STRATEGIC PLACEMENT OF DISTRIBUTED GENERATION CAPACITY

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ABSTRACT

Many methods have been proposed to define the optimal locations and capacities of distributed generation (DG) as a means of ensuring that the maximum amount of DG can be connected to existing and future networks. One aspect missing from existing approaches is the capability to efficiently site and size a predefined number of DGs. Here, a method combining optimal power flow and genetic algorithms aims to meet this requirement. Its use would be in enabling Distribution Network Operators to search a network for the best sites and capacities available to strategically connect a defined number of DGs among a large number of potential combinations. Some applications of the proposed methodology confirmed its effectiveness in siting and sizing an assigned number of DG units.

INTRODUCTION

Distributed generation (DG) creates a variety of well-documented impacts on distribution network operation and implies significant changes to planning and design practices [1], [2]. Traditional options to mitigate adverse impacts remain costly for developers and Distribution Network Operators (DNOs). Further, current DNO policies of assessing DG connections on a first come-first served basis must be adapted to avoid 'sterilizing' parts of the network [3]. In order to make best use of the existing network DNOs should encourage development at the most suitable locations by issuing information to developers regarding the existence of spare connection capacity or from locational signals created by connection pricing. Therefore, DNOs require a reliable and repeatable method of quantifying the capacity of new DG that may be connected to distribution networks without the need for reinforcement.

The challenge of identifying the best network locations for DG has attracted significant research effort, albeit referred to by several terms: optimal 'capacity evaluation' [3], 'DG placement' [4], or 'capacity allocation' [5]-[7]. While the literature suggests a wide range of objectives and a variety of constraints, two distinct approaches to the problem exist:

- finding optimal locations for defined DG capacities,
- finding optimal DG capacities at defined locations.

The first approach aims to site DG of specified, discrete, capacities at the best sites. This problem has generally been tackled using genetic algorithms (GAs) [8]–[9] or other methods [4], [10] which can handle discrete formulations. For example, in [9] a GA was used to place generators of discrete capacities in order to minimize losses, costs and network disruption, while [10] adopted a heuristic approach where an investment-based objective function determines optimal DG site and size, assumed to be a multiple of a given capacity. In [11] an optimization technique, based on GAs and optimal power flow has been applied to minimize the active and reactive power generation costs together with the installation costs of DG. The prejudging of capacity means that some opportunities that are smaller or larger than the standard will not be selected, resulting a non-optimal solution.

The second approach requires the user to specify the network locations of interest and the algorithm will guide capacity growth at each location whilst respecting network constraints. The methods tend to use continuous functions of capacity solved using analytical approaches like optimal power flow [3]–[5], linear programming [6] or gradient search [12]. These approaches are robust, well defined and accepted and the outcome repeatable. A downside is that where a large number of locations are searched the perceived optimal solution may contain a number of sites with very small capacities. While this may be the case mathematically, the upfront costs of connection suggest the very small plant would not be economic. Specifying a minimum capacity at each location would unduly bias the analysis and potentially result in the algorithm being unable to find a feasible solution. The major issue with these approaches is how to determine the best set of locations.

As both approaches require capacity or location to be pre-specified, in this paper a method is presented that overcomes these limitations. It is a hybrid method that uses a GA to search a large range of combinations of locations, employing Optimal Power Flow (OPF) to define available capacity for each combination. Although this is achieved at the expense of requiring the number of DG units to be pre-specified this opens up the potential to examine the benefits of strategic placement of small numbers of DG.

COMBINED GA-OPF OPTIMAL CAPACITY ALLOCATION

Optimal capacity allocation aims to define the optimal capacity of new generation that may be accommodated within the existing network, subject to a range of constraints imposed by statutory regulations (e.g., voltage limits), equipment specification (e.g., thermal limits on lines and transformers) or other operational or planning limits. In line with existing and traditional DNO practice in the UK these assessments are made assuming the worst case situation of maximum DG output at minimum load which provides the largest reverse power flows and voltage rise [1], [13].

The optimal DG capacity is deemed to be from the viewpoint of the DNO. The attitude of the DNO towards DG will be dependent on the benefits or costs associated with connection which will vary between systems. A significant driver of the costs and benefits will be the regulatory rules or incentives applicable to DG. Here the simplest case in which the DNO is interested in maximising connected DG capacity, is described.

This method requires the user to define the number of DG units to be connected rather than constraining the locations or unit size of generators. The Genetic Algorithm generates and optimizes combinations of locations from those possible for the network in question. For each combination of locations, an optimal power flow is used to define the capacity available for this combination: in essence the OPF computes the GA's fitness function. This information is fed back to the GA which searches for the optimal connectable capacity as viewed by the DNO. As such, this combination method should deliver the best locations as well as the capacities available for a user-specified number of DG. The methodology is shown in Fig. 1 and explained in more detail as follows.

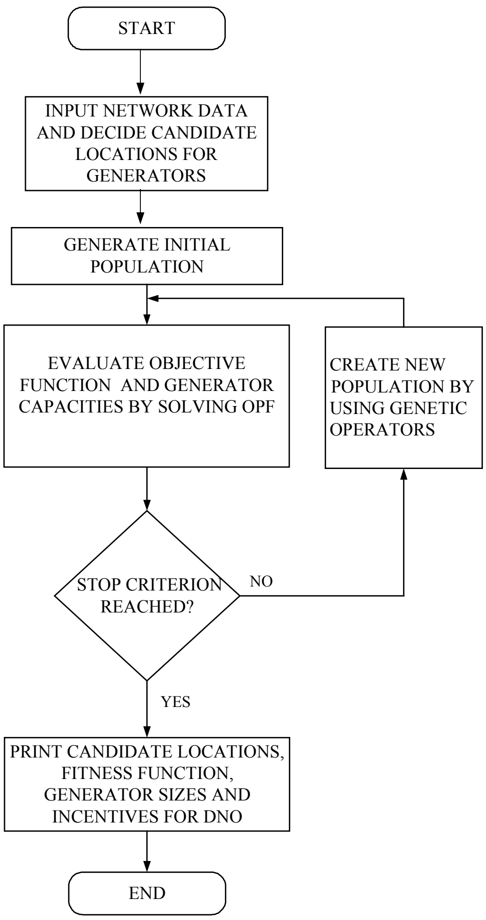

Fig. 1. Schematic of the GA-OPF methodology

Optimal capacity allocation using OPF

For a given set of locations, the network capacity available for new DG can be found using OPF following the approach of [3] and [5]. The maximum DG capacity can be determined by modelling DG as generators and, by maximising the benefit of all these generators, the DG capacity is maximised. The generator capacity cost function can take a range of forms depending on the situation; here, a linear function is assumed:

$$f_{OPF} = \sum_{g=1}^{n} C_g \cdot P_g \quad (1)$$

where C_g represents the benefit the DNO derives from connecting generator g of capacity P_g .

The constraints on the growth of DG include: the energy source limiting DG unit size; a power factor constraint to ensure operation in power factor control mode (although more active control may enhance capacity, e.g., [13], [14]); quality of supply standards requiring voltages to be maintained close to nominal as well as the thermal capacity of each circuit. Although feasible to include using the methods presented in [5]-[6], fault level constraints have not been included here.

Genetic Algorithm

The genetic algorithm is used to efficiently search the range of combinations of DG locations for a specified number of DG units. The GA will randomly generate the initial population of solutions by defining a set of combinations of buses. Each combination is represented by a vector of integers identifying individual buses. For each solution, defining locations for DG in the initial population, the OPF procedure nested in the GA algorithm computes the optimal capacities considering the worst case of minimum load [1], [13], according to the objective function (1).

CASE STUDY

Implemented in Matlab®, the technique was applied to a 69-bus 11 kV radial distribution system with two substations. With complete network data given in [15], the network diagram is shown in Fig. 1. The system operates within voltages limits of ±6% of nominal and thermal limits of 3 MVA for all lines. All DG units were assumed to have fixed power factors of 0.9 lagging. The minimum active and reactive loads are 4.47 MW and 3.06 MVA, respectively. For illustration, the objective function assumes that the DNO benefits to the tune of £2.50 per year for every kW of new DG connected; this value is currently that applicable in the UK. Incidentally, in the absence of any other objectives the value of the benefit is essentially arbitrary as all locations will be favoured equally [3].

The GA uses a normalized geometric ranking scheme as a selection mechanism, while the simple crossover and the binary mutation are employed as genetic operators. An elitism mechanism, ensuring the best member of the population is not lost, is also adopted. A GA population size of 30 was selected and the algorithm stops if the best solution does not improve by £100/year over 50 generations and if the number of generations reaches 300: these values were found to guarantee the convergence of the algorithm to a satisfactory solution.

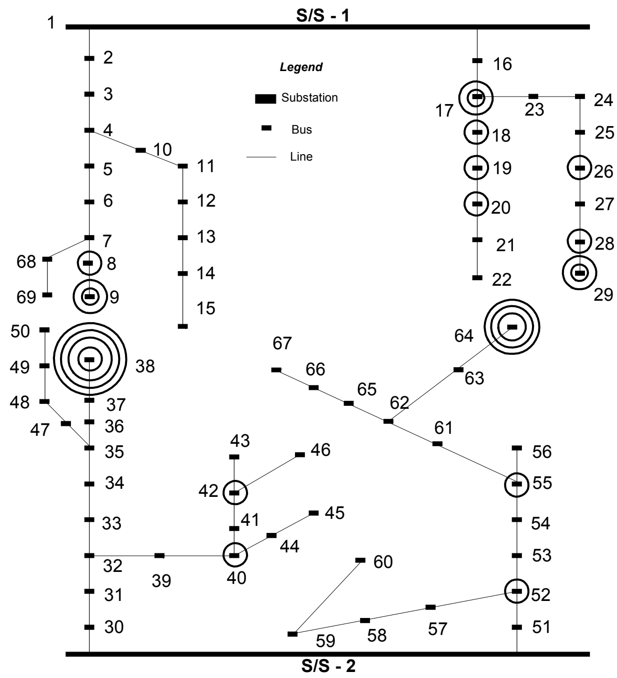

Fig. 2. Optimal location of DG across all 4 cases (one circle per case)

A series of simulations were run to define the optimal connection points and capacities for a defined number of potential DG units. These were for the best set of 3, 5, 7 and 9 units located within the 67 possible sites.

The optimal locations and capacities for the four DG cases are shown in Table I along with the values of the objective function, equating to the annual payments accruing to the DNO. The locations selected for the four cases are illustrated in Fig. 2 with each circle representing an appearance in one of the optimal sets. In all cases the limiting factor on DG capacity is voltage rise.

There is a tendency for similar locations to be favoured across the four cases: Bus 38 appears in all four cases, while Bus 64 appears in three, with three other locations featuring in two of the assessments. In many of the cases the optimal locations appear to be towards the end of the feeders or close to branch points. In the cases examined here, the network offers several times more potential sites than potential DG resulting in capacity being spread across different feeders.

Bus	**Number of DGs**			
	3 DG	**5 DG**	**7 DG**	**9 DG**
8		1.769		
9			1.672	1.648
17		0.041	0.055	
18	2.634			
19		2.885		
20				2.402
22			1.801	
26				0.101
28				0.103
29			0.216	0.119
38	0.424	1.823	1.867	1.884
40			0.059	
42				0.060
52	4.028			
55				1.001
64		0.862	1.725	1.155
Total	7.087	7.379	7.394	8.472
Objective (£/year)	17,716	18,447	18,486	21,180

Table 1 Optimal DG Location/Capacities

This occurs as the voltages at buses on the same feeder are strongly interdependent, with DG capacity at one bus tending to crowd out that of others. As such, with the low numbers of generators, the method will connect maximum generation at locations that are relatively far apart, electrically. It would be expected that as the number of DG increases the greater the likelihood of two or more DG being located on the same feeder with consequent voltage interdependence. The overall connectable capacity increases with the number of DGs, with capacity increasing by 20% between the 3 and 9 unit cases. This is reflected in the value of the objective function (nominally representing the DG benefit) which rises as more capacity is connected, increasing from almost £18k to above £21k over the range of cases identified here. The maximum connectable capacity will continue to rise until DG is sited at every location [3].

DISCUSSION

The method presented here attempts to overcome limitations to determining optimal DG capacity within existing approaches described in the literature. The combination of OPF and GA techniques provides a means of finding the best combination of sites within a distribution network for connecting a predefined number of DGs. As such, it would allow DNOs to search a given network for the best sites to strategically connect specified number of DG among a large number of potential combinations. DNOs could use this information to plan for DG connections in a desired order over a given time horizon thus overcoming difficulties with current first come-first served connection policies.

The intention here is to provide a means of analysing the optimal connection of broadly deterministic energy sources within applicable deterministic network constraints. The approach could be adapted to cope with variable energy sources and probabilistic network constraints to allow a cost-benefit approach to be taken.

CONCLUSIONS

A method combining optimal power flow and genetic algorithms aims to provide a means of finding the best combination of sites within a distribution network for connecting a predefined number of DGs. In doing so it overcomes known limitations inherent in currently available techniques to optimize DG capacity. Its use would be to enable DNOs to search a network for the best sites to strategically connect a small number of DGs among a large number of potential combinations.

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