Neurocomputing 148 (2015) 175–180

Contents lists available at ScienceDirect

Neurocomputing

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

Particle swarm optimization for power system state estimation

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ARTICLE INFO

Article history:
Received 24 April 2012
Received in revised form
27 October 2012
Accepted 29 October 2012
Available online 29 July 2014

Keywords:
State estimation
Power system
Artificial intelligence
Particle swarm optimization
Genetic algorithm

ABSTRACT

The electrical network measurements are usually sent to the control centers using specific communication protocols. However, these measurements contain uncertainties due to the meters and communication errors (noise), incomplete metering or unavailability of some of these measurements. The aim of state estimation is to estimate the state variables of the power system by minimizing all measurement errors available at the control center. In the past, many traditional algorithms, based on gradient approach, have been used for this purpose. This paper discusses the application of an artificial intelligence (AI) algorithm, the particle swarm optimization (PSO), to solve the state estimation problem within a power system. Two objective functions are formulated: the weighted least square (WLS) and weighted least absolute value (WLAV). The effectiveness of PSO over another AI optimization algorithm, genetic algorithm (GA), is shown by comparing both two solutions to the true state variable values obtained using Newton–Raphson (NR) algorithm.

1. Introduction

It is important for the energy management system (EMS) applications in a power system control center that the measurements allow monitoring of this power system. With the increase interest in integration of more distributed generations (DGs) to the power system, the EMS center needs to have real-time and accurate estimate values of loads, voltage magnitudes, generator and DGs power outputs, etc. required for a good management and planning of the network. This is only possible if all state variables (voltage magnitudes and angles at each bus) of the power system are known. However, only few measurements which usually contain errors are available at this center [1]. State estimation is an important tool for EMS, which makes it possible to estimate the state variables of the power system based on the limited measurements. State estimation algorithms fit measurements made on the system to a mathematical model in order to provide a reliable data base for other monitoring, security assessment and control functions [2]. Much research has been undertaken on state estimation techniques, and online state estimators are being implemented in many power network. In the application of state estimation, consideration must be given to a number of practical difficulties. Telemetered values are subject to random noise and also to gross errors associated with equipment malfunction [3].

To solve the power system state estimation (PSSE) problem, several authors have used traditional approaches based on derivative method such as Newton, Gradient descent, linear programming methods, etc. [2,4–6]. However, it has been shown that these traditional methods present some inadequacies. The Newton and Gradient methods both suffer from the difficulty in handling inequality constraints [7]. On the other hand, the linear programming method suffers from oscillation and slow convergence problems when the iterative step is not selected properly during the linearization of both objective and constraint functions [8].

A common limitation of traditional optimization methods is the fact that they are local minima-based algorithms while the PSSE is highly nonlinear problem. The high nonlinearity characteristic of PSSE causes the search space of this problem to have several local minima, which may lead to a local solution instead of a global one [9]. A local solution of PSSE search space would therefore lead to a huge error between the estimated state variables and their corresponding true values. Moreover, it is known that if the initial state variable values are not well selected, the traditional methods will suffer from the convergence problem. The other issue of these algorithms is their computational complexity and restrictions that are usually imposed on the objective function like differentiability, continuity, or convexity [10].

Artificial intelligence (AI) algorithms are considered as a powerful tool in solving nonlinear and complicated search space [11]. The advantage of AI algorithms is due to the fact that they only require the fitness function (performance index or objective function) to guide the search, unlike the traditional algorithms which need gradient (derivative) information. One of AI algorithms is the particle swarm optimization PSO which has many

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http://dx.doi.org/10.1016/j.neucom.2012.10.049
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advantages over other AI algorithms such as genetic algorithm (GA) [10,12]. PSO allows lower computational time and memory compared with GA, and can be easily programmed with basic mathematical and logic operation. It also requires less parameter tuning [10]. With this in mind, this paper takes over the advantages of PSO in solving PSSE problem.

The corruption of telemetered raw data measurements is simulated by introducing statistically a random error in the measurements obtained after running Newton–Raphson (NR) load flow algorithm. The solutions obtained from load flow (before introducing errors) are therefore considered as true solutions and used as benchmark solutions in evaluating the effectiveness of PSO solutions. Genetic algorithm (GA) is used in order to evaluate the PSO performance over this other AI algorithm. Since this work is not aimed at GA and NR algorithms, the reader may refer respectively to references [13–15] for information about these two algorithms. Two approaches in solving state estimation problem, the weighted least square and weighted least absolute value, are used. Matlab is used for simulation.

2. State estimation

The general estimation consists of estimating the state vector x based on a set of measurements z in the presence of an error e. A mathematical model describing the functional relations between z, x and e is described in Eq. (1) [2,16,17]. This model is expressed in the form of a set of nonlinear equations which relates the measurements z and the true state vector x.

$$z_i = f_i(x) + e_i \quad \text{or} \quad e_i = z_i - f_i(x) \tag{1}$$

where

$i = 1, 2, 3, \ldots, m$

z_i is the ith measurement (measurement vector of dimension m);
$f_i(x)$ is the nonlinear function relating state variables with measurements. This is usually the power injections or power flow equations.
x is the state vector of dimension n;
e_i is the ith measurement noise vector;
m: the number of measurements.

Power state estimation is therefore based on minimizing the sum of all errors between available measurements and calculated measurement variables contained in the function $f(x)$. For the safe operation of the power system, boundary constraints are set for each state variable.

The problem of state estimation is usually formulated as a weighted least squares (WLS) problem, which is solved by efficient numerical techniques [18]. The objective function to be minimized is chosen as a weighted sum of squares of the measurement residual. However, WLS method is highly sensitive to bad data in the measurement set [3]. In order to avoid this, a different formulation of the state estimation problem has been used. It defines the sum of the weighted absolute values of the measurement residuals as the objective function. Due to its automatic bad data rejection property, WLAV estimation method is used in topology errors identification [18].

2.1. WLS methods

The weighted least square (WLS) estimate can be found by minimizing the following objective function [18]:

$$\min \quad J(x) = \sum_{i=1}^{m} w_i^2 (z_i - f_i(x))^2 = \sum_{i=1}^{m} \frac{1}{\sigma_i^2} (z_i - f_i(x))^2 \tag{2}$$

where,

σ_i^2 is the variance of ith measurement;
$i, m, e_i, f_i(x)$ are the same as defined previously;
w_i is the weight of the measurement i.

2.2. WLAV methods

The weighted least absolute value (WLAV) estimate for x can be found by minimizing the following objective function [18]:

$$\min \quad J(x) = \sum_{i=1}^{m} w_i |z_i - f_i(x)| \tag{3}$$

All the parameters and variable in Eq. (3) are above defined.

The nonlinear functions containing the state variable to be estimated $f_i(x)$ are the active and reactive power injections, active and reactive power flows, whose equations can be found from [18]. In this work, only some bus voltage magnitudes and power injections are assumed to be measured. The active and reactive power injections are given in polar form, as follows:

$$P_i = V_i \sum_{j=1}^{NB} V_j |Y_{ij}| \, \text{Cos} \, (\delta_i - \delta_j - \theta_{ij}) \tag{4}$$

$$Q_i = V_i \sum_{j=1}^{NB} V_j |Y_{ij}| \, \text{Sin} \, (\delta_i - \delta_j - \theta_{ij}) \tag{5}$$

where:

- P_i is the active power injection at bus i;
- Q_i is the reactive power injection at bus i;
- V_i and V_j are voltage magnitude at bus I and j;
- δ_i and δ_j are voltage angles at bus I and j;
- $|Y_{ij}|$ is the magnitude of bus-admittance element i,j and θ_{ij} its angle;
- NB is the number of bus.

Eqs. (4) and (5) represent different functions $f_i(x)$ in Eqs. (1)–(3) whose voltage magnitudes and angles are to be estimated for a given set of available measurements z_i.

2.3. Constraints

The constraints of this problem are the limits of each state variable, which are the voltage magnitude and voltage angle at each bus of the network. These constraints are respectively, given as follows:

$$V_i^{min} \le V_i \le V_i^{max} \tag{6}$$

$$\delta_i^{min} \le \delta_i \le \delta_i^{max} \tag{7}$$

3. Overview of the proposed algorithm

3.1. Particle swarm algorithm principle

Particle swarm optimization (PSO) is one of the artificial intelligence (AI) algorithms introduced by Kennedy and Eberhart