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A comparison of heuristic optimization techniques for optimal placement and sizing of photovoltaic based distributed generation in a distribution system

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ABSTRACT

This paper presents the application of heuristic optimization techniques for determining optimal placement and sizing of photovoltaic-based distributed generation (PVDG) in a distribution system. The objective functions of the optimization problem, consider a real power loss, voltage deviation, average voltage total harmonic distortion (THD) and system average voltage dip magnitude (SAVDM). Various heuristic optimization techniques were applied and compared in order to determine the optimum placements and sizing of PVDG in IEEE 69-bus radial distribution system. This paper proposed the improved gravitational search algorithm (IGSA) and its performances are compared with two other algorithms such as the gravitational search algorithm (GSA) and particle swarm optimization (PSO). A comparison of the performances is also made using optimization techniques when PVDGs are fixed at critical buses. The test results showed that IGSA outperformed GSA and PSO in finding the optimal PVDG locations and sizes.

1. Introduction

Distributed generations (DGs) are small generating units that are installed mainly, near the load centers and in strategic points of the electric power distribution system. There are two types of DGs which are inverter-based and non-inverter based DGs. Examples of technologies applied in DGs are micro-turbines, fuel cells, wind and solar energy. DGs can be connected to satisfy consumer's local demand or supplying energy to the remaining of the electrical system (Borges and Falcao, 2003). In order to sustain the benefits of DG, the location, capacity, type and number of DGs must be optimum. Therefore, a feasibility study needs to be performed since a power system may be affected by the DG installation. In Kadir et al. (2014), a study was done to evaluate the power quality impact of renewable type of DGs in a distribution system. Many research works have been carried out to find the optimization method for DG installation using analytical, numerical and heuristic methods (Borges and Falcao, 2003).

Genetic algorithm (GA) has been applied for determining the optimal allocation of DGs in a meshed distribution system (Akorede et al., 2011). A hybrid method which is a combination of particle swarm optimization (PSO) and nonlinear optimal power flow (OPF) was used to determine the optimum location and size of multiple DGs (Dias et al., 2012). PSO is widely being used in DG optimal allocation due to its effectiveness and simplicity and in El-Zonkoly (2011), it is applied for determining optimal locations and size of DGs with respect to various load models. Other heuristic optimization techniques applied to identify the location and size of DGs are such as the ant colony optimization (ACO) in Lingfeng and Singh (2008), and the harmony search algorithm in Nekooei et al. (2013). Other research works on optimal allocation of DGs, consider the use of analytical method in Hung and Mithulananthan (2013), Hung et al. (2010) and Elsaiah et al. (2014), which is said to be easily implemented and perform faster than the other optimization methods (Georgilakis and hatziargyriou, 2013). Numerical methods applied for the optimal allocation of DGs are such as ordinal optimization, sequential quadratic programming and nonlinear programming (Jabr and Pal, 2009; Morales et al., 2011; Atwa and El-Saadany, 2011).

The objective of this paper is to identify the best optimization method for determining the optimal location and sizing of photovoltaic distributed generation (PVDG) in a distribution system

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and implementing a comparative study on three heuristic optimization techniques, namely, improved gravitational search algorithm (IGSA), PSO and GSA. The optimization problem considers minimization of system real power loss, average voltage deviation, average voltage total harmonic distortion (THDv) and system average voltage dip magnitude (SAVDM). A comparison is also made with and without optimum location and capacity of PVDG in the IEEE 69-bus radial distribution system. Methods such as Newton-Raphson load flow, harmonic load flow and method of fault position are combined with the heuristic optimization techniques to obtain the best solution or optimum fitness function.

2. Problem formulation

An optimization problem can be defined as the maximization of an objective function while satisfying a number of equality and inequality constraints. A multi-objective optimization is formulated for optimum PVDG placement and sizing by minimizing total power loss, voltage deviation, average THDv and system average voltage dip magnitude (SAVDM), which is expressed as follows:

$$F_{min} = (\gamma p_{loss}) + (\beta THD_v) + (\chi V_{dev}) + (\eta SAVDM) \tag{1}$$

From Eq. (1), F can be defined as the fitness function, THD_v is the percentage of the average THDv, V_{dev} is the percentage of voltage deviation at all system buses, and $SAVDM$ is the percentage of system average voltage dip magnitude. γ is the coefficient of p_{loss}, β is the coefficient of THD_v, χ is the coefficient of V_{dev} and η is the coefficient of $SAVDM$. The sum of the coefficient factor method is used to decide the relative importance of the objectives in order to obtain the best optimum solution. The coefficient factors are assumed to be 0.25 each since all of the objectives are important in order to install DGs with lower power loss, more stable voltage and enhanced power quality.

The total real power loss, average THD_v, V_{dev} and $SAVDM$ are given by:

$$p_{loss} = \sum_{i=1}^{n} p_{loss_i} \tag{2}$$

$$THD_v = \frac{\sum_{i=1}^{m} THD_{v_i}}{m} \tag{3}$$

$$V_{dev} = \frac{V_{i_{ref}} - V_i}{V_i} \tag{4}$$

$$SAVDM = bi1 - \frac{\sum_{i=1}^{m} VDA_i}{m} \tag{5}$$

where n is the number of lines, m is the number of buses, $V_{i_{ref}}$ is the reference voltage at bus i and V_i is the actual voltage at bus i. VDA_i is the voltage dip amplitude at bus i. The bus voltage must be kept within permissible operating range throughout the optimization process and the total harmonic level at each bus must be less than or equal to the maximum permissible level. The inequality constraints are expressed as follows:

$$V_{min} \leqslant |V_i| \leqslant V_{max} \tag{6}$$

$$THD_{v_i} \leqslant THD_{v_{max}} \tag{7}$$

V_{min} is the lower bound and V_{max} is the upper bound of bus voltage limits. $|V_i|$ is the RMS value of the i th bus voltage and $THD_{v_{max}}$ Is the maximum permissible level at each bus, which is 5%.

3. Improved gravitational search algorithm

GSA was proposed as a solution to solve optimization problems by Rashedi et al. (2009). The development of this algorithm is based on the law of motion and Newton's law of gravity. The algorithm comprises of a collection of search agents that are considered as objects that interact with each other through a gravitational force. The performance of agents is measured by their masses and a global movement due to gravitational force causes the objects to move towards other objects with heavier masses. The slow movement of heavier masses guarantees the utilization step of the algorithm and corresponds to good solution. GSA consists of four parameters that are position, inertial mass, active and passive gravitational mass. The position represents the solution, while the gravitational and inertial masses are determined using a fitness function. The optimum solution in the search spaces represented by the heaviest mass (Sabri et al., 2013). The computational procedures of GSA consider the following equations:

- ith agent's position can be given by:

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^n), \quad \textbf{for } i = 1, 2, \ldots, n \tag{8}$$

- In the meanwhile, the detailed position of each ith agent is given by:

$$X_i^n = \left[(Size, VC, Place)_1, (Size, VC, Place)_2, \ldots, (Size, VC, Place)_n\right] \tag{9}$$

where X_i^n is the position of each ith agent, $Size$ is the capacity of PVDG, VC is the voltage control and $Place$ is the location of the PVDG.

- The update of gravitational constant (G) is given by:

$$G(t) = G_0 \frac{T - t}{T} \tag{10}$$

where $G(t)$ is the gravitational constant value at each time, t and G_0 is the gravitational constant value at the first quantum-interval of time, t_0. T is the total number of iterations.

- The update of mass (M) considering a weighting range between 0 and 1, corresponds to the following fitness:

$$m_i(t) = \frac{fitness_i(t) - worst(t)}{best(t) - worst(t)} \tag{11}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{n} m_j(t)} \tag{12}$$

where $fitness_i(t)$ is the fitness value of the agent i a time t, and $worst(t)$, and $best(t)$ are the maximum and minimum fitness values, respectively.

- The update of K_{best} is given by:

$$K_{best} = K_{best\_final} + \left[\frac{T - t}{T}(100 - K_{best\_final})\right] \tag{13}$$

- The total force (F) is calculated by using the following equations:

$$F_{ij}^d = G \frac{M_{ij}}{R_{ij} + \varepsilon}\left(x_j^d - x_i^d\right) \tag{14}$$

$$R_{ij} = \|X_i, X_j\|_2 = \sqrt{\sum_{d=1}^{D}\left(x_j^d - x_i^d\right)^2} \tag{15}$$

$$\varepsilon = \textbf{small coefficient}, 2^{-52}. \tag{16}$$

- As a stochastic approach, the total force on agent, i in the d dimension a randomly weighted sum of the dth components of the force exerted from other agents. The total force is given as