Application of Vector Immune System to Distribution Network Reconfiguration

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Abstract

Distributed energy generation facilities, often based on renewable energy sources, have changed the classical management of Distribution Networks. Optimisation tools are useful to change the grid configuration improving its capability and exploiting an optimal flow of power within the network. There are different criteria for the evaluation of the network performance like losses, voltage profile, reliability indicators etc. that are often in contrast, requiring thus a multiobjective optimisation. Network reconfiguration by changing its topology is a technique that leads to a combinatorial formulation. The Vector Immune System algorithm can be adapted to deal with this issue and has been applied to the definition of the network reconfiguration with original implementations for the generation of the first population and for the mutation operator. Results on an industrial example are presented.

Keywords: distribution networks; multiobjective optimization; topological reconfiguration; vector immune system.

1 Introduction

Distribution Netowrks (DN) are a part of the electrical systems that, in the classic paradigm, transfer power from the transmission grid toward the end-users. While the transmission grid is usually extended at the country level, connects several power stations and has high voltage (HV) level to reduce the losses on the lines, DN brings power inside a town or a rural zone and is exerted at medium voltage (MV) level. In the last few years the increase in Distributed Generation (DG) deployment, often based on Renewable Energy Sources (RES), has changed the management of DNs as the power flow, historically going from transmission grid to end-users, now can be reverted and the DN can become an active component of the electrical system.

This new operating condition requires that the Distribution Network Operator (DNO), the owner and manager of the DN, manages the grid in a new way, exploiting the new power flow configuration: for instance balancing the local power generation and the consumption reducing the power transfer and line losses [1].

New management strategies require the simulation and the optimisation of the power flow, increasing the research on this topic [2], in addition new coordination measures for the connection of distributed energy resources and their control are of primary interest in research on this topic [3, 4]. DNs have a peculiar operational scheme: they are usually weakly meshed networks operated leaving some of the branches open so that the system has a radial topology. In this way load busbars are supplied only by one line and this helps the protection of faults along lines. Branches left open, or *tie branches* as they are usually called, can be used to reconfigure the supply system if some of the lines are out of service due to faulty conditions. Network reconfiguration, for instance changing the open/closed status of some of the branches in the DN, can redirect the power flows, increasing some of the DN performance indexes. The formulation is combinatorial since the degrees of freedom of the problem are the on/off states of the switches connecting branches to the network.

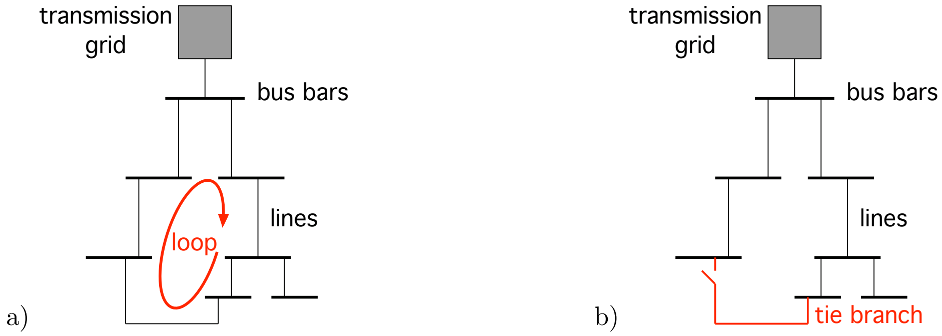

Figure 1: Distribution Network layout, main components are the connection to the transmission grid, the lines and the busbars where power is delivered to end-user loads. a) weakly meshed topological structure; b) opening one line belonging to the loop the structure becomes radial.

There are different DN performance indexes like the losses along the branches, the voltage profiles, the reliability indicators and others. Network topological arrangement can be chosen in order to optimise these indexes. As it is often found in the practice, these indicators are conflicting, that is, for example, reconfiguring the DN for minimising losses can lower the reliability index of the system. A thorough optimisation process should take into account all targets and thus the process requires a multi-objective procedure.

Starting from these considerations, a multiobjective stochastic combinatorial optimisation procedure the *Vector Immune System* (VIS), has been adapted to the problem.

VIS had been developed starting from the family of Artificial Immune System (AIS) algorithms [10] which had alredy been used for DN optimization [12].

In this work, however, two important improvements are made with reference to existing applications: the initial population is not generated randomly, and a particular operator, fulfilling the peculiarity of the problem, has been defined so that local exploration of the search space can be efficiently performed.

In the following the numerical formulation of the problem is described and then its implementation inside a Vector Immune System [5] procedure is highlighted. Eventually, the application of the procedure to a real test case is presented and results discussed.

2 Distribution Network operations

The typical structure of a DN is reported in Figure 1: it is a weakly meshed structure (Figure 1 a) that is operated in radial topology. To reach the radial configuration a number of lines has to be opened, and the number of lines to be kept open is one for each loop (Figure 1 b).

By analysing the DN structure, the following considerations can be made:

- the number of nodes or bus-bars is N assuming that the high voltage connection node, called *root node*, is numbered as 0;
- the total number of branches in the DN N_b;
- the minimum number of branches to connect every node in radial configuration requires to keep N branches closed;
- as a consequence the number of branches left open, or *tie-branches*, is $N_t = N_b - N$.

Given a DN topology, a tree can be built along its branches by means of a search algorithm. Starting from the *root node* the tree branches belongs to the radial configuration while co-tree branches can be left open and become the *tie-branches*. The choice of the tree along network edges is not univocal and the total number of possible trees for a given topology can be computed by the Kirchhoff theorem [6]. Once the *tree building* has been performed, a renumbering of nodes and branches can be performed. In fact, the topological analysis of a radial DN can be studied in an efficient way if the following numbering convention is used [7]:

1. *root node* is added to the *node list* and *branch list* is empty;
2. branches belonging to the tree and connected to the nodes added to the *node list* in the previous step are inserted into the *branch list* and numbered with increasing order, in this way new nodes are added as the end point of new branches;

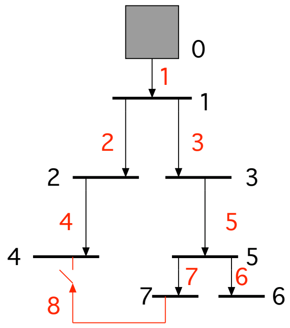

Figure 2: Distribution Network numbering convention as described in the text: lines from $1 \div 7$ are belonging to the radial configuration, line 8 is a *tie-branch*.

3. each node belonging to the set of newly added branches gets the same number of the branch reaching it and is added in the *node list*;
4. procedure is restarted from step 2 until all nodes in the network have been added.

At the end of the procedure all branches that do not belong to the *branch list*, that is the co-tree branches, becomes *tie-branches* and are added to the *branch list* with with index greater than N. An example of the result of the previous procedure is shown in Figure 2. Since the number of closed lines in the radial solution is N, closing a tie-branch creates a loop or a closed path along the branches. The numbering convention adopted allows to find easily the loops formed by the closure of each single *tie-branch* [7]. In fact, by defining the following matrices:

- A incidence matrix of the radial network ($N \times N$);
- u unit matrix ($N_t \times N_t$);
- k tie-branch incidence matrix ($N_t \times N$).

the loops formed by each *tie-branch* are defined by the incidence of each branch to the loop by matrix C of dimensions $(N_t \times N + N_t) = (N_t \times N_b)$ computed as:

$$C = \begin{bmatrix} -(A * k^T)^T \\ u \end{bmatrix}^T \tag{1}$$

where the operator ^{T} stands for matrix transposition.

By making reference to Figure 2, closing *tie-branch* 8 a loop is formed and the matrix C formed is given by:

$$\begin{array}{cc} \begin{array}{cccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \end{array} & \\ \begin{bmatrix} 0 & -1 & 1 & -1 & 1 & 0 & 1 & 1 \end{bmatrix} & 1 \end{array} \tag{2}$$

where loop 1 is formed by all branches but 1 and 6. The orientation of the loop is set by the one of the tie-branch and incidence of loop branches is defined as consequence.

Once the loop formed by closing one *tie-branch* has been defined, a radial configuration can be created again by opening any of the branches belonging to the loop. This operation, called *branch exchange* [8], ensures that the new network topology is radial and that all busbars are supplied.

Summing up the previous considerations, radial configurations can be created either by a tree searching algorithm that works on the complete network or by *branch exchange*, moving from one radial configuration to another.

The previous notation that assigns to each of the lines in the DN a status 0/1 depending on the open/closed state of its switch, allows to define a unique code for each of the possible configurations of the network topology: in the tree search all branches belonging to the tree will have label 1 and co-tree ones will have 0, while one swap 0/1 will be applied in the *branch exchange* operation.

3 Performance indexes

Once DN topology has been defined, the two main operators, *tree building* and *branch exchange* can be used to explore the space of DN configurations with the aim of increasing its performance indexes. There are several quantities that can be computed but in the present analysis only three of them will be used:

3.1 Line losses

Line losses P_{loss} are defined as the sum of all resistive losses on the closed DN branches (eq. 3). Line current I_j in the j-th branch (characterized by series resistance R_j) can be calculated by a load flow computation on the DN, taking as known the loads and generators connected to the busbars. Network reconfiguration should try to minimise losses.

$$P_{loss} = \sum_{j=1}^{N_b} R_j \cdot I_j^2 \tag{3}$$

The problem of network reconfiguration is typically applied to Distribution Networks, at the MV level. In fact, as previously mentioned, these networks are weakly meshed but radially operated. On the contrary, Low Voltage (LV) networks are usually radial and do not allow for reconfiguration. However, if HV/MV and MV/LV transformers are included in the network model, also transformers losses can be taken into account by the optimization algorithm, together with line losses.

3.2 Voltage deviation

Voltage deviation: due to current loading on the branches, the voltage values V_k in busbars are generally different from the rated voltage value $V^{\ nom}$. Due to DG, voltage deviation can be positive close to busbars where power is injected or negative in case of power flow from *root node* to end-users. As in the previous case, voltage deviations should be minimised. In our work we minimize the maximum voltage deviation observed in the network (eq. 4):

$$max|V^{\ nom} - \{V_k\}|, \quad k = 1 \div N \tag{4}$$

3.3 Reliability index SAIFI

Reliability of DN is important and it can be quantified by several indexes. The main indexes that can be used are the *system average interruption duration index* (SAIDI), the *System Average Interruption Frequency Index* (SAIFI), the *customer average interruption duration index* (CAIDI), the *customer average interruption frequency index* (CAIFI), the *momentary average interruption frequency index* (MAIFI).

In this work the *system average interruption frequency index* (SAIFI) has been employed, as it can be computed easily as it depends on the network topology and does not require information on the restoration times or on the single customers. For these reasons it was chosen to demonstrate the multiobjective optimization.

SAIFI can be computed as:

$$SAIFI = \frac{\sum_{j=1}^{N} p_j \cdot f_j}{\sum_{j=1}^{N} p_j} \tag{5}$$

where f_j is the frequency of interruptions of each aggregated load, measured in interruptions per year, while p_j is the number of end-users of that aggregated load. SAIFI is therefore a weighted average of the interruption frequency of the different loads of the DN. SAIFI is dependent on DN topology, and must be recomputed at each topological variation. In fact, considering different failure rates for the different network components (lines, circuit breakers, etc.), based on the network topology it is possible to calculate f_j for all loads. Also SAIFI has to be minimised to increase DN performance.

3.4 Calculation of the indexes and checking of constraints

While SAIFI index can be directly calculated based on the network topology, line losses and voltage deviations can be computed only after a load flow has been performed. In this work, the load flows on the different DN topologies generated through *tree building* and *branch exchange* are calculated using Matpower [9], a package of `MATLAB`® M-files for solving power flow and optimal power flow problems. Network data is firstly converted from the internal algorithm data format into the Matpower data structure and then the Matpower *runpf* routine is called to solve the power flow by Newton's Method. As a result, bus voltages, line power flows and network losses can be directly retrieved for the calculation of the objective functions.

After the calculation of the load flow, it is also possible to discard unfeasible network configurations, in case the maximum allowed current loading of some lines is exceeded, or in case the maximum and minimum voltage bounds are violated.

4 Vector Immune System

The search for optimal configuration can be performed through the VIS algorithm [5]. VIS algorithm has been developed starting from the family of Artificial Immune System (AIS) algorithms [10] implementing the Pareto ranking scheme for evaluation of individual solutions [11]. The main features of AIS algorithm are:

- focus on diversity of solutions, implemented through a series of independent microevolution processes running in parallel within the algorithm;
- use of mutation as the only operator for creation of new configurations.

The first characteristics makes AIS suitable for the solution of Vector Optimisation Problems (VOP) where the exploration of a set of solutions on the Pareto Front instead of a single solution is required. Starting from this consideration, VIS implements a strategy where diversity of solutions is enforced in the objective functions space. Details on the algorithm can be found in [5].

AIS algorithms have already been applied to DN multiobjective optimization through network reconfiguration, for example in [12]. Alonso et al. in their work were generating the initial population by randomly creating a forest of radial trees, and the mutation operation was the random operation of a switch. In this work, however, the VIS procedure is adapted to the DN topological problem by two new features, which are described in the following sections.

4.1 Initial population

The initial population of N_{pop} individuals is created by running the *tree building* function N_{pop} times using the Kruskal's algorithm [6]. This algorithm looks for a tree on a weighted graph set and returns the tree that minimises the sum of branch weights. To enforce diversity in the initial population weights on branches are arbitrarily set creating N_{pop} points in a N_b dimensional space according to the Latin Hypercube scheme [13]. Once weights are computed as points in the N_b dimensional space, they are assigned to the branches and then *tree building* is applied ensuring diversity and exploration of the configuration space.

4.2 Mutation operator

The second point in the previous item list allows to implement the *branch exchange* technique to mutate locally one configuration. In this way, mutation consists in a random alteration of a radial solution where only one 0/1 state is flipped. By performing the mutation with the *branch exchange* technique, the generated clones are for sure new feasible radial network configurations: it is therefore not necessary to check the radiality constraint or if portions of the DN are islanded.

In the proposed algorithm, a tie-branch is chosen randomly among the N_t tie-branches, and it is closed forming a loop. Again randomly, a line belonging to the same loop is opened to complete the *branch exchange* mutation.

5 Case study

The above described VIS procedure has been applied firstly to a case study proposed in the literature [14] where a topological reconfiguration technique applied to loss minimisation is carried out. The network has $N = 119$ and $N_b = 133$ leading to $N_t = 15$. VIS procedure was run and the results obtained when considering only power losses, thus taking in consideration only one extremum of the Pareto front in a losses-voltage deviation case, were compared with the results in [14]. The minimum value of losses reported in [14] was of 1.294 MW while the result obtained by VIS was 1.229 MW.

After the validation phase, the VIS procedure has been run on the DN of a medium size town in Northern Italy which constitutes, by size and complexity of topological connections, a thorough test for the algorithm. The DN is made of $N = 758$ buses and $N_b = 781$ branches, resulting in $N_t = 24$ tie-lines. The results obtained by the procedure are in this case compared with those obtained by an independent optimiser running inside the commercial network simulation software `NEPLAN` [15]. The topological configuration used by the DNO in standard running conditions has also been used as comparison.

A two objectives case was run using in turn two of the three performance indexes. In the future, after an optimization of the computation time, it will be possible to run also an optimization involving more than two objectives. Here results are presented for two different cases: losses vs. voltage deviation and losses vs. SAIFI index.

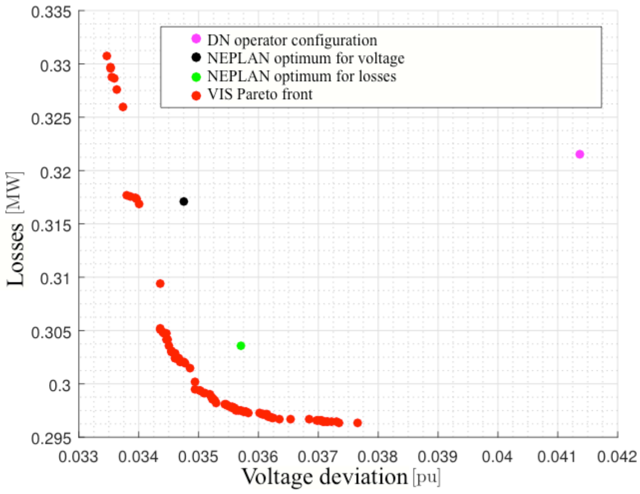

Figure 3: Power losses vs. Voltage deviation run: Pareto Front and reference configurations.

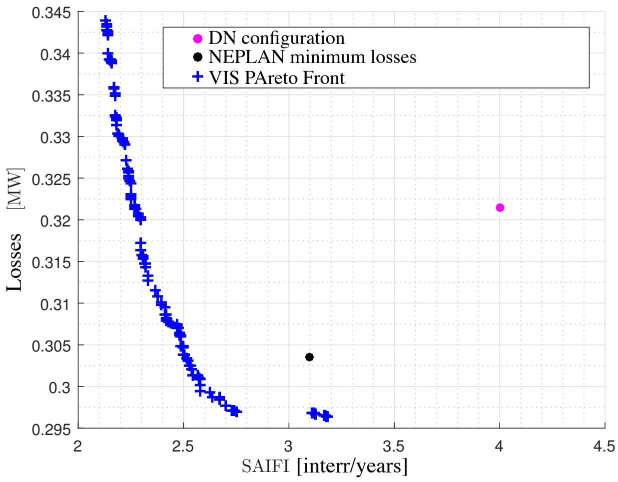

Figure 4: Power losses vs. SAIFI run: Pareto Front and reference configurations.

For the evaluation of SAIFI, failure rates of the different network components are needed. For these tests, all circuit breakers are considered having the same failure rate, while for the MV cables, the failure rate is considered proportional to the cable length [16].

The control parameters for VIS were: $N_{pop} = 15$, $N_{clones} = 5$, $N_{gen} = 50$, minimum percentage of new random individual at each generation 5%, number of clonal cycles before the population is assessed for diversity $N_{csel} = 5$. With these parameters each optimisation run gave rise to a total number of objective function evaluations equal to 18750. The procedure run on a Intel core 2 duo, 2.53 GHz and RAM of 4GB with a running time of 110 minutes.

6 Discussion and perspectives

The results obtained in terms of Pareto fronts in both cases are presented in Figures 3 and 4. By the plots it can be seen that the Pareto front is in both cases reaching values that are better than the ones obtained by commercial software `NEPLAN` and than the standard configuration adopted by the DNO. Also the reliability of the solution is good, as it can be seen by the analysis of Figure 5, where a statistical analysis of ten different independent runs on the case losses vs SAIFI is presented. In all runs the VIS procedure was able to find the same minimum value of losses and also the distribution of the final population does not highlight relevant differences among the runs.

The convergence process of the procedure to the final Pareto Front is also worth commenting. As it is shown

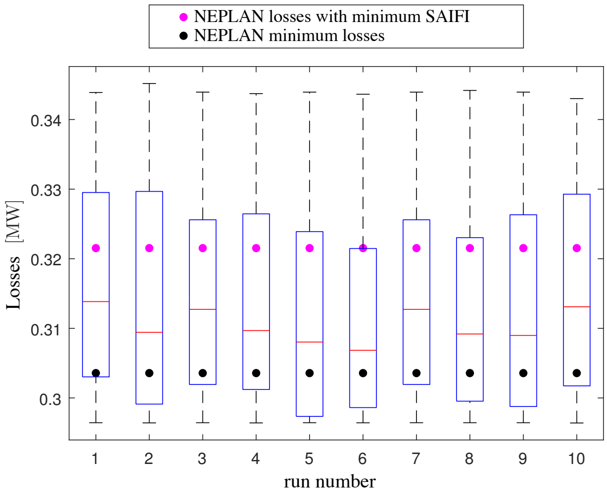

Figure 5: Analysis of stability of VIS final population on ten different runs.

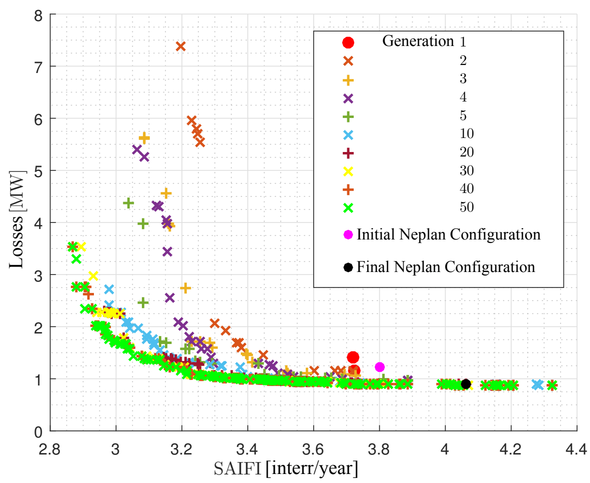

Figure 6: Convergence of memory set to the final Pareto Front.

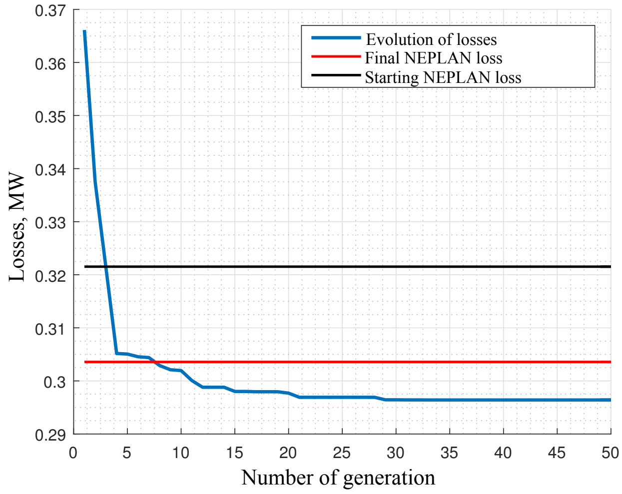

Figure 7: Evolution on losses vs the number of generations.

in Figure 6 for a particular run of the procedure, the shape of the memory set in the objective plane is moving toward the final front. As it can be seen after 10 generations the Pareto Front is already well approximated and following process is able to refine part of the front.

Starting from the previous consideration, the computational time of the procedure can be further reduced by decreasing the number of generations because, at least in the present case, the convergence on the final value is reached earlier, as it is apparent from Figure 7. In any case, the processing times are compatible with the comparative evaluation of different loads or DG production configurations.

As a conclusion, the VIS procedure has shown good capabilities and is promising as a tool for the optimisation of DN.

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