

An integrated OPF dispatching model with wind power and demand response for day-ahead markets

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Article Info

Article history:

Received Aug 22, 2018

Revised Mar 12, 2019

Accepted Apr 3, 2019

Keywords:

Demand response

Electricity markets

Monte-Carlo simulations

Optimal power flow (OPF)

Wind power

ABSTRACT

In the day-ahead dispatching of network-constrained electricity markets, renewable energy and distributed resources are dispatched together with conventional generation. The uncertainty and volatility associated to renewable resources represents a new paradigm to be faced for power system operation. Moreover, in various electricity markets there are mechanisms to allow the demand participation through demand response (DR) strategies. Under operational and economic restrictions, the operator each day, or even in intra-day markets, dispatches an optimal power flow to find a feasible state of operation. The operation decisions in power markets use an optimal power flow considering unit commitment to dispatch economically generation and DR resources under security restrictions. This paper constructs a model to include demand response in the optimal power flow under wind power uncertainty. The model is formulated as a mixed-integer linear quadratic problem and evaluated through Monte-Carlo simulations. A large number of scenarios around a trajectory bid captures the uncertainty in wind power forecasting. The proposed integrated OPF model is tested on the standard IEEE 39-bus system.

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1. INTRODUCTION

Nowadays, the power system operation involves the competitive participation of renewable generation and DR resources. Wind power generators are participating in electricity markets under different incentives and the power system operator faces an important challenge related with the wind power intermittency and unpredictability [1-3]. In this context, the integration of demand response resources represents a new resource to be allocated in the power system operation [4]. The integration of DR resources in the markets leads to technical and economic challenges associated with the integration of DR resources into the reserve markets. The focus of this paper is on the formulation of an integrated model to dispatch economically a power system under wind power integration and DR participation.

This paper provides a day-ahead dispatching framework including the integration of wind power generation and demand response resources in the OPF formulation. Specifically, the model proposed in this paper is formulated as a mixed-integer linear quadratic optimization problem, and the evaluation is performed through Monte-Carlo simulations to capture the uncertainty related with the wind power generation. DR resources are modeled as dispatchable loads, which indicates the demand tendency to shed its consumption at determined price.

The wind power output has an intermittent nature, so, the integration of wind power generation requires ancillary services such as regulation, contingency reserve and others to compensate wind power

ramps. The generation system reliability of the system may be reduced in case of unpredicted decreases in wind power because the available ramping capability of the system may not be sufficient to accommodate those changes. The day-ahead dispatching with wind power has been addressed widely. The optimal power flow (OPF) formulation have been extended to account for the variable nature of wind power generation. For instance, in [5-8], the intermittent nature of wind power generation is captured using probabilistic techniques. A stochastic unit commitment model is presented in [9], where authors propose a framework to quantify the impact of large-scale wind power integration into power systems. The uncertainty in the wind generation is addressed by means of scenarios and demands are considered to be fixed. Others authors have suggested stochastic optimization (SO) based on scenarios to cope with wind power uncertainty in the unit commitment problem [10-12]. SO employs several scenarios along with their associated probabilities to simulate possible uncertainties during the period. In [13], an optimal generation scheduling method including renewable energy, distributed resources and storage systems is solved using a particle swarm optimization algorithm. In addition, in [14], the authors propose an enhanced genetic algorithm to solve the optimal power flow.

On the other hand, the integration of demand side resources into electricity markets has drawn a lot of attention. DR is a strategy to utilize electricity demand as a distributed resource with real possibilities to improve efficiency and reliability of electricity networks. Usually, the demand in power system is considered inelastic to the prices. However, a substantial amount of electricity demand is elastic such as plug-in electric vehicle (PEV) [15] charging batteries, heating ventilation, air conditioning, and this report [16] indicates that one third of residential demand in U.S. is flexible.

Several studies are researching about the participation of demand side resources in the procurement of energy and reserve services. Seminal studies [17-19] have developed pool based market structures considering the participation of demand side resources into the energy and reserve markets. The demand side resources (i.e., DR resources) are technically capable of providing ancillary services given the flexibility and the possibility to alleviate large and unexpected wind ramp events [20, 21]. Distribution companies or aggregators usually manage DR resources [22]. The aggregators represent technically and financially various users in order to bid DR reductions in electricity markets. This paper addresses the day-ahead dispatching including wind power bids and DR bids.

The paper is organized as follows. The problem formulation is presented in Section II. In Section III, the proposed procedure is tested using the IEEE 39-bus test system. The results are analyzed and discussed. Section IV provides some concluding remarks.

2. PROBLEM FORMULATION

The notation for the OPF dispatching model including wind power generations and DR resources is expressed in terms of power generation for each unit, the load following reserves and the binary commitment variable for thermal units. The complete set of variables are described as follows:

2.1. Notation

t	Index over time periods.
T	Set of indices of time periods in the planning horizon, typically $\{1 \dots n_t\}$.
i	Index over injections (generation units, dispatchable or curtailable loads).
j	Index over scenarios.
I'	Indices of all units (generators) available for dispatch in any time t .
f	Index of wind farms.
N_F	Set of indices of all units (wind farms and generators) available for dispatch in any time t .
b	Index of loads.
$P_{D_{MAX}}$	Max., power demand for unit i at time t .
N_B	Set of indices of all loads at time t .
F_{ti}	Load flexibility of demand for unit i at time t .
p^{ij}	Active injection for unit i of scenario j at time t .
p_w^{if}	Wind power forecast as offered in the market for unit f at time t .
P_D^{ij}	Real power demand for unit i of scenario j at time t .
$C_p^{ij}(\cdot)$	Cost function for active injection i at time t .
$C_D^{ij}(\cdot)$	Cost function of upward and downward regulation of the demand from unit i at time t .
D^{tb}	Demand power at time t .

δ_+^i, δ_-^i Upward/downward load-following ramping reserves needed from unit i at time t for transition to time $t+1$.

$C_{\delta_+}^i, C_{\delta_-}^i$ Cost of upward and downward load-following ramp. Reserve for unit i at time t .

$P_{MIN}^{ij}, P_{MAX}^{ij}$ Limits on active injection for unit i in the scenario j at time t .

$\delta_{MAX+}^i, \delta_{MAX-}^i$ Upward/downward load-following ramping reserve limits for unit i .

u^i Binary commitment state for unit i in period t .

v^i, w^i Binary startup and shutdown states for unit i in period t .

C_v^i, C_w^i Startup and shutdown costs for unit i at time t

α_+^i, α_-^i Startup and shutdown costs for unit i at time t

2.2. Formulation

The problem formulation is expressed as a mixed-integer linear quadratic optimization problem (MILP), where the optimization variable x is comprised of all the p , δ_+^i , δ_-^i , u , v and w variables corresponding to power generation for each unit, the load following reserves and the binary commitment variable for thermal units.

Objective Function: The objective is expressed as the minimization $f(x)$

$$\min_x f(x) \quad (1)$$

Subject to

$$g(x) = 0 \quad (2)$$

$$h(x) \leq 0 \quad (3)$$

$$x_{\min} \leq x \leq x_{\max} \quad (4)$$

where $f(x)$ is comprised of three components.

$$f(x) = f_p(p) + f_{lf}(\delta_+, \delta_-) + f_{uc}(u, w) + f_{dr}(u, w) \quad (5)$$

Cost of active power dispatch

$$f_p(p) = \sum_{t \in T} \sum_{i \in I^t} [C_p^i (P^{ij})] \quad (6)$$

Cost of load-following ramp reserves

$$f_{lf}(\delta_+, \delta_-) = \sum_{t \in T} \sum_{i \in I^t} [C_{\delta_+}^i (\delta_+^i) + C_{\delta_-}^i (\delta_-^i)] \quad (7)$$

Startup and shutdown cost

$$f_{uc}(v, w) = \sum_{t \in T} \sum_{i \in I^t} [C_v^i v^i + C_w^i w^i] \quad (8)$$

Cost of demand response

$$f_{dr}(v, w) = \sum_{t \in T} \sum_{i \in I^t} [C_D^i (P_D^{ij})] \quad (9)$$

This minimization is subject to the following constraints, for all: $t \in T$ all $j \in J^t$ and all $i \in I^t$:

Constraints:

Power balance constraints,

$$\sum_{i \in I^T} p^{ij} + \sum_{i \in I^T} P_D^{ij} + \sum_{f \in N_F} p_w^{fj} = \sum_{b \in N_B} D^{ib} \quad (10)$$

Nonlinear transmission flow and voltage limits as inequality constraints,

$$h^{ij} (V^{ij}, p^{ij}) \leq 0 \quad (11)$$

Load-following ramping limits and reserves,

$$0 \leq \delta_+^i \leq \delta_{\max+}^i \quad (12)$$

$$0 \leq \delta_-^i \leq \delta_{\max-}^i \quad (13)$$

Injection limits and commitments,

$$u^{ii} P_{\min}^{ij} \leq p^{ij} \leq u^{ii} P_{\max}^{ij} \quad (14)$$

Startup and shutdown events,

$$u^{ii} - u^{(t-1)i} = v^{ii} - w^{ii} \quad (15)$$

Integer constraints,

$$u^{ii} \in \{0,1\}, v^{ii} \in \{0,1\}, w^{ii} \in \{0,1\} \quad (16)$$

Flexibility interval of the demand

$$0 \leq F_i \leq P_{D\max} \quad (17)$$

3. SIMULATIONS RESULTS

The IEEE 39-bus test system is examined in this section to test the integrated model that considers wind power generation DR resources. The day-ahead dispatching framework proposed as a MILP problem is solved using GUROBI 7.5.1 [23] under the Matpower platform [24]. The case IEEE 39-bus test system includes 10 generators; the data is listed in Table 1. The cost data are equal to report in [25] and [26]. Table 2 lists the quadratic cost functions for each generator in the IEEE 39-bus system according to [27]. The system daily load curve is shown in Figure 1 with a maximum peak of 4531 MW at hour 20 and a minimum of 1840 at hour 3.

Table 1. Generator data for the IEEE 39 bus system

Gen. #	$C_{\delta+}$	$C_{\delta-}$	C_v	C_w	P_{\min}	P_{\max}
1	6.9	6.9	920	736	0	250
2	6.9	6.9	920	736	0	678
3	6.9	6.9	920	736	0	650
4	6.9	6.9	920	736	0	632
5	6.9	6.9	920	736	0	508
6	6.9	6.9	920	736	0	650
7	6.9	6.9	920	736	0	560
8	6.9	6.9	920	736	0	540
9	6.9	6.9	920	736	0	830
10	6.9	6.9	920	736	0	1000

Table 2. Cost functions

Gen.	Cost Function [\$]
1	$C_1 = 0.00194P^2 + 7.85P + 310$
2	$C_2 = 0.0035P^2 + 8.5P + 260$
3	$C_3 = 0.00482P^2 + 7P + 78$
4	$C_4 = 0.00128P^2 + 6.4P + 459$
5	$C_5 = 0.0024P^2 + 6P + 80$
6	$C_6 = 0.0032P^2 + 5.8P + 400$
7	$C_7 = 0.0053P^2 + 6.24P + 120$
8	$C_8 = 0.00185P^2 + 8.4P + 60$
9	$C_9 = 0.0025P^2 + 5.75P + 450$
10	$C_{10} = 0.00142P^2 + 8.2P + 510$

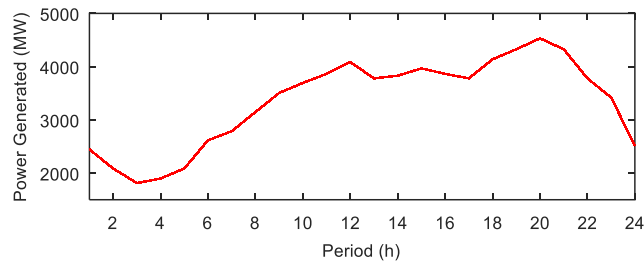


Figure 1. System daily load curve

This model considers a wind power integration level of 20% with respect to the peak load level. A large number of scenarios around a trajectory bid captures the uncertainty in wind power forecasting by the wind power generator as shown in Figure 2.

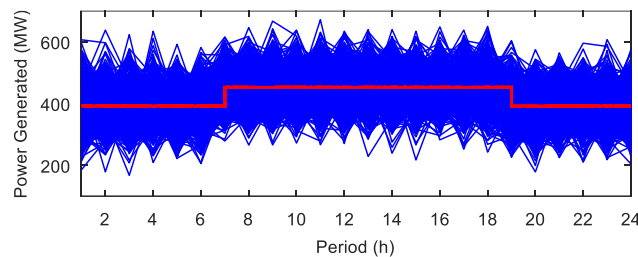


Figure 2. Wind power generation profile

DR offers incentives designed to induce lower electricity use at times of high market price. For this simulation, four loads provide demand response services, and the power quantity, which they are willing to reduce in a certain time, is 1295 MW. The incentives represented as cost functions are shown in Table 3.

Table 3. Load data for the demand response

Load	Bus	Demand Power [MW]	Cost Function [\$]
1	8	522	$C_1 = 0.00128P^2 + 6.4P + 459$
2	15	320	$C_2 = 0.00128P^2 + 6.4P + 459$
3	23	247.5	$C_3 = 0.00128P^2 + 6.4P + 459$
4	28	206	$C_4 = 0.00128P^2 + 6.4P + 459$

For five hundred (500) scenarios, this paper quantifies the demand response frequency and its magnitude in MW for each load. Each scenario runs over 24 hours according to the system daily load and it considers a forecasted trajectory for the wind integration. In Figure 3, can observe the frequency and quantity of flexibility for the load in the bus 8. It is observed the demand response is maximum all the time. Each time that this load is shed, it is shed at 522 MW. While that for the load in the bus 15, Figure 4 shows sometimes the quantity of DR required is around 270 MW, 295 MW, and 305 MW, although the 75% of time the DR required is at the maximum value. The results for demand response in the bus 23, see Figure 5, are similar to the results in the Figure 4, almost all the time the DR is dispatched at maximum. In Figure 6, the load in the bus 28 exhibit a similar dispatching to the loads in the buses 15 and 23.

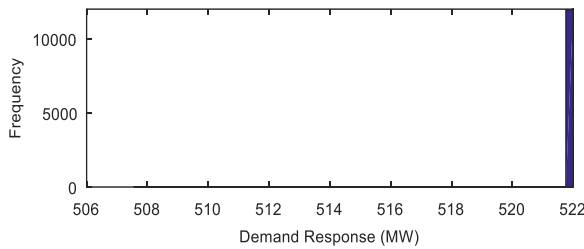


Figure 3. Demand response in the bus 8

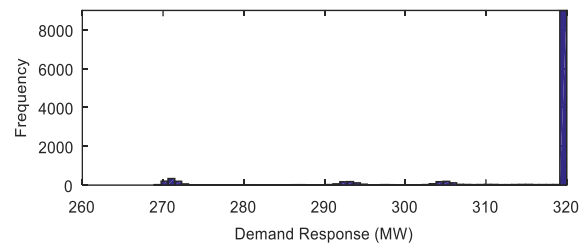


Figure 4. Demand response in the bus 15

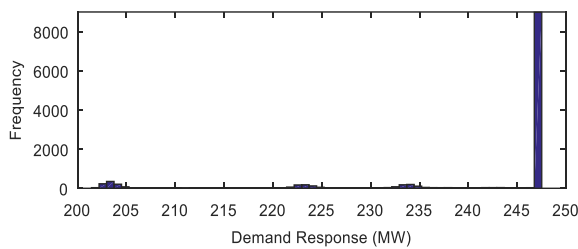


Figure 5. Demand response in the bus 23

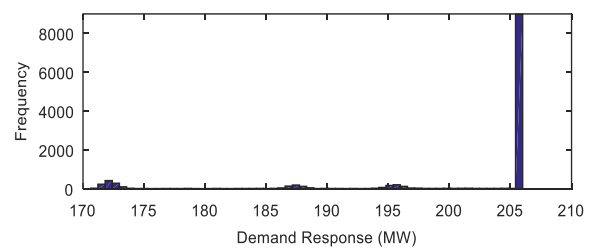


Figure 6. Demand response in the bus 28

Now, in Figure 7 shows the percentage of DR with respect to the available capacity. It is observed that in the hour 3, 13, 16 and 17 for the 24 horizon planning, the DR is not dispatched at maximum. For instance, in the hour 13, the load in the 28 responds at 40% for the maximum value available. At the peak demand for the system, at hour 20, all loads are dispatched as DR resources.

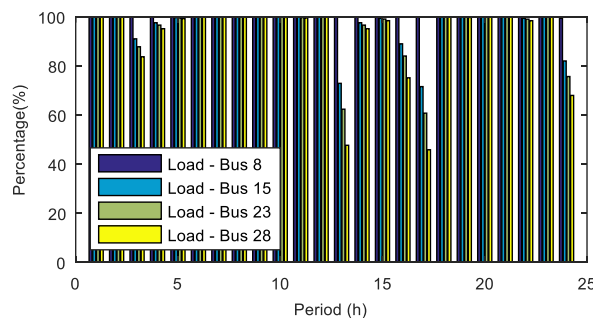


Figure 7. Demand response for all loads in the power system

In order to quantify the benefits for DR participation in the power system operation, the probability density function for the power generation cost is calculated in the 24-hour horizon. The realizations correspond to the trajectories generated around the bid made by the wind power generator. Figure 8 shows the power generation cost under 500 scenarios with DR available for dispatching while the Figure 9 shows the power

generation cost without DR available. In order to compare the results for both cases, mean and standard deviation for each case are calculated. The savings for the power generation cost is \$8271. The result represents the savings can be made in the power generation cost if the demand is flexible. Table 4 compares the mean and variance parameters for both cases, with DR and without DR.

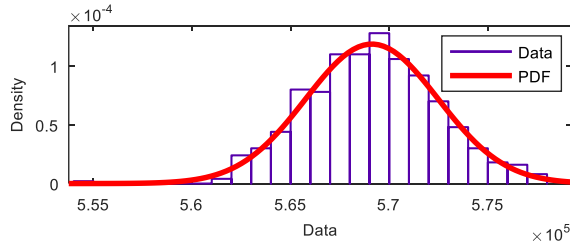


Figure 8. Cost objective function with DR

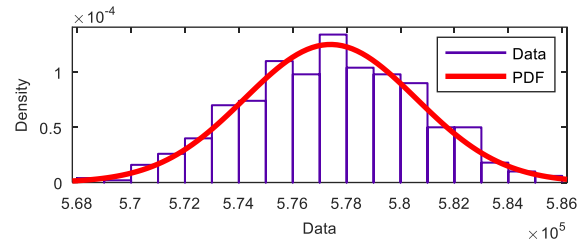


Figure 9. Cost objective function without DR

Table 4. Gaussian parameters for the cost objective function with DR and without DR

Parameter	Estimate without DR	Estimate with DR	Difference
Mean	\$577,400	\$569,120	\$8,271
standard deviation	\$3,190	\$3,360	-

In order to quantify DR benefits, others cost functions are set up to provide insight about the dispatching cost. Table 5 provides six cost functions for demand response. This cost functions represents the willing of each load to provide DR. The plot for those cost functions are shown in Figure 10.

Table 5. Incentive based demand response

Ref.	Cost Function [\$]
A	$C_A = 0.000128P^2 + 1.4P + 439$
B	$C_B = 0.00248P^2 + 2.4P + 449$
C	$C_C = 0.00128P^2 + 6.4P + 459$
D	$C_D = 0.00528P^2 + 6.4P + 469$
E	$C_E = 0.00928P^2 + 6.4P + 479$
F	$C_F = 0.015221P^2 + 6.4P + 489$

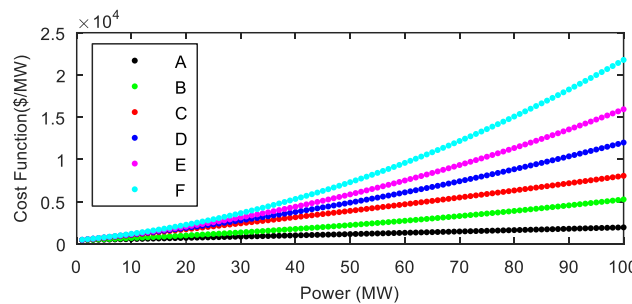


Figure 10. Cost functions for demand response

The power generation cost varies according to different incentives for DR as shown in Figure 11. For instance, the case F, in Figure 10, shows a cost function with high bid for DR. The case A corresponded to a situation with a lower cost function, however, the dispatching is not the lower. For the cases evaluated, the optimal solution corresponds to the case C, the cost function C is between the cases A and F.

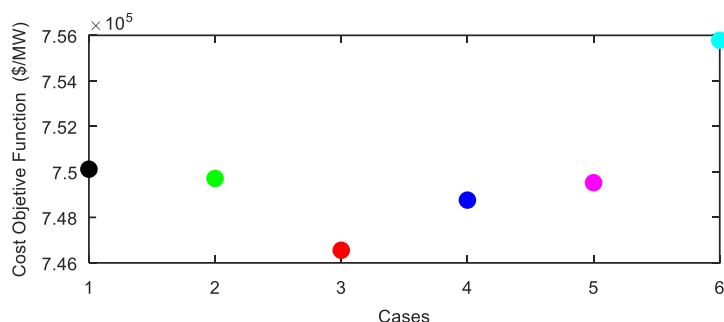


Figure 11. Cost objective function for different incentives to DR

4. CONCLUSION

In this paper, presented an integrated OPF model that explicitly includes wind power generation and demand response resources for day-ahead dispatching in constrained electricity markets. Demand response is integrated into the model as flexible loads with willing to bid day-ahead. Observed that considerable savings in power generation cost could be achieved if the demand participates in the markets. The numerical results show that the wind power uncertainty can be captured using trajectories from a Monte-Carlo simulation.

ACKNOWLEDGEMENTS

The authors acknowledge the support of the Universidad Autónoma de Occidente in Colombia.

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