Electrical Power and Energy Systems 61 (2014) 305–317

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Optimum placement of active power conditioners by a dynamic discrete firefly algorithm to mitigate the negative power quality effects of renewable energy-based generators

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ARTICLE INFO

Article history:
Received 4 May 2013
Received in revised form 25 March 2014
Accepted 27 March 2014

Keywords:
Active power conditioner
Optimal placement
Dynamic firefly algorithm
Power quality
Electric vehicle
Dynamic optimization

ABSTRACT

This paper presents a novel solution for the optimal placement and sizing of active power conditioners in future smart distribution systems by using the dynamic discrete firefly algorithm. The proposed method aims to mitigate the power quality effects of hybrid renewable energy-based generators and electric vehicle stations in smart grids. A multi-objective optimization problem is formulated to improve the voltage profile, minimize the voltage total harmonic distortion, and reduce the total investment cost. The performance analysis of the proposed algorithm is conducted on a modified IEEE 16-bus test system by using Matlab software. The results are then compared with the conventional stationary firefly algorithm, hybrid improved genetic algorithm, and dynamic particle swarm optimization. The comparison proves that the proposed optimization algorithm is the most effective method among the other methods and that the proposed method can precisely determine the optimum location and size of active power conditioners in distribution systems.

Introduction

Environmental issues that are related to the CO_2 emissions of conventional power plants have gained considerable attention in the past decades. Thus, pollution-free renewable energy-based generators (REGs) such as photovoltaic (PV) systems and wind turbine (WT) or hybrid systems have been proposed as alternative sources of electricity, particularly in future smart distribution systems [1]. Upgrading or planning conventional distribution systems by using single or hybrid REGs have certain economic and operational advantages, such as improved power balance during peak demand and reduction in investment and operational costs because of the flexible REG capacities [2]. However, the use of dispersed and time-varying hybrid REGs results in bidirectional power flow, which either improves or worsens power quality (PQ)-related problems in smart distribution systems [3]. In addition to REGs, electric vehicle (EV) technology and electric vehicle stations (EVSs) are rapidly being developed to reduce oil dependence and minimize greenhouse gas emissions. However, the negative influence of EVs and EVSs on system performance and power quality such as voltage drop and harmonic distortion should be considered in system planning [4]. To mitigate the negative power quality effects of hybrid REGs and EVSs and to improve general power quality to meet the system baseline and standard requirements, suitable types of custom power devices (CPDs) such as active power conditioners (APCs) should be used in strategic locations based on economic feasibility.

To date, many heuristic optimization-based techniques have been proposed to solve the optimal placement and sizing problems of CPDs under a steady-state condition. Different objective functions and constraints have been introduced in heuristic optimization-based techniques to minimize device cost and mitigate certain power quality disturbances such as voltage sag and harmonic distortion. A fuzzy system has been applied to locate APCs optimally by minimizing harmonic distortion in active power systems [5]. The basic genetic algorithm (GA) and niching GA (NGA) have been applied to install several CPDs optimally such as the dynamic voltage restorer and thyristor voltage regulator to minimize the imposed costs caused by voltage sags and improve the overall network sag performance of power systems [6–8]. The applied NGA has the ability to explore a wider search space and decrease the probability of convergence in local optima. A binary gravitational search algorithm has also been proposed to solve the optimal placement problem of D-STATCOM and improve the reliability index of distribution systems [9]. Furthermore, given

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http://dx.doi.org/10.1016/j.ijepes.2014.03.062
0142-0615/

the discrete nature of the optimal placement and sizing problems of CPDs, several discrete optimization techniques such as discrete non-linear programming [10] and discrete particle swarm optimization (DPSO) [11,12] have been proposed to minimize the harmonic distortion and improve system reliability.

Considering the dynamic nature of real power systems and the operation dependency of REGs and EVSs to varying weather and loading conditions, the use of the steady-state conditions of system components and their operations is no longer applicable to system analysis. Therefore, certain system components cannot be accurately modeled in the steady state. For example, the quasi steady-state model of batteries, which is widely used in power system analysis, cannot represent the rapid variations of the performance characteristics of a battery bank at a fully discharged state. The same problem may arise for most REG systems when their characteristics vary with changing weather conditions. Therefore, given that time-to-time variations in system characteristics are necessary to apply the optimization process in hybrid power systems, the problem should be formulated as a dynamic optimization problem.

This paper presents a new optimization technique by using the dynamic discrete firefly algorithm (DDFA) to determine the optimal size and location of APCs in a distribution system with hybrid REGs and EVSs. A multi-objective problem is formulated to minimize the average voltage total harmonic distortion (THD_V), the voltage deviation at each sampling instant, and the total investment cost, which includes installation and incremental costs. The voltage limits, APC capacity limits, power flow limits, and THD_V for each individual bus are considered constraints in the optimization problem. To evaluate the performance of the proposed DDFA, a modified IEEE 16-bus test system consisting of an EVS and three REGs, including WT, PV, and fuel cell (FC) power generation systems, is used and simulated in Matlab. The results are compared with the results obtained by the stationary firefly algorithm (SFA), hybrid improved genetic algorithm (HIGA) [13], and DPSO [14] to evaluate the effectiveness and accuracy of the proposed DDFA.

System modeling

This section briefly discusses the applied dynamic model and required control methodology of REGs, EVSs, and APCs.

WT system model

Among the various types of WT, the doubly fed induction generator (DFIG)-WT is relevant to this study because of its advantages in improving power system stability and reliability during peak load or disturbance conditions. The DFIG also provides more flexibility in controlling active and reactive powers independently. The DFIG-WT is a three-phase machine with two stator windings, including power and control windings, and a special rotor cage that can operate in induction and synchronous modes. To model a DFIG-WT in synchronous mode with p_p pole pair, the voltages at stator and rotor windings can be expressed as follows [15]:

$$v_p = R_p i_p + j\omega_p \lambda_p + \frac{d\lambda_p}{dt} \tag{1}$$

$$v_c = R_c i_c + j(\omega_p - (p_p + p_c)\omega_r)\lambda_p + \frac{d\lambda_c}{dt} \tag{2}$$

$$v_r = R_r i_r + j(\omega_p - p_p\omega_r)\lambda_r + \frac{d\lambda_r}{dt} = 0 \tag{3}$$

where v, R, i, ω, λ, and p are the voltage, resistance, current, angular speed, mechanical angular displacement, and pole number, respectively; subscripts p, c, and r represent the power, control, and rotor windings, respectively.

In the same manner, the flux linkage vector for all types of winding can be defined as follows:

$$\lambda_p = L_p i_p + M_{pr} i_r \tag{4}$$

$$\lambda_c = L_c i_c + M_{cr} i_r \tag{5}$$

$$\lambda_r = L_{pr} i_p + M_{cr} i_c + L_r i_r \tag{6}$$

where L and M are the self and mutual inductance of the windings, respectively.

Therefore, the electromagnetic torque can be expressed as the following:

$$T_e = -\frac{3}{2} p_p \mathrm{Im}\left[\lambda_p^* i_p\right] - \frac{3}{2} p_c \mathrm{Im}\left[\lambda_c^* i_c\right] \tag{7}$$

If the d-axis of the rotating flux is aligned with the power winding flux linkage, the power winding reactive power and rotor speed can be controlled by the d- and q-axes of the control winding current. Figs. 1 and 2 present the detailed rotor side and grid-side converter control diagrams of the DFIG-WT based on the d- and q-axes current control. The rotor-side converter must inject variable rotor currents into the rotor circuit to attain decoupled active and reactive power control, where the grid-side converter must balance the power injected into the direct current (DC)-link capacitor and maintain a constant voltage [16].

PV system model

The electric characteristics of a PV unit are commonly expressed in terms of the current–voltage or power–voltage relationships of the cell. The equivalent electrical circuit of a typical crystalline silicon PV module is shown in Fig. 3a, where I, I_L, and I_d are the output terminal current, light-generated current, and diode current, respectively; R_s and R_{sh} are the internal resistance and shunt resistance of the module, respectively. The value of R_s strongly depends on the quality of the used semi-conductor, and any variations in R_s value can dramatically change the PV output [17]. Based on Fig. 3a, the output current of the module is expressed as follows:

$$I = I_L - I_d - \frac{V_o}{R_{sh}} \tag{8}$$

where V_o is the voltage on the shunt resistance.

By using the classical diode current expression [18] and ignoring the last term, the output current I can be rewritten as follows:

$$I = I_L - I_o\left(e^{q(V+IR_s)/nKT_r} - 1\right) \tag{9}$$

where I_o is the saturation current, q is the electron charge, n is the curve-fitting constant, K is the Boltzmann constant, T_r is the temperature, and n is the ideality factor, which has a value between one and two.

Furthermore, the saturation current I_o at different operating temperatures can be expressed as the following:

$$I_o = I_{o-Tr} \times \left(\frac{T}{T_r}\right)^{\frac{3}{n}} \times e^{\frac{-qV_g}{nK\times(1/T-1/T_r)}} \tag{10}$$

where

$$I_{o\text{-}T_r} = \frac{I_{sc\text{-}T_r}}{e^{\frac{qV_{oc\text{-}T_r}}{nKT_r}} - 1} \tag{11}$$

V_g is the band gap voltage, $V_{oc\text{-}Tr}$ is the open circuit voltage, and $I_{sc\text{-}Tr}$ is the short circuit current at the rated operating conditions.

The photocurrent I_L in Eq. (9) is directly proportional to the solar radiation level G (W/m^2) and can be expressed as follows: