 MW/15 minutes. In the illustrative example, to the same scenario, both static SCED and look-ahead SCED are applied, as shown in Table 3 and Table 4, respectively.

Table 3 Illustrative Example: Static Dispatch (Infeasible)

	0:00	0:05
Ava. Wind	35MW	25MW
G1	60MW	70MW
G2	35MW	25MW
Total G	95MW	95MW
Load	95MW	105MW

When the wind generation, under static dispatch, drops from 35 MW to 25 MW and demand increases from 95 MW to 105 MW, the coal power plant cannot ramp up in such a short moment and therefore it results in a loss of load of 10 MW.

Table 4 Illustrative Example: Look-ahead Dispatch (Feasible)

	0:00	0:05
Ava. Wind	35MW	25MW
G1	70MW	**80MW**
G2	25MW	25MW
Total G	95MW	105MW
Load	95MW	105MW

This infeasible issue can be avoided with look-ahead SCED. The change in wind resources and demand will be considered beforehand; although more coal capacity is used instead of inexpensive wind generation in the first interval, the demand can be satisfied by the total generation in the second interval. This example illustrates that, due to the fact that multi-stage is considered within look-ahead SCED, the security of the dispatch with look-ahead SCED improves upon the conventional dispatch approach.

3.2 Look-ahead Dispatch with Inelastic Demand

This section presents the look-ahead dispatch model with inelastic demand. In Figure 15, the conceptual diagram of a look-ahead dispatch with inelastic demand is provided. Different from the conventional static dispatch model, look-ahead dispatch does not only make optimization decision over next step but make an overall optimal decision over a look-ahead window.

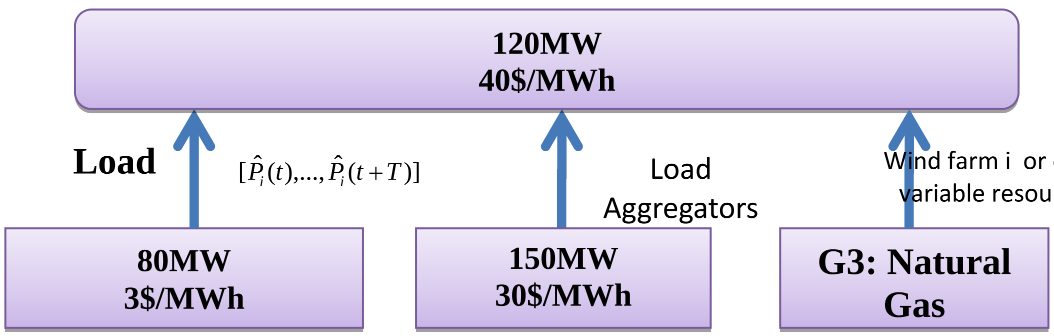

Figure 15 Look-ahead dispatch conceptual diagram

Typical look-ahead windows in look-ahead dispatch can range from 10 minutes to up to 1 hour. The dynamic programming decisions will be made for every step and an optimal plan for the whole horizon. Nevertheless, only the first step decision will be implemented. Before next step decision making, all the input information such as wind generation forecast, load forecast will be updated for the improved quality of decision-making.

$$\min : f = \sum_{k=1}^{T} \sum_{i \in G} C_{G_i}(P_{G_i}^k) \tag{3}$$

Subject to

$$\sum_{i \in G_j} P_{G_i}^k = P_D^k, k = 1 \ldots T, j \in N \tag{4}$$

$$\sum_{i \in G} P_{SU_i}^k .. SU_D^k, k = 1 \ldots T \ \sum_{i \in G} P_{G_i}^k = \sum_{i \in D} P_{D_i}^k, k = 1 \ldots T \tag{5}$$

$$\sum_{i \in G} P_{SD_i}^k \geq SD_D^k, k = 1 \ldots T \tag{6}$$

$$-\mathbf{F}^{\max} \leq \mathbf{F}^k \leq \mathbf{F}^{\max}, k = 1 \ldots T \tag{7}$$

$$-P_{Di}^R \leq \frac{1}{\Delta T}(P_{G_i}^k - P_{G_i}^{k-1}) \leq P_{Ui}^R, i \in G, k = 1 \ldots T \tag{8}$$

$$P_{G_i}^k + P_{SU_i}^k \leq P_{G_i}^{\max}, i \in G, k = 1 \ldots T \tag{9}$$

$$P_{G_i}^k - P_{SD_i}^k \geq P_{G_i}^{\min}, i \in G, k = 1 \ldots T \tag{10}$$

$$P_{G_i}^{\min} \leq P_{G_i}^k \leq P_{G_i}^{\max}, k = 1 \ldots T \tag{11}$$

$$0 \leq P_{SU_i}^k \leq P_{Ui}^R \Delta T, k = 1 \ldots T \tag{12}$$

$$0 \leq P_{SD_i}^k \leq P_{Di}^D \Delta T, k = 1 \ldots T \tag{13}$$

The mathematical formulation of a look-ahead dispatch with inelastic demand are formulated as (3)-(13), where, G is the set of all available generators; $C_{G_i}(P_{G_i})^k$ is the generation cost of generator i; $P_{G_i}^k$ is the output level of generator i at time step k, with $P_{G_i}^{\max}$ and $P_{G_i}^{\min}$ as its upper and lower bounds; $P_{D_i}^k$ is the load level of bus i at time step k; $P_{N_j}^k(\theta)$ is the nodal power injection in bus j at time step k; $\mathbf{F}^k$ is the vector of the branch flow at time step k and $\mathbf{F}^{\max}$ is the vector of the branches' capacity.

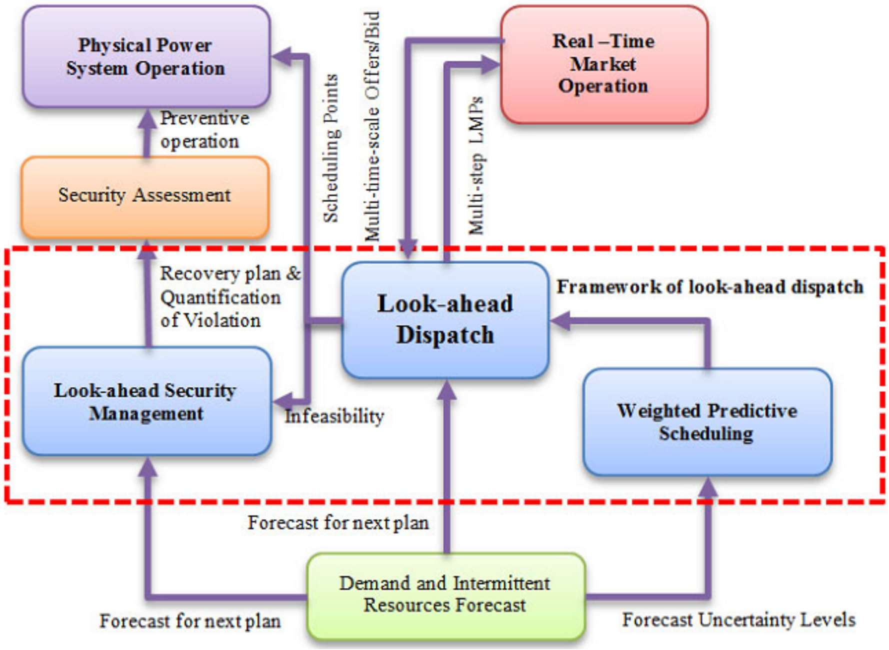

Figure 16 Framework of enhanced look-ahead dispatch

Among the formulation presented above, the objective function (3) is to minimize the total generation cost. Equality constraints (4) are the energy balancing equations. Inequality constraints (5) and (6) are the constraints of upward/downward STDC requirement constraints. The inequality constraints from (7) to (13) are transmission capacity constraints, ramping capability constraints, mixed generator capacity constraints, and the upper and lower bounds of the decision variables, respectively.

3.3 Early Detection and Optimal Corrective Measures of System Insecurity

One of the major advantages of look-ahead economic dispatch is to better utilize available resources to enable a larger feasibility region, as discussed in the previous section. However, due to the uncertainty of the renewable resources and potential contingencies [34], there is always the chances that a feasible dispatch plan which satisfies all security constraints does not exist. We define these situations as infeasibility in look-ahead SCED. The infeasibility is related with insecurity of system operation. It is possible to improve the robustness and security of scheduling operation by handle infeasibility issues appropriately.

In two of our major works [30, 33], we proposed an enhanced look-ahead dispatch framework. Besides the core look-ahead dynamic dispatch functionality, two more modules are introduced into look-ahead dispatch decision-making.

One is the look-ahead security management. It detects the potential security problems for power system operation and works out an optimal recovery plan to help the system avoid the security challenge at minimized cost. The other is the weighted predictive scheduling. It is used to reduce the negative impacts of uncertainty in power system decision making.

3.3.1 Relaxing Variables

We define *Relaxing variables* in previous our paper [33]. *Relaxing variables* are introduced to handle infeasibilities. They are deployed to relax the constraints and make the problem feasible. High penalty terms associated with the relaxing variables are added in the objective function to eliminate the chances that the relaxing variables become alternatives to the original decision variables when the problem is feasible.

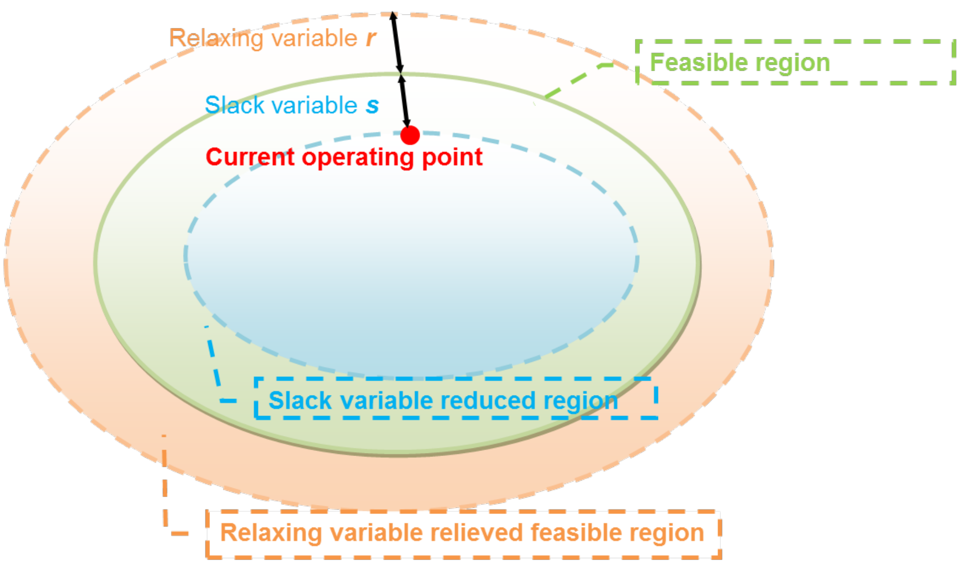

Figure 17 Conceptual illustration of relaxing variables

In Figure 17, the relaxing variables are illustrated by distinguishing them with slack variables. A slack variable characterizes the distance from the current operating point to the boundary of the feasible region, which can ensure that the current operating point is within its feasible region. The relaxing variable *r* at optimality indicates the minimal distance from the current status to the status which gives a feasible solution.

3.3.2 Early Identification of Infeasibility

In an economic dispatch problem, infeasibility is usually related to security issues in the physical power system, which refers to certain violations of the operating constraints (e.g., the overloading of transmission lines, generators' ramping constraints and so on) or to regional or system-wide imbalances between the energy supply and demand. Any of these violations may cause contingencies or blackouts in the power system, and lead to severe consequences.

In power system real-time operations, it is very important to identify potential security problems in advance. The available measures for handling security problems depend on how much time remains for taking the measures. If the security issue is detected one to two hours ahead, a much broader set of corrective measures can be deployed. On the other hand, if the security violation is detected only 10-15 minutes prior to real-time, the number of corrective measures available will be much fewer.

The value of our proposed approach is that this approach implemented in a look-ahead scheduling framework will enable the scheduling framework to identify future security risks.

With the introduction of relaxing variables into security constraints and the problem can be formulated as follows:

$$\sum_{i \in G_j} P_{G_i}^k - P_{D_j}^k + r_{N_j}^k = 0, k = 1 \ldots T, \ j \in N \tag{14}$$

$$-\mathbf{F}^{max} - r_F^k \le \mathbf{F}^k \le \mathbf{F}^{max} + r_F^k, k = 1\ldots T \tag{15}$$

$$-P_i^R - r_{R_i}^k \le \frac{P_{G_i}^k - P_{G_i}^{k-1}}{\Delta T} \le P_i^R + r_{R_i}^k, i \in G \tag{16}$$

$$P_{G_i}^{min} - r_{G_i}^k \le P_{G_i}^k \le P_{G_i}^{max} + r_{G_i}^k, i \in G, k = 1\ldots T \tag{17}$$

$$0 \le P_{SU_i}^k \le P_{Ui}^R \Delta T + r_{SU_i}^k, i \in G, k = 1\ldots T \tag{18}$$

$$0 \le P_{SD_i}^k \le P_{Di}^D \Delta T + r_{SD_i}^k, i \in G, k = 1\ldots T \tag{19}$$

where $r_{N_j}^k$ are the relaxing variables of the nodal energy balance equations, r_F^k are the relaxing variables of the transmission constraints, $r_{R_i}^k$ are the relaxing variables of the ramping constraints, $r_{G_i}^k$ are the relaxing variables of the generator capacity constraints, and $r_{SU_i}^k$, $r_{SU_i}^k$ are the relaxing variables of the upward/downward short-term dispatchable capacity constraints, respectively.

By incorporating the relaxing variables, the objective function of the look-ahead SCED can be formulated as (20).

$$\min f = \sum_{k=k_0}^{T} \sum_{i \in G} C_{G_i}(P_{G_i}^k) + I(r_{N_j}^k, r_F, r_{R_i}, r_{G_i}, r_{SU_i}, r_{SD_i}) \tag{20}$$

$I(.)$ is defined as the identification function of the violated constraints. $I(.)$ is suggested to be modeled as a linear or a quadratic function[2]. The coefficients of the relaxing variables in $I(.)$ indicate the sensitivity of the detection of constraints from various categories (e.g., ramping, transmission capacity). Because infeasibility may be caused by a violation of multiple constraints, the sensitivity of the different constraints must be specified according to the interest of detection. For example, if the system operator is more concerned with (or more interested in) the violation of the energy balance constraint

[2] If $I(.)$ is a linear function, the relaxing variables should be non-negative and then the relaxing variables of bidirectional constraints such as ramping constraints, capacity constraints can be split into two parts which indicate the violations of upward and downward constraints, respectively.

than of the other constraints, the sensitivity $s_j, j \in C_i$ of the constraints in that category C_i should be higher than the sensitivity of the constraints in the other categories $C_l, l \neq i$. A later section will discuss how to find out all the potential factors causing the same infeasible scenario.

$$\eta_j = \frac{\max_i(|\xi_i|)\chi}{s_j^{\gamma_j(k)}}, s_j \in (0,1), \chi \gg \max(|\xi_i|) \tag{21}$$

The coefficients of relaxing variable η_j are given by (21). In (21), $\gamma_j(k)$ is the discrimination degree among the constraints over different time-steps. $\gamma_j(k)$ is the function of time step k, ξ_i is the coefficient of the ith decision variable in the original objective function, and χ is the parameter to differentiate the relaxing variable terms from the original decision variable terms. Therefore, χ is suggested to be a large number (e.g., 10^4).

It is preferred, for a conservative look-ahead strategy, to identify the potential risks in an earlier rather than a later stage. The sensitivity of function $I(.)$ subject to constraints at different stages is suggested to be monotonically decreasing as time step k increases. This is implemented by the discrimination degree $\gamma_j(k)$, which is a function of time step k in a look-ahead plan, as described in (22). In addition, the choice of coefficient ς_j needs to obey (22) in order to guarantee the priority relationship of the various constraint categories at all-time steps (e.g., ramping constraints versus transmission capacity constraints).

$$\gamma_j(k) = \frac{\varsigma_j}{k} + 1, \min_{j \in C_u}(s_j)^{\gamma_j(1)} \ldots \max_{j \in C_v}(s_j), 0 < u < v \tag{22}$$

The linear form of $I(.)$ is presented in (23), where the relaxing variables and the corresponding coefficients are in vector form.

$$I(r) = \eta_{el}^T r_{el} + \eta_E^T r_E + \eta_F^T r_F + \eta_R^T r_R + \eta_G^T r_G \tag{23}$$

If the whole plan is feasible, in look-ahead SCED real-time operations, all the relaxing variables are equal to zero and the optimal solution is the same as for the look-ahead SCED in (23). However, if infeasibility exists, the corresponding relaxing variable will become positive. The value of the relaxing variable indicates how much the violation of that constraint is. With the appropriate configuration of the relaxing variables in (23), the solution of the relaxed problem identifies and quantifies the potential insecurity in the system.

Because of the sophistication of power system operations, sometimes infeasibility can be caused by the violation of multiple constraints belonging to different categories (e.g., ramping rates v.s. transmission constraints). It is helpful to identify all of the potential factors causing the security issues and report the information by category in terms of system operators' prioritized concerns. We propose an enumeration tree approach in the LSM to accomplish this.

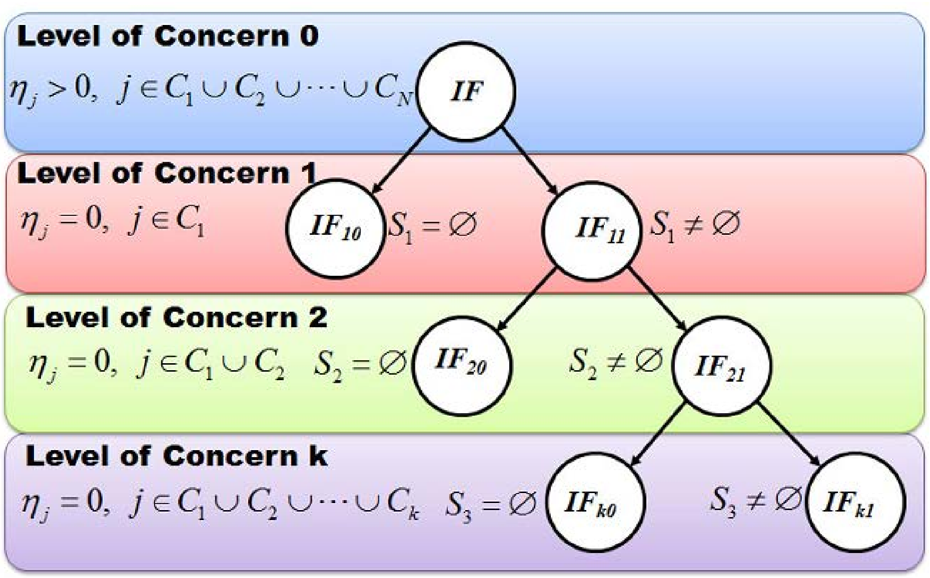

Figure 18 Enumeration tree approach to the identification of multiple factors

We define the security constraint categories set. The sets of security constraint categories $C_j =$ { constraints | belong to security constraint category j } are defined in terms of their priority to the operators' concerns (or interests): C_j has a higher priority to the system operator than C_i , where $0 < j < i$. The algorithm doing the enumeration is described as follows.

STEP 1 (Initialization): Generate the initial full constraint set $C_T = C_1 \bigcup C_2 \bigcup \dots \bigcup C_N$, configure the coefficients of relaxing variable η_i . Go to Step 2.

STEP 2 (Optimization): Solve the infeasibility identification problem (20) subject to (14) -(19). Go to Step 3.

STEP 3 (Termination test): If the feasibility region of the relaxed problem is empty, namely $S_k = \varnothing$, the identification process is terminated. It is reported that the constraints of the category at the current level of concern k do not cause the infeasibility and any constraints with lower priority $\{j \mid j > k\}$ do not cause the infeasibility either. End the program, otherwise go to Step 4.

STEP 4 (Extension): If the feasibility region of the relaxed problem is not empty, namely $S_k \neq \varnothing$, however, all the non-zero relaxing variables do not belong to the category of the current level of concern k . The system operator is to be informed that the constraints of the category at the current level of concern k do not cause the infeasibility and the infeasibility is caused by some lower prioritized constraints $\{j \mid j > k\}$. Go to Step 6, otherwise, go to Step 5.

STEP 5 (Selection): The system operator is going to be reported the constraints with non-zero relaxing variables which are responsible to the infeasibility. Go to Step 6.

STEP 6 (Configuration): Set the coefficients of all the constraints which belong to the category of the current level of concern k to zero, namely $\eta_j = 0, j \in C_k$. Move to the next level $k = k+1$. Go back to Step 2.

For illustrative purpose, the whole process is depicted in Figure 18. By means of this process, the system operators will be informed of not only the factors about which they care the most but also of all the other potential factors causing this infeasibility, ranked in the order of their prioritized concerns.

3.3.3 Optimal Corrective Solution

By facilitating the concept of relaxing variable, the optimal corrective solution can be worked out at a minimal operating cost when system operations are infeasible.

$$R_M = \{r_{M_i} \mid \text{available measures for system recovery}\} \tag{24}$$

In power system operation, there are various corrective measures which can help the system recover from infeasibility (e.g., spinning reserve, non-spinning reserve, responsive demand, the fast-response unit, and tie-line support). Different corrective measures have different response speeds and operating costs. Generally, fast resources are more valuable (and expensive) than slow resources. Each corrective measure can be represented by a relaxing variable r_{M_i}. The set of all the available measures for system recovery is represented by R_M in (24).

$$\min f_R = f + R(r_M) \tag{25}$$

The objective function of the optimal corrective solution can be modified from the original objective function (3) to the objective function of (25). $R(r)$ is the recovery cost function, which can be defined as a linear function of the relaxing variables r_M. Sometimes, there might be a non-linear relationship between the cost and capacity of the corrective measures. It is suggested to use a linear step-wise model to formulate this relationship for the sake of algorithm efficiency and simplicity. The coefficients of $R(r)$ are given by the marginal operating cost of the various corrective measures.

$$g(x)+r_M..0, r, r_M..0 \tag{26}$$

In the relaxed problem, the security constraints are formulated as (26). The original constraints $g(x)$ may be impacted by some corrective measures and thus get relaxed. r_M are the relaxing variables of the corrective measures. By solving this problem, an optimal corrective plan is worked out, which can recover the system from infeasibility at the lowest operating cost.

Due to the various conditions of various power systems, it should be noted that the mathematical model should be modified according to the practical circumstances of the power system. The introduction of relaxing variables is suggested to take into account the results of the infeasibility identification in terms of the time steps and areas impacted by the infeasibility as well as by the degree of the violation.

3.4 Look-ahead Dispatch with Price Responsive Demand

This section discusses the modeling of look-ahead dispatch with price responsive demand. As the demand elasticity comes into the picture, the modeling of the economic dispatch changes. In Figure 19, the dispatch system will handle both offers from the supply side and the bids from the demand side.

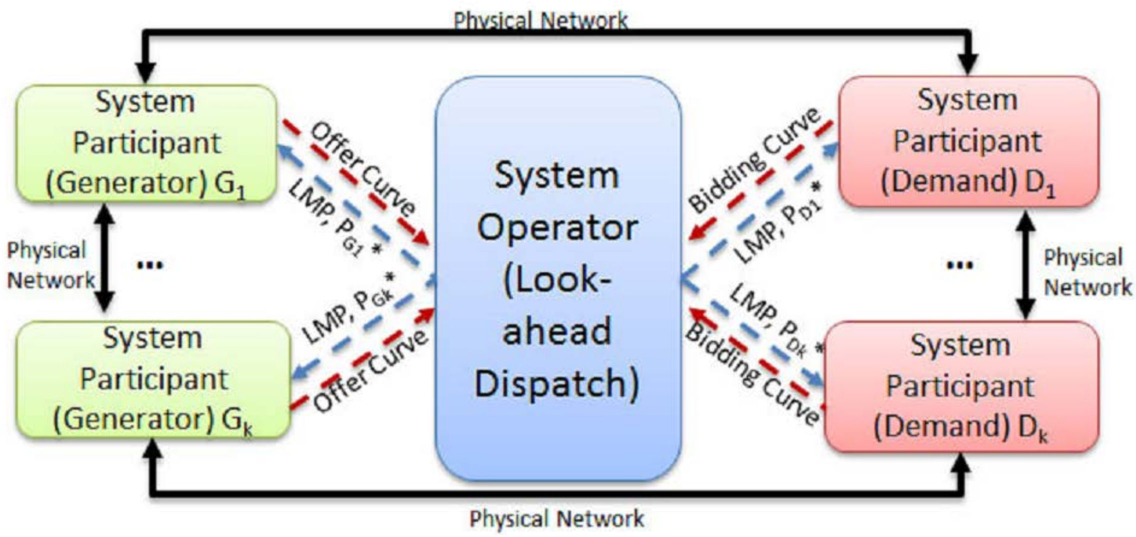

Figure 19 Information exchange for look-ahead dispatch with price-responsive demand

For a look-ahead dispatch with price responsive demand, the every-step dispatch decision will be made upon overall optimal benefit for the look-ahead horizon which considers the generation cost and demand benefits (in modern electricity market, these factors represent themselves in terms of bids.). For each time step, only the first step decision will be implemented in the real operation and the forecast of all the resources in the rest of the plan will be updated for next-step decision-making.

$$\max : f = \sum_{k=1}^{T}\left[\sum_{i\in D} B_{D_i}(P_{D_i}^k) - \sum_{i\in G} C_{G_i}(P_{G_i}^k)\right] \tag{27}$$

Subject to

$$\sum_{i\in G} P_{G_i}^k = \sum_{i\in D} P_{D_i}^k + P_L^k, k = 1\ldots T \tag{28}$$

$$\sum_{i\in G} P_{SU_i}^k \le SU_D^k, k = 1\ldots T \tag{29}$$

$$\sum_{i\in G} P_{SD_i}^k \le SD_D^k, k = 1\ldots T \tag{30}$$

$$-\mathbf{F}^{\max} \le \mathbf{F}^k \le \mathbf{F}^{\max}, k = 1\ldots T \tag{31}$$

$$-P^{R}_{Di} \le \frac{1}{\Delta T}(P^{k}_{G_i} - P^{k-1}_{G_i}) \le P^{R}_{Ui}, i \in G, k = 1\ldots T \tag{32}$$

$$P^{k}_{G_i} + P^{k}_{SU_i} \le P^{\max}_{G_i}, i \in G, k = 1\ldots T \tag{33}$$

$$P^{k}_{G_i} - P^{k}_{SD_i} \ge P^{\min}_{G_i}, i \in G, k = 1\ldots T \tag{34}$$

$$P^{\min}_{G_i} \le P^{k}_{G_i} \le P^{\max}_{G_i}, k = 1\ldots T \tag{35}$$

$$P^{\min}_{D_i} \le P^{k}_{D_i} \le P^{\max}_{D_i}, k = 1\ldots T \tag{36}$$

$$0 \le P^{k}_{SU_i} \le P^{R}_{Ui}\Delta T, k = 1\ldots T \tag{37}$$

$$0 \le P^{k}_{SD_i} \le P^{D}_{Di}\Delta T, k = 1\ldots T \tag{38}$$

The mathematical formulation of a look-ahead dispatch with inelastic demand are formulated as (27)-(38), where, G is the set of all available generators; $C_{G_i}(P_{G_i})^k$ is the generation cost of generator i; $P^k_{G_i}$ is the output level of generator i at time step k, with $P^{\max}_{G_i}$ and $P^{\min}_{G_i}$ as its upper and lower bounds; D is the set of all price responsive demand, $B_{Di}(P^k_{D_i})$ is the benefit of price responsive demand i, $P^k_{D_i}$ is the dispatched demand level of bus i at time step k; P^k_L is the inelastic portion of the demand at time step k; $\mathbf{F}^k$ is the vector of the branch flow at time step k and $\mathbf{F}^{\max}$ is the vector of the branches' capacity.

The objective function (27) is to minimize the total generation cost. Equality constraints (28) are the energy balancing equations. Inequality constraints (29) and (30) are the constraints of upward/downward STDC requirement constraints. The inequality constraints from (30) to (38) are transmission capacity constraints, ramping capability constraints, mixed generator capacity constraints, and the upper and lower bounds of the decision variables, respectively.

4. Application of Look-ahead Dispatch with Price Responsive Demand

We implement the look-ahead dispatch in a real-scale power system to quantify and evaluate the benefits of advanced dispatch model with price responsive demand. This chapter presents the real-scale system setup and provides the analysis and discussion for the numerical experiments.

4.1 Real-scale Power System Setup

The benchmark system we used in this project is the ERCOT system (2011 planning case). ERCOT covers 85% of Texas load supporting 23 million consumers in Texas. In the ERCOT system, there are 40,530 circuit miles of high-voltage transmission lines, 550 generating units. The peak demand last summer was 68, 305 MW. The total installed capacity is 74,000 MW. Total energy consumption in 2012 was 324 billion kilowatt-hours. The market size of ERCOT is about $34 billion USD.

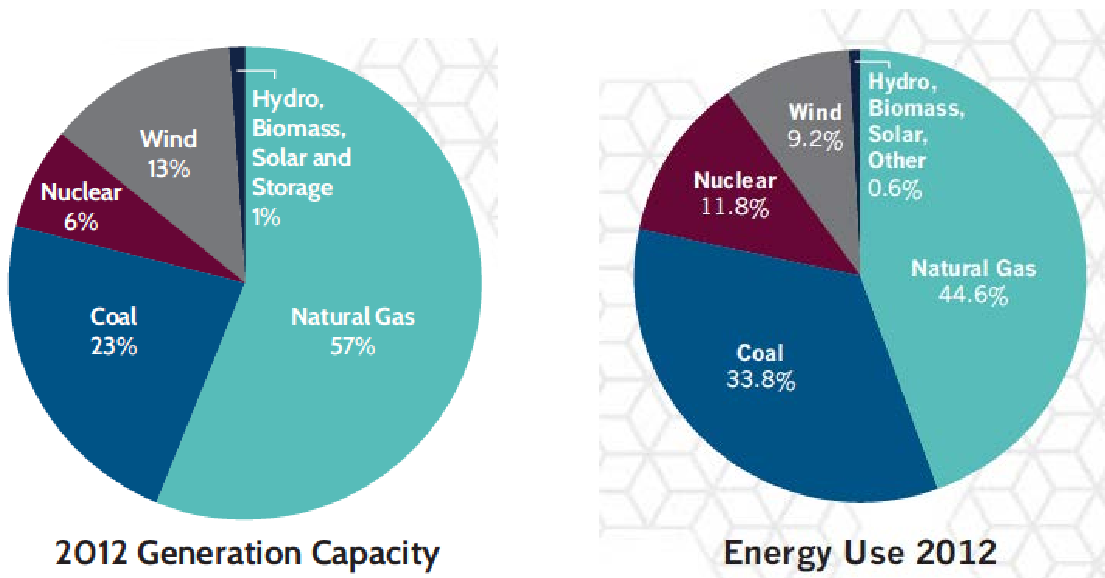

Figure 20 ERCOT quick facts 2012

The generation portfolio in ERCOT is presented in Figure 20. The major power sources in ERCOT are natural gas units and coal units. However, ERCOT is leading in wind generation penetration in US for 13% installed capacity. For the energy usage, natural gas generation counts for 45%, coal generation counts for 34%, nuclear generation counts for 12% and wind generation counts for 9%. The rest (less than 1%) includes solar, biomass, hydro etc.

4.2 Numerical Experiments and Results Analysis

For the benchmark system, it is necessary to use published market information to verify its effectiveness. To accomplish this, we developed and conducted a static dispatch in the benchmark system and compare the dispatch results with the published dispatch results. The comparison is presented in Figure 21. As is observed, for most of the major units, the dispatch levels are fairly close to each other, which justify the effectiveness of our benchmark system.

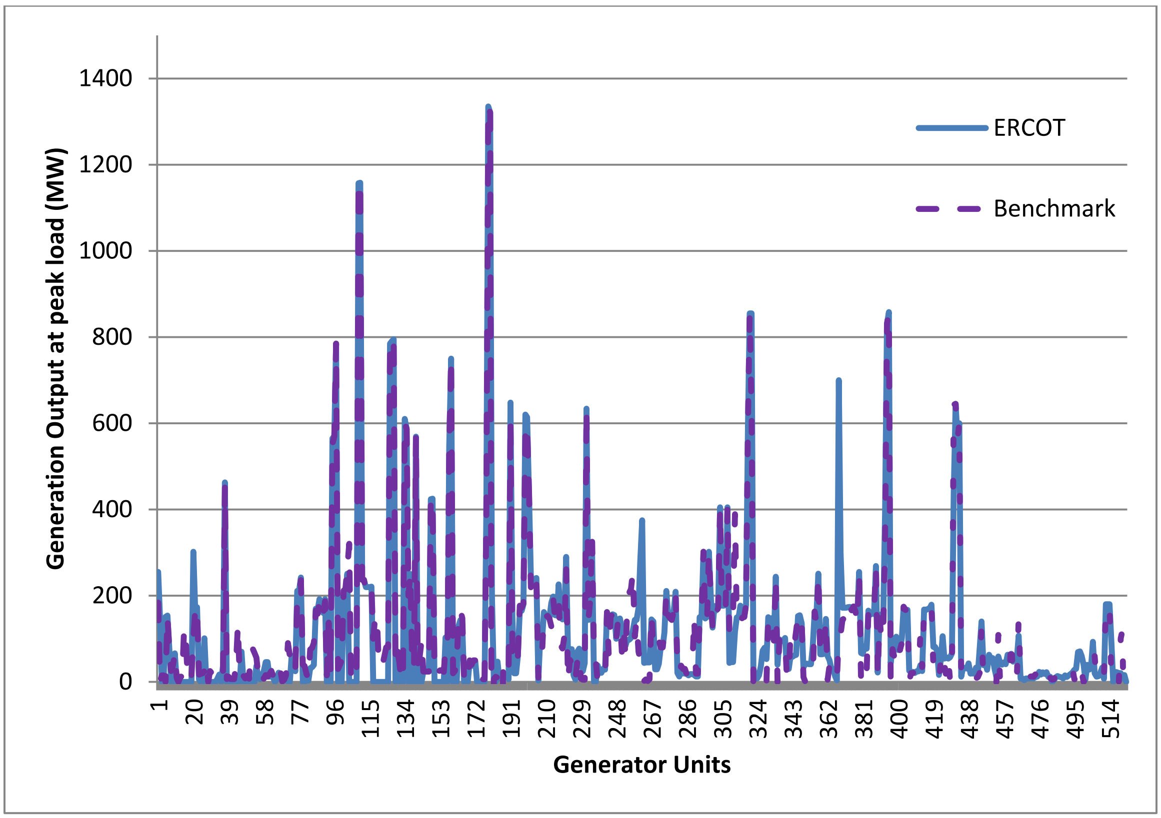

Figure 21 Generation output during peak load time

Before introducing the price responsive demand, preliminary study by comparing the economic performance between the conventional static dispatch and look-ahead dispatch is conducted. The comparison results are provided in Table 5.

Table 5 Comparison of Two Dispatch Methods for a Typical Day (Jul 11, 2009)

Period	Benchmark SCED	Look-ahead (30 min)	Difference
Entire Day Cost	$ 26,191,710	$ 26,144,585	$ 47,125
Early Morning Cost	$ 3,514,925	$ 3,506,689	$ 8,326
Peak Wind Period Cost	$ 1,226,447	$ 1,219,948	$ 6,499
Wind Generation	96,071 MWh	96,432 MWh	361 MWh

As we can see from Table 5, the look-ahead dispatch enables a higher overall total economic benefit. The advantage is even more obvious during peak wind period. In addition, by adopting the look-ahead dispatch, the wind generation (wind resource utilization) also increases and avoids some of the wind curtailment.

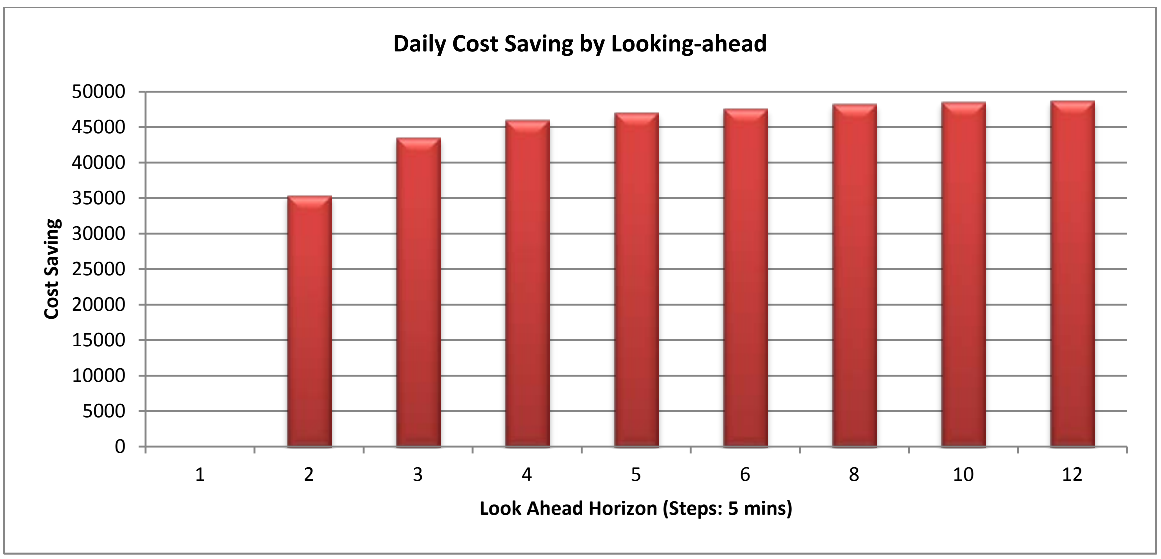

Figure 22 Look-ahead horizon response of total savings

For look-ahead economic dispatch, look-ahead horizon is a key parameter which impacts the final yielded benefit improvement as well as required computation efforts. The total savings under various look-ahead horizons are presented in Figure 22. As we can see, the longer look-ahead horizon results in higher economic benefits (assume there is no forecast inaccuracy considered). It also needs to be noted that there is a clear pattern of benefit saturation. After a certain length of the look-ahead horizon, the additional benefits by extending the horizon is very limited.

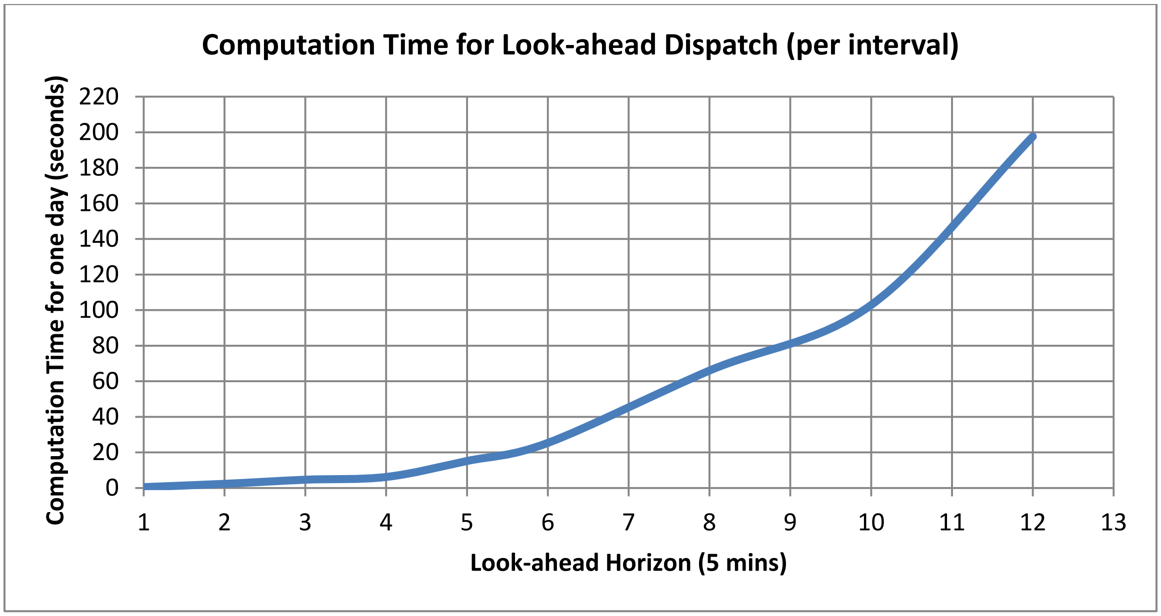

Figure 23 Comparison of computation efforts for different look-ahead horizons

Computation efforts are another key factor which needs to be considered when implementing the look-ahead dispatch, especially in real-time markets. The comparison of such impacts is depicted in Figure 23. Looking at the curve, we can learn that the longer look-ahead horizon causes more computation power. In correlation to Figure 22, we suggest there is an optimal selection of the look-ahead horizon which gives a good tradeoff between the benefits improvement and computational efforts.

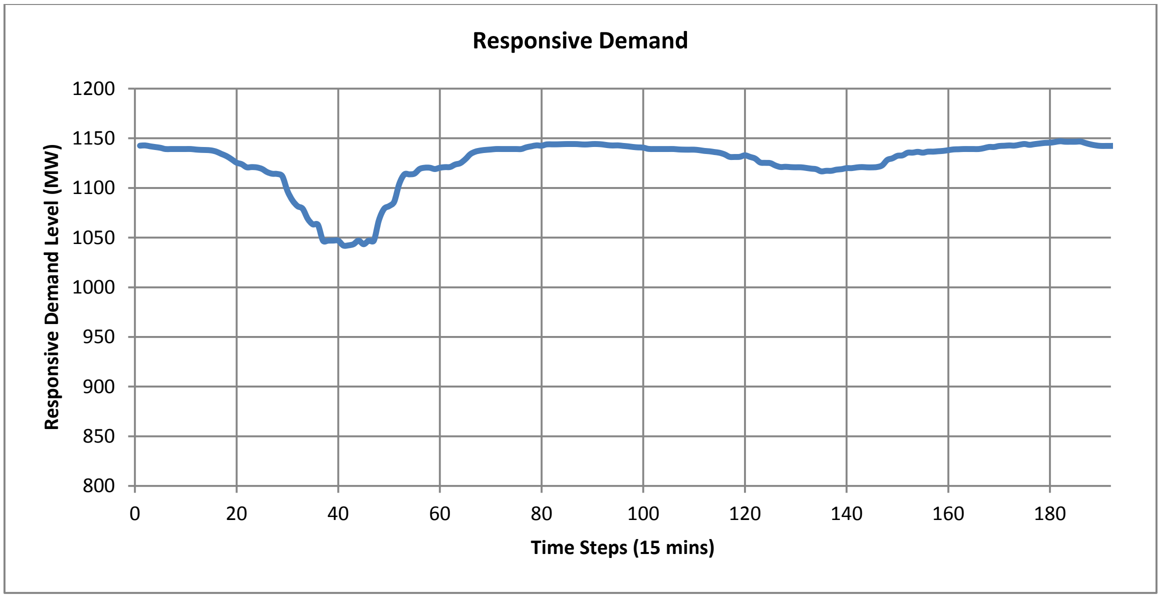

Figure 24 Price responsive demand: model behavior

The next part of this section evaluates the benefits of look-ahead dispatch with price responsive demand. Figure 24 and Figure 25 present the basic demand response under given pricing signal. Provided the pricing signal in Figure 25, the price responsive demand behavior is shown in Figure 24.

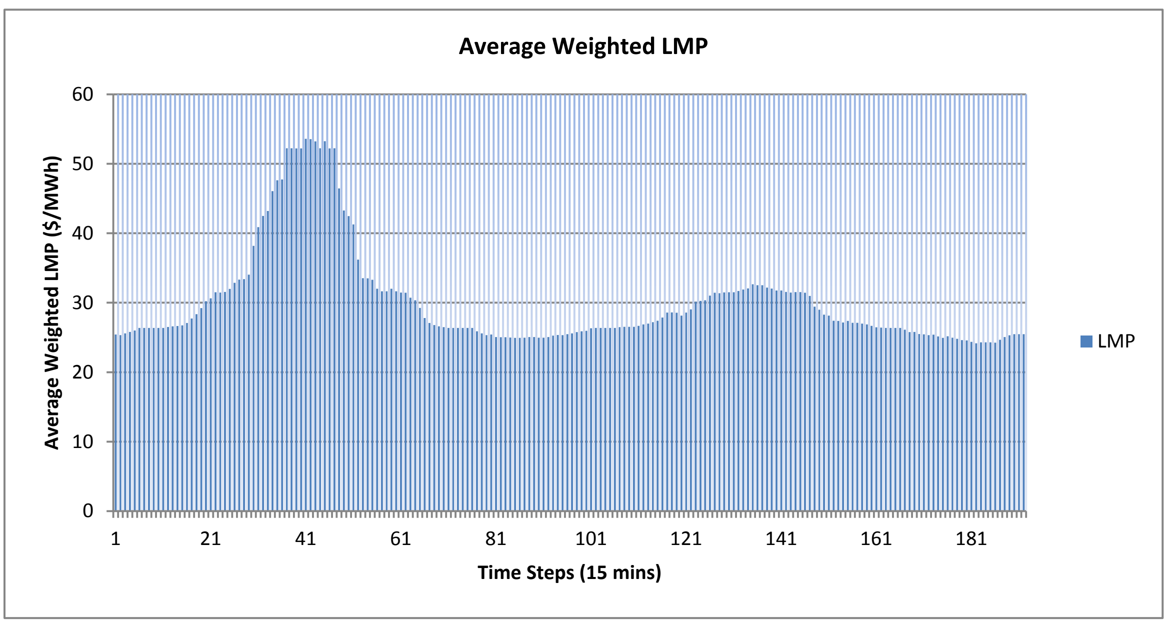

Figure 25 Price responsive demand: LMP pattern

As we can see from Figure 24, when the price goes high, the demand will drop and when the price goes low, the demand will increase.

Table 6 Economic Benefits: Elastic versus Inelastic Case

	Elastic Case (Million Dollars)	Inelastic Case (Million Dollars)	Ratio (%)
Overall Social Welfare	$ 17,122.67	$ 15,921.61	7.54%
Generation Revenue	$ 6,320.84	$ 6,251.17	1.11%
Generation Cost	$ 4,816.62	$ 4,808.72	0.16%
Generation Surplus	$ 1,504.22	$ 1,442.44	4.28%
Inelastic Demand Expenditure	$ 7,127.66	$ 7,280.06	-2.09%
Elastic Demand Benefit	$ 2,539.95	$ -	-
Inelastic Demand Benefit	$ 20,671.27	$ 21,759.23	-5.00%
Elastic Demand Expenditure	$ 465.11	$ -	-
Total Demand Surplus	$ 15,618.45	$ 14,479.17	7.87%

Then we introduce the price responsive demand into the look-ahead dispatch model. The comparison of economic benefits between look-ahead dispatch and static dispatch is presented in Table 6. As we can see from Table 6, by incorporating the look-ahead dispatch, both parties in the market can get more benefits. On generators side, the generation profit has increased by about 4%. On demand side, the total demand surplus has increased by about 8%. Overall social welfare has increased by about 7.5%.

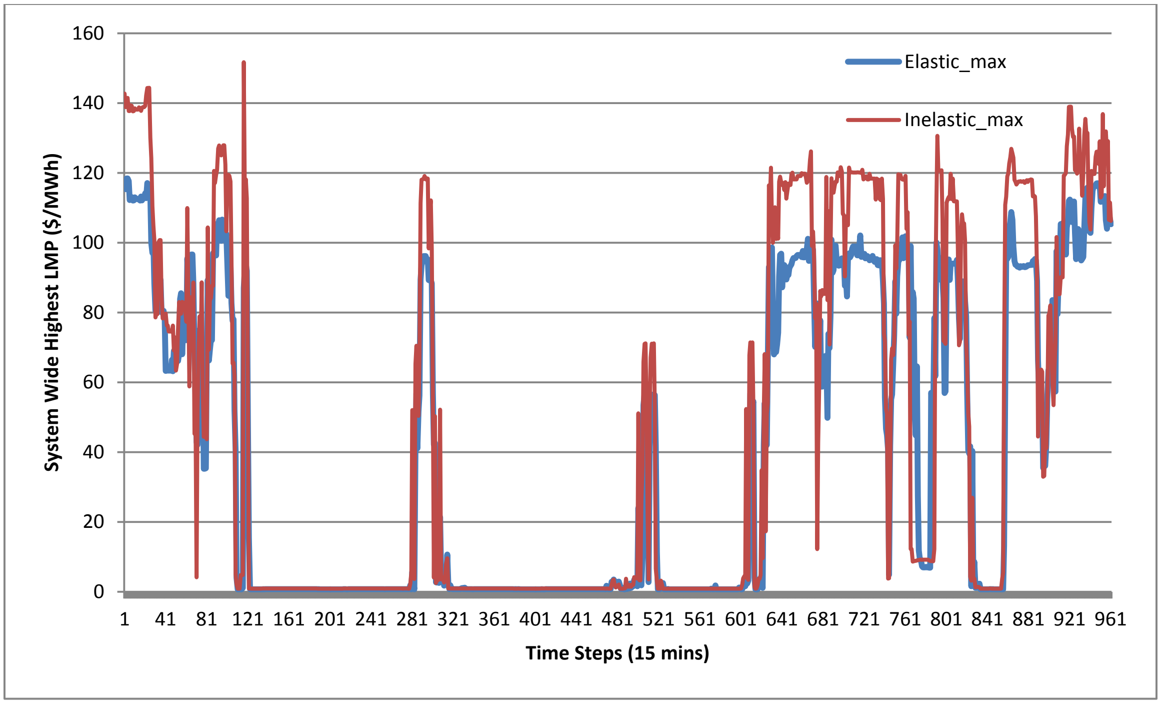

Figure 26 Market behavior: system-wide highest LMPs

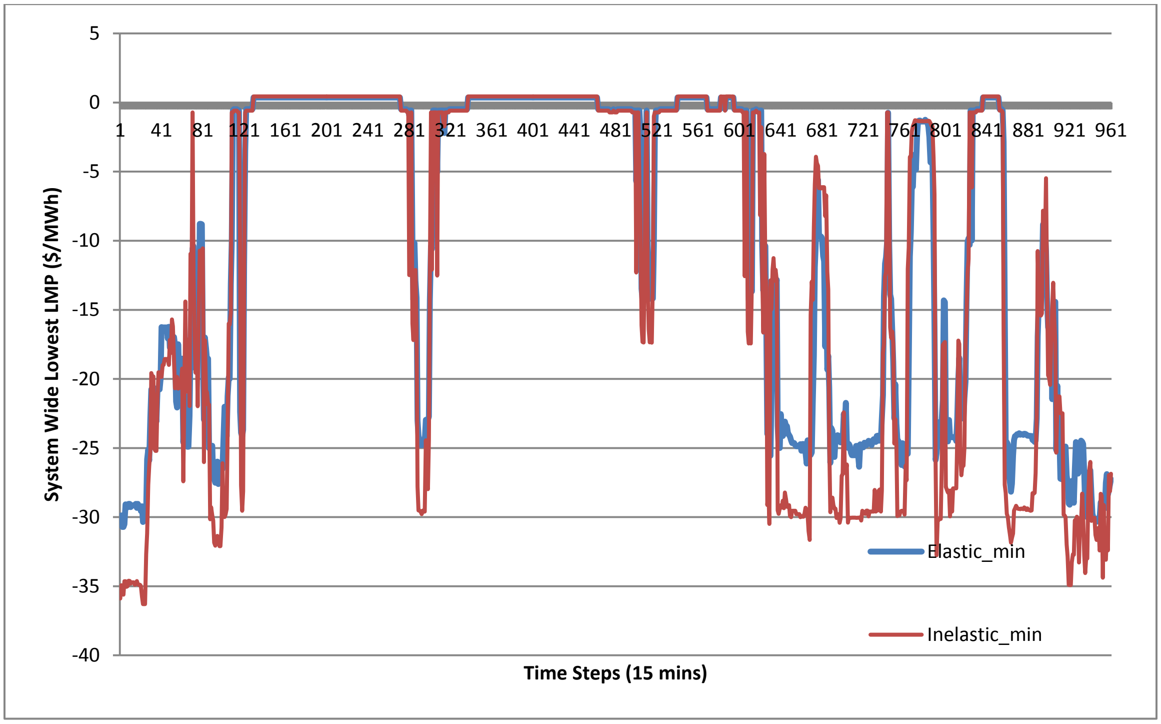

Figure 27 Market behavior: system-wide lowest LMPs

Besides the economic benefits, the impact of look-ahead dispatch and price responsive demand on price behavior also requires careful investigation. Figure 26 and Figure 27 present the system-wide highest and lowest LMP patterns, respectively. As we can see, by incorporating the look-ahead dispatch with price responsive demand, the temporal price volatility is reduced. This observation is also confirmed by conducting the whole statistical analysis as shown in Table 7.

Table 7 Standard Deviation of the LMPs: Impacts due to Demand Elasticity

	Elastic	Inelastic	Difference
Temporal LMP STD	63, 098	72, 567	13.05%
Spatial LMP STD	985, 466	1, 103, 669	10.71%

As provided in Table 7, the standard deviation of look-ahead dispatch with price responsive demand is 13% lower than the static dispatch with inelastic demand temporally (over the whole year). Similarly, the standard deviation of look-ahead dispatch with price responsive demand is 10% lower than the static dispatch with inelastic demand spatially (over the whole system).

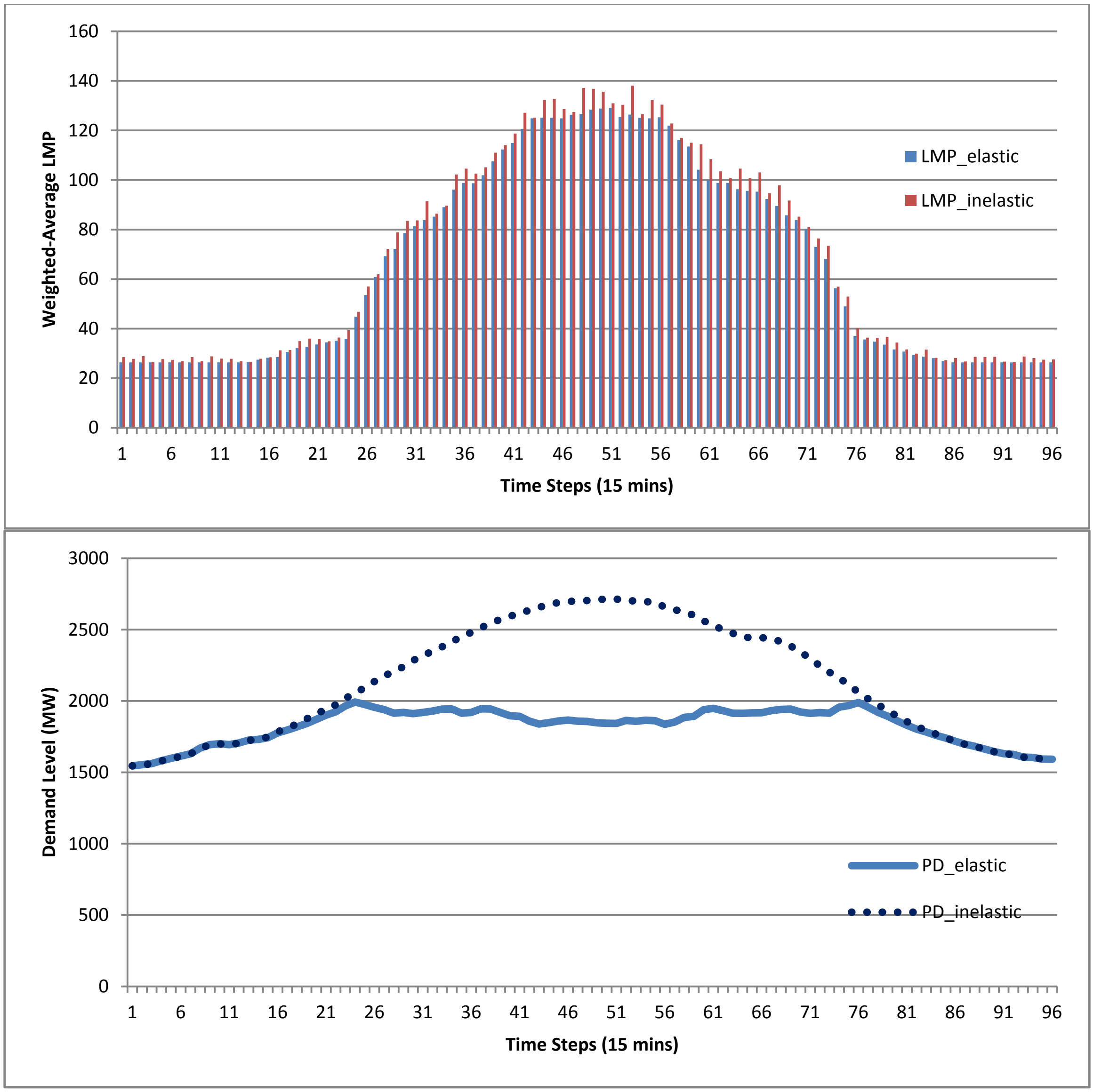

Figure 28 Price responsive demand behavior: summer case

In Figure 28, a typical high demand (one of the summer day) demand is selected to see the behavior of price responsive demand. As we can observe, the look-ahead dispatch with price responsive demand can successfully reduce the peak load and peak price during the noon time.

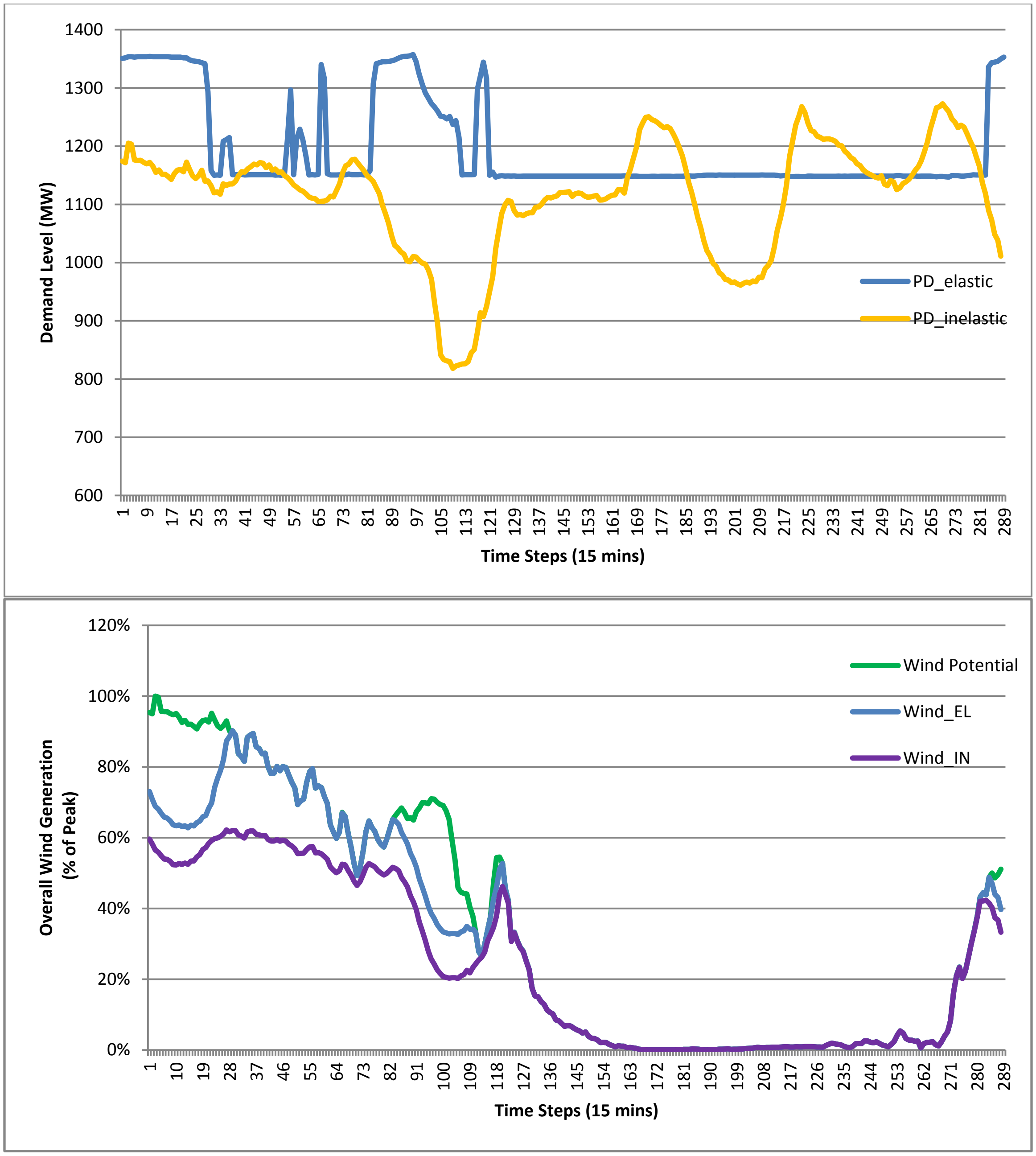

Figure 29 Price responsive demand behavior: high wind case

Another important scenario of interest is the high wind scenario. As is presented in Figure 29, the look-ahead dispatch with price responsive demand can effectively increase the wind generation utilization, and reduces the wind generation curtailment.

5. Conclusions

This project conducts first-of-its-kind empirical study quantifying the benefits of combining look-ahead dynamic dispatch with price responsive demands for integration of variable energy resources.

Based on substation level demand response data and site-specific wind generation data from ERCOT, this project developed algorithms and a case study to quantify: (i) The price elasticity of demand for typical users, and (ii) the economic benefit of look -ahead dispatch with price responsive loads. The benefits include not only improved social welfare, but also reduced wind curtailment and smoothed price behavior. While the study is based on a particular system, the methodologies are generalizable towards other regions as well.

This empirical study opens the door to many future research questions. While the observation from this project suggests that look-ahead dispatch reduces the price volatility in the real-time markets, it remains further investigation to fully understand the fundamental coupling among look-ahead, elastic demand, and price volatility. The econometric estimation of price elasticity is based on classical econometric methods; however, it will be important to recognize the context of different loads in order to gain better models of price responsive loads with temporal shifts. How to reconcile tradeoff of physics-based load modeling and data-driven load modeling in markets with time-varying prices still remains an open challenging question. Last but not least, future work will investigate other alternative demand response programs such as coupon incentive-based DR to harness flexibility from various categories of loads in the smart grid.

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