Coordinated Scheduling of Wind-Thermal Gencos in Day-Ahead Markets

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ABSTRACT

This paper presents a stochastic mixed-integer linear programming approach for solving the self-scheduling problem of a price-taker thermal and wind power producer taking part in a pool-based electricity market. Uncertainty on electricity price and wind power is considered through a set of scenarios. Thermal units are modeled by variable costs, start-up costs and technical operating constraints, such as: ramp up/down limits and minimum up/down time limits. An efficient mixed-integer linear program is presented to develop the offering strategies of the coordinated production of thermal and wind energy generation, aiming to maximize the expected profit. A case study with data from the Iberian Electricity Market is presented and results are discussed to show the effectiveness of the proposed approach.

KEYWORDS: Mixed-integer linear programming; stochastic optimization; wind-thermal coordination; offering strategies.

1 INTRODUCTION

The negative environmental impact of fossil fuel burning and the desire to achieve energy supply sustainability promote exploitation of renewable sources. Mechanisms and policies provide subsidy and incentive for renewable energy conversion into electric energy [1], for instance, wind power conversion. But as the wind power technology matures and reaches breakeven costs, subsidy is due to be less significant and wind power conversion has to face the electricity markets for better profit [2]. Also, the incentives for wind power exploitation are feasible for modest penetration levels but will become flawed as wind power penetration increases [3]. EU in 2014 has of all new renewable installations a 43.7% based on wind power and is the seventh year running that over 55% of all additional power capacity is form renewable energy [4]. The growing worldwide usage of renewable energy is a fact, but electricity supply is still significantly dependent on fossil fuel burning, for instance, statistics for electricity supply in 2012 accounts that the usage of fossil fuel burning is more than 60% [5].

Deregulation of electricity market imposes that a generation company (GENCO) has to face competition to obtain the economic revenue. Periodic nodal variations of electricity prices [6] have to be taken into consideration. The wind power producer (WPP) has to address wind power and electricity price uncertainties to decide for realistic bids, because cost is owed either in case of excessive or moderate bids due to the fact that other power producers must reduce or increase production to fill the so-called deviation [7]. While the thermal power producer has to address only electricity price uncertainty.

2 STATE OF THE ART

Thermal energy conversion into electric energy has a significant state of art on optimization methods to solve the unit commitment problem (UC), ranging from the old priorities list method to the classical mathematical programming methods until the more recently reported artificial intelligence methods [8]. The priority list method is easy implemented and requires a small processing time, but does not ensure a convenient solution near the global optimal one [9]. Within the classical methods are included dynamic programming and Lagrangian relaxation-based methods [10]. The dynamic programming method is a flexible one but has a limitation known by the "curse of dimensionality". The Lagrangian relaxation can overcome the previous limitation, but does not necessarily lead to a feasible solution, implying further processing for satisfying the violated constraints in order to find a feasible solution, which does not ensure optimal solution. The mixed integer linear programming (MILP) method has been applied with success for solving UC problem [11]. MILP is one of the most successful explored methods for scheduling activities because of flexibility and extensive modeling capability [12]. Although, artificial intelligence methods based on artificial neural networks, genetic algorithms, evolutionary algorithms and simulating annealing have been applied, the major limitation of the artificial intelligence methods concerning with the possibility to obtain a solution near the global optimum one is a disadvantage. So, classical methods are the main methods in use as long as the functions describing the mathematical model have conveniently smoothness.

Deregulated market and variability of the source of wind power impose uncertainties to WPP. These uncertainties have to be conveniently considered, i.e., processed into the variables of the problems [13] to be addressed by a WPP in order to know how much to produce and the price for bidding.

A WPP in a competitive environment can benefit without depending on third-parties from: a coordination of wind power production with energy storage technology [14]; a financial options as a tool for WPP to hedge against wind power uncertainty [15]; a stochastic model intended to produce optimal offer strategies for WPP participating in an electricity market [16]. The stochastic model is a formulation explicitly taking into account the uncertainties faced by the scheduling activities of a WPP [17], using uncertain measures and multiple scenarios built by computer applications for wind power and electricity price forecasts [18]. The participation in bilateral contracts is suitable for thermal power producers in order to hedge against price uncertainty [19,20].

3 PROBLEM FORMULATION

3.1 Day-Ahead Market

The uncertainties about the availability of wind power may result in differences between the energy traded with a WPP and the actual quantity of energy delivered by the WPP. The revenue R_t of the GENCO for hour t is stated as:

$$R_t = \lambda_t^D P_t^{offer} + I_t \qquad (1)$$

In (1), P_t^{offer} is the power at the close of the day-ahead market accepted to be traded and I_t is the imbalance income resulting from the balancing penalty of not acting in accordance with the accepted trade. The total deviation for hour t is stated as:

$$\Delta_t = P_t^{act} - P_t^{offer} \qquad (2)$$

where P_t^{act} is the actual power for hour t.

In (2), a positive deviation means the actual power traded is higher than the traded in the day-ahead market and a negative deviation means the power is lower than the traded. Let λ_t^+ be the price paid for excess of production and λ_t^- the price to be charged for deficit of production. Consider the price ratios given by the equalities stated as:

$$r_t^+ = \frac{\lambda_t^+}{\lambda_t^D}, r_t^+ \le 1 \quad \text{and} \quad r_t^- = \frac{\lambda_t^-}{\lambda_t^D}, r_t^- \ge 1 \qquad (3)$$

In (3), the inequalities at the right of the equalities mean, respectively, that the positive deviation never has a higher price of penalization and the negative one never has a lower price of penalization in comparison with the value of the closing price.

3.2 Wind-Thermal Gencos

The operating cost, $F_{\omega i t}$, for a thermal unit can is stated as:

$$F_{\omega i t} = A_i\, u_{\omega i t} + d_{\omega i t} + b_{\omega i t} + C_i\, z_{\omega i t} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{4}$$

In (4), the operating cost of a unit is the sum of: the fixed production cost, A_i , a fixed associated with the unit state of operation; the added variable cost, $d_{\omega i t}$, part of this cost is associated with the amount of fossil fuel consumed by the unit; and the start-up and shut-down costs, respectively, $b_{\omega i t}$, and C_i , of the unit. The last three costs are in general described by nonlinear function and worse than that some of the functions are non- convex and non-differentiable functions, but some kind of smoothness is expected and required to use MILP, for instance, as being sub-differentiable functions.

The functions used to quantify the variable, the start-up and shut-down costs of units in (4) are considered to be such that is possible to approximate those function by a piecewise linear or step functions. The variable cost, $d_{\omega i t}$ is stated as:

$$d_{\omega i t} = \sum_{l=1}^{L} F_i^{\,l} \delta_{\omega i t}^{l} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{5}$$

$$p_{\omega i t} = p_i^{\min} u_{\omega i t} + \sum_{l=1}^{L} \delta_{\omega i t}^{l} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{6}$$

$$(T_i^{\,1} - p_i^{\min}) t_{\omega i t}^{1} \le \delta_{\omega i t}^{1} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{7}$$

$$\delta_{\omega i t}^{1} \le (T_i^{\,1} - p_i^{\min}) u_{\omega i t} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{8}$$

$$(T_i^{\,l} - T_i^{\,l-1}) t_{\omega i t}^{l} \le \delta_{\omega i t}^{l} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t, \quad \forall\, l = 2,\ldots, L-1 \tag{9}$$

$$\delta_{\omega i t}^{l} \le (T_i^{\,l} - T_i^{\,l-1}) t_{\omega i t}^{l-1} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t, \quad \forall\, l = 2,\ldots, L-1 \tag{10}$$

$$0 \le \delta_{\omega i t}^{L} \le (p_i^{\max} - T_{\omega i t}^{L-1})\, t_{\omega i t}^{L-1} \qquad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{11}$$

In (5), the variable cost function is given by the sum of the product of the slope of each segment, $F_i^{\,l}$, by the segment power $\delta_{\omega i t}^{l}$. In (6), the power of the unit is given by the minimum power generation plus the sum of the segment powers associated with each segment. The binary variable $u_{\omega i t}$ ensures that the power generation is equal to 0 if the unit is in the state offline. In (7), if the binary variable $t_{\omega i t}^{l}$ has a null value, then the segment power $\delta_{\omega i t}^{1}$ can be lower than the segment 1 maximum power; otherwise and in conjunction with (8), if the unit is in the state on, then $\delta_{\omega i t}^{1}$ is equal to the segment 1 maximum power. In (9), from the second segment to the second last one, if the binary variable $t_{\omega i t}^{l}$ has a null value, then the segment power $\delta_{\omega i t}^{l}$ can be lower than the segment l maximum power; otherwise and in conjunction with (10), if the unit is in the state on, then $\delta_{\omega i t}^{l}$ is equal to the segment l maximum power. In (11), the segment power must be between zero and the last segment maximum power.

The nonlinear nature of the start-up costs function, $b_{\omega i t}$, is normally considered to be described by an exponential function. This exponential function is approximated by a piecewise linear formulation as in [2] stated as:

$$b_{\omega i t} \geq K_i^{\beta}\left(u_{\omega i t} - \sum_{r=1}^{\beta} u_{\omega i t-r}\right) \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{12}$$

In (12), the second term models the lost of thermal, i.e., if the unit is a case of being in the state online at hour t and has been in the state offline in the β preceding hours, the expression in parentheses is equal to 1. So, in such a case a start-up cost is incurred for the thermal energy that are not accountable for added value in a sense of that energy has not been converted into electric energy. The maximum number for β is given by the number of hours need to cool down, i.e., completely lose all thermal energy. So, for every hour at cooling and until total cooling one inequality like (12) is considered.

The units have to perform in accordance with technical constraints that limit the power between successive hours stated as:

$$p_i^{\min} u_{\omega i t} \leq p_{\omega i t} \leq p_{\omega i t}^{\max} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{13}$$

$$p_{\omega i t}^{\max} \leq p_i^{\max}(u_{\omega i t} - z_{\omega i t+1}) + SD\, z_{\omega i t+1} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{14}$$

$$p_{\omega i t}^{\max} \leq p_{\omega i\, t-1}^{\max} + RU\, u_{\omega i t-1} + SU\, y_{\omega i t} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{15}$$

$$p_{\omega i t-1} - p_{\omega i t} \leq RD\, u_{\omega i t} + SD\, z_{\omega i t} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{16}$$

In (13) and (14), the upper bound of $p_{\omega i t}^{\max}$ is set, which is the maximum available power of the unit. This variable considers: unit's actual capacity, start-up/shut-down ramp rate limits, and ramp-up limit. In (16), the ramps-down and shut-down ramp rate limits are considered. In (14)–(16), the relation between the start-up and shut-down variables of the unit are given, using binary variables for describing the states and data parameters for ramp-down, shut-down and ramp-up rate limits.

The minimum down time constraint is imposed by a formulation stated as:

$$\sum_{t=1}^{J_i} u_{\omega i t} = 0 \quad \forall\, \omega, \quad \forall\, i \tag{17}$$

$$\sum_{t=k}^{k+DT_i-1} (1 - u_{\omega i t}) \geq DT_i\, z_{\omega i t} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, k = J_i + 1 \ldots T - DT_i + 1 \tag{18}$$

$$\sum_{t=k}^{T} (1 - u_{\omega i t} - z_{\omega i t}) \geq 0 \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, k = T - DT_i + 2 \ldots T \tag{19}$$

$$J_i = \min\{\, T, (DT_i - s_{\omega i 0})(1 - u_{\omega i 0})\}$$

In (17), if the minimum down time has not been achieved, then the unit remains offline at hour 0. In (18), the minimum down time will be satisfied for all the possible sets of consecutive hours of size DT_i. In (19), the minimum down time will be satisfied for the last $DT_i - 1$ hours.

The minimum up time constraint is also imposed by formulation stated as:

$$\sum_{t=1}^{N_i}(1-u_{\omega i t})=0 \quad \forall\, \omega, \quad \forall\, i \tag{20}$$

$$\sum_{t=k}^{k+UT_i-1} u_{\omega i t} \geq UT_i\, y_{\omega i t} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, k = N_i + 1 \ldots T - UT_i + 1 \tag{21}$$

$$\sum_{t=k}^{T}(u_{\omega i t} - z_{\omega i t}) \geq 0 \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, k = T - UT_i + 2 \ldots T \tag{22}$$

$$N_i = \min\{\, T, (UT_i - U_{\omega i 0})\, u_{\omega i 0}\}$$

In (20), if the minimum up time has not been achieved, then the unit remains offline at hour 0. In (21), the minimum up time will be satisfied for all the possible sets of consecutive hours of size UT_i. In (22), the minimum up time will be satisfied for the last $UT_i - 1$ hours.

The relation between the binary variables to identify start-up, shutdown and forbidden operating zones is stated as:

$$y_{\omega i t} - z_{\omega i t} = u_{\omega i t} - u_{\omega i t-1} \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{23}$$

$$y_{\omega i t} + z_{\omega i t} \leq 1 \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{24}$$

$$y_{\omega i t} + z_{\omega i t} \leq 1 \quad \forall\, \omega, \quad \forall\, i, \quad \forall\, t \tag{25}$$

The total power generated by the thermal units is stated as:

$$\sum_{i=1}^{I} p_{\omega i t} = p^{g}_{\omega t} + \sum_{m=1}^{M} p^{bc}_{m t} \quad \forall \omega, \forall i, \forall t\, , \forall m \tag{26}$$

In (26), $p^{g}_{\omega t}$ is the actual power generated by the thermal units for the day-ahead market and $p^{bc}_{m t}$ is the power contracted in each bilateral contract m.

3.3 Objective Function

The offer submitted by the GENCO is the sum of the power offered from the thermal units and the power offered from the wind farm $p^{D}_{\omega t}$. The offer is stated as:

$$p^{offer}_{\omega t} = p^{th}_{\omega t} + p^{D}_{\omega t} \quad \forall \omega, \;\; \forall t \tag{27}$$

The actual power generated by the GENCO is the sum of the power generated by the thermal units and the power generated by the wind farm. The actual power is stated as:

$$p^{act}_{\omega t} = p^{g}_{\omega t} + p^{d}_{\omega t} \quad \forall \omega, \;\; \forall t \tag{28}$$

In (28), $p^{g}_{\omega t}$ is the actual power generated by the thermal units and $p^{d}_{\omega t}$ is the actual power generated by the wind farm for each scenario ω.

Consequently, the expected revenue of the GENCO is stated as:

$$\sum_{\omega=1}^{N_\Omega}\sum_{t=1}^{N_T}\pi_\omega\left[\left(\lambda^D_{\omega t}P^{offer}_{\omega t}+\lambda^D_{\omega t}r^+_{\omega t}\Delta^+_{\omega t}-\lambda^D_{\omega t}r^-_{\omega t}\Delta^-_{\omega t}\right)-\sum_{i=1}^{I}F_{\omega i t}\right] \quad \forall\omega,\ \forall t \qquad (29)$$

Subject to:

$$0\le p^{offer}_{\omega t}\le p^M_{\omega t} \quad \forall\omega,\ \forall t \qquad (30)$$

$$\Delta_{t\omega}=\left(p^{act}_{\omega t}-p^{offer}_{\omega t}\right) \quad \forall\omega,\ \forall t \qquad (31)$$

$$\Delta_{t\omega}=\Delta^+_{t\omega}-\Delta^-_{t\omega} \quad \forall\omega,\ \forall t \qquad (32)$$

$$0\le \Delta^+_{t\omega}\le P_{t\omega}d_t \quad \forall\omega,\ \forall t \qquad (33)$$

In (29), the revenue from the bilateral contracts are not included, however the cost of thermal production includes the total power generated by the thermal units stated in (26).

In (30), $p^M_{\omega t}$ is maximum available power, limited by the sum of the installed capacity in the wind farm, $p^{E\max}$, with the maximum thermal production stated as:

$$p^M_{\omega t}=\sum_{i=1}^{I}p^{\max}_{\omega i t}+p^{E\max} \quad \forall\omega,\ \forall t \qquad (34)$$

Some system operators require non-decreasing offers to be submitted by the GENCO. Non-decreasing offers is considered by a constraint stated as:

$$(p^{offer}_{\omega t}-p^{offer}_{\omega' t})(\lambda^D_{\omega t}-\lambda^D_{\omega' t})\ge 0 \quad \forall\ \omega,\omega',\quad \forall\ t \qquad (35)$$

In (35), if the increment in price in two successive hours is not null, then the increment in offers in the two successive hours has two be of the same sign of the increment in price or a null value.

4 CASE STUDY

The proposed stochastic MILP approach is illustrated by a case study of a GENCO with a WTPP, having 8 units with a total installed capacity of 1440 MW, the data is in [21]. Data from the Iberian electricity market for 10 days of June 2014 [19] are used for the energy prices and the energy produced from wind farm. This data is shown in Fig. 1.

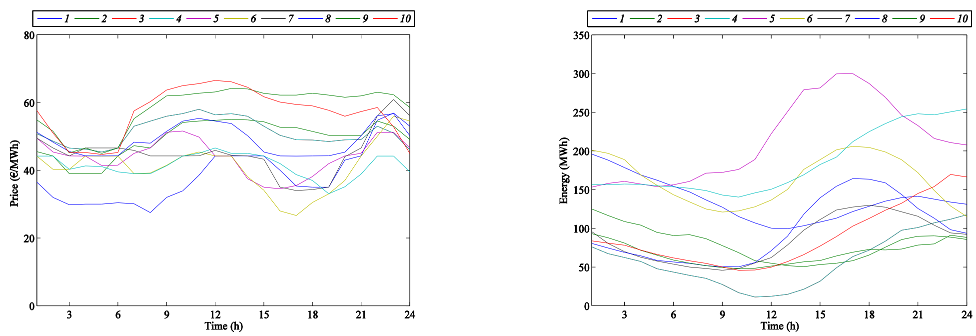

Fig 1. Iberian market June 2014 (ten days); left: prices, right: energy.

The nondecreasing offer is required. The energy produced is obtained using the total energy produced from wind scaled to the installed capacity in the wind farm, 360 MW. The expected results with and without coordination in the absence of bilateral contracts are shown in Table 1.

Table 1. Results with and without coordination

Case	Expected profit
Wind uncoordinated (€)	119 200
Thermal uncoordinated (€)	516 848
Coordinated Wind and thermal (€)	642 326
Gain (%)	0,99

The non-decreasing energy offer for the coordinated and uncoordinated approach is shown in Fig. 2 for two different hours.

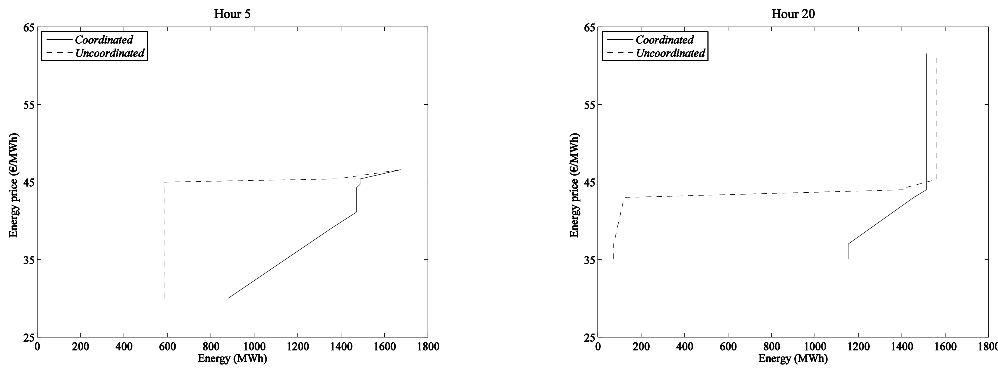

Fig 2. Bidding energy offers.

In Fig. 2, the coordination allows for a minimum value of power offered higher than the one offered without coordination and allows for a lower price of the offering, which is a potential benefit to into operation.

For the bilateral contracts 10 levels of energy contracted are simulated for the same market conditions described above. The power contracted in the bilateral contracts and the impact of bilateral contracts treated as a deterministic problem in the energy offered in the day-ahead market is shown in Fig. 3, where the energies are the average of the ten market scenarios for each level of energy from the bilateral contract.

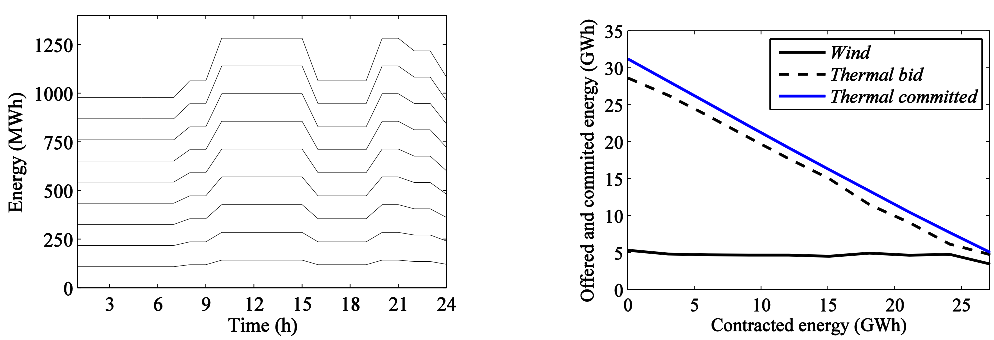

Fig 3. Left: bilateral contract; right: market scenarios energy average.

In Fig. 3, the part of the energy offered from the wind is practically constant and the committed energy is always lower than the part of the energy offered from the thermal units. As the energy contracted increases and approaches the limit capacity of the thermal units, the difference between the committed energy and the part of the energy from the thermal units wind decreases as decreases the part of the energy offered from the wind.

5 CONCLUSION

A stochastic MILP approach for solving the offering strategy and the self-scheduling problem of a price-taker thermal and wind power producer is developed in this paper. The main results are the short-term bidding strategies and the optimal schedule of the thermal units. A mixed-integer linear formulation is used to model the main technical and operating characteristics of thermal units. The coordinated offer of thermal and wind power proved to provide better revenue results than the sum of the isolated offers. The stochastic programming is a suitable approach to address parameter uncertainty in modeling via scenarios. Hence, the proposed stochastic MILP approach proved both to be accurate and computationally acceptable, since the computation time scales up linearly with number of price scenarios, units and hours on the time horizon. Since the bids in the pool-based electricity market are made one day before, this approach is a helpful tool for the decision-maker.

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