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Reactive power and voltage control based on general quantum genetic algorithms

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ABSTRACT

This paper presents an improved evolutionary algorithm based on quantum computing for optimal steady-state performance of power systems. However, the proposed general quantum genetic algorithm (GQ-GA) can be applied in various combinatorial optimization problems. In this study the GQ-GA determines the optimal settings of control variables, such as generator voltages, transformer taps and shunt VAR compensation devices for optimal reactive power and voltage control of IEEE 30-bus and 118-bus systems. The results of GQ-GA are compared with those given by the state-of-the-art evolutionary computational techniques such as enhanced GA, multi-objective evolutionary algorithm and particle swarm optimization algorithms, as well as the classical primal-dual interior-point optimal power flow algorithm. The comparison demonstrates the ability of the GQ-GA in reaching more optimal solutions.

1. Introduction

During the history of science of computational intelligence many evolutionary algorithms (EA) were proposed having more or less success in solving various nonlinear engineering optimization problems. Among them the best are considered to be the popular particle swarm optimization (PSO) (Kennedy & Eberhart, 1995), the ant-colony systems (ACS) (Dorigo, 1992) and the cultural algorithms (Reynolds, 1994). In the last years the effort is continued by the same and other researchers generating more effective EA. The reason for the growing development of EA is that mathematical optimization methods, such as nonlinear programming, quadratic programming, Newton–Raphson based techniques, sequential unconstrained minimization and interior point algorithms, have failed in handling non-convexities and non-smoothness in engineering optimization problems. The main advantage of EA is that they do not require the objective functions and the constraints to be differentiable and continuous (Esmin, Lambert-Torres, & De Souza, 2005; Lee, 2005; Lee & El-Sharkawi, 2003; Lee & El-Sharkawi, 2002; Vlachogiannis & Lee, 2006a; Vlachogiannis, 2006). However, their main problem remains the same, the achievement of the global best solution in a short computing time.

The two above-mentioned aspects sparked off the introduction of a more robust EA based on quantum mechanics to solve real-world nonlinear constrained optimization problems. Specifically in this paper, the reactive power and voltage control problems are solved by means of a quantum computing inspired genetic algorithm. In general, quantum computing was introduced in the early 1980s by Feynmann (1986, 1982) and Beinoff (1980). Quantum computers will operate on superposition of all classical search states, allowing them to evaluate properties of all states in about the same time a classical machine requires for a single evaluation. Superposition is described by a state vector $\mathbf{S}$ (represented by symbol-ket $|\mathbf{S}\rangle$), consisting of complex numbers, called amplitude amplifications (Hogg & Portnov, 2000). Under these circumstances, quantum computing in the future could play a significant role in computer science. Recent researches (latest 1990s) face quantum computing as a new evolutionary technique reducing the complexity of global optimization problems. They can be classified in two fields: One focuses on generating new quantum algorithms using evolutionary techniques such as genetic programming (Malossini, Blanzieri, & Calarco, 2004; Rylander, Soule, Foster, & Alves-Foss, 2001; Spector, Barnum, Bernstein, & Swamy, 1999) and the other concentrates on quantum-inspired evolutionary computing for classical computers (Han & Kim, 2000, 2002, 2004; Narayanan & Moore, 1996; Wang, Tang, & Wu, 2005; Zhang, Li, Jin, & Hu, 2004). In the last field, some quantum genetic algorithms (QGA) have been recently proposed for some combinatorial optimization problems, such as travelling salesman problem (Narayanan & Moore, 1996), knapsack problem (Han & Kim, 2000, 2002, 2004), filter design (Zhang et al., 2004) and numerical optimization problem (Wang et al., 2005).

In this paper, a QGA named general quantum genetic algorithm (GQ-GA) for combinatorial optimization problems in power engi-

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neering is introduced. The proposed GQ-GA is characterized by theoretical background and search capability compared with state-of-the-art QGA (Han & Kim, 2000, 2002, 2004; Narayanan & Moore, 1996; Wang et al., 2005; Zhang et al., 2004) and other classical GA and meta-heuristic evolutionary techniques such as PSO. These achievements are based on the concept of quantum theory that one quantum state (q-gene) can represent at least the superposition of two single states. So, one individual (q-chromosome) in GQ-GA can represent many states at the same time and there are weak relationships between individuals (q-chromosomes) since each one of them is determined by current best solution and its probability, that is, the history of individual (q-chromosome) up to date (Hogg & Portnov, 2000).

Specifically, the proposed GQ-GA algorithm aims to determine the optimal settings of control variables, such as voltage magnitudes, transformer taps and shunt VAR compensation devices considered as q-chromosomes of GQ-GA for two optimization problems, namely minimization of (a) real power losses in transmission lines and (b) sum of voltage deviations on load busses. Results of GQ-GA on the networks of IEEE 30-bus and 118-bus system are compared to those given by other evolutionary computational techniques such as (a) the enhanced GA (Bakirtzis, Biskas, Zoumas, & Petridis, 2002) (next called classical GA), (b) multi-objective EA (Abido & Bakhashwain, 2005), (c) hybrid H-PSO (Esmin et al., 2005), (d) global variant (PSO-PC) based on passive congregation (Vlachogiannis, 2006), (e) local variant (CLONEPAC) PSO based on passive congregation (Vlachogiannis, 2006) and (f) PSO based on coordinated aggregation (CA) (Vlachogiannis & Lee, 2006a, 2006b), as well as classical primal-dual interior-point OPF algorithm (De Souza, Honorio, Torres, & Lambert-Torres, 2004). The comparison demonstrates the superior performance of GQ-GA in finding more optimal solutions.

The paper is organized as follows: the problems of reactive power and voltage control are formulated in Section 2. Section 3 presents the basic concept of quantum computing. Section 4 introduces the GQ-GA algorithm. Performance evaluation of GQ-GA in comparison with the other evolutionary computational and classical algorithms is presented in Section 5. Final conclusions and further research are outlined in Section 6.

2. Reactive power and voltage control

The proposed GQ-GA is tested and compared with other EA and conventional OPF algorithms on optimal steady state performance of power systems in terms of minimization of (a) power losses in transmission lines and (b) sum of voltage deviations on load busses while satisfying several equality and inequality constraints. Since the main focus of this paper is the performance evaluation of the first introduced GQ-GA, two nonlinear optimization problems are separately studied. It is noticeable that in the case of minimization of sum of voltage deviations, the objective function is very sensitive to the control variables. Thus, a clearer picture of the effectiveness of the proposed algorithm is given.

The first objective is to minimize the real power losses in transmission lines that can be expressed as

$$J_1 = P_{\mathrm{Loss}}(\mathbf{x},\mathbf{u}) = \sum_{l=1}^{Nl} P_l, \tag{1}$$

where $\mathbf{x}$ is the vector of depended variables, $\mathbf{u}$ is the vector of control variables, P_l is the real power losses at line-l and Nl is the number of transmission lines.

The second objective is to optimize the voltage profile of the power system. This is realized by minimization of the sum of voltage deviations at load buses that can be expressed by

$$J_2 = VD(\mathbf{x},\mathbf{u}) = \sum_{i=1}^{Nd} |V_i - V_i^{\mathrm{sp}}|, \tag{2}$$

where V_i is the voltage at load bus-i, V_i^{sp} is the pre-specified reference value at load bus-i, which is usually set at the value of 1.0 pu, and Nd is the number of load buses.

As search space in both problems, the following two vectors are considered:

$$\mathbf{x}^{\mathrm{T}} = [V_{L_1}, V_{L_2}, \ldots, V_{L_{Nd}}, Q_{G_1}, Q_{G_2}, \ldots, Q_{G_{Ng}}, S_{L_1}, S_{L_2}, \ldots, S_{L_{Nl}}], \tag{3}$$
$$\mathbf{u}^{\mathrm{T}} = [V_{G_1}, V_{G_2}, \ldots, V_{G_{Ng}}, t_1, t_2, \ldots, t_{NT}, Q_{C_1}, Q_{C_2}, \ldots, Q_{C_{NC}}], \tag{4}$$

where $\mathbf{x}$ is the vector of depended variables consisting of load bus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_L, and $\mathbf{u}$ is the vector of the control variables consisting of generator voltages V_G, transformer tap settings t, and shunt VAR compensations Q_C.

The equality constraints of both optimization problems are typical load flow equations as follows:

$$P_{G_i} - P_{D_i} - f_{P_i}(\mathbf{x},\mathbf{u}) = 0, \tag{5}$$
$$Q_{G_i} - Q_{D_i} - f_{Q_i}(\mathbf{x},\mathbf{u}) = 0, \tag{6}$$

where f_{P_i} and f_{Q_i} are the real and reactive power flow equations at bus-i, respectively; P_{G_i} and Q_{G_i} are the generator real and reactive power at bus-i, respectively; P_{D_i} and Q_{D_i} are the load real and reactive power at bus-i, respectively.

The inequality constraints in both problems represent the system operating constraints:

- *Generation constraints:* Generator voltages V_G and reactive power outputs Q_G are restricted by their limits as follows:

$$V_{G_i}^{\min} \leqslant V_{G_i} \leqslant V_{G_i}^{\max}, \quad i = 1, 2 \ldots, NG, \tag{7}$$
$$Q_{G_i}^{\min} \leqslant Q_{G_i} \leqslant Q_{G_i}^{\max}, \quad i = 1, 2, \ldots, NG, \tag{8}$$

where NG is the number of generators.

- *Switchable VAR constraints:* Switchable VAR compensations Q_C are restricted by their limits as follows:

$$Q_{C_i}^{\min} \leqslant Q_{C_i} \leqslant Q_{C_i}^{\max}, \quad i = 1, 2, \ldots, NC, \tag{9}$$

where NC is the number of switchable VAR sources.

- *Transformer constraints:* Transformer tap settings t are bounded as follows:

$$t_i^{\min} \leqslant t_i \leqslant t_i^{\max}, \quad i = 1, 2, \ldots, NT, \tag{10}$$

where NT is the number of transformers.

- *Functional operating constraints:* This term refers to the constraints of load voltages at load buses V_L and transmission line loadings S_L as follows:

$$V_{L_i}^{\min} \leqslant V_{L_i} \leqslant V_{L_i}^{\max}, \quad i = 1, 2, \ldots, Nd, \tag{11}$$
$$S_{L_i} \leqslant S_{L_i}^{\max}, \quad i = 1, 2, \ldots, Nl. \tag{12}$$

The inequality constraints (8), (11) and (12) are included in the objective functions (1) and (2) as penalty factors.

3. Quantum computing concept

The basic concept of quantum computing is addressed in this section (Han & Kim, 2000, 2002, 2004):

The smallest unit of information stored in a two-state quantum computer is called a quantum bit or qubit. A qubit may be in the