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Impact of Demand Response on Thermal Generation Investment with High Wind Penetration

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Keywords

demand response, electricity markets, generation capacity investment, wind energy

Disciplines

Industrial Engineering | Systems Engineering

Comments

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Impact of Demand Response on Thermal Generation Investment with High Wind Penetration

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Abstract—We present a stochastic programming model for investments in thermal generation capacity to study the impact of demand response (DR) at high wind penetration levels. The investment model combines continuous operational constraints and wind scenarios to represent the implications of wind variability and uncertainty at the operational level. DR is represented in terms of linear price-responsive demand functions. A numerical case study based on load and wind profiles of Illinois is constructed with 20 candidate generating units of various types. Numerical results show the impact of DR on both investment and operational decisions. We also propose a model in which DR provides operating reserves and discuss its impact on lowering the total capacity needed in the system. We observe that a relatively small amount of DR capacity is sufficient to enhance the system reliability. When compared to the case with no DR, a modest level of DR results in less wind curtailment and better satisfaction of reserve requirements, as well as improvements in both the social surplus and generator utilization, as measured by capacity factors.

Index Terms—Generation Capacity Investment, Wind Energy, Demand Response, Electricity Markets.

NOTATION

A. Sets

H	set of diurnal hour types, indexed by h
I	set of candidate thermal generators, indexed by i
K	set of days in the study period, indexed by k
L	set of load seasons, indexed by l

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M	set of thermal technologies, indexed by m
S^l	set of scenarios in load season l , indexed by s
T^l	set of hours in load season l , indexed by t
T^k	set of hours in a day k , indexed by t
T^h	set of hours of type h , indexed by t
Y^m	set of candidate units of thermal technology m , indexed by i

B. Binary Decision Variables

u_i	set to 1 if candidate thermal generator i is built, 0 otherwise
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C. Continuous Decision Variables

$d_{t,s}$	demand, in hour t , under scenario s , MW
$ens_{t,s}$	energy not served, in hour t , under scenario s , MWh
$g_{i,t,s}$	generation output of generator i in hour t under scenario s , MWh
$r_{i,t,s}$	operating reserve provided by generator i , in hour t , under scenario s , MW
$rns_{t,s}$	reserve not served, in hour t , under scenario s , MW
$wc_{t,s}$	wind curtailment, in hour t , under scenario s , MWh
$wg_{t,s}$	wind output, in hour t , under scenario s , MWh

D. Parameters

a_t	intercept for inverse demand function, \$/MW
b_t	slope for inverse demand function, \$/MW/MW
c_i	generation cost for generator i , \$/MWh
c^{ens}	energy not served cost, \$/MWh
c^{rns}	reserve not served cost, \$/MW
d_t^0	benchmark load in hour t , MW
d_{peak}	peak load over all load seasons, MW
DR_{per}	DR capacity as a percentage of peak load
DRR_{per}	percentage of operating reserves to which the DR capacity can contribute
$drr_{t,s}$	amount of reserve from the DR capacity, in hour t , under scenario s , MW
F_i	annual fixed O&M cost for generator i , \$/year
inv_i	annualized investment cost for generator i , \$/MW/year
$MAXSP_i$	maximum operating reserve for generator i
$MaxDec_i$	ramp down limit for generator i , MW/hr
$MxInc_i$	ramp up limit for generator i , MW/hr
\bar{P}_i	maximum power output for generator i , MW
P_s	probability of scenario s
RM	reserve margin for load, MW

$\overline{W}_{t,s}$	available wind power, in hour t , under scenario s , MW
$WR_{t,s}$	reserve margin for wind, in hour t , under scenario s
θ_l	number of weeks in load season l

I. INTRODUCTION

ENVIRONMENTAL concerns and higher costs of fossil fuels are receiving considerable attention. Governments are making efforts towards energy efficiency, renewable energy and load management to establish a more efficient and clean power system. In the United States, government policies regarding energy efficiency and renewable energy provide incentives for installation of smart home and building technologies, energy savings solutions for both industrial and commercial sectors, and renewable energy [1]. Different levels of energy efficiency resource standards (EERS) and renewable portfolio standards (RPS) are implemented in different states [2].

Wind energy may serve at least 20% of the total electricity generation of the United States by 2030 [3]. Clean energy with zero fuel cost will bring both economic and environmental benefits. However, unlike traditional thermal units, wind generation fluctuates depending on weather conditions, and can exhibit large variations from hour to hour. The uncertainty and variability from wind power must be taken into account in the power generation capacity investment problem. Towards this end, we propose a centralized generation investment model that considers wind power as the only uncertainty, and includes continuous operational constraints; e.g., ramp up/down constraints of thermal generators, to achieve a tradeoff between accuracy of modeling operational decisions and computational complexity of dealing with the binary variables to express more detailed unit commitment constraints.

Demand response (DR) programs add demand-side flexibility to the power system, which can help accommodate the supply-side uncertainty and variability, which are increased by wind power. DR programs and the market rules of different independent system operators (ISOs) or regional transmission organizations (RTOs) are summarized in [4]. In the PJM market, DR can be either economic and respond to electricity prices, or emergency-based in response to grid reliability events. Usually, an emergency DR program registration induces a mandatory commitment while an economic DR program is voluntary [5]. In PJM, economic DR programs pay the DR participants the spot price for the amount of load curtailed. DR participants anticipate the price and offer their load curtailment supply function as a bid into the day-ahead or real-time market. The trigger LMP is set to \$75/MWh [6]. Besides, DR in the PJM market is also allowed to participate in the synchronized reserve market but limited to contribute a maximum of 25% of total reserves required in each reserve zone for reliability concerns [7]. The evolution and current status of emergency, economic, and ancillary

services based on DR programs with different objectives in PJM and NYISO were discussed in [8]. An empirical study summarizes the current existing DR resources in the United States, which can potentially contribute to a peak load reduction of 10% [9]. The benefits of incorporating the DR program include peak load reduction, less price volatility, and higher capacity factors of baseload units. In our paper, we use demand elasticity to represent the demand bids in the market, under the assumption that the demand bids reflect the underlying price elasticity. Hence, DR is modeled as an aggregated price-responsive demand from the system.

We investigate how price-responsive demand influences the optimal investment decisions and the ability to integrate wind power into the system. In our investment model, the wind penetration is modeled as an external factor that is enforced by energy policy incentives such as renewable portfolio standards (RPS). The DR capacity levels are also considered as model inputs which can as well be determined by government policy and incentives; e.g. energy efficiency resource standards (EERS). With a high wind penetration level, additional operating reserves are required to deal with the wind forecast error in real-time operation, and the required reserve amounts are varied depending on different wind power levels.

Besides DR programs, other facilities such as hydro pumped storage, hydrogen storage, distributed generators, and electric vehicle batteries can also contribute to the load flexibility. In this paper, we focus on the capacity impact of the DR programs. Similar impacts are expected to result from the other facilities. However, the investigations of those impacts are beyond the scope of our paper.

Generally speaking, a generation investment model has a long term planning horizon, and separate generation companies make their own decentralized investment decisions in deregulated electricity markets. In this paper, our goal is to examine the wind's impact on the system and explore how DR can help cope with the wind's variability. Therefore, we do not model the market interactions between decision makers and the dynamic aspects of expansion planning. Instead, we formulate a one-period static centralized generation investment model. Under certain assumptions, the results could still be interpreted as what a perfectly competitive market would yield. We also do not consider impacts of the transmission and distribution network constraints. Congestion could lead to more curtailment of renewable and more diversity in prices, which could increase the impact of DR; thus, the results of our model may understate the effects of price-responsiveness in demand.

The contributions of this paper are threefold: (1) We present a stochastic generation capacity investment model with wind uncertainties at different DR capacity levels. (2) We discuss DR's impact on the optimal investment and operational decisions, and conclude that a relatively small amount of DR capacity can benefit the system. We find that as DR capacity increases, the marginal benefit is reduced or will no longer exist. (3) We propose a model that can treat DR as both a price responsive demand and as a resource for the reserve market, and compare its results with the ones in which DR is modeled

only as a price responsive demand in the energy market.

This paper has the following structure. A literature review is provided in Section II. In Section III, we present the generation capacity investment model. Sections IV and V, respectively, describe a case study of a wind-thermal test power system with wind and load data from Illinois, and discuss detailed observations of numerical results. Finally, we summarize conclusions in Section VI.

II. LITERATURE REVIEW

An accurate wind power representation is essential for the unit commitment (UC) problem, where all the physical constraints of the thermal units must be taken into account. Several stochastic UC models have been proposed to address wind power uncertainty in operational decisions [10] [11]. For capacity expansion, previous work includes a generation expansion problem with wind integration investigated in [12], where UC of four typical weeks and an extreme winter week is combined with a generation expansion decision to capture the load and wind variation over a year. Incorporation of UC constraints into a generation expansion model with wind power was discussed in [13]. A group commitment decision variable was proposed to reduce computation time and a numerical study for a full year (8760 hours) was conducted. The hourly wind profile was formulated as negative load and no renewable energy curtailment was considered in [12] [13].

For operational analysis, a UC model with real time DR, formulated as a linear price sensitive demand bidding function, was solved as a mixed integer quadratic programming problem in [14]. In [15], a new centralized market clearing mechanism with complex bids was developed to model the characteristics of a price sensitive demand function with consideration of load shifting. In [16], a UC problem with integration of wind energy and DR was modeled as a linear function with different levels of elasticity. A review of empirical studies of the long- and short-term price elasticity of demand for electricity was summarized and a framework was proposed in [17] to evaluate the real-time elasticity, which turned out to be relatively low, compared to the other empirical studies. An even lower elasticity was observed from their own empirical study. A new demand response bidding mechanism was proposed in [18] based on a price elasticity matrix to account for different inter-hour DR shifting patterns so that the DR participation can be better handled by the smart grid and result in increased market efficiency. Both own- and cross-elasticities were derived based on eight years of real-time rating experience for different types of industrial consumers [19]. Demand response was modeled in appliance-level details from both a system perspective and strategic consumers' points of view, in which the consumers were assumed as either price takers or oligopolistic players in determining their demand responses to the market [20]. A real-time demand response model to maximize consumer's utility function in 24 hours of a day was presented in [21]. The benefits of real-time pricing were also demonstrated [22] [23] in facilitating wind integration, decrease in loss of load event,

and increased social surplus.

Further research investigated DR's impact on capacity investment decisions. The capacity impacts of demand response were discussed in [24], which concluded that although more flexible DR programs can improve the decreasing returns of scale in capacity value, excessive amounts of DR also possess decreasing returns to scale. In [25], the authors integrated the DR programs into three expansion models with wind power, and both the own- and cross-elasticities of DR were considered. The impact of energy efficiency on the optimal generation mix and the optimal wind penetration level was also discussed.

The capacity investment model in our paper accounts for the wind uncertainty and conducts scenario reduction to select representative wind profiles to represent this uncertainty. Continuous operating constraints are also included in the model to capture the impact on the system of increasing net demand variability caused by high wind penetration levels. Additional operating reserve requirements are calculated depending on different wind power levels to avoid the energy shortage resulting from the day-ahead wind forecasting error in real-time operations. Besides, different models of DR deployment (other than modeling it as a linear price responsive demand function), are considered so that the DR capacity can also contribute to operating reserves.

III. MODELS

In this section, we introduce a two-stage stochastic program for capacity investment with demand response, where the first stage consists of investment decisions, the second stage represents operations in some future year, and the only uncertainty pertains to wind. The investment decision u_i is the first-stage decision variable that is scenario independent, whereas the operational decisions $g_{i,t,s}$, $ens_{t,s}$, $rns_{t,s}$, $wg_{t,s}$, $r_{i,t,s}$, $wc_{t,s}$, $d_{t,s}$ are all second stage decision variables that are scenario dependent. The two-stage stochastic model takes into account future uncertainty and determines an optimal investment with the minimum expected total cost. The stochastic generation capacity investment model consists of equations (1) – (12). Time periods, t , represent hours and all power quantities are assumed to be constant over an hour.

$$\max \sum_{l \in L} \theta_l \sum_{s \in S^l} P_s \sum_{t \in T^l} (\frac{1}{2} b_t d_{t,s}^2 + a_t d_{t,s} - \sum_{i \in I} c_i g_{i,t,s} - c^{ens} ens_{t,s} - c^{rns} rns_{t,s}) - \sum_{i \in I} u_i (Inv_i \bar{P}_i + F_i) \quad (1)$$

$$\sum_i g_{i,t,s} + wg_{t,s} + ens_{t,s} = d_{t,s} \quad \forall l, t \in T^l, s \in S^l \quad (2)$$

$$\sum_i r_{i,t,s} + rns_{t,s} \geq d_{t,s} RM + \bar{W}_{t,s} WR_{t,s} \quad \forall l, t \in T^l, s \in S^l \quad (3)$$

$$d_t^0 - d_{t,s} \leq d_{peak} DR_{per} \quad \forall l, t \in T^l, s \in S^l \quad (4)$$

$$d_{t,s} - d_t^0 \leq d_{peak} DR_{per} \quad \forall l, t \in T^l, s \in S^l \quad (5)$$

$$\sum_{t \in T^k} d_{t,s} = \sum_{t \in T^k} d_t^0 \quad \forall l, s \in S^l, k \in K \quad (6)$$

$$g_{i,t,s} + r_{i,t,s} \leq u_i \bar{P}_i \quad \forall i \in I, l, t \in T^l, s \in S^l \quad (7)$$

$$r_{i,t,s} \leq \bar{P}_i MAXSP_i \quad \forall i \in I, l, t \in T^l, s \in S^l \quad (8)$$

$$wc_{t,s} + wg_{t,s} = \bar{W}_{t,s} \quad \forall l, t \in T^l, s \in S^l \quad (9)$$

$$g_{i,t,s} \leq g_{i,t-1,s} + MxInc_i \quad \forall i \in I, l, t \in T^l, s \in S^l \quad (10)$$

$$g_{i,t,s} \geq g_{i,t-1,s} - MxDec_i \quad \forall i \in I, l, t \in T^l, s \in S^l \quad (11)$$

$$u_i \in \{0,1\}, g_{i,t,s}, ens_{t,s}, rns_{t,s}, wg_{t,s}, r_{i,t,s}, wc_{t,s}, d_{t,s} \geq 0 \quad (12)$$

The objective (1) is to maximize the system total net surplus, which consists of consumers' willingness to pay less the total annualized investment and fixed cost, as well as the total operational cost including the costs of generation, energy not served and reserve not served, accumulated over the hours in a year. The consumer inverse demand functions with intercept, a_t , and slope, b_t , in hour t are derived in Section III.A. Constraints (2) and (3) are the hourly energy balance and reserve requirement constraints. The reserve requirement in hour t under scenario s is composed of two parts: one as a percentage of the load $d_{t,s}$ and the other one as a percentage of the available wind power level $\overline{W}_{t,s}$, where the latter percentage itself depends on $\overline{W}_{t,s}$, as further explained in the case study (Section IV.C). Constraints (4) and (5) set a limit on the amount of load shaving/shifting within an hour, constrained by the DR capacity as a percentage of the peak load. Here we simplify DR modeling by setting a constant limit on load shaving and shifting in all hours. Another way to model the maximum load increase/decrease $|d_{t,s} - d_t^0|$ from the benchmark load is to assume it is not only as a proportion of peak load d_{peak} but also constrained by the benchmark load d_t^0 in that hour t . Equation (6) imposes an energy balance constraint within a day so that the total amount of load shaving equals the total amount of the load shifting within 24 hours in a day. Constraints (7) and (8) set generation and reserve limits for each generator. Equation (9) indicates wind energy balance by letting the wind output and wind curtailment equal available wind energy. Constraints (10) and (11) are the ramping up and down constraints.

A. Price Responsive Demand

We assume the consumers can respond to real time pricing to determine their amount of power consumption and model the DR as a linear price responsive demand function. The inverse demand function can also be viewed as a consumers' utility function that reflects their willingness to pay for a given quantity of energy. The utility functions are varied in different hours t , due to the different levels of demand caused by season, day/night time, etc.

The process for deriving the parameters of price responsive demand curves is as follows, where we consider a generic hour and suppress the subscript, t . Given a pair consisting of a reference price p^{ref} , a reference load d^{ref} , and a price elasticity ε at that reference point, the inverse demand function can then be calculated as in [16] by the definition of the demand elasticity given in equation (13).

$$\frac{(d-d^{ref})/d^{ref}}{(p-p^{ref})/p^{ref}} = \varepsilon, \quad (13)$$

so that

$$p = bd + a, \text{ where } b = \frac{p^{ref}}{d^{ref}\varepsilon} \text{ and } a = \left(1 - \frac{1}{\varepsilon}\right)p^{ref}. \quad (14)$$

Given benchmark loads $\{d_t^0, t \in T_l, l \in L\}$, one way to generate pairs $\{d_t^{ref}, p_t^{ref}\}$ is to first solve a deterministic cost minimization capacity investment model without wind power. We eliminate equation (9) and consider a single scenario labeled $s=0$, having probability 1, of zero wind power for each load season in equations (3). The objective in (15) is to minimize the total investment and fixed cost, as well as total

operational cost including the costs of generation, energy not served and reserve not served. The constraints (16) and (17) replace the variable $d_{t,s}$ in constraints (2) and (3) with the parameter d_t^0 . Variable p_t^0 is the dual variable of the load balance constraint (16).

$$\min \sum_{i \in I} u_i (Inv_i \bar{P}_i + F_i) + \sum_{l \in L} \theta_l \sum_{t \in T^l} (\sum_{i \in I} c_i g_{i,t,0} + c^{ens} ens_{t,0} + c^{rns} rns_{t,0}) \quad (15)$$

$$\sum_i g_{i,t,0} + ens_{t,0} = d_t^0 \quad \forall l, t \in T^l \quad [p_t^0] \quad (16)$$

$$\sum_i r_{i,t,0} + rns_{t,0} \geq d_t^0 RM \quad \forall l, t \in T^l \quad (17)$$

$$u_i \in \{0,1\}, g_{i,t,0}, ens_{t,0}, rns_{t,0}, r_{i,t,0} \geq 0 \quad (18)$$

Rather than computing different reference prices for every hour in the study horizon, we partition the hours within a day into types, such as day and night. For each type, the reference price is calculated as the demand-weighted average price among all the hours of that type in equation (19). Therefore, the same set of hours, $t \in T^l \cap T^h$, share the same reference price, p_t^{ref} .

$$p_t^{ref} = \frac{\sum_{t \in T^l \cap T^h} d_t^0 p_t^0}{\sum_{t \in T^l \cap T^h} d_t^0} \quad \forall l, k, t \in T^l \cap T^h \quad (19)$$

Given the p_t^{ref} calculated in (19) as energy weighted average price and letting d_t^{ref} equal d_t^0 , we have a pair $\{d_t^{ref}, p_t^{ref}\}$ in each hour t from which to derive the inverse demand function.

Because of the quadratic term $\frac{1}{2}b_t d_{t,s}^2 + a_t d_{t,s}$ in the objective function, the extensive form of the stochastic program, given by equations (1) – (12), is a mixed integer quadratic programming (MIQP) problem, which can be solved by CPLEX.

The objective function (1) can be linearized by a stepwise function that approximates the inverse demand function (14), which converts the MIQP problem into a mixed integer linear programming (MILP) problem for faster solution by CPLEX. To improve the approximation accuracy, the step size can be reduced at the expense of additional computational time.

B. Demand Response Modeled as Operating Reserve

In some of the DR programs, the DR capacity can also participate in the operating reserve market. Here we consider a generation capacity investment model where DR programs are not only represented as price-responsive demand, but also contribute to providing reserves.

The reserve constraint (20) includes a component $drr_{t,s}$, which is the amount of reserve from the DR capacity. For the purpose of system reliability, we assume $drr_{t,s}$ can not exceed a certain amount as a percentage DRR_{per} of the total reserve requirement. The load shifting/shaving constraints (4), (5) change accordingly to equations (22), (23). Constraint (22) implies that load reduction plus the DR capacity contributing to operating reserves cannot exceed the total DR capacity. Further, constraint (23) implies that DR capacity is also allowed to be part of the operating reserves in the hours of load shifting, and also sets the DR capacity as the limit of the total load shifted plus the DR capacity that accounts for part of the operating reserves. The new model includes constraints (1), (2), (6) – (12), and (20) – (24).

$$\sum_t r_{i,t,s} + drr_{t,s} + rns_{t,s} \geq d_t^0 RM + \overline{W}_{t,s} WR_{t,s} \quad \forall l, t \in T^l, s \in S^l \quad (20)$$

$$drr_{t,s} \leq DRRper(d_t^0 RM + \overline{W}_{t,s} WR_{t,s}) \quad \forall l, t \in T^l, s \in S^l \quad (21)$$

$$d_t^0 - d_{t,s} \leq d_{peak} DRper - ddr_{t,s} \quad \forall l, t \in T^l, s \in S^l \quad (22)$$

$$d_{t,s} - d_t^0 \leq d_{peak} DRper - ddr_{t,s} \quad \forall l, t \in T^l, s \in S^l \quad (23)$$

$$drr_{t,s} \geq 0 \quad (24)$$

IV. CASE STUDY ASSUMPTIONS

A. Benchmark Load

The benchmark load data are deterministic and based on a real 2006 annual hourly load profile from two large utilities, AMEREN and COMED, in the state of Illinois, from which one week in April as low load season, August as high load season, and December as medium load season, are selected. Loads are scaled to a new load profile with a peak load of 2500 MW. The three weeks add up to 504 hours in total. Since we assume that the high, medium and low load seasons each represent 1/3 of the year, multipliers θ_l equal 52/3 to obtain operational costs on an annual basis.

B. Wind Resource Uncertainty

To capture the impact of wind uncertainty on both investment and operational decisions, wind scenarios are constructed based on the real year 2004-2006 annual hourly wind profiles (realized generation) from the state of Illinois, derived from 15 potential wind power sites in the Eastern Wind Integration Study (EWITS) [26]. Each weekly wind profile represents one scenario, and each scenario corresponds to a particular load season l . The weeks from March to June are defined as the low load season; from July to October as the high load season, and November to February as the medium load season. In total, 51 wind scenarios are generated from 51 weeks of complete wind hourly profiles in the 3-year data for each load season l . The scenarios corresponding to different load seasons are independent of each other. Equal probability is assumed for each of the 51 scenarios in each set S^l .

We assume a high wind penetration level in the case study. We scale the hourly wind profile with total wind capacity as 1140MW and let $\sum_{l \in L} \sum_{t \in T^l} \sum_{s \in S^l} P_s \overline{W}_{t,s}$ equal 30% of the total benchmark load $\sum_{l \in L} \sum_{t \in T^l} d_t^0$.

Scenario reduction is performed to reduce the computational effort. In related numerical studies with reduced sets of 30, 20, and 3 scenarios, we found that the case with 3 scenarios takes much less computational time and is sufficient to represent the wind uncertainty space since there are only minor changes in investment decisions compared to the cases with 30 and 20 scenarios [27]. Therefore, for each load season l , $|S^l| = 3$ scenarios are selected to represent the wind uncertainty. The scenario probabilities were calculated to best approximate the original scenario space, using the scenario reduction method in [28] [29]. Fig. 1 presents the three different load seasons and the three scenarios corresponding to each of them with 30% wind penetration level. The scenario probabilities are listed in Table I.

TABLE I
SCENARIO PROBABILITIES BY DIFFERENT LOAD SEASONS

Load Season l	Scenario $s=1, 4, 7$	Scenario $s=2, 5, 8$	Scenario $s=3, 6, 9$
high load	0.4706	0.1765	0.3529
medium load	0.6078	0.2549	0.1373
low load	0.1765	0.1176	0.7059

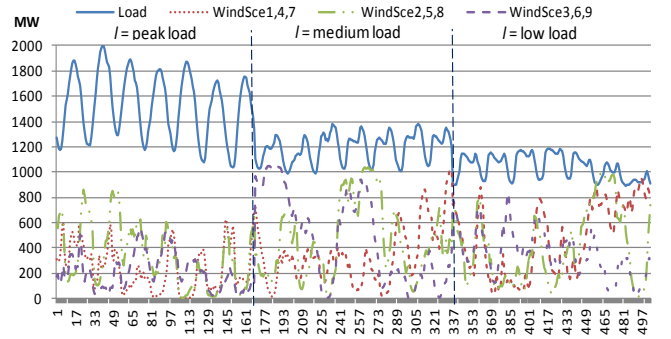


Fig. 1. Hourly load profile and three wind scenarios corresponding to each load season l with 30% wind penetration levels.

For simplicity, we present the benchmark load profiles and wind scenarios at different load seasons together in Fig. 1. Note, however, that wind scenarios 1, 2, 3 are included in the scenario set $S^{l=high}$; 4, 5, 6 in $S^{l=medium}$; and 7, 8, 9 in $S^{l=low}$; and the selections of a scenario from each set are independent.

C. Operating Reserves for Load and Wind

Operating reserves are required to handle forecasting uncertainties in load and wind power. We therefore impose an operating reserve consisting of two parts: a $RM=10\%$ for load and a variable WR to cover the potential forecasting error from the real-time wind power. The parameter WR is assumed to depend on the wind output levels. To determine an adequate amount of WR , we conducted a statistical test based on the 2006 hourly data for both day-ahead wind forecast (DA) and real-time wind generation (RT) as a percentage of the wind capacity. The data are first divided into several groups depending on the different forecasting levels: less than 10% of the wind capacity (<10%), 10% to 20% (<20%), through 50% to 60% (<60%), and the last one, 70% to 100% (<1), due to the small number of the sample size with such a high forecasting level. The relative forecasting error is then calculated as $(DA - RT)/DA$. Operating reserves for wind, WR , are intended to cover the insufficient real-time wind generation when it is over-forecasted; i.e., with $(DA - RT)/DA$ being a positive value. Thus, upper-tail percentiles of the relative error are calculated in Table II for different forecasting levels.

TABLE II
PERCENTILES FOR RELATIVE FORECASTING ERROR BY DIFFERENT FORECASTING LEVELS

Wind Level	<10%	<20%	<30%	<40%	<50%	<60%	<1
Sample Size	452	1987	2099	1473	1125	784	834
95 th	0.964	0.933	0.764	0.528	0.378	0.226	0.093
90 th	0.933	0.880	0.658	0.416	0.284	0.148	0.041
70 th	0.813	0.642	0.423	0.175	0.036	-0.042	-0.058
50 th	0.620	0.438	0.246	0.003	-0.106	-0.187	-0.138

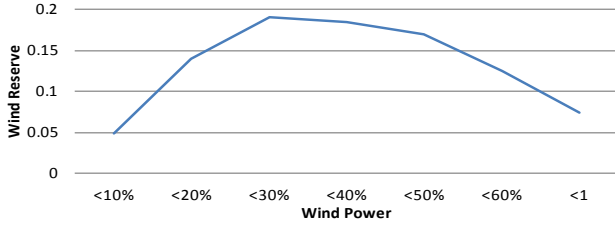


Fig.2. Wind reserve as a function of wind power, both as fraction of total wind capacity

To prevent power insufficiency from wind over-forecasts, we used the 95th percentile as the parameter assumption for WR; e.g., if day-ahead wind forecast level is less than 10% of the total wind capacity, its corresponding $WR_{t,s}$ is set to 0.964 and we have $P\left(\frac{DA-RT}{DA} \leq 0.964\right) = P(DA - RT \leq 0.964DA) = 0.95$. In this case, we assume that the total reserve requirement for the wind forecast is equal to $0.964\overline{W}_{t,s}$, which can be used to cover the shortage in cases when the real time wind output is less than the day-ahead forecast. Note that whereas WR decreases for higher wind levels, the absolute reserve requirement is highest for medium wind levels, when the forecast uncertainty is the highest, as shown in Fig. 2. With the chosen confidence level, the reserve amount should be sufficient to make up for the shortfall 95% of the time, assuming a well calibrated DA forecast.

D. Candidate Units

TABLE III
PARAMETERS FOR CANDIDATE UNITS

Technology	Base		Medium		Peak	
	Cand. 1-2	3	4-7	8-10	11-15	16-20
INV_i (\$/YEAR/ MW)	244600	219653	83923	86086	83579	57064
F_i (\$/YEAR/ MW)	35970	29670	14390	14620	6980	6700
c_i (\$/MWh)	19.21	19.21	54.19	49.406	92.82	80.07
\overline{P}_i (MW)	325	650	270	200	42.5	105
$MxInc_i$ /MxDec _i (MW/hr)	170	250	150	100	42.5	105

We assume that investments can be made in any of 20 units including 3 baseload, 7 medium and 10 peaking units; i.e., there are no existing units in the system. For each technology, there are two different types. The parameters of the units are based on [30] and summarized in Table III.

E. Inverse Demand Function

A unique demand function is generated for each combination of load season and diurnal hour type to model the consumers' load flexibility responsive to the market price. Their corresponding inverse demand functions (14) represent the consumers' total utility from the electricity consumption, and slopes b_t and intercepts a_t can be calculated accordingly.

The number of different reference prices, as we previously defined in equation (19), is $|L| \times |H|$. In our case study, we consider $|L| = 3$ load seasons and $|H| = 2$ hour types as day and night. Therefore, we have in total six different reference

prices. The daytime hours are assumed to be the hours from 9am until 8pm; while hours at night run from 9pm until 8am. We calculate one reference price in equation (19) for each set of the hours. The reference prices p_t^{ref} , $t \in T^l \cap T^h$, for day and night types are in Table IV. The reference loads d_t^{ref} are assumed to equal the benchmark loads d_t^0 , and the demand elasticity ε is -0.2 [31].

TABLE IV
REFERENCE PRICE FOR DIFFERENT DIURNAL HOUR TYPES AND LOAD SEASONS

Type h	Load Season l			
		low	medium	high
	day	43.702	49.410	130.632
night	30.019	42.631	50.933	

In Fig. 3, inverse demand functions selected from each of the hour sets, $t \in T^l \cap T^h$, are calculated based on their pair of the reference price and load presented in Table IV, and the elasticity ε . Because the demand increase/decrease from the reference demand d_t^{ref} is limited by the DR capacity, which equals $d_{peak}DRper$, the demand interval for each inverse demand function is within $[d_t^{ref} - d_{peak}DRper, d_t^{ref} + d_{peak}DRper]$ and the price should also be within its corresponding interval, accordingly enforced by model constraints (4) and (5). In general, we can see that load in the high load season has a steeper demand curve (i.e., is less flexible) than in the low load season; and the demand curve in the day time is steeper than in the night time.

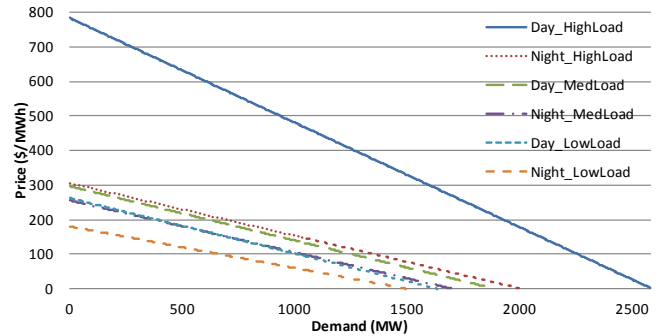


Fig.3. Examples of inverse demand functions selected from the six different categories

For the case study, we derive a stepwise inverse demand function with a step size of 100.

The demand response (DR) capacity $DRper$ is modeled as a percentage of the peak load. We vary the values between 0% and 30% and examine the different DR capacity levels' impact on the investment and operational decisions.

F. Penalty Costs

Penalty costs, c^{ens} and c^{rns} , for unserved energy and reserve are assumed to be 3500 \$/MWh and 1100 \$/MWh, respectively, based on the current practice at MISO [32]. However, estimates of these parameters are usually based on surveys and would vary from system to system.

V. NUMERICAL RESULTS

We examine the generation capacity investment models at different DR capacity levels: 0%, 5%, 10%, 15%, 20%, and 30%. The objective function (1) in the model is linearized and therefore reformulated as a mixed integer programming (MIP) problem, as explained above. The relative MIP gap is set to 0.1%. The MIP problem has 15 binary variables, 52,920 continuous variables and 151,263 constraints in total. All the case studies are run on a 2X Intel Xeon E5430 server with 32 (8x4) GB DDR2 667 MHz RAM in the Ubuntu operating system.

The DR program enables load flexibility by load shifting from peak hours to off-peak hours, as illustrated in Fig. 4. With 30% wind penetration level, the peak thermal load is reduced from 2500MW to 2310MW. With DR15%, the hourly load profile is leveled off and the peak load is further decreased from 2310MW to 2148MW. The net thermal load, also called net load, is defined as the load less the wind power output.

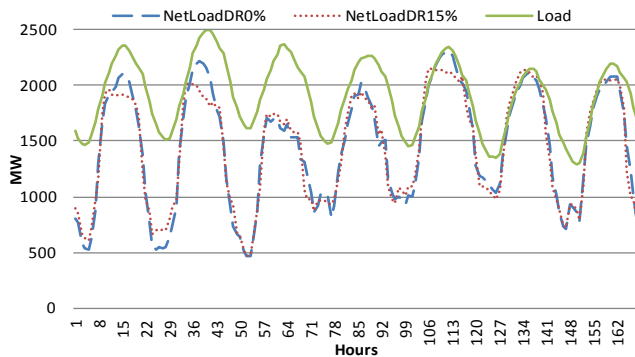


Fig. 4. Net thermal load at DR15% of the high load week with wind scenario 2 compared with net thermal load at DR0% and benchmark original load, with the daily total energy as a constant

A. Demand Response's Impact on Investment and Operational Decisions

In general, as DR capacity increases, there are three major observations:

1) Less thermal capacity investment

Due to the high penalty cost c^{ens} and c^{rns} , the required generating capacity is mainly determined by the peak net load and its operating reserve at the peak hours. As more DR capacity becomes available, DR capacity shifts the net thermal load to the off-peak hours and the peak load is reduced, so that less capacity is needed.

Compared to DR0%, DR5% builds one fewer peak unit of 105MW; DR10% builds one fewer medium unit of 200MW; and DR20% and DR30% give the same investment decisions as DR15%, namely to build one fewer medium unit of 270MW. A sensitivity study is conducted with the elasticity at 0.1 and 0.3. Similar patterns of capacity investment decisions at varied DR capacity levels are observed in Fig. 5.

In terms of different technologies, it is mainly the level of investment in medium units that is influenced by the DR capacity. The net thermal load and reserve requirement of a high load week is illustrated in Fig. 6. The base units, 975MW in total, serve the base load all the time most efficiently; while the peak units are favored to deal with the load variability.

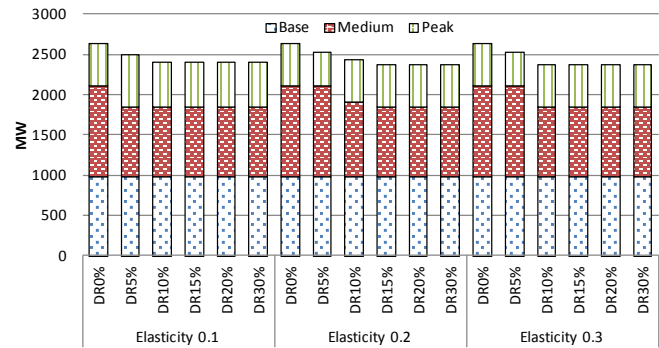


Fig. 5. Optimal investment decisions at different DR capacity levels under varied assumption for demand elasticity

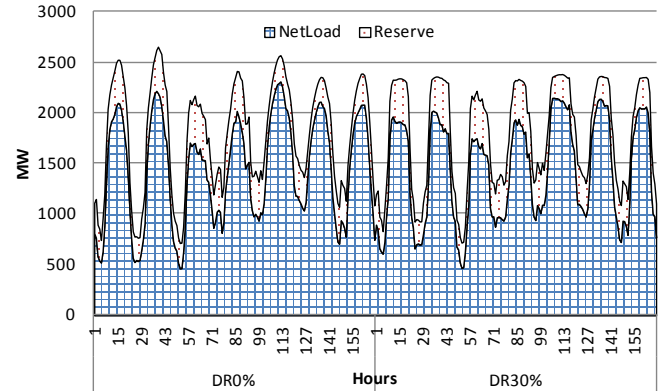


Fig.6. Net thermal load and reserve of a high load week with wind scenario 2 at DR0% and DR30%

2) Less load/reserve curtailment and wind curtailment

There is no load curtailment in any of these DR cases. As DR capacity increases from DR0% to DR15%, reserve and wind curtailment both decrease. Like the expansion results shown in Fig. 5, the reserve and wind curtailment for DR20% and DR30% remain the same as for DR15%.

In both the DR5% and DR10% cases, there are peak hours where DR capacity reduction reaches its maximum limit. It is observed that the load shifting decision is mainly driven by the occurrence of load/reserve curtailment since this only happens when the DR reduction reaches its limit. Due to the high penalty cost of load/reserve curtailment, DR helps to reduce the cost. In Table V, when DR capacity is increased to 15%, it indicates that the system has enough DR capacity so that reserve curtailment no longer occurs and DR no longer reaches its maximum capacity.

TABLE V
EXPECTED WIND CURTAILMENT PERCENTAGE, EXPECTED RNS COST AND MAXIMUM DR USAGE PERCENTAGE AT DIFFERENT DR CAPACITY LEVELS

	Expected Wind Curtailment Percentage	Expected RNS Cost	Maximum DR Usage Percentage
DR0%	0.1805%	3,537,718	0.00%
DR5%	0.0444%	1,647,350	5.00%
DR10%	0.0417%	436,044	10.00%
DR15%	0.0415%	0	13.64%
DR20%	0.0415%	0	13.64%
DR30%	0.0415%	0	13.64%

As DR capacity increases, wind curtailment is also reduced to some extent. DR contributes to more load flexibility that

helps reduce wind curtailment by increasing load in situations with surplus wind. However the difference is not very significant, since the wind curtailment is quite low even when there are no DR programs in the system. The curtailment percentage can be further reduced to the maximum at 0.0415% after adopting the DR programs. These curtailment occasions are all due to the wind output being higher than the system demand.

3) Reduced Marginal Benefit of DR Capacity

The total surplus, measured by the objective function (1) in the capacity investment model, increases as DR capacity increases from 0% to 15%, with decreasing marginal benefits. The objective values increase, respectively, by 0.49%, 0.66%, and 0.73% for DR5%, 10% and 15% compared to the case with no DR capacity, DR0%. The DR20% and DR30% objective values are the same as in DR15%. The increases in the social surplus also suggest how much investment should be spent on DR equipment.

In our investment model, the DR capacity levels are modeled as external model input, which can be driven by government policy and incentives. However, investment costs in DR appliances should be justified by the system benefit increased by the DR program. The model results indicate a decreasing marginal benefit of DR investment and that a system social surplus cannot always be increased by a higher DR capacity.

B. Demand Response Modeled as Operating Reserve

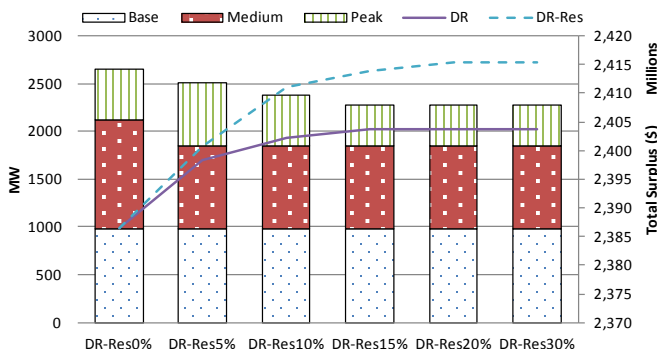


Fig. 7. Optimal investment decisions and total surplus (\$) at different DR capacity levels

Based on the model that includes equations (1), (2), (6) – (12), and (20) – (24), the optimal investment decisions are shown in Fig. 7. Here we assume DRR_{per} is 25% of the total reserve requirement in equation (21) based on the assumption from PJM [7]. The MIP problem has 15 binary variables, 54,432 continuous variables and 154,287 constraints in total. Because the DR can also provide reserves, the total thermal capacity is decreased at each DR capacity level, compared to the results in Section IV.G. The “DR-Res” in Fig. 7 represents the investment model that allows the DR in reserve markets. In Fig. 7, the total surpluses of the “DR-Res” are higher than the “DR” models. However, like “DR”, the marginal benefit of the “DR-Res” model is also decreasing and the capacity level remains the same after DR capacity reaches 15% of the peak load. The results show the benefit, in terms of increasing surplus, of having DR contribute to providing operating

reserves. The conclusion agrees with the intuition since it helps take full advantage of the DR capacity.

C. Demand Response’s Impact on System Efficiency

To investigate the demand response’s impact on system efficiency, we calculate the average capacity factors (CF) for different technologies at various DR levels.

We take into account both the generation and reserve output from the generators. The generation and reserve CF, CF_i^{gen} and CF_i^{res} for individual generator are defined as $\frac{\sum_t \theta_l \sum_{s \in S^l} P_s \sum_t g_{i,t,s}}{\sum_t \theta_l \sum_{s \in S^l} P_s \sum_t \bar{P}_i}$ and $\frac{\sum_t \theta_l \sum_{s \in S^l} P_s \sum_t r_{i,t,s}}{\sum_t \theta_l \sum_{s \in S^l} P_s \sum_t \bar{P}_i}$. The average CF for a type of technology is then calculated as capacity weighted CF, $\frac{\sum_{i \in Y^m} u_i \bar{P}_i CF_i}{\sum_{i \in Y^m} u_i \bar{P}_i}$, where the thermal technology type m can be base, medium or peak.

The total average CFs for the three different technologies increase by 3.4%, 21.0% and 6.4%, respectively, for base, medium and peak with increasing DR capacity from 0% to 30% shown in Fig. 9. Specifically for the generation CF, they respectively increase by 0.8%, 9.4% and 311.5%. The reserve CFs for base and medium are also increased, while the peak units have a decreased reserve CF by -18.3%.

We conclude that the system becomes more efficient with higher CFs for the generators. Besides, the medium and peak units are most likely to be built for meeting the reserve requirement since a significant part of their capacities contributes to the reserve market. These observations also indicate the reason why letting the DR capacity be an additional source for the operating reserves can lower the optimal thermal capacity investment, as shown in Section V.B.

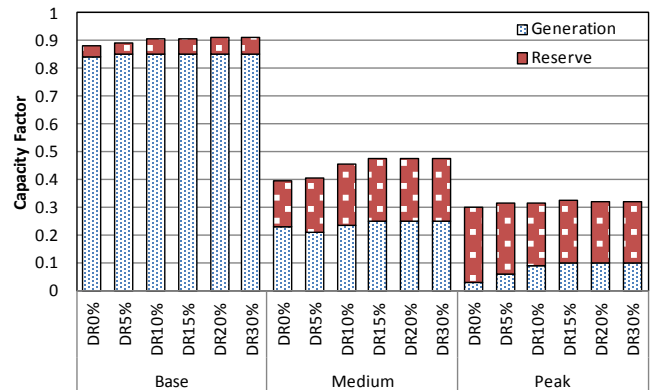


Fig. 8. Generation and reserve capacity factors for base, medium and peak units at different DR levels

VI. CONCLUSIONS

We investigate a generation capacity investment and resource adequacy problem with consideration of demand response at a high wind penetration level. To better capture the wind variability’s impact on short term operations, we incorporate continuous operational constraints within our annual capacity investment model. DR is modeled as price responsive demand function. Both the wind and DR capacity levels are considered as external model parameters, which can

represent government policies and incentives. To account for the long-term wind variability in the model, we employ scenarios to represent alternative weekly wind patterns for each load season. Short-term wind forecasting uncertainty is represented through increased operating reserve requirements.

The investment model maximizes the total system surplus considering consumers' welfare represented by their linear inverse demand functions, less the total investment, fixed and variable generation cost, and energy/reserve not served costs. Upon linearizing the objective function, the problem becomes a MILP.

Based on the results of the case study, we observed decreasing capacity levels, reserve and wind curtailment, and increasing social surplus, as the DR capacity increases. The results indicate that DR mainly replaces intermediate generation capacity. Base units are still considered to be the most efficient technology to cover the base load in all the hours and peaking units are needed to deal with the net load variation and operating reserves. We also introduce a model with consideration of the DR capacity as a source of operating reserves, which further reduces the optimal generation capacity level and increases the social surplus. The results also imply that DR leads to an increase in system efficiency through higher capacity factors for the generators.

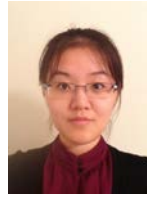
In general, we conclude that DR programs are a viable resource for accommodating wind power in system operation, which in turn reduce the need for investment in generation capacity. However, a decreasing marginal benefit of DR is observed and, therefore, we conclude that a relatively small amount of DR capacity, e.g. 10%-15% of peak benchmark load, can provide most of the potential benefit resulting from the DR programs. A higher level of DR in the system might not be worth the initial investment in the DR appliances.

When interpreting the results, it is important to keep in mind that the proposed generation capacity investment model, for computational complexity concerns, only considers the continuous operating constraints instead of taking into account all the UC constraints, which require the inclusion of many discrete decision variables. In the paper, we simplify the DR modeling as an inverse step-wise demand function, set a constant limit on the DR in all hours, and assume that the total daily energy consumption is constant. Moreover, we do not consider the cost of introducing more DR in the system, and we do not model the dynamic aspects of generation expansion and DR adoption. In future work, we intend to investigate the implications of these modeling assumptions and also consider the impacts of the transmission network.

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