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Location and contract pricing of distributed generation using a genetic algorithm

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ABSTRACT

This paper presents an approach based on a specialized genetic algorithm (GA) to determine the location and contract pricing of dispatchable distributed generation (DG) units in distribution systems. The proposed approach is based on a nonlinear bilevel programming framework that involves the interests of two different agents: the DG owner who procures the maximization of the profits obtained from the energy sales, and the Distribution Company (DisCo), which procures the minimization of the payments incurred in attending the forecasted demand. To meet the forecasted demand the DisCo can purchase energy either from the wholesale energy market or from the DG units within its network. The proposed GA determines both the location and contract pricing of the DG units that would render maximum profits to the DG owner, subject to the minimization of payments procured by the DisCo. To show the effectiveness of the proposed approach, several tests were carried out on a modified IEEE 34-bus and 85-bus distribution networks.

1. Introduction

Distributed generation can be understood as the production of electricity by small generators located in the distribution network or near the loads they are attending [1]. In the past few years the electric industry has witnessed an increased interest in DG. This interest has been motivated by several factors such as recent advances in generation technologies that have rendered generation units smaller and feasible, an increasing awareness of environmental issues, and the need for more flexible electric systems.

The technical and economic impacts of DG have been widely studied in the specialized literature [2–7]. As most of the potential benefits of DG depend on the size and location of the new generating units, their optimal location and sizing has received special attention. In this regard, there are several methodologies that have been proposed in the literature to optimally size and allocate DG. These methodologies include analytical approaches [8,9], classical optimization [10–12] and metaheuristics [13–18].

Ref. [8] presents analytical approaches for optimal placement of DG in distribution systems considering uniformly, centrally, and increasingly distributed loads. In [9] an analytical expression and a methodology based on the exact loss formula are proposed in order to determine the size and location of DG that would minimize power losses. In [10] a methodology based on classical optimization is proposed to determine the optimal placement and penetration level of DG with the objective of minimizing costs and power losses. In [11] the locational marginal prices (lmps) along with the consumer payment are used to identify the candidate buses where to allocate the DG. In [12] an optimization model including binary decision variables is proposed to solve the distribution system planning problem including the size and location of new DG units.

Several metaheuristic approaches have also been applied to the problem of finding the optimal location of DG units. In [13] a multi-objective evolutionary algorithm is proposed to maximize the benefits of DG by limiting the deterioration of the network performance due to DG units not connected in optimal locations. In [14] a GA is presented to determine the allocation and sizing of DG considering nodal pricing for profit, loss reduction and voltage improvement. In [15] a Tabu Search metaheuristic is proposed to find the optimal location of DG units that would minimize power losses. In [16] this technique is also applied using a multi-objective optimization approach. In [17] a Particle Swarm optimization technique for the optimal allocation of DG is presented, being the objective function the minimization of power losses. In [18] this technique is also applied to improve voltage profile and reduce total harmonic distortion as well as power losses. The main difference between the aforementioned methodologies and the proposed GA consists in a bilevel approach to the problem that considers a different objective function.

A bilevel programming problem (BLPP) is a hierarchical optimization problem consisting of two levels. Each level corresponds to an agent with an objective function and subject to a set of constraints. The upper level agent is known as the leader and is

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Nomenclature

Indexes

n, m	bus indexes
j	distributed generation unit index
l_{mn}	index of line connecting nodes m, n

Parameters

$\rho_{SE}(t)$	wholesale energy price at the substation in period t (€/MW h)
Δ_t	length of the time interval t (h)
S_{lmn}^{Max}	maximum apparent power limit in the line connecting nodes m, n (MVA)
V_n^{Max}	maximum voltage limit in bus n (V)
V_n^{Min}	minimum voltage limit in bus n (V)
P_{DGj}^{Max}	maximum active power limit of DG unit j (MW)
P_{DGj}^{Min}	minimum active power limit of DG unit j (MW)
P_{SE}^{Max}	maximum active power limit of the substation (MW)
P_{SE}^{Min}	minimum active power limit of the substation (MW)
Q_{SE}^{Max}	maximum reactive power limit of the substation (MVAR)
Q_{SE}^{Min}	minimum reactive power limit of the substation (MVAR)
Q_{DGj}^{Max}	maximum reactive power limit of DG unit j (MVAR)
Q_{DGj}^{Min}	minimum reactive power limit of DG unit j (MVAR)
c_{DGj}	production cost of DG unit j (€/MW h)
$P_{Dn}(t)$	active power demand in bus n in period t (MW)
$Q_{Dn}(t)$	reactive power demand in bus n in period t (MVA)
g_{mn}	real part of element m, n of the admittance matrix (mho)
b_{mn}	imaginary part of element m, n of the admittance matrix (mho)
N_{DG}	number of DG units

Variables

$P_{SE}(t)$	active power supplied by the substation in period t (MW)
$Q_{SE}(t)$	reactive power supplied by the substation in period t (MVA)
$P_{DGj}(t)$	active power supplied by the DG unit j in period t (MW)
$Q_{DGj}(t)$	reactive power supplied by the DG unit j in period t (MVA)
$V_n(t)$	voltage magnitude of node n in period t (V)
θ_{mn}	angle between nodes m, n
λ_{DGj}	contract price of DG unit j (€/MW h)
μ_{nj}	binary decision variable indicating the allocation of DG unit j in bus n
P_{lmn}	real power in line connecting nodes m, n (MW)
Q_{lmn}	reactive power in line connecting nodes m, n (MVAr)
S_{lmn}	apparent power in line connecting nodes m, n (MVA)

Sets

J	set of indexes of DG units
T	set of time intervals
N	set of indexes of network nodes

subject to the optimization problem of the lower level agent known as the follower. In this case, the two decision-making agents are the DG owner (leader) and the DisCo (follower). On one hand, given a fixed number of DG units with a predefined capacity, the DG owner pretends to maximize the profits that would be obtained from the energy sold to the DisCo. For this, he must decide the most suitable locations and contract price offers for each DG unit. On the other hand, the DisCo procures the minimization of the payments incurred in attending the forecasted demand. For this, the DisCo must decide the quantity of energy to be purchased from the DG units and from the wholesale energy market through the substation.

To decide the amount of energy to be purchased from each supplier, the DisCo must take into account not only energy prices, but also the impact that this energy has in its network. An effective way to consider these two aspects is by means of an optimal dispatch based on an AC optimal power flow.

In a conventional wholesale electricity market generating agents decide over their price and quantity bids, and are paid at the market clearing price. However, in the market structure envisaged in this paper the DG owner decides over the contract prices, while the DisCo determines the quantity of energy to be purchased, consequently, only dispatchable DG technologies are considered in the model. Furthermore, a single DG owner who might have several DG units is considered. For each unit, the DG owner is interested in finding the location and contract price that would maximize total profits.

The main feature of a BLPP is that the decisions made by the upper level agent (the DG owner) must anticipate the reactions of the lower level agent (the DisCo). In this sense, a bilevel programming problem is equivalent to a single-round Stackelberg game [19]. The players of this game are the leader and the follower. The leader makes its move first anticipating the reaction of the follower, and then the follower makes its move reacting to the strategy adopted by the leader. In this case the leader is the DG owner who must decide over the location and contract prices of his units, and the follower is the DisCo which reacts to the offer of the DG owner buying more or less energy. An interesting fact is that the DG owner knows the DisCo will decide over the energy to be purchased based on an optimization procedure. Then, it anticipates the reaction of the DisCo considering such optimization procedure as one of the constraints of its own optimization problem. This relationship is depicted in Fig. 1.

Due to its hierarchical structure even a BLPP with linear upper and lower level optimization problems (known as linear BLPP) is NP-hard [20]. Therefore, a nonlinear BLPP that includes integer variables, as the one in this paper, is a more complex and challenging problem. These types of problems can be better solved using metaheuristics than conventional optimization procedures [21].

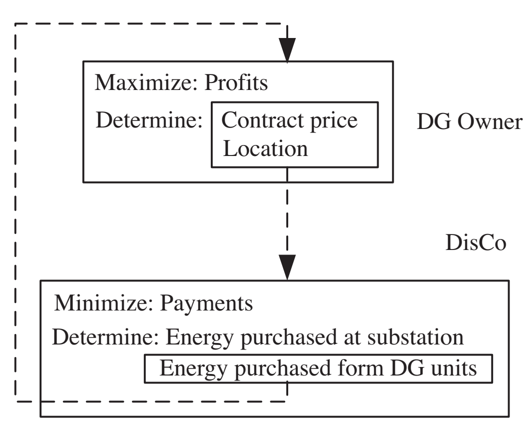

Fig. 1. Bilevel programming diagram.