

Stochastic Real-Time Scheduling of Wind-thermal Generation Units in an Electric Utility

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Abstract—The objective of dynamic economic dispatch (DED) problem is to find the optimal dispatch of generation units in a given operation horizon to supply a pre-specified demand, while satisfying a set of constraints. In this paper, an efficient method based on Optimality Condition Decomposition (OCD) technique is proposed to solve the DED problem in real-time environment while considering wind power generation and pool market. The uncertainties of wind power generation as well as the electricity prices are also taken into account. The above uncertainties are handled using scenario based approach. To illustrate the effectiveness of the proposed approach, it is applied on 40, 54 thermal generation units, and a large-scale practical system with 391 thermal generation units. The obtained results substantiate the applicability of the proposed method for solving the real-time DED problem with uncertain wind power generation.

Index Terms—Dynamic economic dispatch, Optimality condition decomposition, Real-time, Scenario based uncertainty modeling, Wind power generation.

NOMENCLATURE

$Pw_{s,t}^{avl}$	Available wind power generation capacity at scenario s and time t (MW)
$I_{i,t}$	Auxiliary binary parameter denotes on/off status of generation unit i in time t
v_{in}^c/v_{out}^c	Cut-in/out speed of wind turbine (m/sec)
Pw_t^f	Forecasted value of wind power generation (as a percent of P_r^w)
λ_t^f	Forecasted value of electricity price
D_t^f	Forecasted value of demand
$P_i^{max/min}$	Maximum/minimum limit of power generation of i^{th} thermal unit
$Pp_t^{max/min}$	Maximum/minimum Power purchased from pool market in time t (MW)
π_s	Probability of scenario s
$P_{i,t}$	Power produced by thermal unit i in time t (MW)
$Pp_{s,t}$	Power purchased from pool market at scenario s and time t (MW)
$wp_{s,t}$	Percent of wind farm capacity available at scenario s and time t
w_s	Percent of wind farm capacity available at scenario s
λ_s	Percent of peak electricity price at scenario s
$Pw_{s,t}$	Power produced by wind farm at scenario s and time t (MW)

P_t^D	Power demand in time t (MW)
P_{peak}^D	Peak power demand (MW)
D_t^f	Percent of forecasted value of demand to the peak demand
Λ	Peak electricity price of pool market
UR_i/DR_i	Ramp-up/down limit of power generation of i^{th} thermal unit (MW/h)
P_r^w	Rated power of wind farm (MW)
v_r	Rated speed of wind turbine (m/sec)
s	Scenario s
t	Time interval t
NS	Total number of scenarios
T	Total number of time intervals
i	Thermal generation unit i
TC	Total costs (\$)
OF	Total benefit (\$)
$\lambda_{s,t}^P$	The price of purchased energy from pool market in time t and scenario s (\$/MWh)
$\lambda_{s,t}^D$	The price of energy sold to consumers in time t and scenario s (\$/MWh)

I. INTRODUCTION

ECONOMIC load dispatch (ELD) is a non-linear constrained optimization problem which plays an important role in the economic operation of power systems [1]–[4]. Dynamic economic dispatch (DED), which is an extension of ELD for a given operation horizon, takes into account the connection of different operating times by considering ramp-rate constraints of thermal generation units. In recent decade, several economic and environmental reasons motivate increasing the share of renewable technologies in electricity generation [5]. However the inherent uncertainties associated with the operation these energy resources and the dynamic constraints like ramp-rate limits make the DED problem more sophisticated. On the other hand, the recent trends toward the smart grids and also the importance of integration of renewable energy sources (regarding environmental concerns) [6], have increased the need for real-time dispatching methodologies. A real-time dispatch method makes dispatching decisions quickly, and is not responsible for extraction of commitment decisions and will not consider start-up costs in any of its dispatching or pricing decisions in the studied horizon [7]. Thus, a powerful tool is needed for handling the uncertainties of renewable energy resources [8]–[10] along with the technical and economical constraints of thermal units. The motivation of this study is to provide such a tool. In other words, in this paper the real-time DED problem is formulated by considering uncertain wind power generation (as an important and most popular renewable energy resource), and it is solved by utilizing OCD approach in real-time environment. Besides, uncertainties in pool market prices are considered in the proposed DED model, in order to make it more realistic and practical.

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A. Literature review

The OCD technique is a powerful theoretical and algorithmic approach for addressing continuous NLP optimization problems, as well as the problems which require exploitation of their inherent mathematical structure via decomposition principles [11]. OCD is based on relaxing the complicating constraints [12]. Complicating constraints are those that if relaxed, the resulting problem decomposes into several simpler problems. The successful applications of the OCD technique have been reported in various research fields such as:

- Multi-area optimal power flow [11]
- OPF for overlapping areas in power systems [13]
- Coordinated voltage control of large multi-area power systems [14]
- Optimal integration of intermittent energy sources [15]
- Predictive control for coordination in multi-carrier Energy Systems [16]
- Decomposed stochastic model predictive control for optimal dispatch of storage and generation [17]
- Integrated water and power modeling framework for renewable energy integration [18]

In recent years, many approaches have been proposed for considering the impact of wind power generation on ELD problem. In [19], a method is proposed which estimates the available wind power and then solves the ELD problem. In [20], a time series of observed and predicted 15-min average wind speeds at foreseen onshore and offshore wind farms locations is proposed. A heuristic method (i.e bacterial foraging algorithm) is proposed in [21] for solving the ELD problem. In [22], [23], the use of battery storage is considered for making the wind turbine dispatchable. In [24], a new method is introduced for generating correlated wind power values and explains how to apply the method when evaluating economic dispatch.

B. Contribution

In this paper, a powerful stochastic real-time DED model is proposed for an electric utility to determine its optimal strategy in supplying the demand of its customers. The thermal units, wind power generation and pool market are taken into account as the energy procurement resources. The uncertainties in wind power generation as well as pool market prices are considered and modeled by scenario based approach. the resultant model is solved using the OCD approach, in real-time environment.

C. Paper organization

This paper is set out as follows: section II provides a general description of OCD algorithm. Section III deals with uncertainty modeling in the proposed real-time DED. Section IV presents DED problem formulation. Application of OCD on the DED problem is presented in Section V. Simulation results are presented in section VI and finally, Section VII concludes the paper.

II. OPTIMALITY CONDITION DECOMPOSITION

Consider an optimization problem with the specified decomposable structure, which consists of N blocks of variables as follows.

$$\max_{X_i} f(X_1, \dots, X_N) = \sum_{n=1}^N f_n(X_n) \quad (1)$$

$$h_n(X_1, \dots, X_N) \leq 0, \forall n = 1, \dots, N \quad (2)$$

$$g_n(X_n) \leq 0, \forall n = 1, \dots, N \quad (3)$$

Where $X_n = [x_{n_1}, \dots, x_{n_{\phi_n}}]$ are the variables for each block n in which the original problem (1)-(3) decomposes. ϕ_n is the cardinality of n -th block of variables. Constraints (2) and (3) represent both equality and inequality constraints of the problem. In the above optimization problem, (2) are the complicating constraints, i.e. by relaxation of these constraints, the overall optimization problem will be decomposed to several (here N independent sub-problems). By investigation of the first-order KKT optimality conditions for the aforementioned problem, which is described in detail in [25], the original problem could be decomposed to N independent sub-problems as follows.

$$\max \left(f_n(X_n) + \sum_{k=1, k \neq n}^N \bar{\lambda}_k^T h_k(\bar{X}_n^*) \right) \quad (4)$$

$$h_n(\bar{X}_n^*) \leq 0 \quad (5)$$

$$g_n(X_n) \leq 0 \quad (6)$$

Where $\bar{X}_n^* = [\bar{X}_1, \dots, \bar{X}_{n-1}, X_n, \bar{X}_{n+1}, \dots, \bar{X}_N]$. It is worth to mention that the variables with above them, are known for n -th sub-problem. Also, λ_k is the obtained value for Lagrange multipliers of k -th complicating constraints, which is obtained in k -th sub-problem. Fig.1 illustrates basic functionality of the OCD approach.

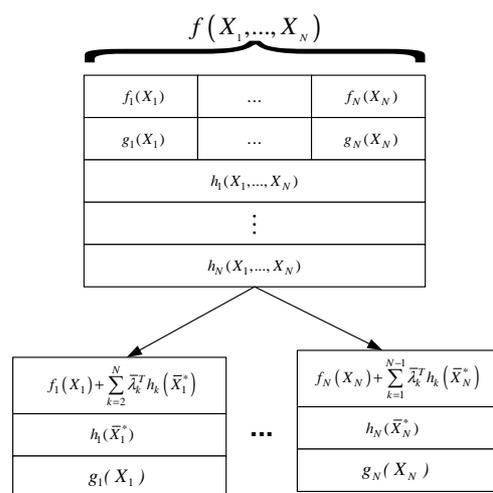


Fig. 1. Decomposition by OCD technique

III. SCENARIO BASED UNCERTAINTY MODELING

The assumptions and technical constraints are described as follows:

A. Assumptions

- The electric utility is paid a fixed price for each MWh which sells to the customers.
- The electric utility has three options for supplying the demand of its customers namely: pool market, thermal generating units and finally the wind turbine power generation.
- The electric utility is assumed to be the owner of the thermal and wind generating units.
- The wind generation and electricity price in pool market are assumed to be uncertain parameters.
- The proposed tool is run every 15-minutes and it considers Δ intervals (the length of each interval is 15 minutes). This rolling window starts at $t = 0$ and moves toward the end

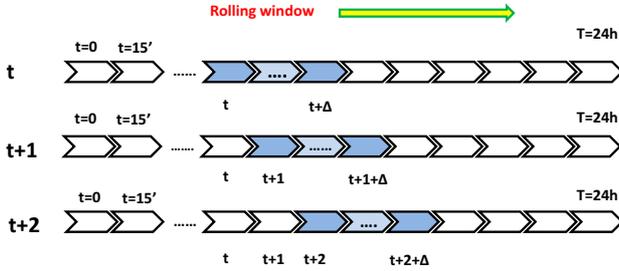


Fig. 2. The rolling window concept of proposed method

B. Uncertainty modeling of wind turbine power generation and electricity prices

The generation power of a wind turbine depends on its input source of energy. The variation of wind speed is a key factor for determination of wind turbine's output. The price of energy in the pool market is determined based on the competition between the market players. The value of price in each hour is an uncertain parameter. The historic data of wind speed in the region and electricity prices can be used to probabilistically model the uncertainties of wind speed [26].

In this paper, it is assumed that the forecasted values of wind power generation (Pw_t^f) and electricity prices (λ_t^f) are available, as depicted in Fig. 3. To define wind power generation scenarios, one can consider beta distribution for wind power [27] or weibull distribution for wind speed beside wind turbine cure [28]. The latter is considered in this paper which is described with more details in Appendix A.

The realization of wind power ($Pw_{s,t}$) and electricity price ($\lambda_{s,t}^P$) are modeled using scenarios around the forecasted value, as shown conceptually in Fig. 4. It is assumed that the actual wind power generation and electricity price is normally distributed around the corresponding forecasted value $\mu = Pw_t^f$ or $\mu = \lambda_t^f$. In this work, 7 scenarios are considered for modeling the uncertain parameter ($\mu, \mu \pm 3\sigma$) as depicted in Fig. 5. The probability of falling into each scenario is indicated on the corresponding area, as shown in Fig. 5. It is assumed that for the employed normal distribution, $\sigma = 0.01\mu$.

It is also assumed that the variation electricity price values are independent with the variations of wind speeds. The scenarios of wind power generations and price values are combined and a

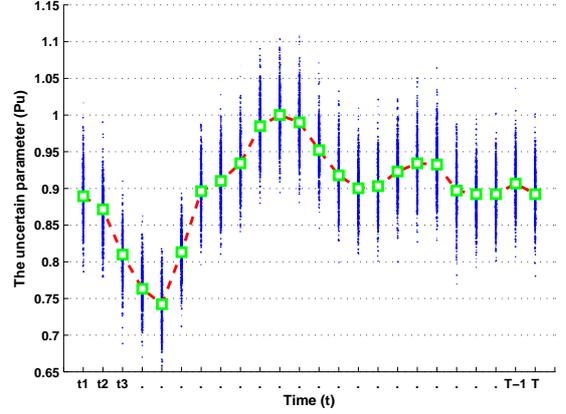


Fig. 3. Scattered realization of the uncertain parameter over the time

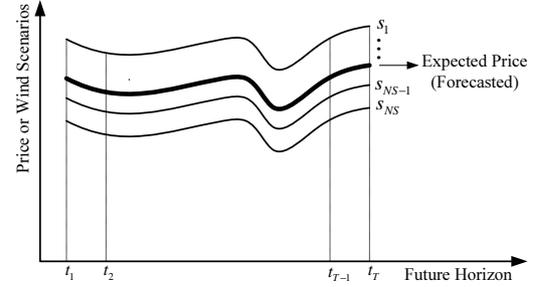


Fig. 4. Scenario modeling around the forecasted value

unique set of scenarios (i.e. 49 scenarios) is constructed. Each scenario contains T available wind power generation and T price values as follows ($\forall t = t_1, \dots, t_T$ and $\forall s = s_1, \dots, s_{NS}$).

$$\lambda_{s,t}^P = \lambda_s \times \lambda_t^f \times \Lambda \quad (7)$$

$$wp_{s,t} = w_s \times Pw_t^f \quad (8)$$

$$Pw_{s,t}^{avl} = \min(wp_{s,t} \times P_r^w, P_r^w) \quad (9)$$

$$P_t^D = D_t^f \times P_{peak}^D \quad (10)$$

If expected value of wind speed is in the interval $[v_r, v_{out}^c]$, considering the wind turbine cure (see Appendix A), wind generators produce their maximum value as long as wind speed is in the above interval. Hence, there is no scenario with wind generation greater than its forecasted value, which is a usual case. This fact is reflected in (9).

IV. REAL-TIME DED PROBLEM FORMULATION

The objective function of the proposed tool is to find the optimal dynamic schedule of the generating units to maximize the total benefits, which is formulated as follows:

A. Total cost of energy procurement

The production cost of thermal units is defined as:

$$C_i(P_{i,t}) = a_i P_{i,t}^2 + b_i P_{i,t} + c_i \quad (11)$$

where a_i , b_i and c_i are the fuel cost coefficients of the i^{th} unit. The total cost paid by the electric utility is calculated as follows:

$$TC = \sum_{s,t} (\pi_s P p_{s,t} \lambda_{s,t}^P) + \sum_{i,t} (I_{i,t} C_i(P_{i,t})) \quad (12)$$

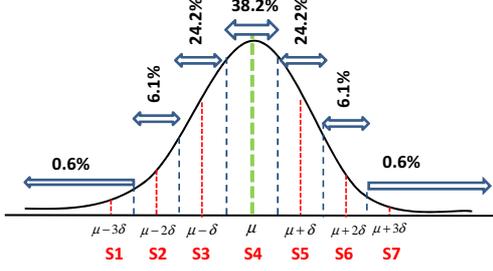


Fig. 5. Normal variation of uncertain parameter around the forecasted value

In each time step and scenario the power balance constraints should be satisfied as follows:

B. Constraints

1) Real power balance

$$\sum_i (I_{i,t} P_{i,t}) + Pw_{s,t} + Pp_{s,t} = P_t^D \quad (13)$$

2) Generation limits of thermal units:

$$P_i^{min} \leq P_{i,t} \leq P_i^{max} \quad (14)$$

3) Ramp up and ramp down constraints: The output power change rate of the thermal unit should be below the pre-specified limits called ramp rates. This is to avoid damaging the boiler and combustion equipment. These limits are stated as follows:

$$P_{i,t-1} - DR_i \leq P_{i,t} \leq P_{i,t-1} + UR_i \quad (15)$$

4) Wind power generation limits:

$$0 \leq Pw_{s,t} \leq Pw_{s,t}^{avl} \quad (16)$$

5) Limits on power exchange with pool market:

$$Pp_t^{min} \leq Pp_{t,s} \leq Pp_t^{max} \quad (17)$$

C. Objective function (total benefit):

In this paper, the objective function (OF) is defined as the total money received from the energy consumers minus the total cost paid for operating the thermal units as follows:

$$OF = \sum_{s,t} \pi_s \lambda_{s,t}^D P_t^D - TC \quad (18)$$

The OF (i.e. total benefit) should be maximized, subject to the above equality and inequality constraints.

V. APPLICATION OF OCD ON THE REAL-TIME DED

In large-scale power systems, the dimension of the DED problem is very large and hence the solution-time is very critical for real-time implementation. To speed up the solution process, the DED problem could be decomposed to a few simpler sub-problems with lower dimensions, and hence with less computational burden. This is accomplished due the multi-period structure of the DED problem. In this paper, the OCD approach is utilized for this aim. OCD is based on relaxing the complicating constraints of the original NLP problem. Complicating constraints are constraints that if relaxed, the resulting

problem is decomposed into several simpler problems [25]. In the DED problem, ramp rate constraints (i.e. (15)) are the complicating constraints [29].

Since the P_t^D and $\lambda_{s,t}^D$ are known parameters and are given data of the problem then maximizing the OF (18) would be the same as minimizing the total costs. By relaxing the ramp rate constraints, corresponding consecutive m and $m + 1$ -th sub-problems (i.e. for $t = t_m$ and $t = t_{m+1}$) of the DED in k th iteration of the OCD are as follows:

- For interval $t = t_m$ (i.e. m -th sub-problem):

$$\min TC_{t_m}^{(k)} = \sum_s \pi_s Pp_{s,t_m}^{(k)} \lambda_{s,t_m}^P \quad (19)$$

$$+ \sum_i I_{i,t_m} C_{i,t_m}(P_{i,t_m}^{(k)}) + \sum_i \phi_{i,t_m}^{(k)} \quad (20)$$

$$C_{i,t_m}(P_{i,t_m}^{(k)}) = a_i (P_{i,t_m}^{(k)})^2 + b_i (P_{i,t_m}^{(k)}) + c_i \quad (21)$$

$$\phi_{i,t_m}^{(k)} = \bar{\mu}_{i,t_{m+1}}^{UR,(k-1)} (\bar{P}_{i,t_{m+1}}^{(k-1)} - P_{i,t_m}^{(k)} - UR_i) + \bar{\mu}_{i,t_{m+1}}^{DR,(k-1)} (P_{i,t_m}^{(k)} - \bar{P}_{i,t_{m+1}}^{(k-1)} - DR_i)$$

Subject to:

$$\sum_i P_{i,t_m}^{(k)} I_{i,t_m} + Pw_{s,t_m} + Pp_{s,t_m} = P_{t_m}^D \quad (22)$$

$$P_{i,t_m}^{(k)} - \bar{P}_{i,t_{m-1}}^{(k-1)} \leq UR_i \quad (23)$$

$$\bar{P}_{i,t_{m-1}}^{(k-1)} - P_{i,t_m}^{(k)} \leq DR_i \quad (24)$$

$$P_i^{min} \leq P_{i,t_m}^{(k)} \leq P_i^{max} \quad (25)$$

$$0 \leq Pw_{s,t_m} \leq Pw_{s,t_m}^{avl} \quad (26)$$

$$Pp_{t_m}^{min} \leq Pp_{s,t_m}^{(k)} \leq Pp_{t_m}^{max} \quad (27)$$

- For interval $t = t_{m+1}$ (i.e. $m + 1$ -th sub-problem):

$$\min TC_{t_{m+1}}^{(k)} = \sum_s \pi_s Pp_{s,t_{m+1}}^{(k)} \lambda_{s,t_{m+1}}^P + \quad (28)$$

$$\sum_i I_{i,t_{m+1}} C_{i,t_{m+1}}(P_{i,t_{m+1}}^{(k)}) + \sum_i \phi_{i,t_{m+1}}^{(k)}$$

$$C_{i,t_{m+1}}(P_{i,t_{m+1}}^{(k)}) = a_i (P_{i,t_{m+1}}^{(k)})^2 + b_i (P_{i,t_{m+1}}^{(k)}) + c_i \quad (29)$$

$$\phi_{i,t_{m+1}}^{(k)} = \bar{\mu}_{i,t_{m+2}}^{UR,(k-1)} (\bar{P}_{i,t_{m+2}}^{(k-1)} - P_{i,t_{m+1}}^{(k)} - UR_i) + \bar{\mu}_{i,t_{m+2}}^{DR,(k-1)} (P_{i,t_{m+1}}^{(k)} - \bar{P}_{i,t_{m+2}}^{(k-1)} - DR_i)$$

Subject to:

$$\sum_i I_{i,t_{m+1}} P_{i,t_{m+1}}^{(k)} + Pw_{s,t_{m+1}} + Pp_{s,t_{m+1}} = P_{t_{m+1}}^D \quad (31)$$

$$P_{i,t_{m+1}}^{(k)} - \bar{P}_{i,t_m}^{(k-1)} \leq UR_i \quad (32)$$

$$\bar{P}_{i,t_m}^{(k-1)} - P_{i,t_{m+1}}^{(k)} \leq DR_i \quad (33)$$

$$P_i^{min} \leq P_{i,t_{m+1}}^{(k)} \leq P_i^{max} \quad (34)$$

$$0 \leq Pw_{s,t_{m+1}} \leq Pw_{s,t_{m+1}}^{avl} \quad (35)$$

$$Pp_{t_{m+1}}^{min} \leq Pp_{s,t_{m+1}}^{(k)} \leq Pp_{t_{m+1}}^{max} \quad (36)$$

where, $\bar{\mu}_{i,t_{m+1}}^{UR,(k-1)}$ and $\bar{\mu}_{i,t_{m+1}}^{DR,(k-1)}$ are Lagrange multipliers corresponding to complicating constraints (15) of $m + 1$ -th sub-problem at previous iteration (i.e. iteration $k - 1$). The dashed parameters (like $\bar{P}_{i,t_m}^{(k-1)}$) are the obtained values of the corresponding variables at the previous iteration (i.e. iteration $k - 1$) of the OCD. It is evidently observed that utilization of the OCD leads to independent sub-problems with much less dimension than the original DED problem, which can be solved quickly in

parallel manner. In other words, the sub-problem for $t = t_m$ only contains the variables (i.e. generation schedules) of that interval, and the variables of neighbour intervals are treated as some constant parameters both in objective function and constraints of that interval. The OCD steps are described as follows:

- Step. 1. Initialization ($k = 1$): In this step, all variables and Lagrange multipliers of complicating constraints (15) are initialized. In this paper, the initial values for variables are chosen by independently solving the relaxed sub-problem (RSPs), with zero initial values for Lagrange multipliers of complicating constraints ($\bar{\mu}_{i,t}^{UR,(0)}$ and $\bar{\mu}_{i,t}^{DR,(0)}$), and neglecting constraints (15). Therefore, $\forall t P_{i,t}^{(0)}$ is known.
- Step. 2. Independently solving of the RSPs in iteration k: In this phase, there are T RSPs to be solved independently, by parallel computation ability and the optimal values for all variables are obtained, along with the Lagrange multipliers of complicating constraints (15). i.e. $\bar{\mu}_{i,t}^{UR,(k)}$, $\bar{\mu}_{i,t}^{DR,(k)}$ and $\bar{P}_{i,t}^{(k)}$; $\forall i, t$ are determined.
- Step. 3. Stopping criterion. The algorithm stops if variables (or the value of OF) do not change significantly in two consecutive iterations [25]. Otherwise, go to Step 2.

The flowchart of the OCD algorithm is depicted in Fig. 6.

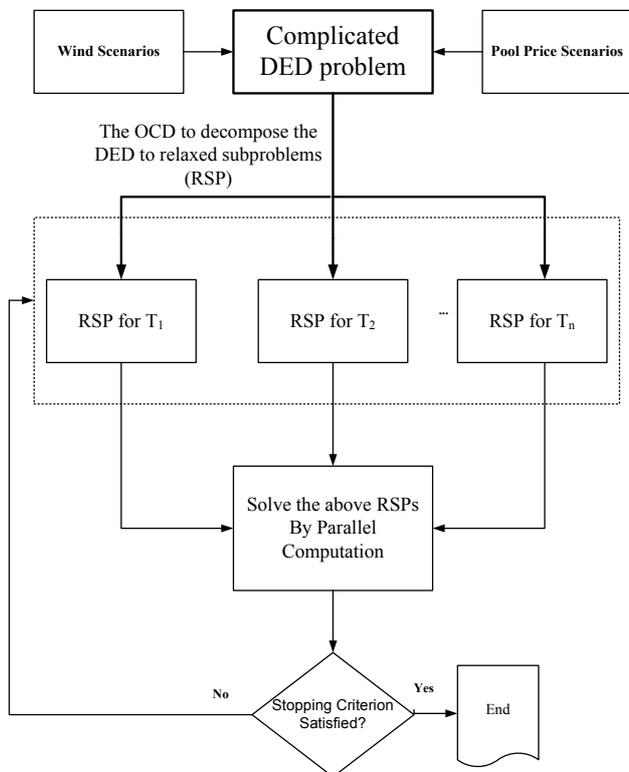


Fig. 6. The flowchart of the OCD algorithm

VI. CASE STUDIES

The proposed model for the DED and the aforementioned OCD algorithm is implemented in General Algebraic Modeling System (GAMS) environment and solved by SNOPT solver. The

electricity price and wind power combined scenarios are given in Table.I.

TABLE I
THE ELECTRICITY PRICE AND WIND POWER SCENARIOS

Scenario	w_s	λ_s	π_s	Scenario	w_s	λ_s	π_s
s ₁	1.03	1.03	0	s ₂₆	1	0.99	0.0924
s ₂	1.03	1.02	0.0004	s ₂₇	1	0.98	0.0233
s ₃	1.03	1.01	0.0015	s ₂₈	1	0.97	0.0023
s ₄	1.03	1	0.0023	s ₂₉	0.99	1.03	0.0015
s ₅	1.03	0.99	0.0015	s ₃₀	0.99	1.02	0.0148
s ₆	1.03	0.98	0.0004	s ₃₁	0.99	1.01	0.0586
s ₇	1.03	0.97	0	s ₃₂	0.99	1	0.0924
s ₈	1.02	1.03	0.0004	s ₃₃	0.99	0.99	0.0586
s ₉	1.02	1.02	0.0037	s ₃₄	0.99	0.98	0.0148
s ₁₀	1.02	1.01	0.0148	s ₃₅	0.99	0.97	0.0015
s ₁₁	1.02	1	0.0233	s ₃₆	0.98	1.03	0.0004
s ₁₂	1.02	0.99	0.0148	s ₃₇	0.98	1.02	0.0037
s ₁₃	1.02	0.98	0.0037	s ₃₈	0.98	1.01	0.0148
s ₁₄	1.02	0.97	0.0004	s ₃₉	0.98	1	0.0233
s ₁₅	1.01	1.03	0.0015	s ₄₀	0.98	0.99	0.0148
s ₁₆	1.01	1.02	0.0148	s ₄₁	0.98	0.98	0.0037
s ₁₇	1.01	1.01	0.0586	s ₄₂	0.98	0.97	0.0004
s ₁₈	1.01	1	0.0924	s ₄₃	0.97	1.03	0
s ₁₉	1.01	0.99	0.0586	s ₄₄	0.97	1.02	0.0004
s ₂₀	1.01	0.98	0.0148	s ₄₅	0.97	1.01	0.0015
s ₂₁	1.01	0.97	0.0015	s ₄₆	0.97	1	0.0023
s ₂₂	1	1.03	0.0023	s ₄₇	0.97	0.99	0.0015
s ₂₃	1	1.02	0.0233	s ₄₈	0.97	0.98	0.0004
s ₂₄	1	1.01	0.0924	s ₄₉	0.97	0.97	0
s ₂₅	1	1	0.1459				

The forecasted values of wind power generation, electricity price and demand values in percent of the corresponding peak values are given in Table II.

TABLE II
THE FORECASTED VALUES OF ELECTRICITY PRICE AND WIND POWER AND DEMAND VALUES (%) OF PEAK VALUE

t	Pw_t^f	λ_t^f	D_t^f
t ₁	100.00	77.79	63.41
t ₂	96.88	75.24	62.12
t ₃	93.75	72.70	61.07
t ₄	91.41	71.92	60.08
t ₅	89.06	71.13	59.07
t ₆	96.48	71.13	58.80
t ₇	95.31	71.13	58.26
t ₈	82.42	71.13	57.78
t ₉	80.86	71.13	57.45
t ₁₀	83.20	71.09	57.36
t ₁₁	81.64	71.05	56.91
t ₁₂	83.20	70.66	56.73
t ₁₃	82.03	70.27	56.82

The length of this moving window is assumed to be $\Delta = 13$ time steps. Each time step is 15 minutes. In this way, at $t = 0$ the window expands to the beginning of $t = 3h$. The proposed approach is implemented on 40-units and 54-units test systems, along with a large-scale 391-units system. For simplicity the price of selling electricity to the consumers is assumed to be constant during the entire horizon and equal to \$15/MWh, \$27/MWh and \$23/MWh for the above systems, respectively.

A. Case-I: 40-units system

In this case, there are 40 thermal units. The technical data of these units is available in [30]. The wind capacity is assumed to be 1800 MW. Also, the peak value of electricity price Λ and demand are assumed to be 12.75 \$/MWh and 12000 MW, respectively. Besides, in this case the maximum/minimum limits on power exchange with pool market is ± 1200 MW.

Without using the OCD approach, total CPU time is obtained 2.944 seconds. In this case the OCD algorithm is converged after 11 iterations, and the total CPU time is equal to 1.060 seconds. This means 63.99% reduction in the CPU time. This

significant reduction in the CPU time, is substantial from the real-time implementation viewpoint of the proposed approach. The optimal schedule of thermal generation units in the studied horizon is given in Table IV. Also, the expected value of purchased power from pool market (in each time step) in this case are shown in Fig. 7. It is observed from this figure that in some hours the electric utility purchases power from pool market, whereas in some others it sells energy to the pool market. The values of OF and CPU time for the iterations of OCD algorithm in this case are given in Table III.

TABLE III
THE VALUES OF OF AND CPU TIME FOR THE OCD ALGORITHM IN CASE-I

Iteration	Total benefit (\$)	CPU-time (s)
1	295170.635	0.047
2	295090.969	0.078
3	295044.194	0.078
4	295040.244	0.078
5	295129.705	0.078
6	295136.803	0.078
7	295122.144	0.078
8	295129.523	0.078
9	295096.667	0.202
10	295130.516	0.078
11	295131.260	0.187
OCD's total time		1.060

TABLE IV
OPTIMAL POWER GENERATION SCHEDULE OF THERMAL UNITS IN CASE-I (MW)

Generator	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	t_{11}	t_{12}	t_{13}
P_1	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0
P_2	70.2	62.2	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0
P_3	92.2	80.0	80.0	80.0	80.0	80.0	80.0	80.0	80.0	80.0	80.0	80.0	80.0
P_4	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0	24.0
P_5	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0	26.0
P_6	81.6	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0
P_7	241.4	216.4	191.4	166.4	145.3	145.3	145.3	145.3	144.6	143.8	136.9	130.0	130.0
P_8	288.7	263.7	238.7	220.6	210.4	210.4	210.4	210.4	209.9	209.3	204.3	199.3	199.3
P_9	286.1	261.1	236.1	224.0	215.3	215.3	215.3	215.3	214.8	214.4	210.1	205.8	205.8
P_{10}	130.0	130.0	130.0	130.0	130.0	130.0	130.0	130.0	130.0	130.0	130.0	130.0	130.0
P_{11}	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0
P_{12}	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0
P_{13}	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
P_{14}	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
P_{15}	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
P_{16}	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
P_{17}	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0	125.0
P_{18}	287.0	259.5	232.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0
P_{19}	289.3	261.8	234.3	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0
P_{20}	297.0	269.5	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0
P_{21}	297.0	269.5	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0	242.0
P_{22}	520.3	492.8	465.3	437.8	410.3	409.1	409.1	409.1	408.2	407.4	399.1	390.8	390.8
P_{23}	520.3	492.8	465.3	437.8	410.3	409.1	409.1	409.1	408.2	407.4	399.1	390.8	390.8
P_{24}	537.9	510.4	482.9	455.4	427.9	424.0	424.0	424.0	423.1	422.2	413.5	404.8	404.8
P_{25}	537.9	510.4	482.9	455.4	427.9	424.0	424.0	424.0	423.1	422.2	413.5	404.8	404.8
P_{26}	470.3	442.8	415.3	387.8	360.3	354.9	354.9	354.9	354.0	353.1	344.2	335.3	335.3
P_{27}	470.3	442.8	415.3	387.8	360.3	354.9	354.9	354.9	354.0	353.1	344.2	335.3	335.3
P_{28}	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
P_{29}	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
P_{30}	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
P_{31}	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
P_{32}	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
P_{33}	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
P_{34}	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
P_{35}	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0
P_{36}	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0	18.0
P_{37}	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
P_{38}	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
P_{39}	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
P_{40}	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0

B. Case-II: 54-units system

In this case, there are 54 thermal generating units. The data of these units and the load profile of the system are given in [30]. In this case, total wind power generation capacity is assumed to be 900 MW. The peak value of electricity price Λ and demand are assumed to be 18.75 \$/MWh and 6000 MW, respectively. Also, for this case the limits on the power exchange with pool market are ± 500 MW.

Table V shows the variations of total benefits versus iterations of the OCD algorithm for this system. As it is observed from this table, the OCD is converged after 7 iterations in this

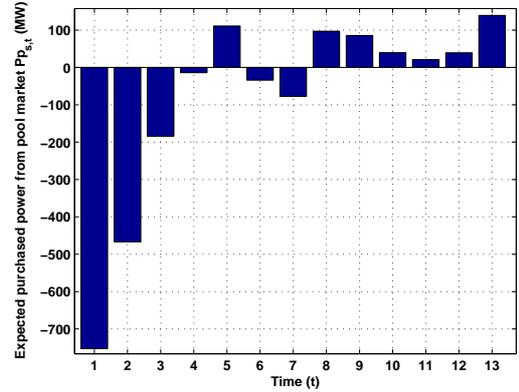


Fig. 7. The expected value of purchased power from pool market (in each time step) in Case-I (+ for purchase/- for buy)

case. The overall CPU time for this problem, using parallel computation ability is 0.368 seconds, which is quite low. If one solves the above model without using the OCD algorithm, the CPU-time would be 3.263 seconds. This means that OCD reduces the computation time about 88.72%. Also, the expected values of the purchased power from pool market (in each time step) in this case are shown in Fig. 8.

TABLE V
THE VALUES OF OF AND CPU TIME FOR THE OCD ALGORITHM IN CASE-II

Iteration	Total benefit (\$)	CPU-time (s)
1	695647.427	0.036
2	695617.371	0.065
3	695595.139	0.040
4	695605.825	0.050
5	695653.832	0.068
6	695631.706	0.069
7	695624.885	0.038
OCD's total time		0.368

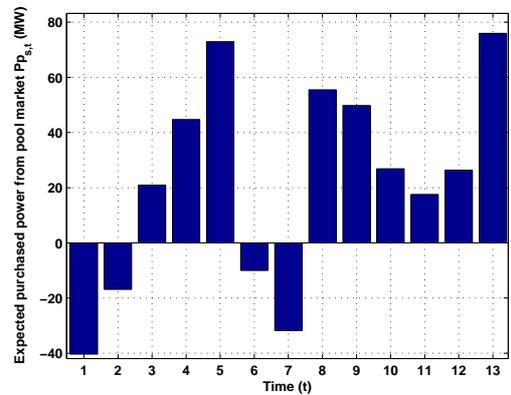


Fig. 8. The expected value of purchased power from pool market (in each time step) in Case-II (+ for purchase/- for buy)

C. Case-III: Practical large-scale case study

In this case, a real-life power system is studied to investigate the applicability of the proposed approach on the large-scale power systems. there are 391 thermal units available in this

system. The technical data of units is given in [30]. The peak demand and nominal wind power generation capacity are 45000 MW and 8000 MW, respectively. The peak of electricity price Λ is assumed to be 10.50 \$/MWh. Also, the limits on the power exchange with pool market are ± 5000 MW in this case. The optimal total benefit and CPU time obtained without using the OCD algorithm are \$1627872.913 and 75.751 seconds, respectively. On the other hand, if OCD is used it would converge in 14 iterations and the total CPU time is 3.186 seconds. This means that utilization of the OCD algorithm reduces the computation time about 95.794 %. This huge reduction in the CPU time justifies the applicability of the proposed algorithm for real-time implementation of the formulated DED problem, especially in the case of large-scale power systems. The expected values of purchased power from pool market of Case-III (in each time step) are shown in Fig.9.

TABLE VI
THE CPU TIME FOR OCD ALGORITHM IN LARGE-SCALE CASE STUDY WITH 391 UNITS

Iteration	Total benefit (\$)	CPU-time (s)
1	1627878.834	0.187
2	1627480.918	0.110
3	1627353.704	0.281
4	1626822.455	0.203
5	1626197.460	0.141
6	1625555.368	0.141
7	1625232.771	0.327
8	1624699.933	0.218
9	1624660.484	0.687
10	1624845.930	0.188
11	1624662.113	0.250
12	1624432.050	0.187
13	1624289.197	0.141
14	1624288.957	0.125
OCD's total time		3.186

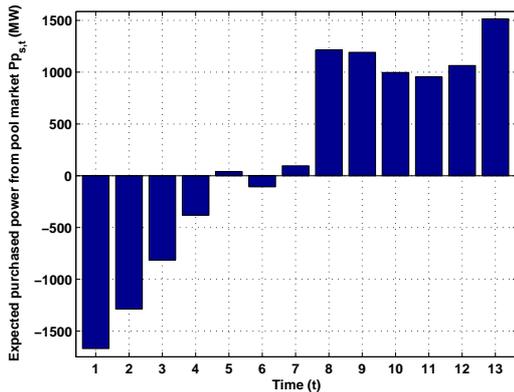


Fig. 9. The expected values of purchased power from pool market (in each time step) in practical Case (+ for purchase/- for buy)

VII. CONCLUSION

This paper presents a probabilistic real-time methodology to find the optimal schedule of thermal generation units at the presence of wind power generation. The uncertainty of wind power generation and electricity price are modeled by scenario based technique. In order to make the proposed approach applicable in case of real-time operation of power systems, optimality condition decomposition is utilized. It is demonstrated

that implementing the proposed OCD technique along with parallel computation ability, reduces computational burden of the DED problem and hence, facilitates its application in real-time environment. The proposed approach is investigated on various test systems. Numerical results show the applicability and usefulness of the OCD for solving the real-time DED problem, especially in the case of large-scale power systems. Also, it is observed from the numerical studies that by increasing the dimension of the system, more reduction in CPU time is obtained, which is very important from the view point of real-time operation of large-scale power systems. Future work will be focused on comparing the performance of the proposed method in comparison to the other existing methods like as Meta heuristic methods (Particle Swarm Optimization [31] and Honey Bee Mating Optimization (HBMO) [32]). The uncertainty of wind power generation as well as the demand uncertainty are considered using scenario approach. However using some risk measures like CVaR can enhance the proposed model. The sensitivity analysis can also be used to check the robustness of the results of the model in the presence of uncertainty [33].

APPENDIX A

WIND POWER GENERATION UNCERTAINTY MODELING

It is assumed that the probability density function (PDF) of wind speed follows the Rayleigh behavior (which is a subset of Weibul distribution) and is known for the wind site as follows [26], [34].

$$PDF(v) = \left(\frac{v}{c^2}\right) \exp\left[-\left(\frac{v}{\sqrt{2}c}\right)^2\right] \quad (37)$$

The occurrence probability of scenario s and the corresponding wind speed v_s is calculated as follows:

$$\pi_s = \int_{v_{i,s}}^{v_{f,s}} \left(\frac{v}{c^2}\right) \exp\left[-\left(\frac{v}{\sqrt{2}c}\right)^2\right] dv \quad (38)$$

$$v_s = \frac{v_{f,s} + v_{i,s}}{2} \quad (39)$$

where $v_{i,s}, v_{f,s}$ define the initial and final values of wind speed's interval in scenario s , respectively.

The characteristic curve of a wind turbine [28], is depicted in Fig. 10. Thus, in each point in the future prediction horizon,

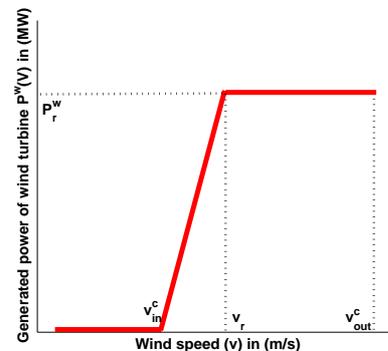


Fig. 10. The power curve of a wind turbine

the forecasted output power of the wind turbine for the above wind profile (as a percent of its rated power, P_r^w), is determined using its characteristics as follows:

$$Pw^f = \begin{cases} 0 & \text{if } v_s \leq v_{in}^c \text{ or } v_s \geq v_{out}^c \\ \frac{v_s - v_{in}^c}{v_r - v_{in}^c} P_r^w & \text{if } v_{in}^c \leq v_s \leq v_r \\ 1 & \text{if } v_r \leq v_s \leq v_{out}^c \end{cases} \quad (40)$$

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