Electrical Power and Energy Systems 54 (2014) 255–267

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Optimal multi-objective distribution system reconfiguration with multi criteria decision making-based solution ranking and enhanced genetic operators

Andrea Mazza, Gianfranco Chicco *, Angela Russo

Politecnico di Torino, Energy Department, Corso Duca degli Abruzzi 24, I-10129 Torino, Italy

ARTICLE INFO

Article history:
Received 25 February 2013
Received in revised form 10 July 2013
Accepted 12 July 2013

Keywords:
Distribution system
Reconfiguration
Multi criteria decision making
Pareto front

ABSTRACT

In electrical distribution system optimisation, the presence of multiple conflicting objectives is effectively addressed by using Pareto front analysis. This paper deals with optimal reconfiguration considering network losses and energy not supplied as multi-objectives. A set of original contributions are provided with reference to the construction and updating of the best-known Pareto front using a genetic algorithm-based solver. The crossover operator is extended to address multi-objective solutions. The mutation operator is extended to handle a broader number of cases. Multi-objective solution ranking is applied by resorting to multi criteria decision making methods during the creation of the offsprings in the crossover operator, as well as to provide an automatic support for the decision maker to identify the preferable solution in the final Pareto front. The proposed approach is applied on two reference test networks, for which the complete Pareto front is calculated from the entire set of multi-objective solutions. The resulting best-known Pareto front is compared with the complete Pareto front using a metric based on geometrical considerations. This comparison framework is helpful to assess the performance of the multi-objective optimisation solvers.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

Distribution system optimisation can be addressed in different contexts and with different objective functions. A general distinction considers distribution system optimal *reconfiguration* in normal and emergency conditions, and distribution system optimisation in a *planning* framework (operational planning at constant load and expansion planning at variable load).

The optimal distribution system reconfiguration problem has been first solved in [1] by considering loss minimisation, using a branch and bound technique in which, starting from the initial network with closed branches, the redundant branches are open until reaching the radial configuration. A refined version of this technique has been proposed in [2,3]. A concept successfully applied is the open-close branch exchange introduced in [4], consisting of starting from a radial configuration, closing an open branch, identifying the loop formed and opening one of the branches belonging to the loop to restore a radial configuration. This concept served to develop an effective deterministic method called iterative improvement [5], in which the open-close branch exchange is performed iteratively, updating the radial configuration to the one producing the best configuration found so far, until stopping into a (local) minimum.

The largest part of the literature papers has considered a single objective function (the reduction of the line losses), taking into account a given set of loads, with one or a few loading levels and no variation in time of the loads. Various methods based on meta-heuristics have been applied to optimal distribution system reconfiguration, starting from the early applications of simulated annealing, genetic algorithms and tabu search. Review indications can be found for instance in [6–10]. A number of recent contributions have addressed the application of different meta-heuristics to the minimum loss reconfiguration problem. A full review of the optimisation formulations and solution techniques is outside the scope of this paper. Some exemplificative references for these meta-heuristics include ant colony [11–13], genetic algorithms (GA) with matroid theory [14], sequential GA [15], improved adaptive GA and branch exchange [16], hybrid differential evolution [17], plant growth [18], integer coded particle swarm optimisation [19], bacterial foraging [20], modified honey bee mating [21], and harmony search [22]. In addition, some papers have used methods like optimal power flow with Benders decomposition [23] and mixed-integer convex programming [24].

The multi-objective framework has been introduced in [25] by considering a trade-off among conflicting objectives such as losses and reliability [26]. In this framework, multi-objective optimal

* Corresponding author. Tel.: +39 011 090 7141; fax: +39 011 090 7199.
E-mail address: gianfranco.chicco@polito.it (G. Chicco).

0142-0615/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ijepes.2013.07.006

reconfiguration has been the subject of various developments in recent years. Different objectives have been considered in addition to losses, such as load balancing [27–32], voltage deviations [27,30,33–35], number of switching actions [36–38], reliability indicators [25,38–42], and emissions [34,35].

The presence of multiple objectives raises the issue of how to consider them simultaneously. The main issues are the different units of the individual objectives, as well as the possible different orders of magnitude of the numerical values of the single objectives. In order to deal with these aspects, [25] considered the weighted sum of per-unitised objectives. The determination of the normalising factors depends on the features of the individual objectives and as such is not an easy task. In [43] the Grey correlation analysis has been used with the aim of avoiding the setting up of problem-dependent and network-dependent maximum/minimum limits on the variables describing the individual objectives, through the identification of problem-independent superior and inferior solutions for each objective.

Another set of applications used fuzzy logic-based approaches, requiring the definition of the minimum and maximum values of the membership functions, with user's dependent selection of these values [27,30,32,40,44,45]. In the hypothesis of minimising the objective function, considering the value L_0 of the objective calculated in the initial network configuration, the maximum value of the membership function is generally defined as $x_L^{max} = L_0/L_0 = 1$. Furthermore, the minimum value of the membership function has to be defined by using an objective function L_{min} conceptually associated with the minimum value of the specific objective. However, the minimum value is not known in advance. For this purpose, the literature provides some guidelines on how to set up the value L_{min} for different types of objectives, typically as the minimum value of the objective under which the solution is considered to be acceptable [27,44]. This choice defines the minimum value $x_L^{min} = L_{min}/L_0$ to be used for constructing the membership function μ_L for the objective L, that is:

$$\mu_L = \begin{cases} 1 & \text{for } x \leqslant x_L^{min} \\ \frac{x_L^{max} - x}{x_L^{max} - x_L^{min}} & \text{for } x_L^{min} < x < x_L^{max} \\ 0 & \text{for } x \geqslant x_L^{max} \end{cases} \tag{1}$$

The optimisation is then formulated either as the weighted sum of the fuzzy membership functions [27,23,36], or with the application of the max–min principle [44], or using a specific maximum geometric mean operator to represent the degree of overall fuzzy satisfaction [30]. In other cases (e.g., [40]), the membership function $\mu_{Li} = L_i / \max\limits_{K=1,\ldots,\dim(L)} \{L_k\}$ contains only the maximum value of the objective functions calculated for the solutions currently considered, and the max–min principle is adopted to find the best configuration.

A different view on multi-objective optimisation takes into account the presence of multiple *conflicting* objectives. In this case, a solution is *non-dominated* when no other solution exists with better values for all the individual objectives. The *Pareto front* is the set containing the non-dominated solutions, interpreted as compromise solutions for the problem under analysis.

The calculation of the compromise solutions can be carried out with different techniques, among which:

- the *weighted sum*of the individual objectives, for convexPareto fronts;
- the ε-*constrained*method, that considers an individual objective as the target to be optimised and sets for all the other objectives a limit expressed by a threshold ε, then progressively reduces the threshold and upgrades the set of non-dominated solutions; this method has been applied to optimal distribution system reconfiguration in [46];
- the *direct* Pareto front construction through heuristic approaches, with an iterative process; some examples are the Strength Pareto Evolutionary Approach, Pareto Archived Evolution Strategy, Non-dominated Sorting Genetic Algorithm II (NSGA II) [47–49], Jumping Genes Evolutionary Multi-Objective Optimisation [50], Multi-Objective Particle Swarm Optimisation (MOPSO) [51] and Evolutionary Particle Swarm Optimisation (MEPSO) [52], and Multi-Objective Tabu Search [53].

The main advantage for using the Pareto front approach is that there is no need for setting up normalising factors or minimum/maximum limits to deal with non-commensurable objectives. The various objectives are orthogonal with each other and the assessment of the non-dominated solutions is totally independent of the units associated with each individual objective. The Pareto analysis is then suitable for addressing problems whose conflicting solutions cannot be assessed by using a single criterion.

Some applications of the Pareto analysis to optimal distribution system reconfiguration have been reported in the recent literature. In [39,42] the objective functions considered are losses and reliability indices. The Pareto front solutions are found in [39] by using a micro-genetic algorithm, and in [42] by using an improved shuffled frog leaping algorithm, in which the compromise solutions are stored in a repository, and a fuzzy clustering technique is applied to limit the size of the repository. In both papers there is no comparison among the Pareto front solutions obtained.

The papers [34,54] address the optimal distribution system reconfiguration together with the sizing of a hybrid (photovoltaic/wind turbine/fuel cell) energy system. In [54] the objectives are the losses, the voltage stability index, the cost of energy generated by distributed generators (DGs) and purchased from the grid, and the total emissions produced by DGs and the grid. The multi-objective artificial bee colony (MOABC) algorithm is used to create the Pareto front. An archive of non-dominated solutions is stored at each iteration, limiting the size of the archive by using the crowding distance operator [47] to eliminate some points by preserving diversity of the solutions in the archive. There is no comparison among the Pareto front solutions. In [34] the objectives are the losses, the voltage deviation, the total energy production cost by the grid and DG, and the total emissions. A multi-objective modified honey bee mating optimization (MHBMO) algorithm is used to generate the Pareto front. The non-dominated solutions are stored in a repository, and the size of the repository is limited by adopting a fuzzy clustering technique. A further fuzzy-based mechanism is used to find the best compromise solution in the Pareto solutions set. For this purpose, the fuzzy membership functions are calculated for all the solutions and for all the objectives. The best compromise solution is the one for which the sum of the membership functions referring to that solution is the highest.

This paper refers to the direct construction and iterative updating of the *best-known* Pareto front (i.e., the evolving approximation of the complete Pareto front). The genetic operators used in the NSGA-II method have been adapted to solve a number of critical aspects of distribution system optimisation, and to take into account the multi-objective nature of the solutions generated during the iterative process. In particular, during the *local improvement* (introduced in the single-objective framework in [55], see details in Section 4) it is required to make choices among the solutions obtained. In the extension of the local improvement to the multi-objective problem, the incorporation of an appropriate method for ranking a set of multi-objective solutions is necessary.

At the end of the entire iterative process, an acceptable best-known Pareto front has to be created, but it is fundamental to both assess the "quality" of the Pareto front obtained and rank the

Download English Version:

https://daneshyari.com/en/article/398857

Download Persian Version:

https://daneshyari.com/article/398857

Daneshyari.com