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Optimal placement of on-load tap changers in distribution networks using SA-TLBO method

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ABSTRACT

This paper presents a multi-objective optimal location of on-load tap changers (OLTCs) in distribution systems at spirit of distributed generators (DGs) based on Teaching–Learning-Based optimization coupled with Simulated annealing algorithm (SA-TLBO). In the suggested algorithm, teacher and learner phases are modified by SA. The proposed algorithm utilizes several teachers and considers the teachers as an external cache to store found Pareto optimal solutions during the search process. The proposed approach allows the decision maker to take one of the Pareto optimal solutions (by trade-off) for different applications. The performance of the SA-TLBO algorithm on a 70-bus distribution network in comparison with other methods such as GA, PSO, SA and TLBO is remarkable.

Introduction

In distribution networks, voltage control is a tough procedure since dynamic load fluctuations eventually influence voltages. Therefore, utilities reinforce their power systems in order to have a better control over voltage variations [1]. A voltage profile can be rehabilitated by using devices such as transformers with on-load tap changers (OLTCs), fixed and controlled capacitor banks and DGs [2,3] Whereas, in distribution networks the utilization of some equipments such as OLTCs depends on their investment costs. Thus, the optimal location of OLTCs becomes a serious subject. Numerous advantages of DGs in distributed systems and probes carried out by research centres. Those present increasing DGs involvement in energy production to even more than 25% in the near future. Hence, intense attention is vital to be paid to DGs impact in power systems, especially on the distribution networks [4–6].

Nowadays, scientists apply fuzzy logic [7] and evolutionary algorithms [8–11] to solve the problem of optimal placement of capacitor banks in distribution networks. In order to optimize tap position and the ON/Off state of the capacitor banks, they use analytical tools such as optimal power flow [12]. In [13–17], the authors survey the optimal location of OLTCs separately from the placement and sizing of the capacitor bank's problem. In the same way, in [18], the authors determined the location of OLTCs by using a sequential algorithm. In [19], the authors use a basic Genetic Algorithm (GA) for choosing the optimal location of OLTCs in radial distribution systems. In these approaches, they have applied a weighted sum strategy in order to solve the multi-objective optimization problem, but this strategy has a defect, in which final solution of these algorithms extensively depends on the values of the weights. Since the optimal operation, in distribution networks is a nonlinear optimization problem and meanwhile optimization algorithms have a broad use in solving both nonlinear and complex optimization problems, so optimal solution could be obtained through evolutionary methods [20–26]. The considered problem objective functions are not the same. So it is difficult to solve this problem by classical approaches used for optimizing single objective problems. Therefore, the proposed algorithm first models the multiple-objectives using fuzzy sets to assess their imprecise nature. Many optimization methods such as Particle Swarm Optimization (PSO), Honey Bee Mating optimization (HBMO) and Ant Colony optimization (ACO) need a set of parameters that affect the algorithm performance. For instance, HBMO requires determination of the drones number, queen's velocity and its variation in each iteration; ACO requires determination of pheromone intensity (chemical material-τ) and it's variation in each iteration and the control parameters for determining the weights of trial intensity and length of the path (γ_1 and γ_2); PSO requires learning factors and the inertia weight which precise adjustment of these parameters is a hard work to handle, but TLBO does not require any parameters to be tuned; therefore, TLBO implementation is simpler. The TLBO algorithm uses two different phases, the teacher phase and the learner phase. In this paper in

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order to improve both the velocity and accuracy of convergence and to avoid premature convergence to the objective function local optimum, we modify both of the teacher phase and learner phase by coupling with SA which we call this modified algorithm as SA-TLBO. In multi-objective problems, the objectives conflict each other, So it is usual to achieve a set of solutions instead of one solution. In order to solve multi-objective problems, some methods can be used. One of these methods is Max–Min that performs by improvement of the worst solution and convert of multi-objective into a single - objective. In new suggested SA-TLBO algorithm the applied method is Pareto optimal solution which works with dominate and non-dominate concept. That is capable of finding a non-dominated solution that represents the best possible trade-offs among the objectives. The decision maker can choose any of the Pareto optimal solutions based on his/her own preferences. For further validation of the proposed algorithm, we test it on a 70-bus test system compared with other evolutionary methods such as GA, PSO, SA and Teaching–Learning-Based optimization (TLBO).

Multi-objective location of on-load tap changers

Objective functions

Total electricity cost

$$\min f_1(\overline{X}) = (P_{\text{sub}} \times \text{price}_{\text{sub}}) + \sum_{i=1}^{N_{\text{DG}}} P_{\text{DGi}} \times \text{price}_{\text{DGi}} \tag{1}$$

$$P_{\text{sub}} = \sum_{j=1}^{n} |V_{\text{sub}}||V_j||Y_{\text{sub}\ ,j}| \cos(\theta_{\text{sub},j} - \delta_{\text{sub}} + \delta_j) \tag{2}$$

$$\overline{X} = \left[\overline{P}_{\text{DG}}, \overline{\text{Tap}}_{\text{OLTC}}, \overline{\text{Location}}_{\text{OLTC}}\right]_{1\times n} \tag{3}$$

$$\overline{P}_{\text{DG}} = \left[P_{\text{DG1}}, P_{\text{DG2}}, \ldots, P_{\text{DG}_{\text{NDG}}}\right] \tag{4}$$

$$\overline{\text{Tap}}_{\text{OLTC}} = [\text{Tap}_1, \text{Tap}_2, \ldots, \text{Tap}_{\text{NOLTC}}] \tag{5}$$

$$\overline{\text{Location}}_{\text{OLTC}} = \left[\text{Location}_{\text{OLTC}_1}, \text{Location}_{\text{OLTC}_2}, \ldots, \text{Location}_{\text{OLTC}_N}\right] \tag{6}$$

$$n = (N_{\text{DG}} + 2 \times N_{\text{OLTC}}) \tag{7}$$

where $\overline{X}$ is state variables vector including active power of DGs, tap positions and location of OLTCs, P_{sub} and $\text{price}_{\text{sub}}$ are the value and price of the injected active power to the network, respectively. N_{DG} is the number of DGs, $P_{\text{DG}i}$ is the active power of the ith distributed generator, $\text{price}_{\text{DG}i}$ is the electricity price of ith distributed generator, V_{sub} and δ_{sub} are the magnitude and angle of slack bus voltage, respectively. $Y_{\text{sub},j}$ and $\theta_{\text{sub},j}$ are the value and angle of admittance between slack bus and jth bus, respectively. V_j and δ_j are the magnitude and angle of voltage at the jth bus, respectively. N_{OLTC} is the number of OLTCs, $\overline{P}_{\text{DG}}$ is active power vector of all DGs, $\overline{\text{TAP}}_{\text{OLTC}}$ is the tap vector which represents the tap positions of all OLTCs, $\overline{\text{Location}}_{\text{OLTC}}$ is the location vector of all OLTCs. In this paper, the main objective is optimal localization of OLTCs, So the variation of load is not considered and loads are supposed as constant power.

The power of the voltage regulator (KVA) is a critical factor of costs, and if OLTC is located when the magnitude of power is greater, the costs have an expressive increase. Although in this paper because the main objective is optimal localization of OLTCs, the number of the applied OLTCs is supposed fixed so in the calculation of $f_1(\overline{X})$ OLTCs prices are not considered, and components of the state variable vector are discrete.

Electrical losses of the distribution system at the presence of OLTCs and DGs

The second objective function considered in this paper is a total loss, which is defined as follows:

$$\min f_2(\overline{X}) = P_{\text{Loss}} = \sum_{i=1}^{N_b} R_i \times |I_i|^2 \tag{8}$$

where N_b is the number of branches, R_i is the resistance of the ith branch and I_i is the current of the ith branch.

Voltage deviation

The third objective function is voltage deviation. It determines the difference between the nodes voltage and reference ones. The voltage deviation is computed as follows:

$$\min f_3(\overline{X}) = \sum_{i=1}^{N_{\text{bus}}} \left| \frac{V_i - V_i^{\text{ref}}}{V_i^{\text{ref}}} \right| \tag{9}$$

where V_i^{ref} is the suitable voltage at ith bus, V_i is the voltage magnitude of the ith bus and N_{bus} is the number of buses.

Constraints

- Active power constraints of DG units:

$$P_{\text{DG}i}^{\min} \leqslant P_{\text{DG}i} \leqslant P_{\text{DG}i}^{\max} \tag{10}$$

$P_{\text{DG}i}^{\max}$ and $P_{\text{DG}i}^{\min}$ are the maximum and minimum active power of the ith DG respectively.

- OLTCs tap position:

$$\text{Tap}_{\text{OLTC}i}^{\min} < \text{Tap}_{\text{OLTC}i} < \text{Tap}_{\text{OLTC}i}^{\max} \tag{11}$$

$\text{Tap}_{\text{OLTC}i}$ is the tap position of the ith OLTC, $\text{Tap}_{\text{OLTC}i}^{\min}$ and $\text{Tap}_{\text{OLTC}i}^{\max}$ are the minimum and maximum tap positions of the ith OLTC, respectively.

- Bus voltage magnitude

$$V_{\min} \leqslant V_i \leqslant V_{\max} \tag{12}$$

V_i, $V_{\max}$ and $V_{\min}$ are the voltage magnitudes of the ith bus and the maximum and minimum values of voltage magnitudes, respectively.

Fuzzy modeling for normalizing objective functions

In this section, a fuzzy method has been proposed to compute the normalized form of objective functions in regard to solve multi-objective optimization. The objective functions are imprecise and not in the same range, so they are formulated as fuzzy sets. A fuzzy set is usually illustrated by a membership function (μ_i). The fuzzy decision-maker function is depicted by the membership function to replace each objective function as a value between 0 and 1. The ith objective function of f_i is depicted by a membership function μ_i and is defined as follows:

$$\mu_i = \begin{cases} 1 & \text{if} \quad f_i \leqslant f_i^{\min} \\ \frac{f_i^{\max} - f_i}{f_i^{\max} - f_i^{\min}} & \text{if} \quad f_i^{\min} < f_i < f_i^{\max} \\ 0 & \text{if} \quad f_i \geqslant f_i^{\max} \end{cases} \tag{13}$$

Pareto optimal solution

Multi-objective optimization is referred to the simultaneous optimization of multiple conflicting objectives, which produces a set of alternative solutions called the Pareto optimal solutions. The Pareto method determines a set of solutions for multi-objective problems by using the dominance concept. A vector dominates another one while all of its components are less than or equal to the component of other vector, and at least one of its component is strictly less than its similar component in other vector [27]. In other words, $\overline{X}_a$ dominates $\overline{X}_b$ as follow: