Journal of Engineering and Applied Sciences 12 (20): 5160-5165, 2017
ISSN: 1816-949X

A Novel Firefly Algorithm for Distribution System State Estimation

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Abstract: Estimation (SE) techniques play important rule to anticipate security possibilities and operation control. Optimizing SE gives a better quicker update on the state operation of the power system without nature of system modelling. In this study, distrusted power system state estimation based on firefly was proposed. Various scenarios including normal operation where centralized and decentralized power area introduced. The IEEE 13 bus systems tested and the results are compared with those obtained Weighted Lease Square (WLS) to demonstrate the validity of the proposed approach.

Key words: State estimation, distributed network, firefly, power system, possibilities, validity

INTRODUCTION

State Estimation (SE) plays important role in power systems control center to better secure operation. Using the state estimation solution operators can determine if the current operating state of the system belongs to a normal, emergency or restorative state. State estimators also provide efficient and accurate monitoring of operational constraints on quantities such as bus voltages and loadings of transmission line (Abur and Exposito, 2004).

Several publications introduce different state estimation according centralize, decentralize estimation and balance and unbalance load using conventional and advance computational algorithm (Gomez *et al*., 2011; Alam *et al*., 2015; Taher and Karimi, 2014). The SE techniques had been developed separately for the transmission line and the distribution network. But the increasing requirement for communication and interaction between transmission and distribution network management systems has led to the development of multilevel or hierarchical SE's which integrate SE and Distribution System State Estimation (DSSE). Lu *et al*. (1995) reviewed and proposed future develop in distribution system state estimation. Hansen and Debs (1995) proposed specific formulations for three phase state estimation models adapting the traditional Weighted Least Square (WLS) method. Chang *et al*. (2007) suggest forward-backward neural network for state estimation procedure using the traditional sweep method. Yeleti (2011), Alsaadi and Gholami (2009) provide the result that multi-stage estimator's takes longer time than the conventional SE methods in term of computational efficiency. The advances of modern intelligent estimation methods such as Artificial Neural Networks (ANNs), Particle Swam Optimization (PSO) and Genetic Algorithms (GAs) have solved the computation time in better extent (Mosbah and El-Hawary, 2016; Hu *et al*., 2016a, b).

This study focus on distribution system state estimation using firefly algorithm. It begins with a brief history of the significance of power system state estimation followed by the presentation of the traditional form of state estimation. It continues with the development of the conventional state estimation equations and then investigates the planned implementation of a decentralized state estimation on two test systems and the associated research and software development. The developed algorithm is tested on 13 bus balanced distribution systems.

Literature review

Weight Least Square Algorithm (WLSA): One of the most prominent static state estimation method based on observation space is Weighted Least Square (WLS) technique (Li, 1996). The WLS algorithm was proposed to solve the static state estimation but its effect was not recognized by industry initially (Deng *et al*., 2000).

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Fortunately, a revised version based on the operational experience from power utilities was developed soon and widely accepted. WLS obtains states of the system that minimize the squared residual error, weighted by noise variances. Let us consider a system whose state vector is x having L elements. In general, nonlinear relationship exists between measurements and x which can be described as:

$$z = \begin{bmatrix} z_1 \\ . \\ . \\ . \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(x_1, x_2, ..., x_n) \\ h_m(x_1, x_2, ..., x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ . \\ . \\ . \\ e_m \end{bmatrix} = h(x) + e \quad (1)$$

Where:

$z \in \mathbb{R}$ = The measurement vector

e = A vector of independent and identically distributed Gaussian noise with zero mean and covariance C.

$h: \mathbb{R}^L \rightarrow \mathbb{R}^M$ = A vector of functions that non-linearly maps state elements to measurement set z

There are several approaches that can be used to obtain the minimum sum of residuals. The Weight Least Square (WLS) algorithm is a popular one due to its greater applicability. The WLS algorithm aims to minimize the sum of the square weighted residuals. For M>>L, the Eq. 1 (Huang *et al*., 2012) becomes over determined system of nonlinear equations. The objective function is given as:

$$J = \arg\min_x \left[z - h(x)\right]^T C^{-1} \left[z(-h(x)\right] \quad (2)$$

Basic firefly algorithm: To develop firefly-inspired algorithms we need to idealize important of the flashing characteristics of fireflies. The Firefly Algorithm (FA) simply described by based on three rules as follows: Unisex of all fireflies therefore each firefly can be attracted to the others regardless of their sex; the brightness is the threshold of attractiveness, so any two flashing fireflies, the less brighter one will move towards the brighter one and same if they both decrease as their distance increases. The landscape of the objective function will dependence on the effect of brightness of a firefly. For optimization problem such as maximization, the brightness will be proportional to the higher value of the objective function. Algorithm 1 shows the main steps of the Firefly Algorithm (FA) based on these three rules can be summarized as follows:

Firefly algorithm:

```
Objective function f (x), x = (x11, ..., xd)^T
Generate initial population of fireflies xi (i = 1, 2, ..., n)
Light intensity Ii at xi is determined by f (xi)
Define light absoiption coelficient γ
While (t<MaiGeneiation)
for i = 1: n all n fireflies
   for j = 1: i all n firefiles
      if (Ij>Ii), move firefly i towards j in d-dimension; end if
      Attractiveness varies with distance r uia exp[-γr]
      Evaluate new solutions and update light intensity
   end for j
end for i
Rank the fireflies and find the current best
end while
Postprocess results and visualization
```

MATERIALS AND METHODS

Proposed method: In order to reach the optimal level of pilot tones, the WLS was used as the objective function for firefly Local Search (LS) algorithm. Moreover, in order to improve the solution quality an LS scheme was carried out where it explored the area less congested in the current archive that may obtain more non-dominated solutions. Figure 1 show the block diagram for state estimation FALS algorithm. These steps had been applied to all non-dominated solutions in E^t which enabled the algorithm to discover the less congested area in the external archive as shown in Algorithm 2.

Proposed state estimation Algorithm 2 (steps of proposed state estimation):

The following algorithm is used for the state estimation.
Step 1) input data
Network configuration, line impedance
Contracted load value
Measurement data
Step 2) set calculation conditions

- Calculation of initial values of state variables

Using measurement data and state variables, initial load-flow calculation is performed.

- Set upper and lower bounds of state variables

Using the results of initial load-flow calculation, the upper and lower bounds of each state variable can be calculated.
Step 3) State estimation
Use parallel PSO algorithm
Step 4) Converge criteria
The algorithm stops looking for a solution if the maximum of a variation of the state variable Xx is smaller than 0.001 and the iteration have reached the maximum number of iteration specified
Setp 5) Bad data detection and identification

- Detection

The method used for bad data detection is the Chi-squarest test.

- Identification

Upon detection of bad data in the measurement set, their identification can be accomplished by further processing of the residuals, namely the Largest Normalized residual test.

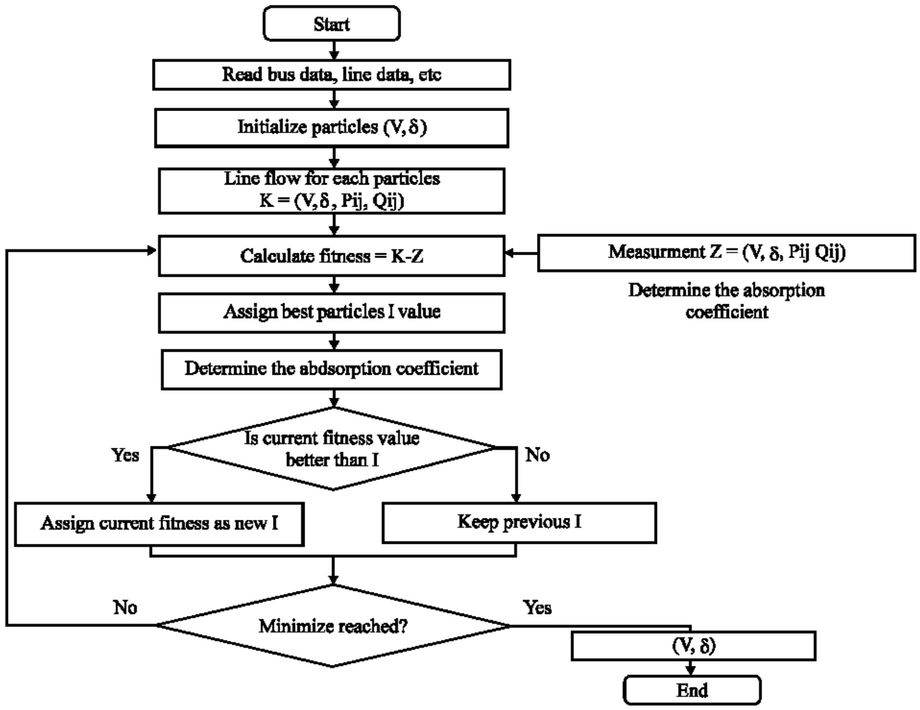

Fig. 1: Proposed firefly estimation technique

RESULTS AND DISCUSSION

Description of test systems: Figure 2 shows the IEEE 13-bus system, consist of 12 transmission lines, 11 loads bus and 2 generator bus. The power flow solution of this bus test system data is shown in Table 1.

Validation: Table 2 gives the details of measurements used and their respective covariance's. The Meters-2 for power injections and 12 for power flows and Number of measurements: Nm = 29 and number of states to be estimated: Nn = 25.

Centralized system state estimation: This estimation is mainly done to compare the accuracy of WSL with the Firefly algorithm solution. Table 3 gives is the solution to the centralized state estimation. In this system bus 1 is used as the slack bus.

Figure 3 shows the comparison of the measured states with the estimated states which are obtained using WLS technique. As you can see that using this technique estimated values are almost equal to the measured values. Good accuracy can be obtained from this technique and this can be seen in Fig. 4. Therefore, from here on in this thesis wherever there is a need to estimate the states the conventional WLS technique will be used.

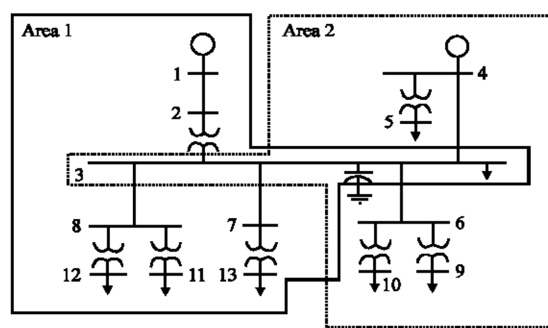

Fig. 2: The 13-bus system with two areas

Table 1: Bus data for IEEE 13-bus system

Bus No.	Voltage Mag. (pu)	Angle (degree)	MW (load)	M_{var} (load)	MW (gen)	M_{var} (gen)
1	1.000	0.000	0.000	0.000	7.353	0.365
2	0.998	-0.132	0.000	0.000	0.000	0.000
3	0.993	-3.485	2.230	-4.000	0.000	0.000
4	0.996	-3.463	0.000	0.000	2.010	1.782
5	1.017	-3.627	0.600	0.530	0.000	0.000
6	0.994	-3.472	0.000	0.000	0.000	0.000
7	0.993	-3.423	0.000	0.000	0.000	0.000
8	0.992	-3.484	0.000	0.000	0.000	0.000
9	1.018	-3.758	1.150	0.290	0.000	0.000
10	1.039	-3.854	1.310	1.130	0.000	0.000
11	0.992	-3.563	0.370	0.330	0.000	0.000
12	1.032	-4.271	2.800	2.500	0.000	0.000
13	1.015	-3.712	0.810	0.800	0.000	0.000
Total	-	-	9.280	1.580	9.363	2.147

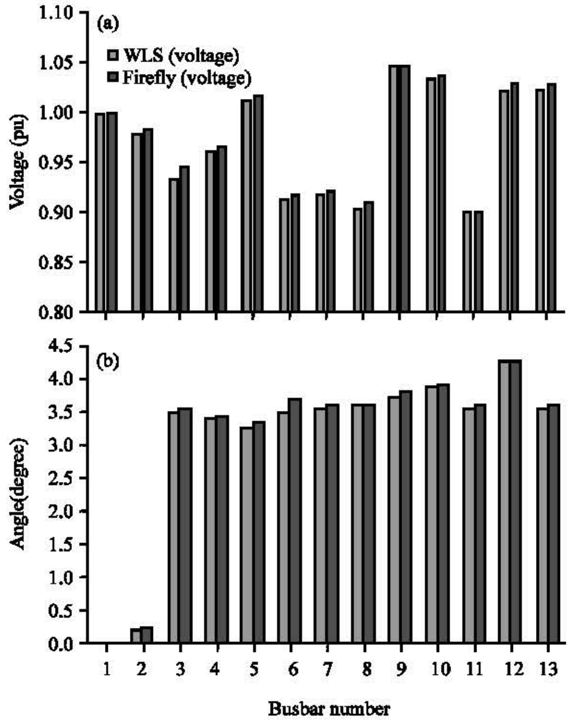

Fig. 3: Comparison of WLS and firefly algorithm: a) Voltage magnitudes and b) Voltage angles

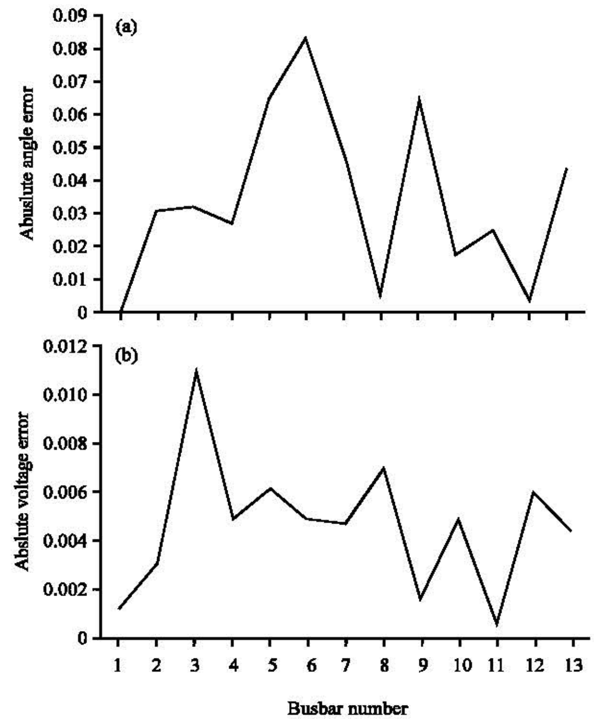

Fig. 4: Error comparison of WLS and firefly algorithm: a) Voltage magnitude and b) Voltage angle

Table 2: Measurements used for 13-bus system

Measurements	Buses	Measurement error
Voltage magnitude	1	9e-2
Reactive power injection	1,3	64e-2
Real power injection	1,3	64e-2
Reactive power flows	2-3, 3-6, 3-7, 4-3, 4-5, 3-8, 6-9, 6-10, 7-13, 8-11, 8-12	64e-2
Real power flows	2-3, 3-6, 3-7, 3-8, 4-3, 4-5, 6-9, 6-10, 7-13, 8-11, 8-12	64e-2

Table 3: Estimated states of 13-bus system

Bus No.	Voltage mag. (pu)	Angle (degree)
1	1.00120	0.000
2	0.98300	-0.243
3	0.94600	-3.523
4	0.96690	-3.412
5	1.01820	-3.318
6	0.91840	-3.684
7	0.92340	-3.587
8	0.91200	-3.601
9	1.04690	-3.791
10	1.03840	-3.891
11	0.90167	-3.579
12	1.02897	-4.243
13	1.02745	-3.596

Decentralized system state estimation: Now, the system is broken into two overlapping areas, i.e., it has one bus (agent) common to both the areas. In this system bus 3 is used as the agent.

Area 1 consists of 8 buses out of which bus-1 is used as the slack bus shown in red color in Fig. 5. As said earlier 3-bus is the agent. Again the agent is initialized (3-bus) before running the power flow and this is done by using all the load buses and generation buses of Area 2, respectively. The power flow is done using Newton-Raphson method and the solution is shown in Table 4.

These estimated states are then compared with the states obtained from the centralized solution (Table 3) and it is assured that only the buses which are present in this area should be compared. This is shown in Fig. 5. Ares 2 as shown Table 5 depicts the division of the 3-bus system into two overlapping areas.

These estimated states are then compared with the states obtained from the centralized solution (Table 3) and it is assured that only the buses which are present in this area need to be compared. This is shown in Fig. 6.

When we look at the above plots both the voltage magnitudes and the angles are converged unlike in the Area 1 where the angles had a big

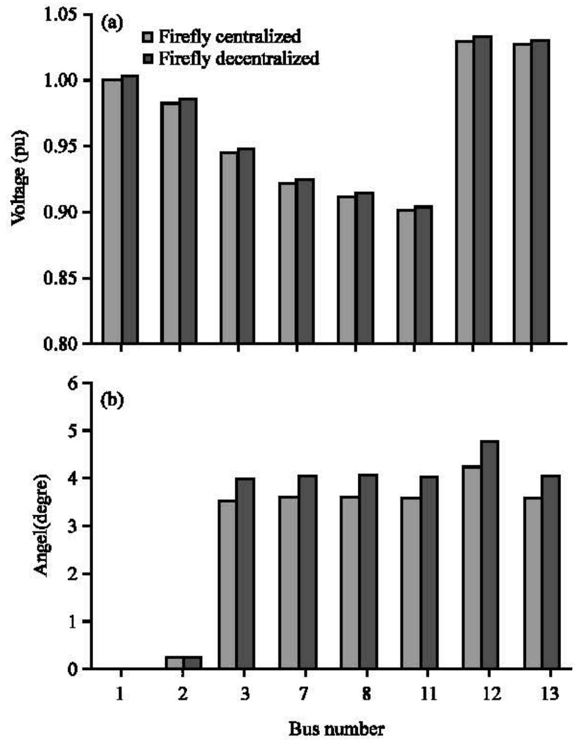

Fig. 5: Comparison of Area 1: a) Voltage magnitudes and b) Voltage angles

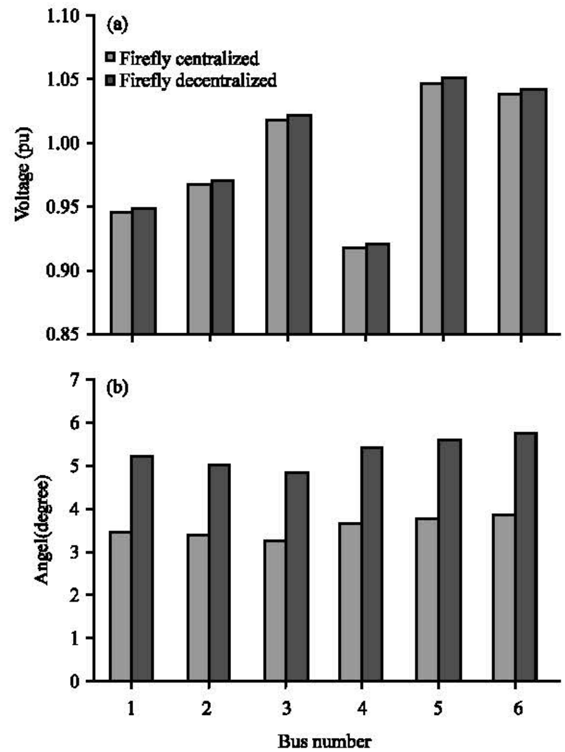

Fig. 6: Comparison of Area 1: a) Voltage magnitudes and b) Voltage angles

Table 4: Power flow solution of Area 1 (8-bus)

Bus No.	Voltage Mag. (pu)	Angle (degree)	MW (load)	M_{var} (load)	MW (gen)	M_{var} (gen)
1	1.0035	0	0.000	0.000	7.315	0.323
2	0.9853	-0.2733	0.000	0.000	0.000	0.000
3	0.9482	-3.9633	3.300	-3.833	0.000	0.000
4	0.9255	-4.0353	0.000	0.000	0.000	0.000
5	0.9141	-4.0511	0.000	0.000	0.000	0.000
6	0.9038	-4.0263	0.810	0.800	0.000	0.000
7	1.0314	-4.7733	0.370	0.330	0.000	0.000
8	1.0298	-4.0455	2.800	2.500	0.000	0.000
Total			7.280	-0.203	7.315	0.323

Table 5: Power flow solution of Area 2 (6-bus)

Bus No.	Voltage Mag. (pu)	Angle (degree)	MW (load)	M_{var} (load)	MW (gen)	M_{var} (gen)
1	0.94848	-5.2069	0.000	0.000	1.956	1.255
2	0.96944	-5.0429	0.600	0.530	0.000	0.000
3	1.02087	-4.9040	-1.103	-0.715	0.000	0.000
4	0.92081	-5.4449	0.000	0.000	0.000	0.000
5	1.04965	-5.6030	1.150	0.290	0.000	0.000
6	1.04113	-5.7508	1.310	1.130	0.000	0.000
Total			1.956	1.255	1.956	1.255

mismatch. This is because Area 2 has the same slack bus as in original test system (13-bus). So, this point will should be considered in future developing a strategy to communicate between the two areas.

CONCLUSION

In this study, the proposed firefly for a distributed state model and a consensus based static state estimation 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 neighbors.

It has been shown that the developed method is practical for current power systems and these methods have also been demonstrated on a benchmark power system model. Simulation results on a radial distribution 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.

ACKNOWLEDGEMENTS

This research done under unfunded grant, however, the researchers would like to thank to the Universiti Teknikal Malaysia Melaka(UTeM) for providing facilities towards the succeful of this research.

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