An Application of an Evolution Strategy in Power Distribution System Planning

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Abstract

Optimal locating and sizing of power distribution substations and feeder layout is a common problem in new expansion planning. This paper is an application of a type of evolution algorithm, called evolution strategy[ES] , in order to obtain optimal locations and sizes for power distribution substations such that the demand is met at minimum cost. The cost function for minimising includes substation investments, medium-voltage network cost and power losses.

1. Introduction

Investments in power distribution systems constitute a significant part of the utilities' expenses. They can account for up to 60 percent of capital budget and 20 percent of operating costs [13]. For this reason, efficient planning tools are needed to allow planners to reduce costs. Computer optimisation algorithms improve cost reduction compared to system design by hand. So, in recent years, a lot of mathematical models and algorithms have been developed. A good review of classical models and issues and a recent overview can be found in [11] and [5] while [14] focuses on selection and application of optimisation methods for distribution design and making a comparative study among them.

A distribution system consists of a number of high-voltage/low-voltage substations and a radial network (loops are only possible for backup) fulfilling technical constraints (voltage drops and equipment capacity) and quality of supply limits, to meet the load demands.

The most common issue in distribution planning deals with the reinforcement of an existing system for growing load demand. However, occasionally, we need to design a system to meet load demand in new areas without existing facilities. This planning is often called "greenfield" [13] planning, because the planner starts with nothing (a green field). An example of the use of this type of planning is described in the following paragraph.

The electricity market has been going through major changes recently due to the introduction of free competition mechanisms. Whereas some segments of the business, such as power generation, admit liberalisation, others, such as distribution, present serious difficulties due to the network being the domain of one company, which creates a de facto monopoly. This means that, at least for the moment, regulation must be established. The office of electricity regulation must have objective instruments available in order to determine the costs derived from distribution in different areas of consumption with the aim of adequately compensating the distribution company. In short, it is very useful to have a tool which allows one to determine the minimum distribution network needed to satisfy supply.

The problem we are dealing with consists of obtaining optimal location and sizes of substations and primary feeder layout and conductor sizes. The cost function for minimising consists of fixed and variable costs. Fixed costs are investments in substations and medium-voltage network. Variable costs correspond to power losses. Voltage drop constraints and minimum level of supply quality must be satisfied.

2. Optimisation method

Over the last few decades, which have given rise to computer development, heuristic methods or metaheuristics have acquired major importance when tackling great problems of combinatory optimisation (simulated annealing [12], genetic algorithms [4], [2], evolution strategies [8], [10], [6], tabu search, etc.). An implementation of a genetic algorithm in power distribution system planning can be found in [7]. In an evolution algorithm, the search for an optimal feasible solution is carried out by starting with a randomly generated set of initial feasible solutions, represented by a computer data structure which has been carefully programmed. The set of initial solutions, which we call the population, evolves progressively, according to rules which are generally inspired by the biological mechanisms of evolution or natural selection, in a similar way to what a population of living beings would do. Thus, like a biological population in which individuals reproduce giving rise to new ones, or these new ones undergo non-determinist changes (mutations), the

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feasible solutions combine with each other to give rise to others (crossing operator) or they are affected by a mutation operator. Adequate selection mechanisms allow the population to evolve, improving the quality of its members (the selection of those best adapted to the medium). Therefore, the key questions in an evolution algorithm are: the way of codifying the set of solutions, the definition of the evolution operators (mutation, crossover,...), and the selection criteria. The method proposed in this paper uses a generalisation for a multi-membered evolution strategy technique in order to determine the optimal locations for the HV/MV substations. This is of the type called $(\mu + \lambda)$-ES developed by Schwefel [9], which is characterised by a population of μ individuals from among which two are randomly selected that give rise to two descendants, through the successive application of a crossover operator and a mutation operator, thus resulting in a larger population of $\mu + \lambda$ individuals. Then, the selection is made from these of μ individuals with best cost function (best adapted) according to the optimisation criterion used. The process is repeated on the new population, progressively improving the quality of the solutions which make up the population, until one is obtained that is considered acceptable (fig. 1).

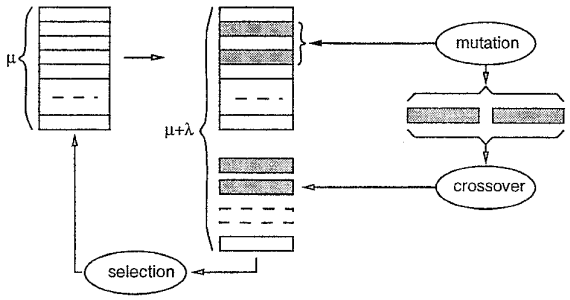


Figure 1. Structure of an ES.

3. Representing individuals

The location of a substation is codified by the pair $(\vec{x}, \vec{\sigma})$ where $\vec{x} = (x, y)$ and $\vec{\sigma} = (\sigma_x, \sigma_y)$ where $\vec{x}$ is the vector of the substation's co-ordinates and $\vec{\sigma}$ the vector of standard deviations used to define the mutation. Each individual in the population constitutes a specific feasible siting for the set of substations, or, in mathematical terms, it defines the point in the space of feasible solutions (those which meet the imposed restraints). Figure 2 shows a scheme of the codification used for each individual. The population on which the ES will be carried out is made up of μ individuals. The start-up individuals are randomly generated, with n being the number of substations considered for all of them. The initial number of substations is calculated on the basis of the total power to be supplied to the loads divided between the average power of the substations (S_m).

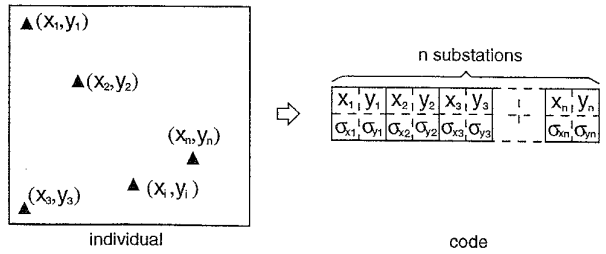


Figure 2. Chromosome corresponding to an individual from the population

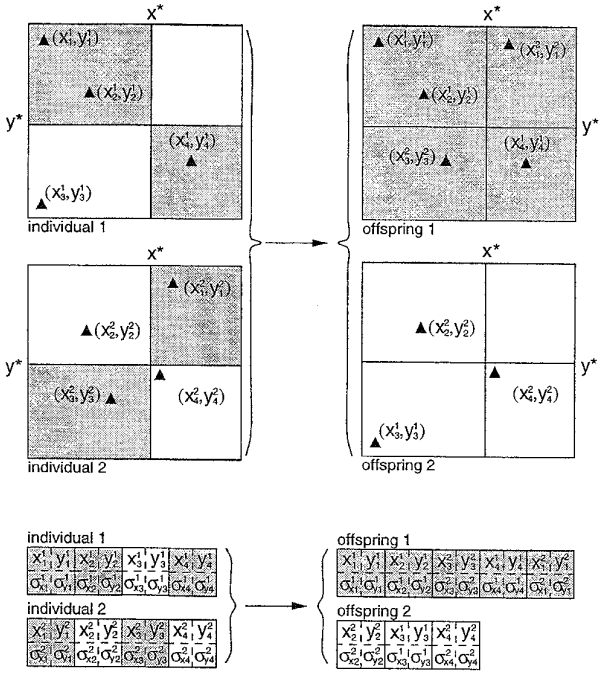


Figure 3. Example of crossover

4. Crossover operator

A recombination operator, similar to a uniform crossover in genetic algorithms, is used which produces one or two offspring starting from two parents randomly selected from population members. The procedure employed to produce descendants consists of the random selection of two co-ordinates x^* and y^* that divide the plane on which the substations are located into four quadrants. This division allows the definition

of seven different areas. Which one of these areas a substation of co-ordinates (x, y) belongs to is determined using the condition in Table. 1.

Table 1. Randomly selected conditions

Option	optional condition
0	$x < x^*$ **and** $y > y^*$
1	$x > x^*$ **and** $y > y^*$
2	$x < x^*$ **and** $y < y^*$
3	$x > x^*$ **and** $y > y^*$
4	condition 1 **or** condition 2
4	condition 1 **or** condition 3
4	condition 1 **or** condition 4

The crossover algorithm can be seen in Procedure 1.

Procedure 1 crossover

```
offspring1 ← ∅ offspring2 ← ∅
select a (x*, y*) point at random
select an option randomly (Table 1)
select first individual from population
while exist gen not selected do
  select gen ((x, y), (σx, σy))
  if condition(option) then
    add gen to offspring1.
  else
    add gen to offspring2.
  end if
end while
select second individual
while exist gen not selected do
  select gen ((x, y), (σx, σy))
  if condition(option) then
    add gen to offspring2.
  else
    add gen to offspring1.
  end if
end while
```

From the description of the crossover operator it can be inferred that the number of substations does not remain unaltered during the evolution process (fig. 3).

5. Mutation operators

Mutation is the most characteristic operator of ES. Indeed, it was originally the only one used. The magnitude of the mutations is of the random nature of behaviour defined by normal distribution of average zero and standard deviation σ. This is in accordance with the biological observation that smaller changes occur more often than larger ones [6]. The σ parameter is included in the codification and could undergo the effects of evolution operators, remain constant or evolve in a determinist way.

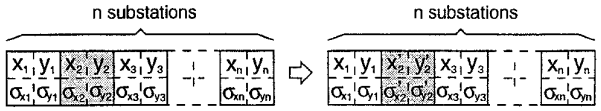


Figure 4. Mutation of the abscissa value for substation No. 2

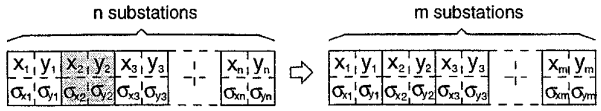


Figure 5. Mutation of a chromosome by the elimination of substation No. 2

Two different types of mutation operator are used. They have an effect on both the location and number of substations.

- Position variation mutation operator (fig. 4): Consist of varying the value of the co-ordinates for a substation chosen at random. The variation with respect to the value it has is reached according to the expression:

$$\sigma'_{x_i} = \sigma_{x_i}.e^{N(0,\Delta\sigma)} \qquad \sigma'_{y_i} = \sigma_{y_i}.e^{N(0,\Delta\sigma)} \quad (1)$$

$$x'_i = x_i + N(0, \sigma'_{x_i}) \qquad y'_i = y_i + N(0, \sigma'_{y_i}) \quad (2)$$

where $\Delta\sigma$ is a parameter.

- Number of substations mutation operator (fig. 5): Consists of reducing or increasing the number of substations. The reductions is equivalent to eliminating the co-ordinates and the deviations, σ, associated to these for a randomly chosen substation. The increase consists of adding new co-ordinates to the chromosome, obtained randomly with their corresponding deviations, σ.

6. Cost function and constraints

In order to evaluate the cost corresponding to an individual $\vec{x}$ (which defines substation locations) is necessary to determine the MV network and substation sizes that minimise the global cost. The function for cost Ψ to be minimised is given by:

$$\Psi = C_{RMT} + \sum_{i=1}^{n} C_{SUB_i} \quad (3)$$

where C_{SUB_i} is the cost of substation i which depends on the demand supplied by substation i (I_i) and C_{RMT}

is the cost of the MV network defined by

$$C_{RMT} = \sum_{F_i \in F} [K_R.I_{F_i}. \sum_{b \in F_i} l_b + \sum_{b \in F_i} (K_I + K_L.I_b^2).l_b] \quad (4)$$

where

F_i	is the set of branches which belong to a main feeder and laterals
F	is the set of feeders (F_i) in the network
I_{F_i}	total intensity supplied by a substation to the feeder F_i
b	is a branch
l_b	is the length of the branch b
K_I	is a coefficient depending on the investment costs
K_R	is a coefficient depending on the reliability costs
K_L	is a coefficient depending on the cost of power losses.

Let N_S be the set of substations and N_Q the set of charges. The following voltage and reliability constraints must be satisfied:

$$\forall q \in N_Q, \quad \sum_{b \in P(q)} K_U.I_b.l_b \leq \Delta U_{max} \quad (5)$$

$$\forall F_i \in F, \quad \sum_{b \in F_i} l_b \leq L_{max} \quad (6)$$

where

$P(q)$	is the path from q to the substation
K_U	is a constant depending on the type of line
ΔU_{max}	maximal voltage drops allowed
L_{max}	maximal extension permitted.

Obtaining $min\{\Psi\}$ implies a process of optimisation based on a heuristic algorithm for network reconfiguration (ANR). This algorithm is based on a branch exchange technique similar to that described in [3], [1]

The ANR algorithm starts with the creation of a radial network connecting every charge to the nearest substation. The cost function corresponding to this initial solution (Ψ^0) is obtained by means of (3). Then, a heuristic process of cost improvement is initiated, which consists of two part executed iteratively. Firstly, the network is broken in two pieces and then the algorithm looks for a new link (branch) which reduces the cost and fulfills constraints.

Let $\Psi^*(\vec{x})$ be an optimum obtained with ANR. The fitness function used in $(\mu + \lambda)$-ES is

$$f(\vec{x}) = \Psi^*(\vec{x}) + \sum_{q \in N_Q} C_{SUB}(I_q).\delta(q) \quad (7)$$

with

$$\delta(q) = \begin{cases} 0 & \text{if } K_U.I_q.l_{qs} \leq \Delta U_{max} \\ & \text{and } l_{qs} \leq L_{max} \\ 1 & \text{otherwise} \end{cases} \quad (8)$$

where $l_{qs} = min\{l_{qk}/k \in N_S\}$ and l_{qk} the euclidean distance between q and k. The non-feasible solution that could appear are penalized by adding the cost of a substation needed to supply the peak load of the infeasible charge (7).



Figure 6. MV network and substation obtained in example area

7. Simplifications for large scale problems

With the aim of reducing the effort of calculus needed to evaluate the fitness function in large scale problems, a simplified version is used. The simplified fitness function $f(\vec{x})$ is evaluated by means of (7) taking into account that $\Psi^*(\vec{x})$ is approximated by $\widetilde{\Psi}(\vec{x}, K)$. So,

$$\widetilde{\Psi}(\vec{x}, K) = K. \sum_{q \in N_Q} (K_I + K_R.I_q + K_L.I_q^2).l_{qs} + \sum_{i=1}^{n} C_{SUB_i} \quad (9)$$

Using $\widetilde{\Psi}(\vec{x}, K)$ with different values for K, we can obtain a set of optimal solutions by means of the evolutionary algorithm. Each one of them is evaluated using the detailed function (7)(with ANR), to select

the best adapted. These solutions can be improved by continuing the evolutionary process with the detailed function.

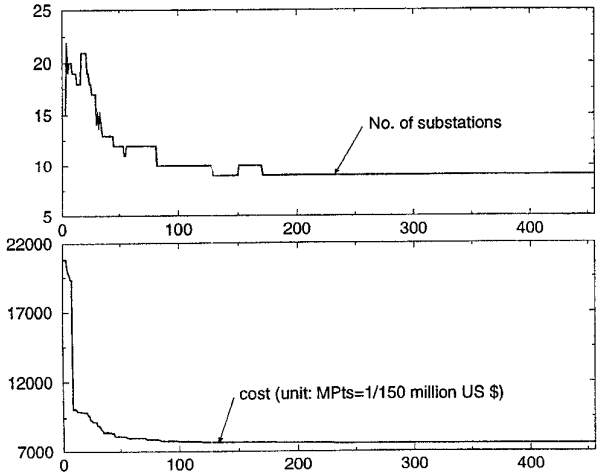


Figure 7. Cost and number of substation against generations

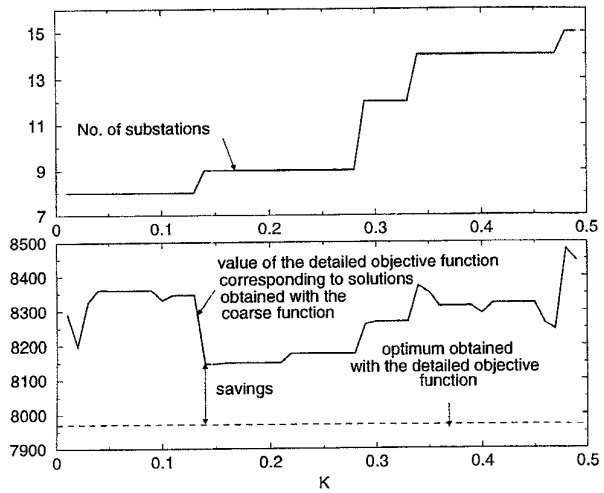


Figure 8. Solutions obtained with different values for parameter K

8. Results

Figure 6 shows the results obtained by running the algorithm in an example area, with urban and rural zones, with a global peak demand of 500 MVA.

A (20+10)-ES was used in this example with the detailed fitness function and an initial standard deviation equal to 2.0 km. Several trials with different values for $\Delta\sigma$ have been done and the algorithm performs better with a value of 0.3. Figure 7 shows cost functions (units in MPts=$\frac{1}{150}$ million US Dollars) and the evolution number of substations against the number of generations obtained.

Figure 8 shows solutions obtained with different cost functions calculated giving values to K and, the optimum savings made though the detailed objective function with respect to the use of coarse functions are shown.

This algorithm has been used to determine the set of substations needed to supply the whole of Spain. Figure 9 presents the results for this large scale application of the algorithm.



Figure 9. Substations obtained with the algorithm in Spain

9. Conclusions

A well-known evolution strategy with specific crossover operator (based on a plan), for optimal locating of substations was developed and the results obtained were satisfactory enough for planning. A great problem for calculating the fitness function value is the necessity of obtaining an optimal MV network corresponding to every possible solution. In order to avoid the heavy effort of calculus needed for evaluating the fitness function, a of simplified functions was used instead of the more accurate but too slow heuristic algorithm which is only used in the final stages. We consider that this strategy was satisfactory. Finally we have investigated the effect produced by the self-adaptation of variance through mutation.

10. Acknowledgments

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