Electrical Power Quality and Utilisation, Journal Vol. XI, No. 1, 2005

OPTIMAL PLACEMENT AND SIZING OF DISTRIBUTED GENERATOR UNITS USING GENETIC OPTIMIZATION ALGORITHMS

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Summary: In this article the authors describe how genetic optimization algorithms can be used to find the optimal size and location of distributed generation units in a residential distribution grid. Power losses are minimized while the voltage profile is kept at an acceptable level. The method is applied on a system based on an existing grid topology with production and residential load data based on measurements. Different scenarios are chosen to run the algorithm. The obtained optimal location and size prove to depend strongly on the given conditions.

Keywords:
Distributed generation
Optimization methods
Microgrid

1. INTRODUCTION

Decentralized generation will become more and more important in the future electricity distribution system. This tendency is increased by the commercial availability of small-scale production units (e.g. fuel cells, micro-CHPs, photovoltaic panels) and the liberalization of the energy market, putting more pressure on the system. Also the support for sustainable development using renewable energy sources plays a key role.

As such, distributed generation is defined as local generation of heat and electricity in the distribution grid. A group of DG units can form a virtual power plant, being centrally controlled and behaving as a single power plant towards the grid. The extreme case is an energy island, in which production and consumption of energy are locally matched. Energy is also kept in balance by local storage and by an optional connection to the main grid across which power is transferred. However, energy islands should have the ability to move from an uncontrolled power mode (when connected to the main grid) to a load tracking mode (while in island mode) [8, 9].

In this new environment characteristics will be fundamentally different compared to a situation in which generation is centralized. There is almost no inertia in the energy sources which is needed for stability reasons. Although storage of energy can have a stabilizing role. The load pattern is more varying in time since the averaging of consumption vanishes due to the small amount of users on such a small-scale low voltage grid. Compared to conventional power plants distributed generation units such as PV cells (depending on solar illumination) or CHPs (depending on heat demand) are undispatchable.

Another fundamental problem is the linking between active power injection and the voltage profile in the grid. In high-voltage (thus mainly inductive) grids an active power injection imbalance will be the cause of a frequency deviation which is equal in the entire grid. The sum of all produced power must be adjusted to keep the grid frequency at nominal level. In low-voltage (more resistive) grids the active power injection will affect the voltage profile throughout the grid. This way the location where active power is injected will be of importance.

All these different aspects of distributed generation sources in a low- or medium-voltage grid will influence the important question of where to place the production units. Different objectives can be put forward, such as highest effciency (i.e. lowest power losses), minimal cost (installation and operation), highest reliability, etc. This optimization problem can be solved in different ways like exhaustive searches [14], Lagrangian based approaches [12] or tabu searches [11].

In this article, the search for the optimal placement and power level of the different types of generation units (in such a way that the power losses are minimized) is a non-convex optimization problem that requires exhaustive search. The use of Genetic Algorithms is proposed, in order to implement the search of the optimal solution. Advantages of genetic algorithms are the ability to avoid being trapped in local optima, and also the expected number of function evaluations before reaching the optimum is significantly reduced compared with exhaustive search methods. This paper is structured as follows. Section 2 describes the general framework of the problem (the grid architecture, the load and production profiles). Section 3 describes the methodology based on Genetic Algorithms. The results are presented on Section 4.

2. GENERAL FRAMEWORK

In this section the general configuration of the problem is addressed, describing the grid topology, power production and load profiles for the different scenarios.

2.1. Grid Topology and Power Production

For this analysis the topology of an existing grid at medium-voltage is used. It consists of 3 lines and 20 nodes, with one aggregated load at each node, as shown in Figure 1. The distributed energy sources used are PV panels and CHP units. Real measurements are used to provide data for the

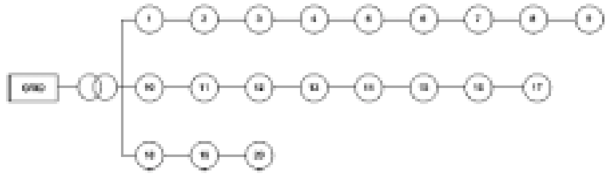


Fig. 1. Grid Topology with 20 nodes

illumination on PV panels and the CHP production which is based on heat demand. The profiles of active power consumption are based on measurements taken in a residential building for a period of one year on a 15 minute basis. Figure 2 shows the production profiles for each generator type.

2.2. Problem Definition

The objective of this analysis is to find the optimal placement and size of CHP and PV generation units, in order to minimize the power loss along the grid lines over a period of 24 hours. In order to assess the effect of Winter and Summer variations on different load situations, the period of 24 hours over which the minimization takes place is defined in the following scenarios:

1. Low Load Scenario (L): From the sets of available daily load profiles, the profile with the highest peak during each season is selected. Another 4 daily profiles are randomly selected. This scenario only contains 1 important load peak over each season.
2. Medium Load Scenario (M): From the sets of available daily load profiles, those with the highest daily peaks on each season are selected. This scenario contains the most important peaks of each season.
3. High Load Scenario (H): The load profiles with highest daily averages are selected on each season. This scenario presents a heavy requirement to the generators.

Each one of these scenarios are computed for Summer and Winter, thus leading to Summer- Low (SL), Summer-Medium (SM), Summer-High (SH), Winter-Low (WL), Winter-Medium (WM) and Winter-High (WH). The different load profiles for each scenario are depicted in Figure 3. As the grid contains 20 load profiles, each one of these sets containing 4 load profiles is repeated 5 times in each scenario.

3. PROBLEM FORMULATION AND METHODOLOGY

In this section, the formalization of the problem and the coding of the Genetic Algorithm is described.

3.1. Power Line Equations

A network with m nodes and n power lines is considered. The network is assumed to be radial, which implies that $m = n + 1$. The topology of the network is defined by a topology matrix $T \in \mathbb{Z}^{n\times(n+1)}$, where each row represents a power line and each column represents a node of the power network. On each row two non-zero elements are present indicating the node where the power line 'starts' (–1) and the node where the line 'ends' (1). The convention is used that –1 is assigned to the node that lies the closest to the power grid. This e.g. allows the conversion of line currents (currents flowing through a power line) to node currents (total current generated or consumed at a node) as

$$I_{\text{node}} = T^{\text{T}} I_{\text{line}} \tag{1}$$

with $I_{\text{node}} \in \mathbb{R}^{(n+1)\times 1}$ a vector denoting the current leaving each node and $I_{\text{lines}} \in \mathbb{R}^{n\times 1}$ the current flowing through each line.

Line impedances are denoted as Z_i, while node and line voltages are denoted as $V_{\text{node},i}$ and $V_{\text{line},i}$ with i denoting the line/node number.

For each node a load is considered that is modeled as a voltage-dependent load, defined by its rated active and reactive power consumption P_{nom}, Q_{nom}:

$$P = \left(\frac{V}{V_{\text{nom}}}\right)^{\alpha} P_{\text{nom}} \tag{2a}$$

$$Q = \left(\frac{V}{V_{\text{nom}}}\right)^{\alpha} Q_{\text{nom}} \tag{2b}$$

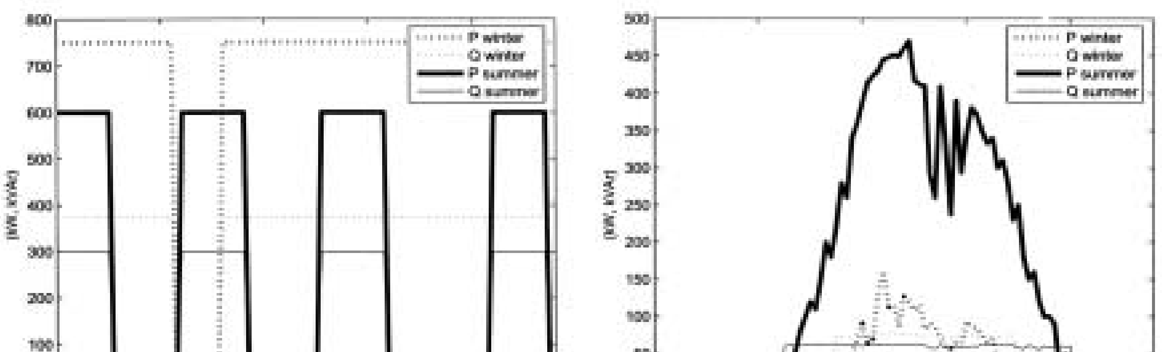
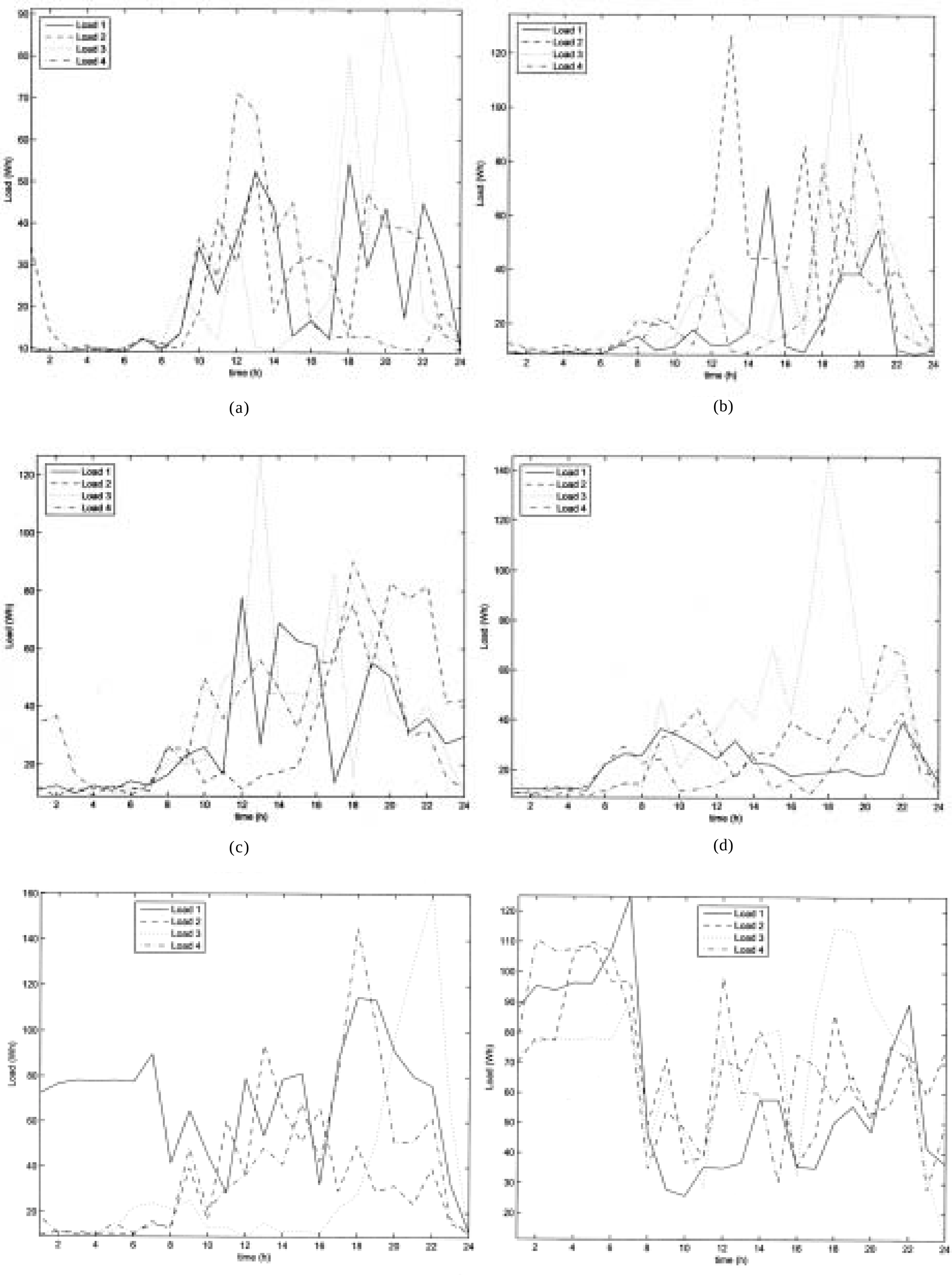


Fig. 2. Production Profiles for CHP (left) and PV (right) generation units for a period of one day



(a) (b) (c) (d) (e) (f)

Fig. 3. Sets of 4 Load Profiles for the different scenarios

where $\alpha = 2$ in case of a resistive load [7]. Both generators and loads are modeled using (2). The nominal active and reactive power of a load attached to node i are denoted as $P_{\mathrm{nom},i}$, $Q_{\mathrm{nom},i}$, while the actual active and reactive power are denoted as P_i, Q_i.

An iterative solution strategy is chosen, consisting of an initialization phase, followed by a fixed number of forward and backward iterations.

Given the voltage of the power grid (i.e., voltage of the node attached to the power grid) V_{grid}, given a network topology T, line impedances Z_i, $i = 1, \ldots, n$ and nominal loads $P_{\mathrm{nom},i}$, $Q_{\mathrm{nom},i}$, the node and line voltages and currents are computed by executing the following steps:

— **Initialization**. The initialization consists of several steps

$$-\text{Set } V_{\text{node},1} := V_{\text{grid}}$$

$$-\text{Set } I_{\text{line},i} := 0, \forall i$$

— **Forward iteration**. This iteration is used to update all node voltages in order to take into account the voltage drop over the power lines.

— **Backward iteration**. This iteration is used to update the power generation and consumption based on the node voltages calculated in the previous forward iteration step and using equations (2). As power injections are updated, so are the line currents. Subsequently, for all nodes $i = n, \ldots, 1$, the line currents of the power lines starting at the given node are updated in order to satisfy the power needs at their ending nodes.

The initialization step is performed once, while the forward and backward iterations are performed several times in order to obtain a converged solution. In case the line currents are small compared to the line impedances (and therefore the line losses are sufficiently small compared to the nominal voltage) the above method can be shown to converge to the correct solution.

The resulting total power loss P_{loss} over the lines is calculated as:

$$P_{\text{loss}} = \text{Re}\left(\sum_i V_{\text{line},i}, I^*_{\text{line},i}\right) \tag{3}$$

By solving the power line equations for all time instants of a set of production and generation profiles for all involved devices connected to the local grid, the total energy lost over an entire day can be calculated for the given configuration. It is this total power loss that is being minimized in the following sections, by modifying the placement of the local power generators.

3.2. Genetic Algorithm Implementation

A Genetic Algorithm (GA) is a search algorithm that is based on the hypothesis of natural selection [6]. The GA is an evolutionary population-based search process that begins with a very large set of initial candidate solutions. These solutions are subjected to selection pressure based on relative fitness and other genetic operators that serve to advance in the search. Each candidate solution is known as a chromosome, and the set of all chromosomes is created from the previous set through the so-called genetic operators (crossover, mutation, tournament, etc.). In any generation, the fitness of each chromosome is defined in such a way that the chromosome with the highest fitness represents the optimal point in the search space. Under certain conditions, it has been proven that the average fitness improves from one generation to the next [5]. GAs have been used recently within the power systems framework [13, 4, 1]. The representation and implementation of the GA for the problem is proposed as follows. Each generator is represented by a string G of 5 binary bits. The first bit represents the state of the generator (1 for on, 0 for off). The remaining 4 bits represent the power level of the generator, discretized between 1/16 and 100%. As an example, the string $G = [1000]$ represents a generator working at minimum capacity; $G = [00000]$ represents a generator which is not operating (or nonexisting); the string $G = [11111]$ represents a generator working at full capacity.

In order to represent the type of each generation, a new string T is defined consisting of the concatenation of 2 strings G (thus T contains 10 bits). Therefore, let $T = G_1 G_2$, where G_1 (resp. G_2) represents a PV (resp. CHP) generator. In this way, the type of each generator is given by the position on the string T. For example, at a given node the string T = [1111100000] represents the situation where only one generator should be placed on that node, and this generator should be a PV working at full capacity. It is assumed, based on this representation, that a maximum of one generator of each type can be placed on any given node.

As each string T represents the generators (and size) to be placed at a given node, the representation of the general location of the generators over the grid is straightforward. A string S is defined consisting on the concatenations of 20 T strings. This sequence S contains 20 (nodes) × 10 (bits per node) = 200 bits. As any string S describes a valid placement and size configuration of generators over the grid, therefore the string S is the chromosome used within the GA.

The implementation of the GA is done with generations consisting of 40 individuals (each one a different string S). The maximum number of generations is set to be 300. The fitness of each individual is given by the objective function, and it also considers a penalization if the voltage goes outside the allowed interval, plus another penalization if the number of generators exceeds 10. The fitness value f for any individual S is:

$$f(S) = P_{\text{loss}} + C_1\delta_1 + C_2\delta_2 \tag{4}$$

where P_{loss} is computed from equation (3); $\delta_1 = \max(0, V_{\min} - V_{\text{line}}) + \max(0, V_{\text{line}} - V_{\max})$, takes a penalty C_1 if the lines voltage V_{line} lies outside the limits, and $\delta_2 = \max(0, N - N_{\max})$ takes a penalty C_2 if the number of generators N on solution S is larger than the maximum allowed number of generators $N_{\max}$. Crossover is performed between individuals, which are selected with a probability that depends on their fitness. Mutation takes place with probability 0.0035 for each bit.

3.3. Implementation Summary

The methodology can be summarized as follows:

1. Generate a set of 40 individuals S.
2. Compute the fitness of the individuals from (4)
3. Repeat for 300 generations:
   — Sort the individuals S according to their fitness
   — Perform genetic operators to produce a new generation of individuals S
   — Compute the fitness of the individuals from (4)
4. The individual S with the best fitness after the 300 generations is the final solution.

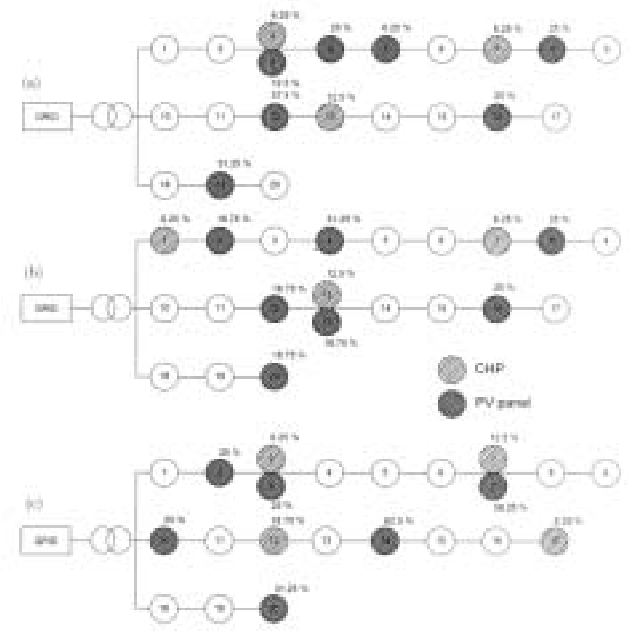


Fig. 4. Results for the different Summer scenarios

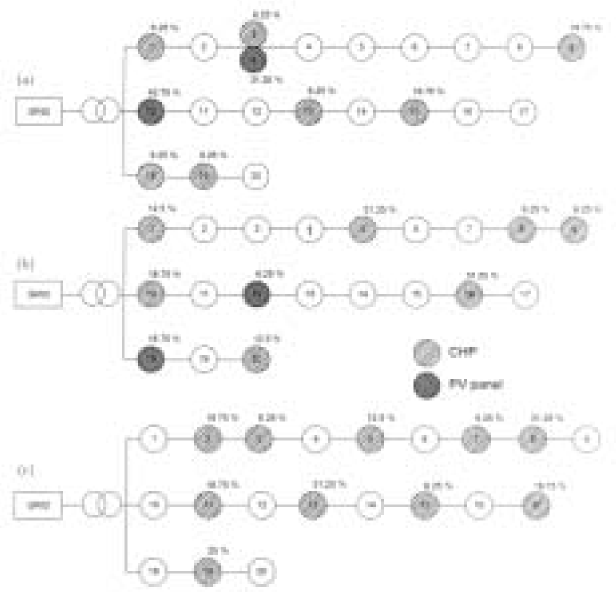


Fig. 5. Results for the different Winter scenarios

4. RESULTS

For each scenario, an optimal final chromosome *S* is found. Each solution represents the location, type and size of generators in the grid. Detailed results are presented in Table 1 and Figures 4–5 for all scenarios; Table 2 shows a summarized description of the different solutions obtained.

Figure 6 shows the evolution of the total power loss for the best chromosome of each generation for the SL scenario. The solution is stable as it remains unchanged for a large number of generations.

As could be expected, in the Summer scenarios more PV cells are chosen by the algorithm as compared to Winter when heat demand (and thus power production by CHP) is higher. It is also clear that for the high demand scenarios, more CHPs are placed compared to the other scenarios within the same season. In Summer, the solution moves from 7 PV generators and 3 CHP units (SL, SM) to 6 PV and 4 CHP (SH). In Winter the situation also moves from 7 CHP and 2 PV (WL, WM) to the solution of using 10 CHP units only (WH). It is also clear that the selected load scenarios translate into different power losses that are related to the magnitude of the load requirement on each case.

An interesting question is to check what would be the power loss along the lines if a generator configuration different than the optimal one is used within each scenario. In particular, it is possible to compute the power loss when the optimal configuration from one scenario is used in a different scenario. Table 3 shows all the losses for the possible combinations of configurations/scenarios. It is clear that the optimal solutions are dependent of each scenario, and using a different one will increase the power loss. However, switching the configurations for within Summer scenarios has a less dramatic effect than switching within Winter configurations. The final column in Table 3 shows the total loss when there are no DG units.

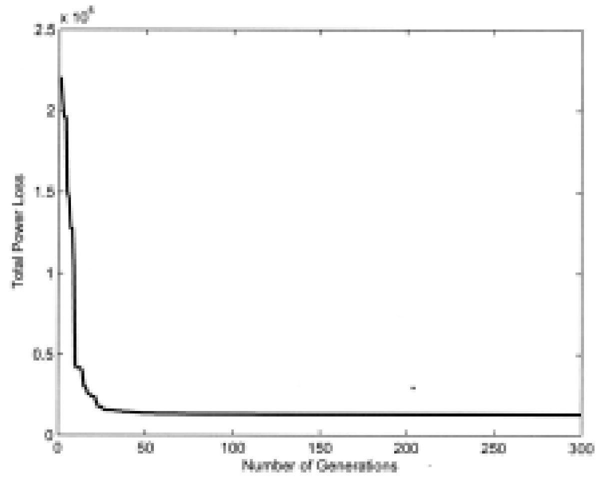


Fig. 6. Evolution of the total power loss along the lines over 300 generations for the SL scenario

Rules of thumb to place generators are not found in the given example. Placement and sizing depend strongly on the given base case scenario. Sometimes it is assumed that a CHP and a PV panel are best combined on one location because of complementary power outputs. In the tested grid this occurs 5 times over all the possible solutions.

5. CONCLUSION

The use of genetic algorithms in distribution networks is known for feeder switching [2] or capacitor placement [10]. In this article this method is extended to placement and sizing of generators based on known generation and load profiles. Simulations are run on a typical distribution grid topology, using load profiles with seasonal variation. Different solutions are obtained for each season, with more PV generators placed in the Summer scenarios, and more CHP gene-

Table 1. Results from the Genetic Algorithm for all scenarios

	Placement, Type and Size (in percentage) of the Generators for the Different Scenarios											
Node	SL		SM		SH		WL		WM		WH	
	CHP	PV	CHP	PV	CHP	PV	CHP	PV	CHP	PV	CHP	PV
1	—	—	6.25	—	—	—	6.25	—	12.50	—	—	—
2	—	—	—	18.75	—	25.00	—	—	—	—	18.75	—
3	6.25	12.50	—	—	6.25	25.00	6.25	31.25	—	—	6.25	—
4	—	25.00	—	31.25	—	—	—	—	—	—	—	—
5	—	6.25	—	—	—	—	—	—	31.25	—	12.50	—
6	—	—	—	—	—	—	—	—	—	—	—	—
7	6.25	—	6.25	—	12.50	56.25	—	—	—	—	6.25	—
8	—	25.00	—	25.00	—	—	—	—	6.25	—	31.25	—
9	—	—	—	—	—	—	18.75	—	6.25	—	—	—
10	—	—	—	—	—	25.00	—	43.75	18.75	—	—	—
11	—	—	—	—	—	—	—	—	—	—	18.75	—
12	—	37.50	—	18.75	18.75	—	—	—	—	6.25	—	—
13	12.50	—	12.50	18.75	—	—	6.25	—	—	—	31.25	—
14	—	—	—	—	—	62.50	—	—	—	—	—	—
15	—	—	—	—	—	—	18.75	—	—	—	6.25	—
16	—	25.00	—	25.00	—	—	—	—	31.25	—	—	—
17	—	—	—	—	6.25	—	—	—	—	—	18.75	—
18	—	—	—	—	—	—	6.25	—	—	18.75	—	—
19	—	31.25	—	—	—	—	6.25	—	—	—	25.00	—
20	—	—	—	18.75	—	31.25	—	—	12.50	—	—	—

Table 2. Summary of the Results and Total Power Loss (kWh) over a period of 24 hours

	SL	SM	SH	WL	WM	WH
Number of CHP Generators	3	3	4	7	7	10
Number of PV Generators	7	7	6	2	2	0
Total Power Loss (kWh)	13.1	22.5	23.4	11.9	29.1	48.1

Table 3. Cross-Comparison of optimal configurations used in different scenarios

	Total power loss (kWh) when using DG Configuration from...						No DG
	SL	SM	SH	WL	WM	WH	
...into scenario SL	**13.1**	13.5	17.5	19.7	32.3	52.9	30.9
...into scenario SM	22.6	**22.5**	26.3	29.3	42.2	62.7	41.2
...into scenario SH	26.9	27.7	**23.4**	36.9	46.0	59.1	63.5
...into scenario WL	18.8	21.0	13.9	**11.9**	27.5	74.7	40.4
...into scenario WM	75.5	71.2	53.7	42.5	**29.1**	47.0	112.2
...into scenario WH	160.0	167.1	130.2	107.7	64.0	**48.1**	219.9

rators placed in the Winter scenarios. It is also shown that using a different placement for any given scenario (different than the optimal solution) increases the power losses, thus suggesting that the placement is dependent on the load profiles being used. The total energy loss in the optimal placement is in each scenario considerably lower (up to a factor 4 or 5) as compared to the case in which there is no DG and all power is taken from the main grid. This stresses the importance of DG and its optimal placement and sizing.

An extension to this work is to include economic considerations. The minimization of the power loss is only a part of the economic cost. This will call up other issues. Besides installation costs there are also production costs, and it is not clear how can they be included. Is the energy price fixed or does a local trading market exist? Also in some countries production of energy using renewables is coupled to green power certificates which can be traded. All these issues have to be well considered in order to keep assumptions realistic. In the given simulations two common types of distributed energy resources are used. This can easily be widened to more types like wind power and small hydro power. Another interesting issue is the use of storage like e.g. flywheels, batteries, superconductive coils,etc.

Sizing of generators is done by discretizing the possible nominal power outputs. To enlarge the number of feasible production sizes the discretization step can be decreased. This leads to longer chromosomes and eventually a more complex algorithm. Another possibility is an algorithm in which the genetic optimization is followed by continuous optimization algorithm which uses the solution of the genetic optimization as a start and searches for small deviations which lead to a more optimal situation.

6. ACKNOWLEDGMENTS

This work was supported by grants and projects for the Research Council K.U.Leuven (GOA-Mefisto 666, GOA-Ambiorics, several PhD/Postdocs & fellow grants), the Flemish Government (FWO: PhD/Postdocs grants, projects G.0240.99, G.0407.02, G.0197.02, G.0211.05, G.0141.03, G.0491.03, G.0120.03, G.0452.04, G.0499.04, ICCoS, ANMMM; AWI; IWT: PhD grants, GBOU(McKnow,Soft4s), the Belgian Federal Government (Belgian Federal Science Policy Office: IUAP V-22; PODO-II (CP/01/40), the EU(FP5- Quprodis;ERNSI, Eureka 2063-Impact;Eureka 2419-FLiTE) and Contracts Research/ Agreements (ISMC/IPCOS, Data4s, TML, Elia, LMS, IPCOS, Mastercard). R.Belmans and B. De Moor are full professors at the K.U.Leuven, Belgium, respectively.

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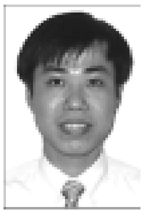

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