

Demand Response Based and Wind Farm Integrated Economic Dispatch

Haijun Xing, *Member, IEEE*, Haozhong Cheng, and Libo Zhang

Abstract—Increased penetration of intermittent renewable energy resources is pushing the grid to prepare more reserves to meet the supply and demand balance. Demand response (DR) is an efficient strategy to reduce the overall load at peak times. In order to fully utilize the application of DR and make DR capable of actively supporting grid operations at all times, this paper builds a DR and wind farm integrated economic dispatch model. The objective is to minimize the total operation costs, such as fuel cost, startup cost, greenhouse gas (GHG) emission costs, and DR cost. DR maximum participating time and DR ramp rate constraints are considered. A system with 10 traditional units, one large-scale wind farm, three types of DR, including interruptible load, direct load control, and load as capacity resource are selected to verify the proposed model. Four DR penetration rates are analyzed: 0%, 10%, 20% and 30%. The results indicate that DR penetration can decrease total operation costs. The lower price DR resource gets the priority to be committed. The DR and wind farm integration is indispensable in the future economic dispatch.

Index Terms—Demand response, economic dispatch, GHG emission, wind farm.

I. INTRODUCTION

ELECTRICITY generation is considered by far the largest producer of CO₂ emissions, accounting for 41% of world CO₂ emissions in 2010 [1]. Increased concerns about greenhouse gas (GHG) emissions caused by fossil-based generating units have led to a continued focus on energy policies. Among many advances that have taken place in recent years to cut CO₂ emissions, the electricity dynamic economic dispatch (DED) is one such method. The objective of DED is to find the optimal generation schedule of the generators in a power system in order to minimize the total operation cost of generators, while all the system constraints are being fulfilled during the operation time [2]–[6].

The traditional DED model minimizes the total cost from units without considering emission even though the minimal

cost leads to lower emissions. However, the unit emission characteristic is not the same as the fuel combustion characteristic. Therefore, operating at the absolute minimum operation cost of generators may no longer be the suitable standard for a modern power system. In this model, moreover, we will need to additionally factor in the GHG emission costs, including the development of renewable energy generation.

In early research, economic dispatch (ED) was first solved using the enumeration method [2]. Subsequently, many papers were published on the subject [3]–[7], in which ED solutions were based on evolutionary algorithms, such as particle swarm optimization (PSO), simulated annealing algorithm (SAA), and genetic algorithm (GA). Economic emission dispatch (EED), an algorithm based on co-ordination equations, was developed in [8] for the effective handling of practical constraints. In [9], GA, micro GA (MGA), and evolutionary programming (EP) are compared to solve the ED problem. Then EP is selected to further solve the EED problem. Reference [10] separates out the unit fuel cost and unit emission and considers them as two objectives; it uses non-dominated sorting GA-II to solve the multiple objective optimization problem and to arrive at pareto-optimal solutions. Reference [11] proposes a mathematical model to factor in wind power generation into the ED problem. Reference [12] proposes a quantum genetic algorithm to solve the ED problem with wind power generation, and discusses the impact on total cost saving for power generation after adding wind power generation.

Although EED and renewable energy are efficient ways to decrease GHG emissions, the challenge is that most popular renewable energies like wind and solar power are intermittent. Increased penetration of intermittent renewable energy resources pushes the grid to prepare more reserves to meet the balance of supply and demand. This in turn rolls back GHG emissions. One option to solve this problem is the use of demand response (DR), which has gained favor to alleviate the problems of energy shortage and environmental deterioration.

DR can be regarded as a virtual plant, which is both flexible and clean. EED with DR, moreover, is able to not only decrease system emission and total operation cost, but also can provide the distribution network operator (DNO) more flexibility to handle the problems in daily operations. It is estimated that globally over 50% of the entire flexibility requirement up until 2050 can be met with the demand side resource, especially for regulation and load following [13]. In [14], ED with gridable vehicles is introduced and PSO is

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H. Xing (corresponding author), H. Cheng, and L. Zhang are with Laboratory of Control of Power Transmission and Conversion, Ministry of Education (Department of Electrical Engineering, Shanghai Jiao Tong University), Shanghai 200240, China (e-mail: xinghj@sjtu.edu.cn; hzcheng@sjtu.edu.cn; sjtu_zhanglibo@163.com).

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proposed to achieve the balance between costs and emission reductions. Reference [15] gives us a perspective that the power system is poised to make great changes where we will be able to control the original grid to adapt to different loads, and in the near future, an overall balance between generation and load can be achieved. The challenges of demand side management (DSM) are introduced in [16], and its advancement are discussed in [17] in which DSM is shown as moving from isolated usage to broad, selective, and intelligent usage. Finally, in [17] the focus shifts to the role of electricity users and their needs, all of which is important in studying the new smart grid.

In this paper, the DR and renewable energy are included in the DED problem so as to fully decrease the total operation cost, including the emission cost. The major contributions of this paper are:

- 1) proposing demand response based and wind farm integrated economic dispatch model, which takes the demand side resources the same as the supply side resources and considers the DR maximum participating time and DR ramp rate constraint;
- 2) raising the consciousness that demand side and supply side resources have the same characteristics and importance;
- 3) verifying the proposed model successfully on a 10-unit system with SAA.

II. DEMAND RESPONSE

DR can be defined as follows [18]: to alter electric use by demand side users from their regular consumption patterns in response to electricity price modifications, or to develop incentive schemes designed to lower electricity consumption when the electricity price is high or when system safety and reliability are endangered. In some ways, demand side resources have the same characteristics as supply side units. Table I shows the comparison of supply side and demand side resources.

TABLE I
SUPPLY SIDE AND DEMAND SIDE RESOURCES COMPARISON

No.	Supply Side Resources	Demand Side Resources
1	Nuclear power plant and large coal-fired power plant with big annual electricity utilization hours to support the base load;	Large industrial load with large maximum load utilization hours, like nonferrous electrolysis, petroleum, chemical and metallurgy industry;
2	Flexible plant to track the load, like gas fired power plant, pumped storage power plant and small coal-fired power plant;	Air-conditioning and electrical vehicle, one-shift enterprise which are easy to be shifted or cut down through policies and techniques;
3	Control the ramp rate of generation unit to limit the impact to the load;	Control the ramp rate of load to decrease the shock effect to the power system safety and stability;
...	...	...

DR has many advantages. It can provide competitive pressure to decrease electricity market prices, increase awareness of energy savings, provide for more efficient market operations, mitigate market power, and enhance power system

reliability. Together with newer technologies, DR can also support the use of renewable energy resources (RES), distributed generation (DG), and so on [19]–[21].

According to the 2012 Federal Energy Regulatory Commission (FERC) report [18], DR can be classified into incentive-based programs and time-based programs. In this survey, four types of DR are seen to make up 80 percent of the total reported potential peak reduction. They are load as capacity resource, interruptible load, direct load control, and time-of-use pricing [18].

In this paper, three types of DR are selected for the proposed model: interruptible load, direct load control, and load as capacity resource.

III. INTEGRATED ECONOMIC DISPATCH MODEL

A. Optimization Model

The supply side and demand side integrated economic dispatch model is shown as follows:

$$\min f = \sum_{t=1}^{NT} \left\{ \sum_{k=1}^{NG} (F_k(P_{Gk,t}) + S_k(P_{Gk,t}) \cdot (1 - u_{k,t-1}) + H_k(P_{Gk,t}) \cdot h_k) \cdot u_{k,t} + \sum_{i=1}^{NC} G_{i,t}(P_{Di,t}) \right\} \quad (1)$$

where NT is the total time segment, NG is the total number of units (wind farm not included), and NC is the total number of DR aggregators. $P_{Gk,t}$, $P_{Di,t}$ are output of k^{th} unit at time t and commitment capacity of i^{th} DR aggregator at time t . $u_{k,t}$ is the status of k^{th} unit at time t . $F_k(P_{Gk,t})$, $S_k(P_{Gk,t})$, $H_k(P_{Gk,t})$ and $G_{i,t}(P_{Di,t})$ are respectively fuel cost function, startup cost function, GHG emission cost function of the k^{th} unit, and cost function of i^{th} DR aggregator. h_k is the penalty cost of unit emission. The detailed formulas are shown below:

$$F_k(P_{Gk,t}) = a_k P_{Gk,t}^2 + b_k P_{Gk,t} + c_k \quad (2)$$

where a_k , b_k and c_k are fuel cost coefficients.

$$S_k(P_{Gk,t}) = \begin{cases} C_k^{\text{HS}}, & T_k^{\text{off}} + T_k^{\text{CS}} \geq t_k^{\text{off}} \geq T_k^{\text{off}} \\ C_k^{\text{CS}}, & t_k^{\text{off}} \geq T_k^{\text{off}} + T_k^{\text{CS}} \end{cases} \quad (3)$$

where C_k^{HS} , C_k^{CS} are respectively hot and cold startup cost of k^{th} unit. t_k^{off} is continuously down duration of k^{th} unit. T_k^{off} is permitted minimum down time of k^{th} unit. T_k^{CS} is cold start time of k^{th} unit.

$$H_k(P_{Gk,t}) = \alpha_k P_{Gk,t}^2 + \beta_k P_{Gk,t} + \gamma_k \quad (4)$$

where α_k , β_k and γ_k are GHG emission penalty coefficients.

$$h_k = F_k(P_{Gk}^{\text{max}}) / H_k(P_{Gk}^{\text{max}}) \quad (5)$$

where P_{Gk}^{max} is the k^{th} unit maximum output limit.

DR costs depend on the type of DR that aggregators participate in. When the DR type is confirmed, the DR cost is decided by the contractual price or the location-based marginal price (LMP).

B. Constraints

1) *Power Balance Constraint*: The total generated power electricity from all the committed units at each hour must be equal to the load demand at the corresponding hour.

$$\sum_{k=1}^{NG} P_{Gk,t} + \sum_{m=1}^{NW} P_{Wm,t} = P_{L,t} - \sum_{i=1}^{NC} P_{Di,t} \quad (6)$$

where NW is total number of wind farms. $P_{Wm,t}$ is the output of m^{th} wind farm at time t . $P_{L,t}$ is the load power at time t .

2) *Spinning Reserve Constraint*: Spinning reserve must be ample during the system operation in order to minimize the load interruption probability, which can be expressed as:

$$u_{k,t} \cdot \sum_{k=1}^{NG} P_{Gk}^{\max} + \sum_{i=1}^{NC} P_{Di,t} \geq P_{L,t} \cdot (1 + R_r) \quad (7)$$

where R_r is the system reserve rate.

Because of the intermittency of the renewable energy resources, wind farms are not taken into consideration in the reserve constraint. The DR participants are assumed to strictly follow the day-ahead contract with the DR aggregators. So the DR is regarded as a virtual power plant, which has a stable output to provide reserve.

3) *Unit Output and DR Participation Constraints*: The power generated by each unit and the DR participation capacity must be within certain limits, which are indicated as follows:

$$P_{Gk}^{\min} \leq P_{Gk} \leq P_{Gk}^{\max} \quad (8)$$

$$P_{Di}^{\min} \leq P_{Di} \leq P_{Di}^{\max} \quad (9)$$

where $P_{Gk}^{\min}$ is the lower power output limit of k^{th} unit. $P_{Di}^{\min}$ and $P_{Di}^{\max}$ are respectively minimum and maximum participating capacity limit of i^{th} DR aggregator.

4) *Unit Minimum Up/Down Time and DR Maximum Participation Time Constraint*: Once the unit is committed or decommitted, there is a predefined minimum time limit after it can be decommitted or committed again. For DR, there is a maximum participation time in order to maintain the basic performance of the electricity instruments.

$$T_{Gk}^{\text{on}} \geq UT_{Gk}^{\min} \quad (10)$$

$$T_{Gk}^{\text{off}} \geq DT_{Gk}^{\min} \quad (11)$$

$$T_{iD}^{\text{on}} \leq T_{iD}^{\max} \quad (12)$$

where $UT_{Gk}^{\min}$, $DT_{Gk}^{\min}$ and $T_{iD}^{\max}$ are respectively the lower limit of the startup time, lower limit of shut down time of k^{th} unit, and maximum participating time of i^{th} DR aggregator.

5) *Unit Ramp Rate and DR Ramp Rate Constraint*: In order to minimize impact to the load from the unit ramp up and ramp down, and to minimize the shock to the power system from the DR ramp up and ramp down, there should be a ramp rate constraint:

$$-R_{Gk}^{\text{down}} \leq P_{Gk,t+1} - P_{Gk,t} \leq R_{Gk}^{\text{up}} \quad (13)$$

$$-R_{Di}^{\text{down}} \leq P_{Di,t+1} - P_{Di,t} \leq R_{Di}^{\text{up}} \quad (14)$$

where R_{Gk}^{down} and R_{Gk}^{up} are ramp down rate limit and ramp up rate limit of k^{th} unit. R_{Di}^{down} and R_{Di}^{up} are ramp down rate limit and ramp up rate limit of i^{th} DR aggregator.

IV. RESULT AND DISCUSSION

The proposed model is tested on a traditional 10-unit system; the corresponding data is shown in Table II. The rated wind farm is 200 MW, the wind cut-in speed, rated speed, and cut-out speed are 5 m/s, 18 m/s, 25 m/s, respectively. The 24-hour forecast wind speed is shown in Fig. 1. The 24-hour load curve is based on [21]. The wind farm output is based on the model in [22].

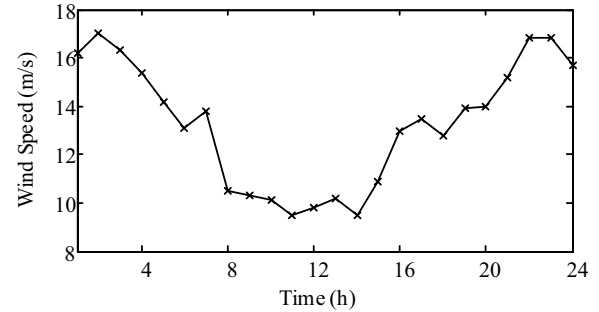


Fig. 1. Day-ahead 24-hour wind speed forecast.

Two kinds of variables need to be determined in solving the DED problem. They are the binary unit on/off status variables and the continuous unit output power variables. Then the optimization problem can be divided into two sub-problems, a combinatorial optimization problem for binary variables and

TABLE II
THE PARAMETER OF ONE TEST SYSTEM

Units	$P_{\max}$ (MW)	$P_{\min}$ (MW)	a (\$/h)	b (\$/MWh)	c (\$/(MW) ² h)	CSC (\$)	HSC (\$)	CST (h)	IS	IST (h)	MUT (h)	MDT (h)	α (lb/h)	β (lb/MWh)	γ (lb/(MW) ² h)
1	455	150	1,000	16.19	0.00048	9,000	4,500	5	1	8	8	8	103.3908	-2.4444	0.0312
2	455	150	970	17.26	0.00031	10,000	5,000	5	1	8	8	8	103.3908	-2.4444	0.0312
3	130	20	700	16.60	0.00200	1,100	550	4	0	5	5	5	300.3910	-4.0695	0.0509
4	130	20	680	16.50	0.00211	1,120	560	4	0	5	5	5	300.3910	-4.0695	0.0509
5	162	25	450	19.70	0.00398	1,800	900	4	0	6	6	6	320.0006	-3.8132	0.0344
6	80	20	370	22.26	0.00712	340	170	2	0	3	3	3	320.0006	-3.8132	0.0344
7	85	25	480	27.74	0.00079	520	260	2	0	3	3	3	330.0056	-3.9023	0.0465
8	55	10	660	25.92	0.00413	60	30	0	0	1	1	1	330.0056	-3.9023	0.0465
9	55	10	665	27.27	0.00222	60	30	0	0	1	1	1	350.0056	-3.9524	0.0465
10	55	10	670	27.79	0.00173	60	30	0	0	1	1	1	360.0012	-3.9864	0.0470

$P_{\max}$ and $P_{\min}$ are the maximum and minimum output of unit, respectively; CSC is the cold startup cost; HSC is the hot startup cost; CST is the cold start time; IS is the unit initial status; IST is the unit initial status time; MUT is the minimum up time; MDT is the minimum down time; a , b , c are the fuel cost coefficient; α , β , γ are the emission penalty coefficient.

a nonlinear optimization problem for unit output confirmation. In this paper, SAA is used to solve the combinatorial optimization, and quadratic programming is used to solve the continuous unit output problem.

SAA simulates the procedure of a metal gradually cooling down, until the total system energy reaches the overall minimum value and stable state. The principle of simulated annealing is based on the manner in which metals recrystallize during the process of annealing. SAA was originally proposed as a combinatorial optimization method [23], which is reported to perform well in power system economic dispatch [5], [24].

Three kinds of DR aggregators are considered. Interruptible load is paid separately at the peak time and non-peak time. During peak time (8:00–21:00), the price is \$40/MWh; at other times the price is \$20/MWh. Direct load control is \$30/MWh at all times. Load as capacity resource is paid according to NYISO N.Y.C Sep 09, 2013 real-time LMP [25]. Spinning reserve is set to 10% of the total demand in order to minimize the probability of load interruptions.

The tests are conducted on a Core(TM) i5-4200M CPU, 2.5 GHz PC. The ramp rate of the units and DRs in this paper is set to 50% of its maximum output. The control parameters of the SAA and cooling schedule follow the scheme from [24].

There is no guarantee that SAA converges to the global optimal solution. Thus, the program is executed 10 times to obtain the best solution. It should be carefully noted that the total generation cost without consideration of wind farm, DR and emission cost is \$564,238 in this paper, which is close to the value presented in [22] under the same condition. So the algorithm used here is applicable.

In order to analyze the effect of DR on the DED, three levels of DR penetration are set. The DR capacity is as follows: 1) 10% DR penetration, i.e., DR1-66.2 MW, DR2-50 MW, DR3-50 MW; 2) 20% DR penetration, i.e., DR1-132.4 MW, DR2-100 MW, DR3-100 MW; and 3) 30% DR penetration, i.e., DR1-198.7 MW, DR2-150 MW, DR3-150 MW.

Table III shows the results, namely, the startup cost can be obtained by subtracting fuel cost, emission cost and DR cost from the total cost. With DR penetration increasing, the costs excluding the unit startup cost decrease. However, there is no exact decreasing or increasing characteristic of emission cost with the DR penetration increasing because when the DR is committed, the unit commitment will be different compared to the previous optimal unit commitment without DR in order to obtain the optimal total cost. This new unit commitment results in either an increase or decrease in the emission cost, which depends on the fuel cost and emission characteristic of the units. The DR cost increase rate is not the same as the DR

penetration increase because the price of DR determines the amount of DR committed.

From Fig. 2, the commitments of units 1 and 2 are lower than the normal unit commitment result without DR integration [22]. Some of the commitment decrease is substituted by DR and wind farms. From Fig. 3 the DR1 interruptible load is mostly committed at non-peak time 1:00–8:00, 23:00–24:00, when the price is \$20/MWh. The DR2 direct load control with price \$30/MWh is only committed at peak load time 12:00–13:00, 20:00. The DR3 load as capacity resource is only committed at the time with lower LBMP or at peak load times. Thus lower DR price can increase DR commitment and decrease the total cost, but the lower DR price can only be accepted by the users at non-peak time. The DR price needs to be systematically designed to increase the DR commitment and decrease the total operation cost and emission cost.

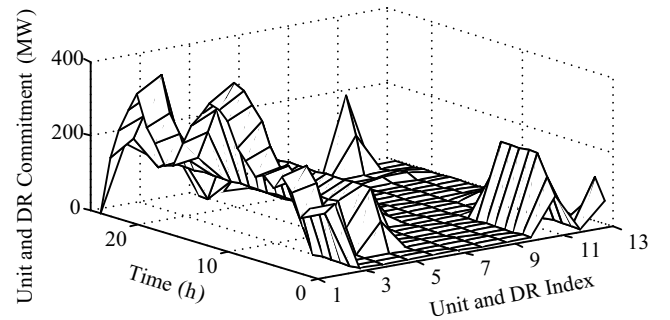


Fig. 2. Unit and DR commitment result with 30% DR penetration, 200 MW wind farm. Index 1–10 is the unit index; index 11–13 is the DR index.

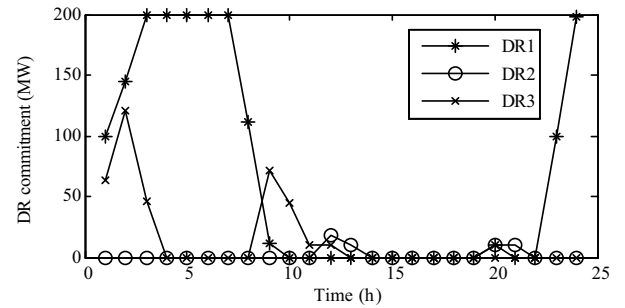


Fig. 3. DR commitment result with 30% DR penetration, 200 MW wind farm.

TABLE III
10-UNIT SYSTEM RESULT WITH DIFFERENT DR PENETRATION AND 200 MW WIND FARM

DR Penetration	Total Cost (\$)	Fuel Cost (\$)	Emission Cost (\$)	DR Cost (\$)
0%	664,664.53	557,020.36	104,474.17	0
10%	656,013.85	511,453.21	114,082.08	26,738.56
20%	647,583.18	491,414.53	113,682.10	38,916.55
30%	644,886.38	483,270.37	111,776.85	45,819.15

TABLE IV
10-UNIT SYSTEM RESULT WITH DIFFERENT DR PENETRATION AND 50 MW WIND FARM

DR Penetration	Total Cost (\$)	Fuel Cost (\$)	Emission Cost (\$)	DR Cost (\$)
0%	734,774.82	597,318.19	134,350.63	0
10%	723,208.81	563,121.52	132,783.61	23,723.68
20%	717,021.41	536,227.67	132,591.56	42,472.17
30%	713,407.91	532,914.95	125,560.29	51,562.66

200 MW wind farm installation. As the intermittency and uncertainties of the wind farm, the application of the day-ahead economic dispatch scheme with the proposed model should provide a supplementary scheme from the short-term real-time scheduling. The scheduling should strictly follow the short-term load and wind forecast.

V. CONCLUSION

This paper proposes a demand response and wind farm integrated economic dispatch model, which takes the demand side resources as the same as the supply side resources. The DR maximum participation time and DR ramp rate constraint are considered. The proposed model is successfully applied to a 10-unit test system with three types of DR. The results indicate that DR penetration can decrease total operation costs. The lower price DR resource gets the priority to be committed. The main contribution of this work is to raise awareness that demand side resources and the supply side resources have the same characteristics and importance. The DR price needs to be systematically designed so as to promote DR development and commitment in daily operations. The proposed model takes the wind farm as a firm generator, which brings no cost and takes no reserve responsibility because of the intermittent characteristic. Large wind farms with proper forecast and reasonable dispatch can take some of the reserve responsibility. How much responsibility the wind farm can take is a topic for future research.

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Haijun Xing (M'15) received his B.Eng. and M.Eng. degrees from the Department of Electrical Engineering from Harbin Institute of Technology, Harbin, China, in 2002 and 2004, respectively. He is now pursuing his Ph.D. degree in electrical engineering from Shanghai Jiao Tong University, Shanghai, China. His research interests include distribution network operation and planning.



Haozhong Cheng received the B.S., M.S., and Ph.D. degrees in power systems from Shanghai Jiao Tong University, Shanghai, China, in 1983, 1985, and 1998, respectively. He is now a Professor at Shanghai Jiao Tong University. His special fields of interest cover power systems planning, voltage stability, harmonics, operation, and deregulation.



Libo Zhang received his B.S. degree in electrical engineering from Zhejiang University, Hangzhou, China, in 2010. He is now pursuing his Ph.D. degree in electrical engineering from Shanghai Jiao Tong University, Shanghai, China. His research interests include power system reliability evaluation and planning.