International Journal of Engineering & Technology, 7 (3.28) (2018) 214-217

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

The Comparison Study Among Optimization Techniques in Optimizing a Distribution System State Estimation

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Abstract

State estimation considered the main core of the Energy Management System and plays an important role in stability analysis, control and monitoring of electric power systems. Therefore, accurate and timely efficient state estimation algorithm is a prerequisite for a stable operation of modern power grids. These papers introduce an intelligent centralized State Estimation method based on Firefly algorithm for distribution power systems. The mathematical procedure of distribution system state estimation which utilizing the information collected from available measurement devices in real-time. A consensus based static state estimation strategy for radial power distribution systems is proposed in this research. The states of these systems are first estimated through centralized approach using the proposed algorithm to compare with power flow algorithm. The result a proved to be computational efficient and accurately evaluated the impact of distributed generation on the power system. In addition, the proposed FA show faster with increasing the number of buses**.**

Keywords: *Estate Estimation; Power System; Firefly Algorithm.*

1. Introduction

The world today is more dependent on electrical energy than any other form of energy. State estimation is a tool that is widely used in electrical energy control centres to improve the quality of directly telemetered data, to provide a way for direct monitoring of network conditions. The state estimation also provide the best available estimate of network model that can be used as a starting point for further real-time power system application such as Voltage Automatic Regulation (VAR) optimization, contingency analysis, congestion management, and constrained re-dispatch [1-3]. State estimation and its subordinate applications such as parameter estimation, bad data identification, breaker status estimation, and external model estimation are widely used in industry with different degrees of success.
In power system state estimation, a measurement may contain gross error because of communication noise, incorrect sign convention or measurement device failure. These measurements are called bad measurements (data) and can lead to biased estimates. Therefore, it is important to implement robust state estimators. Estimators with high breakdown points, which are the smallest amount of contamination that can cause an estimator to give an arbitrarily incorrect solution [4] have been investigated and developed by researchers. Some of these have also been applied to power system state estimation. Among these robust estimators [5], the Least Absolute Value (LAV) estimator was shown to have desirable properties where its implementation can be made computationally efficient by taking advantage of power system's properties [6].
In this paper, a novel framework to perform Firefly algorithm based dynamic state estimation in a distributed way is proposed considering increasing complexity associated with large-scale power system. According to Dynamic State Estimation (DSE) can be implemented in a distributed environment by decomposing the systems into subsystems to increase the computational speed of DSE process in large scale power systems [7]. To validate the proposed algorithm based on (FA) compared with Weighted Lease Square (WLS), GA, and PSO, estimation for standard IEEE 14 bus.

2. Related Work

2.1. Power State Estimation

State Estimation (SE) plays a key role in security frameworks as one of the major application used in energy management system (EMS) [8]. Describe the role of SE in power systems control centre in above Figures. This includes a survey about the numerical algorithms for state estimation, topology processing, bad data identification, and network observability. The SE accesses measurements from monitored areas of the control centre to determine the best estimate of the state of the power system based on these redundant measurements [9]. The state of the power system refers to voltage magnitude and angle at every bus of the control area, since other attributes of the power system, such as the real and reactive power injections at each bus can be calculated from the state variables.
The convergence property of the WLS state estimator is a critical issue for real time monitoring and control of power grids. In addition to the three reasons mentioned in the last section that cause ill-conditioned gain matrix, the topology error can also cause the WLS state estimator to diverge without reaching a solution. The

fact that the WLS did not converge due to the existence of a topology error was an indirect factor leading to the blackout. Besides, it is known that the load levels became severe before the blackout. The impact of topology errors on the convergence characteristics of the WLS state estimator during the blackout when the loads gradually increase. Topology errors can be broadly classified in two categories: branch status errors and substation configuration errors. Branch status errors include branch exclusion error and 18 branches inclusion error.

Selective monitoring of the generation and transmission system has been providing the data needed for economic dispatching and load frequency. Besides this, the task of operate the system safely has become more difficult. To help avoid major system failures and regional power blackouts, electric utilities have installed more extensive Supervisory Control and Data Acquisition (SCADA) [10]. Throughout the network to support computer based systems at the operations control centre. Continuously, the SCADA system receives measurements of state variables on the power system networks. Transducers from power system measurements are subject to errors (bad data) like any measurement devices. If errors are relative small, the errors may be undetected. Besides, if the errors are considerable, the output of the measurement devices may be unacceptable and/or useless. In power systems, the voltage magnitudes and the phase angles at buses are the primary state variables. Normally, the process is surrounded by imperfect measurements. Therefore, the process is based on statistical criteria of the true values of the state variables in order to minimize a selected objective.

2.2 Global Optimization Methods

In most cases, the objective functions in nonlinear optimization problems are not convex. Traditional optimization methods (such as gradient-based approaches) can only find local optimal values [3, 11]. Moreover, the results from traditional optimization methods often have strong connections with the initial values. To overcome these problems, global optimization methods are suggested in this paper. Global optimization methods can only guarantee to achieve acceptable solutions. Usually, finding the global optimal results will take plenty of time and resources. Sometimes it is not profitable to do so. If the improvement is insignificant, then it is probably a bad deal to take the time to find the global optimal solution. Therefore, if the result is very close to the global optimal solution, it can be viewed as an acceptable solution. In global optimization methods, some concessions have to be made (for instance, increasing their objective function values in some iterations) to allow potential solutions to escape from the local optimum. Most of the time, there is no way to determine if a global optimal value is already achieved or not, so global optimization methods usually need to take plenty of iterations without bias. This requirement will in turn force the scheme of the global optimization methods to be as simple as possible. In the following sections of this chapter, two of the most representative heuristic global optimization methods (Genetic Algorithm, and Particle Swarm Optimization) are introduced. These three global optimization methods can be easily programmed and are well suited for solving reactive power dispatch problems [12].

3. Methodology

The proposed method utilized in this paper is focused on find the optimum state estimation for distributed network. The first part developing power and load flow simulation tool using M-file MATLAB software which is an integer optimization problem where by the results will either be the selected bus to increase load or line contingency for any transmission line.

At each iteration, every particle determines a possible set of estimated values for voltages magnitudes and voltages angles. Then, they are used to calculate the other estimated values such as real and reactive loads, real and reactive power generation at buses, and real and reactive power flow through the transmission lines. Once all the estimated values are obtained [13], the fitness function described below is evaluated as in (1):

$$J = \min \left\{ \begin{array}{l} \left[\sum_{i=1}^{N_b} \frac{\left[V_i^{meas} - V_i^{est}\right]^2}{\sigma_{V_i}^{\,2}}\right] + \left[\sum_{i=1}^{N_G} \frac{\left[P_i^{meas} - P_i^{est}\right]^2}{\sigma_{P_i}^{\,2}}\right] + \left[\sum_{i=1}^{N_L} \frac{\left[P_i^{meas} - P_i^{est}\right]^2}{\sigma_{P_i}^{\,2}}\right] + \\ \left[\sum_{i=1}^{N_G} \frac{\left[Q_i^{meas} - Q_i^{est}\right]^2}{\sigma_{Q_i}^{\,2}}\right] + \left[\sum_{i=1}^{N_b} \frac{\left[Q_i^{meas} - Q_i^{est}\right]^2}{\sigma_{Q_i}^{\,2}}\right] + \\ \left[\sum_{i=1}^{N_T} \frac{\left[P_{flow}^{\ meas} - P_{flow}^{\ est}\right]^2}{\sigma_{P_{flow}}^{\ \ 2}}\right] + \left[\sum_{i=1}^{N_b} \frac{\left[Q_{flow}^{\ meas} - Q_{flow}^{\ est}\right]^2}{\sigma_{Q_{flow}}^{\ \ 2}}\right] + \end{array} \right\} \quad (1)$$

where

Nb: number of buses

NG: number of generation buses

NL: number of load buses

NT: number of transmission lines measurement

Vi: measured value for the voltage magnitude at bus i

V_i^{est} : estimated value for the voltage magnitude at bus i

σ_{Vi}^2: variance of the measurement of the voltage magnitude at bus i

P_i^{meas} : measured value for the real power injection at bus i

P_i^{est} : estimated value for the real power injection at bus i

σ_{Pi}^2: variance of the measurement of the real power injection at bus i

Q_i^{meas} : measured value for the reactive power injection at bus i.

Q_i^{est} : estimated value for the reactive power injection at bus i.

σ_{Qi}^2: variance of the measurement of the reactive power injection at bus i

P_{flow}^{meas} : measured value for the real power flow through transmission line k.

P_{flow}^{est}: estimated value for the real power flow through transmission line k.

σ_{Pflow}^2: variance of the measurement of the real power flow through transmission line

Q_{flow}^{meas} : measured value for the reactive flow through transmission line k.

Q_{flow}^{est}: estimated value for the reactive flow through transmission line k.

σ_{Qflow}^2 : variance of the measurement of the reactive flow through transmission line k

In a power system network, the measured quantities are MW, MVAR, MVA, and voltage magnitude. These quantities are represented by zi in (1). As presented before, fi represents functions dependable of estimated values (x1, x2,…, xN). These functions are nonlinear functions and are used to calculate the estimated values corresponding to measured values zi. Only the voltage magnitude functions are linear, where fi is simply unity times the particular xi that corresponds to the voltage magnitude being measured. The following expressions correspond to the fi functions of power injections and flows: Estimation of real power injected into the system at bus i is represented in (2):

$$P_i = \sum_{j=1}^{Nb} \{|V_i| \times |V_j| \times [G_{ij} \times \cos(\theta_i - \theta_j) + B_{ij} \times \sin(\theta_i - \theta_j)]\}$$

Estimation of reactive power injected into the system at bus i:

$$Q_i = \sum_{j=1}^{Nb} \{|V_i| \times |V_j| \times [G_{ij} \times \sin(\theta_i - \theta_j) + B_{ij} \times \cos(\theta_i - \theta_j)]\}$$

Estimation of real power flow through transmission line i-j:

$$P_{ij} = |V_i|^2 (G_{ij}) - |V_i| \times |V_j| \times [G_{ij} \times \cos(\theta_i - \theta_j) + B_{ij} \times \sin(\theta_i - \theta_j)]$$

Estimation of reactive power flow through transmission line i-j:

$$Q_{ij} = -|V_i|^2 \left(\frac{B_{capij}}{2} - B_{ij}\right) - |V_i| \times |V_j| \times [G_{ij} \times \sin(\theta_i - \theta_j) + B_{ij} \times \cos(\theta_i - \theta_j)]$$

where:
Pi: real power injection at bus i
Qi: reactive power injection at bus i
Gij: transfer conductance between buses i and j
Bij: transfer susceptance between buses i and j
θ_i : voltage angle at bus i
θ_j: voltage angle at bus j
Bcapij: total line-charging susceptance of transmission line between buses i and j

These steps had been applied to all non-dominated solutions in Et, which enabled the algorithm to discover the less congested area in the external archive as shown in **Error! Reference source not found.**.

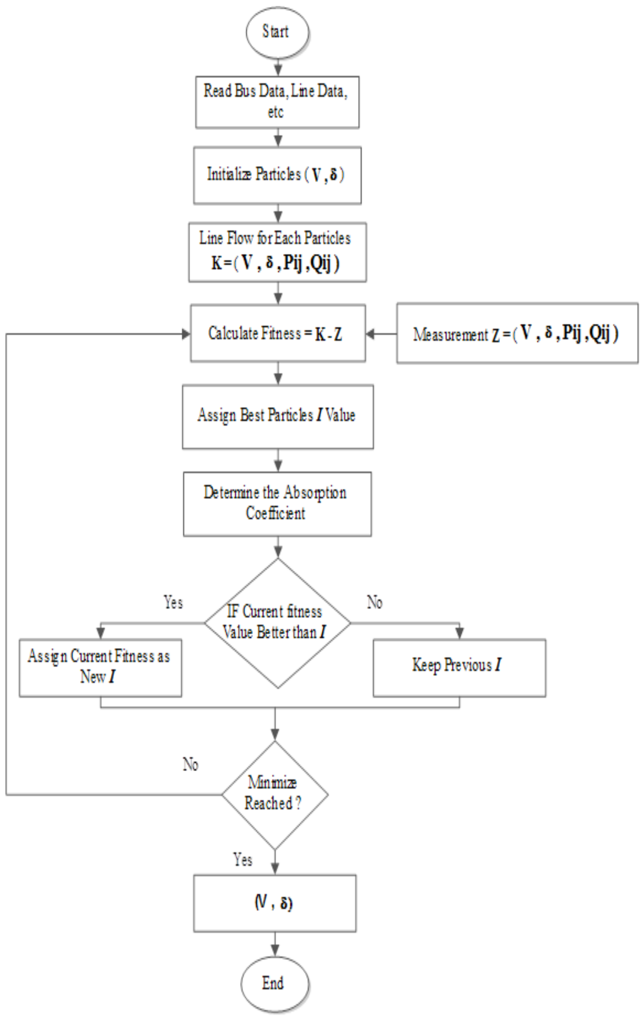

Fig. 1: Proposed method using Firefly Algorithm technique

4. Results and Discussion

The IEEE 14 Node Distribution Feeder is an actual feeder with a nominal voltage of 12.66 kV. The test case was slightly modified in order to properly evaluate the impact of state estimation on the various power system parameters. More validation for proposed FA compared with PSO and GA [14] based on IEEE 14 bus system. **Error! Reference source not found.** shows this test system 32 measurements as 14 bus active power, 14 bus reactive power, and four voltage magnitudes at bus 1, 7, 11 and 14.

(3)

(4)

Table 1: Measured values for IEEE 14-bus

Bus	V	Q	P
1	1.0653	0.1473	2.3219
2	–	0.3680	0.1994
3	–	0.0833	0.9397
4	–	0.0478	0.4783
5	–	0.0214	0.0693
6	–	0.1610	0.1113
7	1.0514	0.0007	0.0101
8	–	0.2094	0.0111
9	–	0.1766	0.2946
10	–	0.0727	0.0661
11	1.0143	0.0136	0.0395
12	–	0.0057	0.0572
13	–	0.0536	0.1298
14	1.0221	0.0476	0.1477

This can be seen from
Table for the voltage magnitudes estimation and from Table 3 for the voltage angles estimation. It can be inferred from the results that the FA have a much better estimate for voltage magnitudes and voltage angles than the original PSO, GA methods gives a better accuracy when estimating the voltage magnitudes and angles.

Table 2: Comparison voltage estimation using Load Flow, FA, PSO and GA

Bus	Load Flow	FA	PSO	GA
1	1.06	1.0608	1.061	1.061
2	1.045	1.0449	1.0448	1.0427
3	1.01	1.01	1.01	1.0110
4	1.0132	1.0133	1.0134	1.0142
5	1.0166	1.01648	1.0163	1.0171
6	1.07	1.0702	1.0706	1.0711
7	1.0457	1.0457	1.0457	10.0471
8	1.08	1.08005	1.0801	1.0871
9	1.03	1.0293	1.0296	1.0316
10	1.0299	1.03	1.0301	1.0306
11	1.0461	1.04605	1.0460	1.0459
12	1.0533	1.0534	1.0537	1.0547
13	1.0466	1.04635	1.0461	1.0461
14	1.0193	1.0191	1.0191	1.0190

Table 3: Comparison power angle estimation using Load Flow, FA, PSO and GA

Bus	Load Flow	FA	PSO	GA
2	-4.9891	-4.98908	-4.989	-4.999
3	-12.7492	-12.7492	-12.7491	-12.75
4	-10.242	-10.2421	-10.2422	-10.2429
5	-8.7601	-8.76023	-8.7604	-8.7611
6	-14.4469	-14.4468	-14.4466	-14.446
7	-13.2368	-13.2369	-13.237	-13.237
8	-13.2368	-13.2368	-13.2371	-13.2371
9	-14.8201	-14.8204	-14.8207	-14.821
10	-15.036	-15.0362	-15.0363	-15.0369
11	-14.8581	-14.8582	-14.8582	-14.86
12	-15.2973	-15.2972	-15.2975	-15.2978
13	-15.3313	-15.3315	-15.3314	-15.332
14	-16.0717	-16.0718	-16.072	-16.0719

Table Error! **No text of specified style in document.** shows the computational time for the performances of each algorithms using FA, PSO, and GA. The FA and PSO are quite close and have a better computation time than the GA. The time computation difference is due to related to update velocity and position calculation process. In addition, the proposed FA show faster with increasing the number of buses.

Table Error! No text of specified style in document.**:** Computation time (second)

System	FA	PSO	GA
IEEE14	0.238	0.250	1.9

5. Conclusion

In this paper, the proposed firefly for a distributed state model and a consensus based static SE method for smart distribution grid. Decentralized power system state estimation has been treated here in a unified and systematic manner. Specially consider the case when for each agent, the local measurement model is underdetermined and all state elements for a particular agent is completely shared with its neighbours. It has been shown that the developed method FA is practical for current power systems and these methods have also been demonstrated on a benchmark power system model. Simulation results radial distribution on a grid show that the proposed method can give satisfactory convergence based on the appropriate selection of agents. The advantages of the Firefly Algorithm are high computational efficiency; accuracy is similar to the integrated solution.

Acknowledgement

The author wishes to thank for the Fundamental Research Grant Scheme (FRGS), which the number is FRGS/1/2016/TK04/FKE-CERIA/F00306 for the funding to support this project and also to thanks to UTeM in providing the facilities and research environment.

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