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Verification of Dependability on Parallel Particle Swarm Optimization Based Voltage and Reactive Power Control

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Abstract: This paper verifies dependability on parallel particle swarm optimization (PSO) based voltage reactive power control. Various evolutionary computation techniques have been applied to reactive power and voltage control (Volt/Var Control: VVC). High penetration of renewable energies and deregulation of power systems require to shorten an interval of the control. One of the practical solutions for this problem is applications of parallel and distributed computing with dependability, which is an ability to keep sustainable control against various accidents. Simulation results with IEEE 14, 30, and 57 bus systems indicate high dependability of the method.

Keywords: Voltage control, Parallel computation, Meta-heuristics, Particle swarm optimization, Dependability

1. INTRODUCTION

One of the important operating tasks of power utilities is to keep voltage within an allowable range in order to maintain high quality customer services,. Therefore, various equipment such as automatic voltage regulators (AVRs) of generators, on-load tap changers (OLTCs), static condensers (SCs), and shunt reactors (ShRs) should be handled in control centers, so that they can inject reactive power and control voltage directly in target power systems in order to follow the load change. VVC determines on-line control strategies in order to keep voltage of target power systems with the above equipment considering the load change and reactive power balance in target power systems.

Recently, reduction of power generation cost is one of the current interested issues of power utilities because of deregulated and competitive environments. Therefore, optimal control strategies in order to minimize power transmission losses is required for VVC in steady state operation conditions. VVC can be formulated as a mixed-integer nonlinear optimization problem (MINLP) with continuous state variables such as AVR operating values and discrete state variables such as tap positions of OLTCs and the number of reactive power compensation equipment such as SCs and ShRs. The objective function can be minimization of power transmission loss of the target power system for steady state operating conditions.

Various methods have been developed for the VVC problem such as fuzzy control, expert system, mathematical programming, and sensitivity analysis (Tomsovic, et al., 1992; Cova, et al., 1995; Ramos, et al., 1995; Le, et al., 1997). After meta-heuristic techniques have been recognized as one of the practical methods for the VVC problem formulated as a MINLP with continuous and various techniques (Fukuyama et al., 2000), various meta-heuristic techniques have been applied to the VVC problem such as genetic algorithm (GA) (Subbaraj, et al., 2009), PSO (Miranda, et al., 2002; Badar, et al., 2012), differential evolution (DE) (Wong, et al., 2007a; Ramirez, et al., 2011), seeker optimization (Dai, et al., 2009), artificial immune system (AIS) (Honorio, et al., 2007), artificial bee colony (ABC) algorithm (Ayana, et al., 2012), and harmony search (Khazali, et al, 2011).

High penetration of renewable energies and deregulation of power systems force power flow to change suddenly and operators in control centers have to control voltage in wider power systems. Therefore, VVC is required to shorten the control interval and handle larger-scale power systems. Namely, VVC is required to realize faster computation to larger-scale problems than ever before. One of the solutions for the problem is applications of parallel and distributed computing. Actually, some researchers have already tried to apply parallel and distributed computing techniques to VVC using meta-heuristic techniques only for realization of fast computation (Wong, et al., 2007b; Li, et al, 2009; Zhang, et al, 2010).

Power system is one of the infrastructures of social community, and sustainable voltage control is crucial for keeping various activities of the social community such as maintaining production of factories, operation of commercial buildings, daily life support in residential areas and so one. Namely, not only fast computation, but also sustainable control (dependability) is strongly required for VVC. From the viewpoint of dependability, meta-heuristic techniques with multiple searching points have a big advantage. Since the algorithms share information among the searching points, they have a possibility to get good solutions even if information from some searching points is not obtained sometimes during the searching process. This feature is crucial for practical applications of parallel and distributed computing techniques to VVC using parallel meta-heuristic techniques in actual operations. As far as the author knows, there are no researches on applications of parallel and

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distributed meta-heuristic techniques to VVC verifying dependability for sustainable control.

This paper presents verification of dependability for parallel particle swarm optimization based VVC. Fast computation and dependability of the parallel PSO has been investigated on IEEE 14, 30, and 57 bus systems. The paper is organized as follows: Section 2 describes a problem formulation of the VVC problem. Section 3 briefly explains a basic PSO, Parallel PSOs and dependability. Section 4 describes a parallel PSO algorithm for VVC. Section 5 describes numerical examples and conclusions are finally drawn in Section 6.

2. PROBLEM FORMULATION OF A VVC PROBLEM

This paper handles VVC in steady state operation conditions and the problem can be formulated as a MINLP with continuous and discrete variables as follows:

2.1 State Variables

The following control equipment is considered as state variables in the VVC problem.
(a)AVR operating value (continuous variable)
(b)OLTC tap position (discrete variable)
(c)The number of reactive power compensation equipment (discrete variable)
Namely, state variables include both continuous and discrete variables. The problem formulation using the above state variables can be expressed as follows.

2.2 Objective Function and Constraints

(1) Objective Function
The objective function is to minimize active power losses in the target power system in steady state operating conditions.

$$\text{minimize } f_c(x,y) = \sum_{i=1}^{n} Loss_i \quad (1)$$

where, n: the number of branches,
x : continuous variables,
y : discrete variables,
$Loss_i$: active power loss (Ploss) at branch i.
(2) Constraints
a) Voltage constraint
Voltage magnitude at each node must lie within its permissible range in order to maintain power quality.

$$V_{min} \le V_i \le V_{max} \quad (2)$$

where, V_i : Voltage at node i,
V_{min} : Minimum allowable voltage,
V_{max} : Maximum allowable voltage.
b) Power flow constraint
Power flow of each branch must lie within its permissible range.

$$Pflow_j \le Pflow_{max} \quad (3)$$

where, $Pflow_j$: Power flow at branch j,
$Pflow_{max}$: Maximum allowable power flow,
The above state variables are treated in load flow calculation as follows. AVR operating values are treated as voltage specification values at PV specific nodes. OLTC tap positions are treated as tap ratio to each tap position. Impedance of the transformer can be calculated using the tap ratio. The number of reactive power compensation equipment is treated as a corresponding susceptance value at PQ specific nodes. Reactive power injection can be calculated using the susceptance value.

3. PARALLEL PARTICLE SWARM OPTIMIZATION

3.1 Basic Particle Swarm Optimization (Kennedy and Eberhart, 2001)

PSO has been developed through simulations of simplified social models. The method is based on researches about swarms such as a school of fish and a flock of birds. PSO is basically developed through simulation of a flock of birds in two-dimension space. The position of each agent is represented by XY-axis position and the velocity (displacement vector) is expressed by vx (the velocity of X-axis) and vy (the velocity of Y-axis). Modification of the agent position is realized by using the position and the velocity information.

State variables (states and their velocities) can be expressed as vectors of continuous numbers. PSO utilizes multiple searching points for search procedures. In the basic PSO, velocity of the state equations can be expressed as follows:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \quad (4)$$

where, v_i^k : velocity of agent i at iteration k,
w : weighting function,
c_i : weighting coefficients,
$rand_i$: random number between 0 and 1,
s_i^k : current position of agent i at iteration k,
$pbest_i$: pbest position of agent i,
gbest : gbest position of the group.
The following weighting function in (4) is usually utilized in the basic PSO (inertia weights approach (IWA)):

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (5)$$

where, w_{max} : initial weight,
w_{min} : final weight,
$iter_{max}$: maximum iteration number,
iter : current iteration number.
The current position (searching point in the solution space) can be modified by the following state equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (6)$$

The procedure of the basic PSO algorithm can be expressed as follows (See fig.1):
(1) Generation of initial searching points (Step 1 in fig.1)
Initial conditions of searching points are usually generated randomly within their allowable ranges.
(2) Evaluation of searching points (Step 2 in fig.1)
The current searching points are evaluated by the objective function of the target problem. Pbests and gbest can be modified by comparing the evaluation values of the current searching points, and current pbests and gbest.
(3) Modification of searching points (Step 3 in fig.1)