Optimal wind turbines placement within a distribution market environment

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A R T I C L E   I N F O

Article history:
Received 27 July 2012
Received in revised form 21 April 2013
Accepted 31 May 2013
Available online 13 June 2013

Keywords:
Wind turbines
Social welfare maximization
Genetic algorithm
Net present value

A B S T R A C T

This paper proposes a hybrid optimization method for optimal allocation of wind turbines (WTs) that combines genetic algorithm (GA) and market-based optimal power flow (OPF). The method jointly maximizes net present value (NPV) related to WTs investment made by WTs’ developers and social welfare (SW) considering different combinations of wind generation and load demand over a year. The GA is used to choose the optimal size while the market-based OPF to determine the optimal number of WTs at each candidate bus. The stochastic nature of both load demand and wind power generation is modeled by hourly time series analysis. The effectiveness of the method is demonstrated with an 84-bus 11.4 kV radial distribution system.

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1. Introduction

1.1. Motivation

Wind turbines (WTs) placement in a distribution network affects several parameters such as voltage profile, line losses, short circuit current and system reliability and these parameters should be assessed before installing the WTs in a distribution network.

Different factors can be considered in the determination of candidate buses for WTs placement: spacing and turbulence, visual impact, noise concerns, environmental considerations, location and distance to people.

When WTs are placed too close to one another, they can create turbulence. Eventually, the turbulence created by the close WTs placement can reduce efficiency by affecting the amount of energy created. WTs are extremely visible, especially when grouped together in a wind farm. Due to the nature of WTs, they must be placed in open areas exposed to wind, which serves to increase their visibility. A solution to the visual impact is to reduce the number of WTs in one location. Early models of WTs were loud. Scientists have recently developed updated models that reduce the noise created by the WT. Placement of WTs in an area where the impact of the noise is minimum can help reducing negative perceptions of WTs. Ideal locations for WTs include coastal areas, open fields, tops of rounded hills or gaps mountain ranges. A consistent and reliable wind source is required to turn the WTs and create the power source. Locating power plants at long distances from people is generally not convenient as in order to keep a high-efficiency link with the rest of the power grid, an expensive array of inverters and transformers is required [1].

Therefore, proper allocation of WTs plays a key role for the improvement of system performance in a distribution system [2]. Furthermore, the optimal placement of WTs is one of the most important aspects for power system planning. WTs allocation at non-optimal places may cause an increase in the network losses and in the generation investment. Therefore, selecting the best places for siting and sizing of WTs in large networks represent a complex optimization problem [3,4].

1.2. Aim and approach

In this paper, a novel method for optimal placement of WTs in distribution networks is proposed. The method combines the genetic algorithm (GA) and the market-based optimal power flow (OPF) to jointly maximize the net present value (NPV) related to the investment made by WTs’ developers and the social welfare (SW) over a year in distribution network operator (DNO) acquisition market. The GA is used to choose the optimal size while the market-based OPF to determine the optimal number of WTs.

The DNO is defined as the market operator of the DNO acquisition market, which determines the price estimation and the optimization process for the hourly acquisition of active power. The uncertainty in wind power generation and load demand is modeled through hourly time-series model of load demand and wind generation. The interrelationships between demand and
generation potential are preserved with their joint probability defining the number of coincident hours over the year.

The proposed method can help WTs' developers to better allocate WTs by considering cost reduction and consumers' benefits; moreover, it is consistent with the topology of the considered distribution system since it considers network constraints and distribution locational marginal prices (D-LMPs).

By following this approach it is expected that WTs will be allocated at buses where they are more advantageous that is near higher loads or in parts of the networks where the loads have maximum value and the consumers' benefit is higher. The method is applied to an 84-bus 11.4 kV distribution network.

1.3. Literature review

A lot of previous works have been carried out to seek the optimal capacities and locations of distributed generators (DGs). In [5], a Tabu search method to obtain the optimal sizes and locations of DGs has been proposed. In [6], the authors proposed a cost based model to allocate DGs in distribution networks in order to minimize DG investment and total operation costs of the network. The objective function is solved using an ant colony optimization (ACO) method. In [7], a novel method for optimal allocation of DGs in distribution systems to minimize the network losses and to guarantee the acceptable reliability level and voltage profile has been proposed. In [8] an optimization technique is suggested to establish the maximum wind power injected into the grid with fixed transmission capacity taking into account the network security. In [9], a numerical algorithm is proposed to estimate the maximum wind energy exploitation in independent electric island networks. In [10], the differences in the improvement patterns of offshore wind power in Europe and US are discussed. In [11] the authors provided an investigation for the wind power investment in Turkey inspiring the interest of wind investment and evaluating the wind generation costs in this country. In [12], a linear programming model is suggested to specify the optimal technology mix, taking into account wind power production as a negative load that influences the variability of the load profile and therefore the network operation. The metaheuristic methods such as GA, particle swarm optimization (PSO), and ACO are used to solve the generation expansion planning problem in [13,14], Virtual mapping procedure (VMP) and penalty factor approach (PFA) are also used to improve the efficiency of the metaheuristic techniques. In [15], the authors proposed a novel method based on PSO to solve an OPF problem considering security constraints to minimize the total operating cost.

1.4. Contributions

To the best of our knowledge, no wind power investment method in distribution level from the point of view of WTs' developers in the market environment by using hybrid GA and market-based OPF has been reported in the literature. For this reason, the proposed method is innovative if compared with other methods reported in the literature.

One of the innovative aspects of the proposed method is that, according to the distribution network topology, it allows WTs' developers allocating WTs at more advantageous locations in terms of earned revenue. This is attained using D-LMPs, a natural extension from the transmission system, able to provide a real-time price to the customer. By using D-LMPs, supply offers and demand bids and the physical aspects of the distribution network, including distribution and other operational constraints are assessed in the proposed method.

Also, by using the proposed method, WTs' developers can evaluate WTs placement taking into account the D-LMPs' values that directly influence their profits.

Another novelty of the proposed method is the participation of WTs' developers in a distribution level market comprising both a day-ahead schedule of WTs and loads according to the market price and a real-time intraday optimization operation. The uncertainty in wind power generation and load demand is modeled through hourly time-series model of load demand and wind generation. The interrelationships between demand and generation potential are preserved with their joint probability defining the number of coincident hours over a year.

1.5. Paper organization

The rest of the paper is organized as follows. Section 2 explains the model features. Sections 3 and 4 describe GA implementation and DNO acquisition market formulation, respectively. Section 5 explains the 84-bus test system while Section 6 presents some numerical results. Discussions and conclusions are presented in Section 7.

2. Model features

2.1. Modeling of time-varying load demand and wind power generation

A future year for the expansion planning is considered and the optimal investment is established for that year. This analysis is known as static expansion planning, is used in this paper for the wind power investment. This static method comprises a proper tradeoff between modeling precision and computational tractability.

The wind generation and load demand are modeled through hourly time series analysis in a year as shown in Fig. 1. The method reduces hourly time-series data to a number of scenarios where the load demand and wind generation for every hour are assigned to a series of bins. Describing the number of coincident hours over the year preserves the interrelationships between potential of load demand and wind power generation with their joint probability [16].

In order to reduce the computational burden of a full time series analysis, wind generation and load demand are aggregated into a controllable number of scenarios on the basis of their joint probability of happening. The number of coincident hours is represented by the duration of each hour as shown in Fig. 1 (right). It splits the demand and generation into a series of bins. In order to show the procedure, ten ranges for demand (i.e. [0, 10%], [10%, 20%], ..., [90%, 100%]) and 11 ranges for wind generation (i.e. [0], [0%, 10%], [10%, 20%], ..., [90%, 100%]) are used. It is seen that with demand higher than 30%, 74 non-zero scenarios are considered in the analysis. Furthermore, low load demand, i.e. 40%, and high wind generation, i.e. 60–100%, present few coincident hours.

The uncertainty in wind power generation and load demand are represented via scenarios. Each demand level is characterized by eleven wind generation levels, i.e. 0–100%. There are seven load demand and eleven wind generation levels. Therefore, jointly considering the load demand and wind power generation levels results in 77 scenarios, i.e. seven load demand levels, with two blocks per level with different sizes and the same price, by eleven wind power generation levels with four blocks per level with the same size and the same price for all blocks.

2.2. The structure of the proposed method

The method combines GA and market-based OPF to maximize the NPV related to the investment made by WTs' developers over a year as shown in Fig. 2. The GA is used to find the optimal sites
(among some pre-selected candidate locations) and sizes of WTs while the market-based OPF, nested in the GA, to specify the optimal number of WTs of the size chosen by the GA. The optimal number is obtained as the maximum number of WTs identified by the market-based OPF among all the scenarios. The WTs' sizes and locations at candidate buses are represented by the optimization variable of the GA, called chromosome. It is a vector of integers, with a length equal to the number of candidate buses $N_c$. As shown in Fig. 3, every element of the vector is related to a candidate bus and varies in the range $[0, N_{\text{sizes}}]$ where $N_{\text{sizes}}$ is the number of WTs’ sizes.

In such a way, different vectors allow representing different investments in WTs, both in terms of selected locations and sizes. Different sizes of WTs identified with a label in the range $[0, N_{\text{sizes}}]$ are considered on the basis of their rating power and power coefficients. Three different sizes of WTs of sizes 1.2, 2 and 3 MW, namely sizes A, B and C, respectively, are considered here. In the example of Fig. 3, WTs of size A are sited at the candidate bus corresponding to the first element of the vector while WTs of sizes B and C are respectively sited at the candidate buses corresponding to the last two elements of the vector. According to this formulation, WTs of the same size can be allocated at each candidate bus. For each chromosome, the NPV is assessed considering the different scenarios. The wind energy sold by WTs’ developers and the D-LMPs in the DNO acquisition market derive from the market-based OPF solution.

The proposed hybrid optimization method runs as follows.

1. Define GA parameters and WTs’ types (size and speed-power curves) to be allocated by WTs’ developers.
2. Set the candidate buses according to the wind energy availability.
3. Model uncertainties associated to load demand and wind generation through hourly time series analysis, as explained in Section 2.1.
4. Calculate the power outputs and offer prices of different sizes of WTs as is explained in Section 5.1.
5. For each chromosome, maximize the SW for the considered scenarios and evaluate the hourly revenue (i.e. multiplication of WTs’ dispatched energy by the D-LMP for each hour) and initial investment cost.
6. Evaluate the annual revenue and the NPV.
7. If one of the stopping criteria is reached go to step (9) otherwise repeat steps (5) and (6) until one of the stopping criteria is reached.
8. The products of the proposed method are the optimal locations, sizes and numbers of WTs.
9. Print the solution.

3. Genetic algorithm implementation

The GA starts with an initial population whose elements are called chromosomes. Chromosomes encode candidate solutions and evolve to better ones. The evolution begins from a number of arbitrarily generated chromosomes. During each iteration, called generation, the objective function for each chromosome in the population is assessed and, based on this assessment; a new population of candidate solution is formed. The new population generated in the next iteration is usually better than those in the current population. The GA uses three kinds of rules at every step including selection rules, crossover rules and mutation rules to produce the next generation from the current population and it continues until some stopping criteria is reached [17].

The GA generates the initial populations by defining a set of vector in the range $[0, 3]$. The number of chromosomes and iterations are set. Each chromosome has a size $N_c$, where $N_c$ is the number of candidate buses. A number of new improved individuals, according to their objective function, at each generation are created by choosing the individuals. After the selection of new population the genetic operators are applied to chosen chromosomes. The iteration procedure is repeated until one of the following stopping criteria is reached: (1) the maximum generation is more than 300, (2) an enhancement in the objective function for five consecutive
Maximize the annualization of the economic benefit function for five consecutive iterations is less than 10^{-6}.

Sensitivity analyses have been carried out to consider different values for the GA parameters such as stopping criteria, population size and genetic operators. From these analyses, it can be seen that the values used here guarantee the convergence of the algorithm to a satisfactory solution.

The NPV to be maximized as the objective function of GA is expressed as follows:

Maximize \[ \text{NPV}(y) = FA \times FC(y) - IC(y) \] (1)

where \( FA \) is annual factor, \( FC \) is the total revenue obtained by selling energy into the DNO acquisition market over the target year and \( IC \) is the initial investment cost. \( FA \) and \( FC \) are calculated as follows:

\[
FA = \frac{(1 + r)^n - 1}{r(1 + r)^n} \tag{2}
\]

\[
FC(y) = \sum_{h=1}^{8760} E^2_d(y) \times \lambda_h(y) \tag{3}
\]

where \( n \) is the lifetime of WT and \( r \) is the discount rate. Here, \( n \) and \( r \) are assumed as 20 years and 3\%, respectively. \( FC(y) \) is the annual revenue and \( y \) is the decision variable of the GA that is a vector of integers in the range \([0, N_{\text{integers}}]\) with a length equal to the number of candidate buses. \( E^2_d(y) \) is the energy dispatched by the installed WT at given hour \( h \) and \( \lambda_h \) is the locational marginal price that is obtained from market-based OPF. For each chromosome, annual revenue is obtained considering the DNO acquisition market formulation as described in the following Section for all the considered scenarios.

### 4. DNO acquisition market formulation

Usually, the energy is purchased from the wholesale market and delivered to final customers by DNO. Nonetheless, due to the power system reconstructing and emerging DGs such as WT, the business of traditional DNO is unbundled into technical and economic tasks. A DNO acquisition market model, called the DNO acquisition market is presented here under a distribution market structure based on Pool and bilateral contracts. The DNO is defined as the market operator of the acquisition market, which determines the price estimation and the optimization process for the acquisition of active power. Dispatchable loads (DLs) and WT send active power offers and bids to the DNO acquisition market in form of blocks for each hour [18]. The DNO's aim is the maximization of the SW [16] (i.e., the maximization of the consumers' benefit function and the minimization of the costs of energy). In other words, the actions carried out by the DNO acquisition market are:

1. A day-ahead schedule of DGs and loads according to the market prices, with every trade day including 24 h trading periods. The dispatch schedules are determined for every trading period [16].

2. A real-time intraday optimization operation that every 15-min changes the scheduling to take into account the operation and economic requirements.

Under the assumed DNO acquisition market, the market clearing quantity and price are determined by maximizing the SW while keeping the distribution network's security. Its maximization implies not only the minimization of the costs related to energy production but also the maximization of the consumers' benefit function. The optimization problem is formulated as follows:

Maximize \[ SW(x, u) = \sum_{j=1}^{N_j} B_j(d_j) - \sum_{i=1}^{N_i} C_i(g_i) \] subject to \[ h(x, u, d, g) = 0 \]

\[ g(x, u, d, g) \leq 0 \]

where \( x \) is the vector of dependent variables, \( u \) is the vector of control variables, \( d \) is the demand vector, \( g \) is the supply vector, \( N_j \) is the set of pool load buses, \( N_i \) is the set of pool generator buses;

\[
B_j(d_j) = \frac{1}{2} m_d d_j^2 + b_j d_j \tag{5}
\]

\[
C_i(g_i) = \frac{1}{2} m_g g_i^2 + b_g i \tag{6}
\]

where \( B_j(d_j) \) and \( C_i(g_i) \) are the production cost and benefit of consumers, respectively, \( p_i \) is the price at which producer \( i \) is willing to supply in €/MWh:

\[
p_i = b_i + m_g g_i, \quad \text{for} \quad i = 1, 2, \ldots , I \tag{7}
\]

where \( b_i \) is the intercept (reservation price \( b_i > 0 \)) in €/MWh, \( m_g \) is the slope \( (m_g > 0) \) in €/MWh, \( g_i \) is the supply in MW, \( p_i \) is the price at which consumer \( j \) is willing to pay in €/MWh:

\[
p_j = b_j + m_d d_j, \quad \text{for} \quad j = 1, 2, \ldots , J \tag{8}
\]

where \( b_j \) is the intercept (reservation price \( b_j > 0 \)) in €/MWh, \( m_d \) is the slope \( (m_d < 0) \) in €/MWh, \( d_j \) is the demand in MW.

For the objective function (1), \( y \) is the variable of the GA while for the objective function (4) the optimization variable \( x \) is the vector of dependent variables, including vector \( L = [V_i, \theta_i, P_g, P_d] \) where \( V_i \) and \( \theta_i \) are voltage and voltage angle at the buses, respectively. \( P_g \) is active power generated by WT and \( P_d \) is active power of DLS. \( \lambda \) and \( \mu \) are Langrangian multipliers and use the Newton’s method to solve the Karush–Kuhn–Tucker (KKT) conditions [20,21].

WTs’ offers and bids of DLs are taken and treated as marginal cost and marginal benefit functions, respectively, then by using the constrained cost variable (CCV) method [19–21] they are converted to the equivalent total cost and total benefit functions and plugged into a matrix as piecewise linear costs.

### 4.1. Constraints of the market based OPF

The equality constraints \( h(x, u, d, g) \) represent the static load flow equations such as Kirchhoff current law and Kirchhoff voltage law.

#### 4.1.1. Equality constraints

\[
0 = \sum_{i=1}^{NG} P_g - \sum_{j=1}^{N_{\text{load}}} P_{dj} - P_{\text{loss}} \tag{9a}
\]

\[
0 = \sum_{i=1}^{NG} Q_g - \sum_{j=1}^{N_{\text{load}}} Q_{dj} - Q_{\text{loss}} \tag{9b}
\]

where \( NG \) and \( N_{\text{load}} \) are the total number of WT and loads, respectively. \( P_{\text{loss}} \) and \( Q_{\text{loss}} \) respectively represent the total active and reactive power losses.

The inequality constraints \( g(x, u, d, g) \) are listed in the following.
4.1.2. Inequality constraints

- Active and reactive power constraints for the interconnection to the external network (slack bus)

\[ p_{b}^{\text{min}} \leq p_b \leq p_{b}^{\text{max}} \]  \hspace{1cm} (10a)

\[ q_{b}^{\text{min}} \leq q_b \leq q_{b}^{\text{max}} \]  \hspace{1cm} (10b)

where \( p_b \) and \( q_b \) are active and reactive power of the slack bus, respectively.

- Voltage level constraints at the buses

\[ v_{i}^{\text{min}} \leq v_i \leq v_{i}^{\text{max}} \]  \hspace{1cm} (11)

where \( v_{i}^{\text{min}} \) and \( v_{i}^{\text{max}} \) are the lower and upper bounds of the bus voltage, respectively.

- Thermal limits of the lines connecting the buses

\[ S_{f} - S_{f}^{\text{max}} \leq 0 \]  \hspace{1cm} (12)

where \( S_{f} \) and \( S_{f}^{\text{max}} \) are the maximum apparent power transfer of wire and power transformers respectively.

\[ 0 \leq p_g \leq p_{g}^{\text{max}} \]  \hspace{1cm} (13)

\[ -\phi \leq d \leq \phi \] \hspace{1cm} (14)

\[ \cos \phi = \frac{p_g}{\sqrt{p_g^2 + q_g^2}} = \text{constant} \] \hspace{1cm} (15)

\[ 0 \leq Q_d \leq Q_{d}^{\text{max}} \] \hspace{1cm} (16)

4.2. Dispatchable load modeling

One way to model price-sensitive or DLs is modeling them as negative generators with related negative costs. This is carried out by determining a generator with a negative output in a range from a minimum injection equivalent to the negative of the highest load value to a maximum injection of zero. Here, it is supposed that DLs have a fixed power factor. Furthermore, an equality constraint to impose a fixed power factor for a negative generator is utilized for a DL modeling. It should be noted that with the description of a DL as a negative generator, if the negative cost relates to the consumer’s benefit function, the minimization of generation cost is equal to SW maximization [19,20].

4.3. Step-controlled primal dual interior point method

The primal dual interior point method (PDIPM) has become an appropriate method for solving the OPFs in the last decades[21–24]. Although the PDIPM fits appropriately with conventional OPFs that use smooth polynomial cost function, it is not capable to solve the market-based OPFs with non-differentiable piecewise cost. The gradient and Hessian variables vary from iteration to iteration noticeably when piecewise cost is taken into consideration. In addition, the decreasing of Newton steps is not achieved. The SCPDIPM that is employed in this paper conquers this problem by monitoring the precision of the quadratic estimation of the Lagrangian during the OPF calculation and decreasing the Newton step if any unexpected derivative alteration causes an imprecise estimation. Applying such an efficient step control method is useful when the normal PDIPM is not capable to enhance the gradient condition [19,20].

5. Test system description

In this section, the distribution system used to test the proposed method is described. The following analyses are based on a modified version of the 84-bus 11.4-kV radial distribution system whose data are given in [25]. The eleven feeders are supplied by two 20 MVA, 33/11.4 kV transformers. The one line diagram of the distribution system is shown in Fig. 4. The candidate buses in the test system are included in the set \{1, 4, 10, 13, 15, 24, 27, 32, 41, 48, 52, 63, 65, 71, 75, 82\}. The WTs operate at power factor of 0.90 lagging. Voltage limits are taken to be ±6% of nominal value, i.e. \( V_{\text{nom}} = 1.06 \), and \( V_{\text{min}} = 0.94 \). The feeders’ thermal limits are given in Table 1 and vary between 60 and 480 A. Dispatchable and fixed loads, with constant power factor equal to 0.90, are served by both the grid and WTs.

The different sizes of WTs, 1.2, 2 and 3 MW are considered by the WTs’ developers. The maximum number of WTs that can be allocated at a given bus is represented by an equivalent number of blocks in the WTs’ offer. At each candidate bus it is assumed that maximum four WTs of each size can be allocated; this requirement is regulated by the accessible land for building WTs. Thus, for each generation level there are four blocks of the same size equal to the rated power of the selected WTs and the same price of 60 €/MWh. In the following subsection, the method of estimating WTs’ offers price is explained.

The offers are assumed at price of 80 €/MWh for the bus connecting the distribution network to the transmission one (slack bus). With regards to the bids for DLs, it is assumed that there are two blocks per demand bid with different sizes as presented in Table 2 and the same price of 150 €/MWh for all blocks.

5.1. Calculation of the WTs’ offer price from the point of view of WTs’ developers

In order to calculate the price of WTs’ offers, financial data, i.e. WTs’ life time, installation cost, depreciation time, interest rate, are considered as summarized in Table 3 [26,27]. The annual cost for WTs is calculated as follows [27]:

\[ \text{Ann. Cost} = \frac{r(1 + r)^n}{(1 + r)^n - 1} \times \text{Inst. Cost} \]  \hspace{1cm} (17)

where \( r \) is the interest rate, \( n \) is the depreciation period in years, \( \text{Inst. Cost} \) is the installation cost, and \( \text{Ann. Cost} \) is the annual cost for depreciation. The capacity factor is evaluated according to the wind generation data and the WTs’ capability curves. For example, for a 1.2 MW WT the capacity factor is about 40%, i.e. 3504 MWh/MW. Therefore, by dividing \( \text{Ann. Cost} \) by equivalent number of hours i.e. 3504 h, the WTs’ offers price with no subsidy is about 56 €/MWh. Therefore, the 1.2 MW WT’s offer price, without subsidies, is assumed as 60 €/MWh. The same approach can be applied considering WTs of different sizes and capacity factors. In order to simplify the analysis, the same price is considered for all the sizes of WTs.
Table 1

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<th>Existing wires</th>
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The proposed method is applied to the abovementioned distribution network. According to a sensitivity analysis, the number of generations and the population size are chosen as 300 and 20, respectively. The method has been implemented in MATLAB® incorporating some features of MATPOWER suite [19,20] and MATLAB® toolbox for GA [28] on a laptop with core i7, 1.6 GHz processor and 4 GB of RAM.

6. Simulation results

The parameters used for the simulations are determined experimentally by using information from several trial runs (i.e. 50 trials are performed for each parameter set with different starting points). The best parameters are selected, after a sensitivity analysis, in accordance with the highest value of the objective function of GA. The capital costs of the three sizes of WTs are listed in Table 4. The maximum NPV obtained by the proposed method is equal to 212.80 M€. The optimal sizes and numbers of WTs at each candidate bus found by the proposed method are given in Table 5.

Table 2

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<td>1.50</td>
<td>0.75</td>
<td>29</td>
<td>73</td>
<td>0.60</td>
<td>0.60</td>
</tr>
<tr>
<td>15</td>
<td>63</td>
<td>1.50</td>
<td>0.75</td>
<td>32</td>
<td>77</td>
<td>0.60</td>
<td>0.60</td>
</tr>
<tr>
<td>16</td>
<td>65</td>
<td>1.50</td>
<td>1.50</td>
<td>33</td>
<td>79</td>
<td>3.00</td>
<td>1.50</td>
</tr>
<tr>
<td>17</td>
<td>71</td>
<td>1.50</td>
<td>0.75</td>
<td>34</td>
<td>82</td>
<td>1.50</td>
<td>1.50</td>
</tr>
</tbody>
</table>
Table 3
Financial data for estimating the offers price for a 1.2 MW WT.

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Life time (years)</td>
<td>20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Installation cost (€/kW)</td>
<td>1200</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depreciation time (years)</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest rate (%)</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of equivalent hours (h)</td>
<td>3504</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capacity factor (%)</td>
<td>40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual cost (€/kW-year)</td>
<td>195.27</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4
Capital costs of WTs.

<table>
<thead>
<tr>
<th>WT size</th>
<th>Rated output power (MW)</th>
<th>Capital cost (€/kW)</th>
<th>Total capital cost (M€)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.2</td>
<td>1200</td>
<td>1.44</td>
</tr>
<tr>
<td>B</td>
<td>2</td>
<td>1120</td>
<td>2.24</td>
</tr>
<tr>
<td>C</td>
<td>3</td>
<td>1050</td>
<td>3.15</td>
</tr>
</tbody>
</table>

Table 5
The optimal numbers, sizes and capacities of WTs obtained by the proposed method.

<table>
<thead>
<tr>
<th>Bus no.</th>
<th>Size</th>
<th>Number</th>
<th>Capacity (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>C</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>10</td>
<td>B</td>
<td>4</td>
<td>8</td>
</tr>
<tr>
<td>13</td>
<td>B</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>15</td>
<td>C</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>24</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
</tr>
<tr>
<td>27</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
</tr>
<tr>
<td>32</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
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<tr>
<td>41</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
</tr>
<tr>
<td>48</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
</tr>
<tr>
<td>52</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
</tr>
<tr>
<td>63</td>
<td>C</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>65</td>
<td>B</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>71</td>
<td>B</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>75</td>
<td>A</td>
<td>4</td>
<td>4.8</td>
</tr>
<tr>
<td>82</td>
<td>B</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td><strong>Total capacity</strong></td>
<td><strong>68.80</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

It is evident from Table 5 that bus 13 has the largest installed capacity (i.e. 8 MW equal to four WTs of size B) while buses 10 and 24 have the lowest one (3 MW equal to one WT of size C).

In fact, the number of installed WTs is limited by voltage and thermal limits as well as by the bids’ values at each bus. For instance, the installed capacity at buses 10 and 24 is limited to 3 MW (one WT of size C) and this is mainly due to the lowest value of both thermal limit of the lines connecting the buses 7–10 and 23–24 (i.e. 60 A) and the bids’ values of DLs if compared to those at the other lines and buses, respectively.

The installed capacity at buses 71 and 82 is 6 MW (four WTs of size B). These buses have higher bids and the higher thermal limits of the lines 70–71 and 81–82 connecting the buses (i.e. 180 A) if compared to previous case.

At bus 13, with the highest thermal limit of the line 12–13 (i.e. 480 A) if compared to previous case, the voltage and thermal limits are not binding and the highest capacity at this bus is installed (i.e. 8 MW equal to four WTs of size B).

As given in Table 6, total WTs capacity of 68.80 MW is installed allowing delivering annual wind energy of 246,840 MW h/year. The total capital cost of the investment is equal to 78.52 M€ while the NPV is equal to 212.80 M€. Also, the total SW over the year is about 273.43 k€/year.

Table 6
Results obtained with the proposed method.

<table>
<thead>
<tr>
<th>Total capacity (MW)</th>
<th>Delivered wind energy (MW h/year)</th>
<th>Total capital cost (M€)</th>
<th>NPV (M€)</th>
<th>Social welfare (k€/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>68.80</td>
<td>246,840</td>
<td>78.52</td>
<td>212.80</td>
<td>273.43</td>
</tr>
</tbody>
</table>

The energy delivered over the first year has the highest value in the case of 70% load demand and 100% wind generation as shown in Fig. 5 and it is due to the highest value of the corresponding number of hours in this case, as shown in Fig. 1.

In order to evaluate and compare the obtained results, ACO is used with the same population size for the GA, the same number of ants, i.e. 20 and the same number of iterations, i.e. 300. It can be observed from Table 7 that the NPV obtained by GA is higher than that obtained by ACO.

As regards with SW, it increases proportionally to the both load demand and wind generation as shown in Fig. 6 for the first year of the planning horizon. It is observed that in the case of minimum load, i.e. 40%, and maximum wind generation level, i.e. 100%, the SW is equal to about 2800 €/h and in the case of maximum load and minimum wind generation, the SW is equal to about 3000 €/h while in the case of maximum wind generation level and maximum load demand this value is equal to about 5800 €/h which is higher...
if compared to previous cases. It is worth pointing out that, in all cases, the SW is higher if compared to that without WTs in the network: in the case of 100% wind generation and 40% load demand the SW increases about 50% if compared to the case with no WTs in the network.

It is evident from Fig. 7 that revenue increases proportionally to the both load demand and wind generation from minimum to maximum. Furthermore, in the case of maximum load demand and maximum wind generation, revenue has the highest value if compared to other cases.

Fig. 8 shows the mean D-LMP. It is evident that by increasing the wind generation level the mean of D-LMP is decreased in all cases. The mean of D-LMP has an inverse relation with wind generation and direct relation with load demand. The mean of D-LMPs in the cases of high wind generation and low load demand has the lowest values. Furthermore, the D-LMPs in all cases are lower if compared to those with no WTs in the network.

7. Discussion and conclusion

In this paper, a hybrid optimization method for optimal allocation of WTs is proposed. The method combines the GA and the market-based OPF to jointly maximize the NPV related to the investment made by WTs’ developers and the SW in DNO acquisition market environment. The GA is used to select the optimal sizes among different sizes of WTs while the market-based OPF to determine the optimal number of WTs in order to maximize the SW considering network constraints.

The DNO acts as the market operator of the DNO acquisition market that estimates the market clearing price and the optimization process for the active power hourly acquisition.

The stochastic nature of both load and wind is modeled by hourly time series analysis. By using the proposed method, WTs can be, in fact, optimally allocated at buses where they are more advantageous, i.e., near higher loads or in parts of the network where the loads have the higher values. The method can help WTs’ developers to better allocate WTs by considering their profit. Moreover, it is consistent with the topology of the distribution system since it considers network constraints and D-LMPs. By using D-LMPs, both supply offers and demand bids and the physical aspects of the distribution network, including distribution and other operational constraint are assessed. Even if the implementation of a distribution-level market based on D-LMP paves the way for real-time pricing, new information and communications technologies are required that can be provided by implementing microgrids and smart grids [29–31]. The presented case study highlighted that WTs’ developers by optimally allocating WTs at buses with the highest D-LMPs can improve their profits, but also increase consumers’ benefits by energy cost reduction and network constraint alleviation.

References

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[18] R. Palma-Behnke, J.L.A. Cerda, L. Vargas, A. Jofre, A distribution company energy acquisition market model with the integration of distribution generation and


