Electrical Power and Energy Systems 77 (2016) 256–262

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Impact of distributed generators in the power loss and voltage profile of three phase unbalanced distribution network

Samir Dahal, Hossein Salehfar *

Department of Electrical Engineering, University of North Dakota, Grand Fork, ND 58202, USA

ARTICLE INFO

Article history:
Received 21 June 2014
Received in revised form 8 October 2015
Accepted 17 November 2015
Available online 10 December 2015

Keywords:
Particle swarm optimization
Unbalanced three-phase optimal power flow
OpenDSS
Distributed generation
Distribution management system
Optimal allocation of DGs

ABSTRACT

In this paper, using particle swarm optimization (PSO) based method is developed to determine the optimal allocation of distributed generators (DGS) on a multi phased unbalanced distribution network. PSO algorithm has been programmed in MATLAB using open source software called OpenDSS in a co-simulation environment to solve the unbalanced three-phase optimal power flow (TOPF) and to find the optimal location and sizing of different types of distributed generators. Using the IEEE 123 node distribution feeder as a test bed, results from the proposed method is compared to those from the repeated load flow (RLF) method. For a realistic study, mixes of all type of DGs are considered. Results indicate that integrating optimally sized DGs at the optimal locations not only reduces the total power loss in the distributed system but improves the voltage profile as well.

Introduction

In recent years, development of "Smart Grid" has influenced the primary focus of research on the electric power production, transmission, and distribution. Among the various attributes of smart grids, flexibility and resiliency of distribution systems [1] and integration of distributed generation (DG) into the power grid [2] are classified as an advanced distribution management system (DMS) [3]. Even though DMS was created as a simple extension of supervisory control and data acquisition (SCADA) from transmission system, it must be equipped with all the methodologies and capabilities that are currently used to analyze the transmission systems. Since DMS is the brain of the smart distribution grid, methods such as optimal DG placement, integrated voltage/var control, distribution power flow (DPF), and contingency analysis must be adapted to the characteristics of common distribution systems [3,4].

The importance of proper DG integration into the distribution system has been investigated in number of studies. Authors in [5–12] have demonstrated the reduction of power loss by optimally sizing and placing DGs in distribution networks. Similarly, in [13–17] optimal sizing and location of DG resulted in improved reliability of the network. As power loss decreases and reliability increases, profit for utility increases as well. Therefore, for utilities integrating DGs in distribution networks provides the dual advantage of meeting the renewable portfolio standard (RPS) and strengthening their infrastructure while reducing the cost. However, most of these studies have been performed on balanced distribution systems. Distribution networks in actual power system are multi phased unbalanced systems because of unequal three phase loads, un transposed lines and conductor bundling [18]. As a result, studies performed on balanced distribution systems fail to provide a realistic insight into the actual problem.

One of the reasons for conducting the optimal allocation problem in a balanced network is the simplicity in solving the optimal power flow. Even though numbers of studies have suggested methods for solving the distribution load flow (DLF) [19–23], they require a complex calculation and thus are very time consuming. A much simpler and effective method for solving three phase optimal power flow (TOPF) has been proposed in [4]. Authors in this study make use of quasi-Newton method which requires the numerical evaluation of gradients. However, a gradient based method has a higher possibility to converge in a local minima making the results inaccurate [24,25]. Furthermore, Newton-based techniques rely heavily on the value of initial conditions and thus, may never converge due to the inappropriate initial conditions [26].

* Corresponding author.
E-mail addresses: samirdahal@gmail.com (S. Dahal), hossein.salehfar@engr.und.edu (H. Salehfar).

http://dx.doi.org/10.1016/j.ijepes.2015.11.038

In the present study particle swarm optimization (PSO) algorithm is used in a co-simulation environment with OpendDSS program to solve the TOPF problem for optimal location and sizing of multiple DGs. Unlike the gradient based optimization methods, the PSO is a heuristic global optimization method with no overlapping and mutation calculations. This not only makes PSO effective but also results in lower computational times [27].

The remainder of the paper is organized as follows. Section 'M ethodology' presents the definition of an objective function, application of PSO, and its parameter tuning. The implementation of the proposed method along with its validation is presented in Sectio n 'Implementation'. In Section 'Results and discussion', results obtained by applying the proposed method are discussed and conclusions are drawn in Section 'Conclusion'.

Methodology

Objective function

PSO has long been used to solve the OPF problems [26,28–30]. In those references, authors have developed methods for single phase OPF. However, the same method of single phase systems can be modified for TOPF. In the present work the method proposed by authors in [4,31] have been modified with a goal of achieving both optimal location and sizing, simultaneously.

The unbalanced TOPF problem can be formulated as follows:

$$\text{Min } F(x, u) \tag{1}$$

Subject to:

$$g(x, u) = 0 \tag{2}$$

$$h(x, u) \leqslant 0 \tag{3}$$

where F is the objective function which needs to be minimized, x is the vector of dependent variables like node voltages and bus loads. u is the vector of independent variables mainly the DGs size and location. g is the equality constraints which represent the load flow equations. h is the system operating constrains like allowable sizes of DGs and voltage stability.

Since the main focus of this study is to strengthen the unbalanced multi phased distribution network while reducing the operating cost by allocating the optimal size and location of DGs, our objective function represents the total power loss of the given distribution network. Hence, the objective function is given as

$$F_{obj} = \sum_{k=1}^{n} P_L(k) \tag{4}$$

where P_L is the power loss in each distribution nodes (or lines) and n is the number of nodes (or lines). In the scope of this work, strengthening distribution networks means improving the voltage profile of the system. This can be achieved by enforcing the voltage at every node in the distribution system to be within the acceptable range of 0.95 pu and 1.05 pu. Hence the following inequality constraint is applied to ensure the acceptable voltage profile of the distribution network.

$$V^{min} \leqslant V_i \leqslant V^{max}, \quad i = 1, \ldots, N \tag{5}$$

where N is the number of nodes. Additionally, availability also dictates the sizes of the DG that can be connected to the Distribution network. This results in the following constraints:

$$P_G^{min} \leqslant P_{Gi} \leqslant P_G^{max} \tag{6}$$

$$Q_G^{min} \leqslant Q_{Gi} \leqslant Q_G^{max} \tag{7}$$

where P_G^{min} and $P_G{}^{max}$ are the available minimum and maximum real powers and Q_G^{min} and Q_G^{max} are the available minimum and maximum reactive powers.

Inequality constraints in Eqs. (5)–(7) can be incorporated into the objective function as quadratic penalty terms as follows [26]:

$$F_{obj} = \sum_{k=1}^{n} P_L(k) + \lambda_P \left(P_{Gi} - P_{Gi}^{lim}\right)^2 + \lambda_V \left(\sum_{i=1}^{N} \left(V_{Li} - V_{Li}^{lim}\right)^2\right) + \lambda_Q \left(\sum_{i=1}^{NDG} \left(Q_{Gi} - Q_{Gi}^{lim}\right)^2\right) \tag{8}$$

where N is number of nodes, NDG is number of DGs, λ_P, λ_V, and λ_Q are penalty factors and

$$V_{Li}^{lim} = \begin{cases} V^{max}; & V > V^{max} \\ V^{min}; & V < V^{min} \end{cases} \tag{9}$$

$$P_{Gi}^{lim} = \begin{cases} P^{max}; & P > P^{max} \\ P^{min}; & P < P^{min} \end{cases} \tag{10}$$

$$Q_{Gi}^{lim} = \begin{cases} Q^{max}; & Q > Q^{max} \\ Q^{min}; & Q < Q^{min} \end{cases} \tag{11}$$

In this study, various types of DGs have been considered.

- Type 1: DGs which can inject only real power such as fuel cells, PV cells, and geothermal power plants.
- Type 2: DGs which can inject both real and reactive power such as synchronous generators.
- Type 3: DGs which can inject real power and absorb reactive power such as induction generators.

Application of PSO

The computational procedures of PSO used in this work are summarized in the following steps:

(1) Individual position and velocity initialization: In this step, n particles are randomly generated. Each particle is an m-dimensional vector, where m is the number of parameters to be optimized. In our study, n is a 3 dimensional vector which represents the value of real power (P_i), reactive power (Q_i), and locations of DGs (L_i). Thus, the position of individual i at iteration 0 is represented by:

$$X_{i,j}(0) = (P_{il}, \ldots\ldots P_{im}), (Q_{il}, \ldots Q_{im}), (L_{il}, \ldots L_{im}), \quad i = 1, \ldots n, \quad j = 1, 2, 3 \tag{12}$$

Here, the $X_{i,j}(0)$ is generated by randomly selecting a value with uniform probability over the jth optimized parameter search space $[X_j^{min}, X_j^{max}]$.
Similarly, each particle are randomly assigned an initial velocity by randomly selecting a value with uniform probability over the jth dimension $[-V_j^{max}, V_j^{max}]$. Thus, the velocity of individual I at iteration 0 is given by;

$$V_{i,j}(0) = (V_{il}, \ldots\ldots V_{im}) \quad I = 1, \ldots n, \quad j = 1, 2, 3 \tag{13}$$

where V_j^{max} has been applied to enhance the local exploration of the problem space [32]. In order to maintain the uniform velocity through all dimensions, the maximum velocity in the jth dimension has been obtained as:

$$V_j^{max} = (X_j^{max} - X_j^{min})/N, \quad N = \text{iteration number} \tag{14}$$

All other parameters, including the local best (Pbest), the global best (Gbest), and the inertial weight parameter are also initialized in this step.

(2) Velocity and position updating: During the flight, each particle knows its best value Pbest and its position up to that point. Moreover, each particle also knows the best value in