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Demand Shifting Bidding in a Hybrid System with Volatile Wind Power Generation

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Abstrak

Mekanisme "price responsive demand shifting bidding" dibahas sebagai solusi alternatif untuk menangani intermitansi dalam pembangkit tenaga angin. Makalah ini mengusulkan sebuah formulasi persamaan pengurangan harga dan pembatasan emisi ekonomi dengan aksentuasi pada integrasi tenaga angin. Analisis ini didasarkan data pembangkitan sistem uji bus IEEE 30 pada pembangkit konvensional dan tenaga angin selama periode 24 jam. Hasil penelitian menunjukkan bahwa pendekatan yang diusulkan dapat mereduksi harga dan menangani intermitansi dalam pembangkit tenaga angin.

***Kata kunci**: pembangkit tenaga angin, price responsive demand shifting bidding, sistem uji bus IEEE 30*

Abstract

Price responsive demand shifting bidding mechanism is discussed as an alternative solution to deal with intermittency in wind generation. This paper proposes a formulation of social welfare equation with price responsive demand shifting bidding and economic emission dispatch with emphasis on integration of wind power. The analysis is based on the IEEE 30 bus test system generation data, with conventional and wind generation plant over a period of 24 hours. It has been demonstrated that the proposed approach leads to reduction in emission as well deal with intermittency in wind generation.

***Keywords**: IEEE 30 bus test system, price responsive demand shifting bidding, wind power generation*

1. Introduction

Due to environmental and energy security benefits there is a positive shift towards the production of electrical energy from renewable sources of energy especially from wind which are clean and abundantly available in nature. On regulatory side in India and many other countries, there are necessities to generate a certain amount of electrical energy from renewable sources. China is the country with the largest installed wind power capacity in the world at the end of year 2010 whereas India's total installed wind power capacity is fifth in the world. It is reported by the Global Wind Energy Council (GWEC) that global installed wind power capacity increased by 24.1% during the year and stands at 197.0 GW in 2010 [1]. Large capacity wind power generators are connected to transmission or sub-transmission systems. At the end of 2010, India had 13.1 GW of installed wind capacity, with 40% operating in the southern state of Tamil Nadu and wind power potential estimated by the Centre for Wind Energy Technology (C-WET) is 49.13 GW [2].

The generation of electric power by conventional sources produces mainly sulfur dioxide, carbon, NOx, and mercury emissions causing acid rain, urban smog, and eventually global climate change in addition to posing significant health risks. Renewable electricity generations mainly from Wind farms help to prevent release of emissions into the atmosphere preventing environment damage. On the other hand, unpredictable, intermittent and volatile nature of wind energy may threaten power system characteristics such as voltages, frequency and generation adequacy which can potentially enlarge the weakness of power systems.

Demand side management (DSM) incorporates energy efficiency (EE), Energy Conservation (EC) and Demand Response (DR). In the most electricity markets; the consumers play a much more limited role than producers. It is widely acknowledged that a more active participation in the market by the demand side could have significant benefits [3]. A good deal of research has been reported on measurement of load elasticity, presuming that industrial, residential and commercial consumers will respond to price signals [3]-[8]. DR at end user's

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premises can reduce generation, transmission and distribution capacity of utility at relatively fractional cost as compared to investment required to provide new capacity. The appropriate demand management in modern interconnected power system with dispersed generation may also result in reduced associated CO2 emissions in day-ahead electricity markets through price responsive demand shifting bidding (PRDS). Su and Kirschen [9] proposed the PRDS bidding for market clearing mechanism of day-ahead markets. PRDS bidding quantify the demand response in day-ahead market, and some responsive customers are able to shift the demand from periods of high locational marginal price (LMP) to the periods of low LMPs. However, the market clearing mechanisms developed in [9] do not take into account the operational and security constraints of transmission networks. Kanwardeep Singh et al. [10] discussed the influence of PRDS bidding on congestion and LMP in Pool-Based Electricity Markets. Impacts of availability based tariff on wind power trading option were analyzed in [11].

This paper investigates these unmatched challenges caused by wind power plants to the optimization problem. PRDS bid, emissions constraints, and fuel costs are considered in the realization of most favorable generation mix for a system with wind power generation. Fuel costs, environmental costs and emissions are considered in the implementation of optimal generation mix for a system with wind generation along with PRDS bid to maximize social welfare. The rest of the paper is organized as follows: Next section 2 describes wind power scenario reduction and PRDS biding mechanism. Section 3 describes research method. Results are presented and discussed in section 4. Finally, section 5 concludes the paper.

2. The Proposed Method

The wind power participation into total production of electrical energy depends upon the forecast of wind momentum. A principal difficulty with modeling wind power production is that the relationship of wind speed to wind power production is extremely nonlinear. The wind power generators require no fossil sources hence, the operational cost of wind units has been assumed to be zero. Different forecasting approaches available can be studied in [12]-[13]. Result of wind power unpredictability can be studied by applying different scenarios into the model. Monte Carlo simulation was popularized by scientist in the 1950s. Monte Carlo simulation is a method that can model thousands of scenarios and helps to model uncertainties of wind power output. It provides a range of possible outcomes together with there probability. Modeling all main and possible scenarios determined by the uncertain variables can be done by Monte Carlo simulation. These scenarios are defined by the probability distributions and their simulation parameters. Many types of probability distributions are used in different situations such as normal, uniform and triangular distributions.

There are many sampling techniques such as Importance sampling, Sobol numbers sampling, Midpoint sampling, Latin hypercube sampling (LHS), and LHS Monte Carlo sampling to eliminate scenarios with very low probability. These techniques are engaged to reduce the computational requirement to simulate large number of scenarios. LHS has the benefit of generating a set of stratified samples that more precisely reflect the shape of a sampled distribution and reduces the number of runs. The general effect is that the mean of a set of simulation results more quickly approaches the ‘true’ value, particularly for models that are simply adding or subtracting a number of variables. The tradeoff between the number of reduced scenarios and the simulation precision is possible by choosing the number of reduced scenarios so that the objective function would not change much or the relative distance between original scenarios and reduced scenarios is within an acceptable level [14], [15]. In this model the number of reduced scenarios is chosen to be ten since the value of objective function at this number does not change much. The scenarios taken were having the higher probabilities. The deviations in wind power have been taken in to account by considering different scenarios. The forecasted wind power generated and reduced scenarios data are taken from [16].

Not all consumers have the facility or the incentive to adjust their demand when prices change. Large part of the power requirement will therefore totally inelastic. In price taking bids, the demand aggregator is ready to accept a specified amount of power at prevailing market price, and its power consumption remains constant irrespective of variations in market price. This kind of bid is required to meet necessary daily services to industrial, residential and domestic loads. In price responsive bids, the price to be paid by a bidder decreases consistently decreasing with respect to increase in power use. Details of PRDS bidding scheme has been formed in [9]. In PRDS bids, an aggregator on behalf of consumers is able to increase or decrease its certain percentage of demand in response to market price. Key factor in PRDS bidding scheme is price responsive consumer who can transfer its demand from peak demand periods of high market price to off peak demand periods in which market price is somewhat low.

The scope of present paper is to study the influence of PRDS bidding in a hybrid system with volatile Wind Power Generation in day-ahead markets.A usual PRDS bid is shown in [10]. Main dissimilarity between PRDS bidding scheme and price responsive demand bidding is that in PRDS bidding during a particular t^{th} period, maximum demand limit can be greater than earlier, to include the fall of load occurred during peak periods due to soaring electricity rate, whereas in price responsive bidding scheme loss of load during peak hours can not recovered in off peak hours. In PRDS bidding aggregator's on behalf of responsive consumers specifies for particular t^{th} period, its maximum, and minimum price bids and maximum power demand which in simplest form can be sum of entire energy need of responsive part. Due to negative slope of PRDS bidding responsive part of demand can be less than its maximum value because aggregator would accept only that part of demand for which its willing price is less than or equal to market declared price. In PRDS bidding aggregator's price responsive part of energy of scheduling period can be consumed in few sub-intervals. In simplest form it can be consumed in a single period. Mathematically, it can be represented as:

$$0 \le D_{RS}^{k,t} \le D_{RS}^{\max,k,t} \qquad \forall t \in T \tag{1}$$

$$\sum_{t \in T} D_{RS}^{k,t} \cdot \Delta t \le E_{RS,k} \tag{2}$$

$$D_{RS}^{\max,k,t} = E_{RS,k} \big/ \Delta t \qquad \forall t \in T \tag{3}$$

where:

$D_{RS}^{k,t}$	Consumption of k^{th} demand shifting consumer at period t;
$D_{RS}^{\max,k,t}$	Maximum consumption of k^{th} demand shifting consumer at period t;
$T,\ \forall t$	Set of scheduling sub-intervals and duration of one sub-interval;
$E_{RS,k}$	Maximum limit on energy consumed under demand shifting bid of k^{th} DistCo during entire scheduling period;

Price taking consumers have infinite marginal value due to vertical curve with respect to power so it can not be included in consumer gross surplus. In optimization problem gross surplus of this type consumers are not included and assumed constant. Thus equations (4) and (5) shows how the consumer gross surplus is calculated based on the accepted demand-side bids and the marginal value that consumers attach to these bids:

$$GS^{k,t} = \sum_{j=1}^{J} MB_{RS}^{k,j,t} \cdot D_{RS}^{k,j,t} \tag{4}$$

$$D_{RS}^{k,t} = \sum_{j=1}^{J} D_{RS}^{k,j,t} \tag{5}$$

where:

$MB_{RS}^{k,j,t}$	Marginal benefit of j^{th} segment of k^{th} demand shifting bidder during t^{th} period;
J	Number of segment of the bid of bidder;
$D_{RS}^{k,j,t}$	Demand of k^{th} bidder during t^{th} hour on j^{th} segment of its bid;
$GS^{k,t}$	k^{th} demand shifting consumer gross surplus at period t;

In this model certain percentage of power for each hour which is price taking can be procured by consumers regardless of market-clearing prices. For a complete and compact formulation of the PRDS bidding mechanism the reader is referred to [9], [10]. In the optimization program used for market-clearing, the bid specifications are translated into constraints: (i) on the demand during each period and (ii) on the total demand over the optimization horizon. This last specification is implemented as an inequality rather than an equality constraint because a demand-side bid below the lowest price at which generators are willing to produce would otherwise prevent the market from clearing. The price responsive bids are converted into a form suitable for mixed-integer linear programming such as in [9].

3. Research Method

The objective is to maximize the social welfare, i.e., the difference between the value that consumers attach to the electrical energy that they buy and the cost of generation that has been formulated based on classical ELD with emission. Equation (6) as proposed in [9] is used to consider economic load dispatch with emission. The proposed social welfare equation after modification is represented as:

$$\phi = Max \sum_{t=1}^{T}\left(\sum_{k=1}^{K} GS^{k,t} - \sum_{i=1}^{N_g} u_G^{i,t} \cdot \left(FC^{i,t} + St_{up}^{i,t} + EEC^{i,t}\right)\right) \tag{6}$$

where:

ϕ	Optimal social welfare;
$FC^{i,t}$	Fuel cost of i^{th} generator at time t;
$u_G^{i,t}$	Status of i^{th} generator at time t (1:on, 0:off);
$EEC^{i,t}$	Blended emission cost of i^{th} generator at time t;
$St_{up}^{i,t}$	Start up cost of i^{th} generator at time t;
N_g	Total number of generators in the network;
K	Total number of demand side bidders;

Fuel cost of i^{th} generator in terms of real power output $P_{gi,t}$ can be expressed as:

$$FC^{i,t} = a_i \cdot P_{gi,t}^2 + b_i \cdot P_{gi,t} + c_i \ \text{\$/hr} \tag{7}$$

where:

$P_{gi,t}$	Real power output of an i^{th} generator at time t;
a_i, b_i, c_i	Fuel cost curve coefficients;

The i^{th} generator startup cost is described in term of the number of hours the generator has been down:

$$St_{up}^{i,t} = \kappa^i + \rho^i \left[1 - \exp\left(-H_{off}^{i,t} / \tau^i\right)\right] \tag{8}$$

where:

κ^i	The i^{th} unit fixed start-up cost part in \$;
ρ^i	Start-up cost of i^{th} unit at t^{th} hour from cold condition in \$;
$H_{off}^{i,t}$	The number of hour's i^{th} unit down at t^{th} hour;
τ^i	Rate of cooling of i^{th} unit

In this optimization problem, for the sake of simplicity, the start-up costs are taken constant, which can be given as:

$$St_{up}^{i,t} = \kappa^{i} \cdot \left(u_G^{i,t} - u_G^{i,t-1}\right) \tag{9}$$

$$St_{up}^{i,t} \geq 0 \tag{10}$$

Emission of i^{th} unit can be expressed as:

$$EC^{i,t} = \alpha_i \cdot P_{gi,t}^2 + \beta_i \cdot P_{gi,t} + \gamma_i \ \text{lb/hr} \tag{11}$$

where:

α_i, β_i, γ_i are emission coefficients;

The fuel cost curves and emission curves of the power plants are modeled as step-wise linear function, in order to approximate the typical quadratic shaped cost curve of a power plant. The dual-objective combined economic emission dispatch problem is converted into single optimization problem by introducing price penalty factor h which convert emission output into equivalent emission cost as follows:

$$EEC^{i,t} = h \cdot EC^{i,t} \ \$/\text{hr} \tag{12}$$

The price penalty factor h merge the emission with fuel cost and sum of merged emission cost, fuel cost and start up cost gives total production cost in \$/hr [17]. Modified price penalty factor approach was proposed in [18] to give exact total operating cost. The price penalty factor h_i is the ratio between maximum fuel cost and maximum emission of i^{th} generator:

$$h_i = FC^{i,\max} / EC^{i,\max} \ \$/\text{lb} \quad i = 1, 2, 3 \ldots\ldots N_g \tag{13}$$

where:

$FC^{i,\max}$ Fuel cost of an i^{th} unit at maximum power output;

$EC^{i,\max}$ Emission of an i^{th} unit at maximum power output;

To find out the modified price penalty factor for a particular load demands following steps are proposed in [18].

- The price penalty factor h_i is calculated.
- Price penalty factors h_i are arranged in ascending order.
- Add the maximum capacity of each unit $P_{gi,\max}$ one at a time, starting from the smallest value h_i until $\sum P_{gi,\max} \geq P_d$.
- Then the modified price penalty factor h_m is computed by interpolating the values of h_i for the last two units by satisfying the corresponding load demand.

In this paper shifted price penalty factor approach is used to accommodate load shifting behavior. The inequality constraint on real power generation $P_{gi,t}$ of i^{th} generator is:

$$P_{gi,\min} \leq P_{gi,t} \leq P_{gi,\max} \tag{14}$$

where:

$P_{gi,\min}$ Minimum value of real power generation of i^{th} generator;

$P_{gi,\max}$ Maximum value of real power generation of i^{th} generator;

If a unit must be "on" for a certain number of hours before it can be shut down, then a minimum up-time (T^i_{UP}) is imposed. On the contrary, the minimum down-time (T^i_{DN}) is the number of hour(s) a unit must stay off-line before it can be brought on-line again. Mathematically, the minimum up/down time constraints for i^{th} unit can be expressed as:

$$\left(T^i_{UP} - H^{i,t-1}_{in}\right)\cdot\left(u^{i,t}_G - u^{i,t-1}_G\right) \geq 0 \tag{15}$$

$$\left(T^i_{DN} - H^{i,t-1}_{off}\right).\left(u^{i,t-1}_G - u^{i,t}_G\right) \geq 0 \tag{16}$$

where:

$H^{i,t}_{in}$ Amount of time i^{th} unit has been running;

Equations (13), (14) are nonlinear. It can be linearized using the method presented by Chang et al. [20]. The UC schedule should provide the exact amount of power to meet the consumer's demand. Therefore:

$$\sum_{i=1}^{N_g} P_{gi,t} + \sum_{nw=1}^{NW} P_{nw,t} = \sum_{k=1}^{K} D^{k,t}_{RS} + \sum_{m=1}^{M} D^{m,t}_{T} \tag{17}$$

where:

$D^{m,t}_{T}$ Consumption of m^{th} price taking bidder at period t;

M Maximum value of real power generation of i^{th} generator;

$P_{nw,t}$ Forecasted generation of nw^{th} wind power unit at time t ;

NW Number of wind power units;

4. Results and Analysis

Mathematically social welfare equation is a decision problem with an objective to be maximized with respect to a series of prevailing equality and inequality constraints. The equation is a mixed-integer non linear problem and includes a large number of integers and continuous variables. Non linear part is converted into piecewise linear function using the technique given in [9]. The market-clearing algorithm described in Section-3 has been applied to several scenarios to assess economic viability of demand shifting and evaluate its impact on emission dispatch and on wind scenarios. The platform used for the implementation of this proposed approach is on INTEL[R], Pentium [R] 4 CPU 3.06 GHz, 512 MB of RAM. Many commercial packages such as CPLEX, LINDO, OSL and XPRESS-MP exist in the market place have been successfully applied to UC problems. In this paper, we use XPRESS-MP to solve the problem [19].

The test system used in the studies consists of IEEE 30 bus system with a total capacity of 435 MW. The IEEE 30 bus system has six generating units. The characteristics of generators, unit constraints and the emission coefficients are given in Table I. The maximum and minimum loads are 396.76 MW and 183.4 MW, respectively, while the total system forecasted energy demand is 6934.76 MWh. The study period is 24-hours. The 24-hour system load and forecasted wind power are presented in Table 2. The proportion of the demand that responds to prices affects the shape of the demand curve. Load participation factor (LPF) is defined as the ratio of the price responsive demand to the total possible demand [9].

The simulated wind power scenarios are assumed to follow a normal distribution with a standard deviation (volatility) of 10% of expected values which is the forecasted value and in the following studies, the number of reduced scenarios is chosen to be ten, taken from [16]. The following three cases are discussed in this paper:

Case 1: Case 1 is the base case without PRDS bidding which applies 11 commitment and dispatch for the forecasted wind power and the other ten simulated wind power scenarios, without considering the correlation between scenarios.

Case 2: In this case, we observe the impact of PRDS on system operation and compare generation dispatch and total system operating cost with and without PRDS.

Case 3: Demonstrate the relationship between LPF and emission at different value of load participation factor from 0 to 0.1.

4.1. Social Welfare without PRDS bidding

With forecasted wind power given in Table 2, we solve the social welfare equation without inclusion of demand shifting and determine the dispatch of non-wind units given in Table 3(a). The cheapest Unit 1 and 2 are always committed. The more expensive Unit 3 and 4 are committed between Hours 1 and 22. Unit 5 is committed between Hours 16 and 21. Unit 6 is committed between Hours 2-7 and 15-21. The system generation cost is $16080.296. To observe the impact of wind power scenarios, we solve ten social welfare equations. The operation costs are shown in Figure 1(a) which range from $16185.804 for Scenario 5 to $15837.475 for Scenario 9. Table 4(a). shows the social welfare equation solutions for the 10 scenarios. Each value in the table shows the number of times certain units are ON in the 10 scenarios. Here, Unit 3 and 4 are ON mainly between Hours 1–22, while Unit 5 is ON mainly between Hours 16–21, while Unit 6 is ON mainly between Hours 3-7 and Hours 15–21.

4.2. Social Welfare with PRDS bidding

To observe the impact of demand shifting we take LPF 0.1. The load and wind profile are same as Case 1. Table 3(b). presents the dispatch of non-wind units for 24 hours. The system generation cost reduces to $15657.407. In all 10 scenarios operation costs are shown in Figure 1(b) which range from $15773.616 for Scenario 5 to $15330.454 for Scenario 10. In this case, for forecasted and all ten scenarios the expensive unit 5 is not dispatched as shown in Table 4(b). These results show the lower cost of using PRDS bidding for supplying the load in the system.

Table 1. Data for IEEE-30 bus system

Gen No	1	2	3	4	5	6
Max (MW)	200	80	50	35	30	40
Min (MW)	50	20	15	10	10	12
γ	0.013	0.02	0.027	0.029	0.029	0.027
β	-0.9	-0.1	-0.01	-0.01	-0	-0.01
α	22.98	25.31	25.51	24.9	24.7	25.3
c	0	0	0	0	0	0
b	2	1.7	1	3.25	3	3
a	0.004	0.018	0.063	0.008	0.025	0.025
Min Up Time (Hrs)	1	2	1	1	2	1
Min Down Time (Hrs)	1	2	1	2	1	1
Shut Down cost	50	60	30	85	52	30
Cold start (Hrs)	2	1	1	1	1	1
Initial unit status	-1	-3	2	3	-2	2
Hot Start up cost	70	74	50	110	72	40
Cold Start up cost	176	187	113	267	180	113

Table 2. Hourly load and forecast wind power

Period	Load (MW)	Wind (MW)	Period	Load (MW)	Wind (MW)
1	232.4	44	13	238	84
2	274.4	70.2	14	259	80
3	320.6	76	15	291.2	78
4	373.8	82	16	324.8	32
5	396.8	84	17	344.4	4
6	380.8	84	18	337.4	8
7	344.4	100	19	330.4	10
8	298.2	100	20	315	5
9	268.8	78	21	285.6	6
10	225.4	64	22	254.8	56
11	205.8	100	23	225.4	82
12	224	92	24	183.4	52

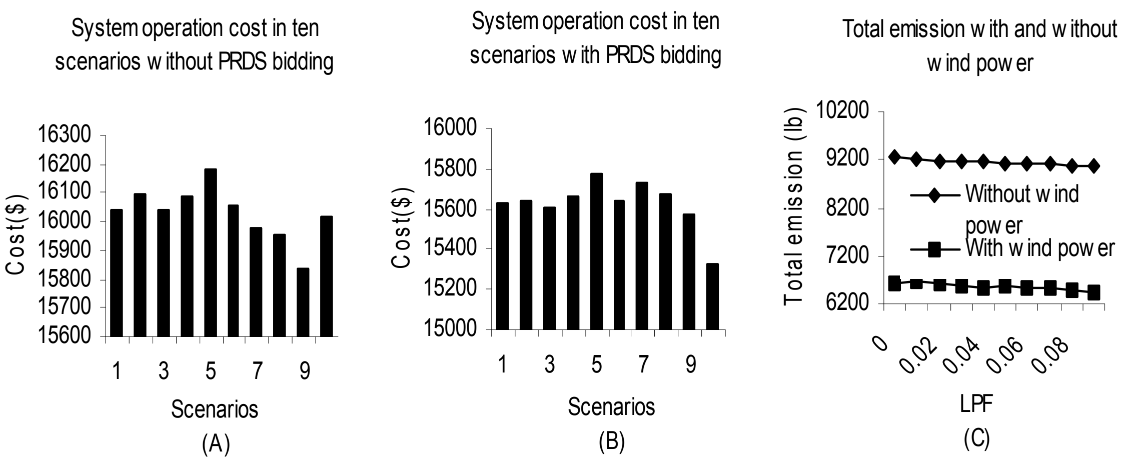

Figure 1. System operation cost

Table 3. Generation Dispatch (MW) with Forecasted Wind Power

(a) without PRDS bidding

Hour	U1	U2	U3	U4	U5	U6
1	100	40	26.67	21.73	0	0
2	100	40	24.53	18.33	0	21.33
3	100	60	26.67	27.27	0	30.67
4	139.5	60	26.67	35	0	30.67
5	150	60	37.09	35	0	30.67
6	144.5	60	26.67	35	0	30.67
7	100	60	26.67	27.07	0	30.67
8	100	44.87	26.67	26.67	0	0
9	100	40	26.67	24.13	0	0
10	100	36.4	15	10	0	0
11	60.8	20	15	10	0	0
12	87	20	15	10	0	0
13	100	29	15	10	0	0
14	100	40	20.67	18.33	0	0
15	100	40	26.67	25.2	0	21.33
16	110.5	60	26.67	35	30	30.67
17	150	60	34.73	35	30	30.67
18	147.1	60	26.67	35	30	30.67
19	138.1	60	26.67	35	30	30.67
20	127.7	60	26.67	35	30	30.67
21	112.3	60	26.67	26.67	23.33	30.67
22	100	45.47	26.67	26.67	0	0
23	100	43.4	0	0	0	0
24	100	31.4	0	0	0	0

(b) with PRDS bidding

Hour	U1	U2	U3	U4	U5	U6
1	100	40	26.67	0	0	0
2	100	50.09	26.67	0	0	0
3	100	40	26.67	26.67	0	21.33
4	102.1	60	26.67	35	0	30.67
5	120.8	60	26.67	35	0	30.67
6	106.4	60	26.67	35	0	30.67
7	100	40	26.67	26.67	0	21.33
8	100	40	26.67	26.67	0	21.33
9	100	40	26.67	26.67	0	21.33
10	100	40	26.67	26.67	0	21.33
11	100	40	26.67	26.67	0	21.33
12	100	40	26.67	26.67	0	21.33
13	100	40	26.67	26.67	0	21.33
14	100	40	26.67	26.67	0	21.33
15	100	40	26.67	26.67	0	21.33
16	108	60	26.67	35	0	30.67
17	150	60	30.29	35	0	30.67
18	143.3	60	26.67	35	0	30.67
19	135	60	26.67	35	0	30.67
20	126.2	60	26.67	35	0	30.67
21	107	60	26.67	26.67	0	30.67
22	100	46.65	26.67	0	0	0
23	100	40	26.67	0	0	0
24	100	41.75	26.67	0	0	0

4.3. Social Welfare with LPF varying from 0 to 0.1

In this section, we study the sensitivity of social welfare results to the size of PRDS bidding with and without wind power. For the same system we use different PRDS with several LPF options as shown in fig. 1(C). It can be seen that with wind power total emission reduces from 9275.748 lb to 6628.245 lb when we do not consider PRDS. By increasing the size of PRDS, the total emission further reduces to 6449.473 lb.

Table 4. Statistics of Unit Commitments in Scenarios

Unit	(a) without PRDS Bidding Hours(1-24)																								(b) with PRDS BiddingHours(1-24)																							
1	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
2	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
3	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	1		10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
4	8	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10			2	3	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	4	3	2
5															1	7	7	7	7	7	7	1			0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6		3	10	10	10	10	10	2							8	10	10	10	10	10	9	1			1	2	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	3	3	3

5. Conclusion

A MIP based social welfare problem including wind and PRDS bidding is described in this paper. The case studies based on an IEEE 30 bus system generator data indicate that the application of PRDS can impact the peak load reduction, system operating cost, emission reduction, commitment and dispatch of the units. Much of the benefits listed here will depend on the load participation factor of PRDS bidding. The example on IEEE 30 bus system generator data showed the effectiveness of the proposed model. The proposed algorithm can be used for the operation planning in the day-ahead as well as the long term planning of wind units in a constrained thermal power system.

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