Power system state estimation using teaching learning-based optimization algorithm

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Article Info

Article history:

Received Sep 20, 2019
Revised Mar 22, 2020
Accepted Apr 7, 2020

Keywords:

Meta-heuristic algorithms
Nonlinear programming
Observability
Power flow analysis
State estimation

ABSTRACT

The main goal of this paper is to formulate power system state estimation (SE) problem as a constrained nonlinear programming problem with various constraints and boundary limits on the state variables. SE forms the heart of entire real time control of any power system. In real time environment, the state estimator consists of various modules like observability analysis, network topology processing, SE and bad data processing. The SE problem formulated in this work is solved using teaching leaning-based optimization (TLBO) technique. Difference between the proposed TLBO and the conventional optimization algorithms is that TLBO gives global optimum solution for the present problem. To show the suitability of TLBO for solving SE problem, IEEE 14 bus test system has been selected in this work. The results obtained with TLBO are also compared with conventional weighted least square (WLS) technique and evolutionary based particle swarm optimization (PSO) technique.

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1. INTRODUCTION

In recent years, several electrical utilities around the globe are developng different knowledge-based applications to inrgrate in the operation of control centers. These methods must be capable of meeting all the important tasks of efficient control system such as numerical stability, computation efficiency, and implementation complexity. Load dispatcher in power system control centre is required to know at all times the value of voltages, currents and power throughout the network. Some of the values such as bus voltage magnitude and power line flows can be measured within a certain degree of variance [1]. Difficulties are further encountered when some of the data is missing either due to meter being out of order or missing transmission.

State estimation (SE) is considered as the process of assigning values to unknown system state variables, based on the measurements obtained from that system. It utilizes the available redundancy, for systematic cross checking of the measurements, to approximate the states as well as generate information in respect of missing observations or gross measurement errors called bad data. The prerequisite for state estimation is that system must be observable with available measurements. States of a power system can also be computed with the load flow calculations, based on equal number of measurements, assuming them to be accurate [2]. However, the implicit error will lead to imperfect data base and prejudice the security monitoring. Whereas, the state estimator is considered as a data processing technique for use on a digital computer to transform measurement vector into an estimate of system's states, which is not only accurate but best reliable also. As the state estimator is required to cater for the needs of online application, computation speed plays a vital role especially when systems are large. Alternate methods of SE are being reported to optimize on computational efficiency, numerical stability, and complexity in implementation [3].

A hybrid algorithm for solving the SE problem by using weighted least square, weighted least absolute value and particle swarm optimization (PSO) methods is presented in [4]. In [5] uses unscented Kalman filter and extended Kalman filter to estimate power system states by a phasor measurement unit (PMU). A comparative analysis of SE in rectangular and polar coordinates has been proposed in [6]. A SE approach for a distribution system considering the condition variables, i.e., node voltage and angle of feeder is proposed in [7]. In [8] presents approach for the implementation of reactive power and/or active power measurements in the SE. An agent-based approach for dynamic SE of power system by taking the advantages of hybrid measurement data is presented in [9]. A hybrid SE method with genetic algorithm and cellular computational network is proposed in [10] to overcome the dimensionality problem of SE.

The application of PSO for solving SE problem within a power system is proposed in [11]. A non-iterative method which has no issues with convergence and doesn't need starting guess is used in [12] for solving the SE problem. A robust and reliable least winsorized square estimator for static SE is proposed in [13]. In [14] proposes an extended Kalman filter based dynamic SE by using PMU data. A SE method including equality constraints to model zero injections and voltage dependent loads is proposed in [15]. A methodology by including the uncertainty in SE is proposed in [16]. An overview of power system SE control by load flow program input data is presented in [17]. A SE approach by considering the measured data obtained from synchronized and unsynchronized sensors is presented in [18].

This paper solves the SE problem of power system as a constrained nonlinear programming problem with various constraints and boundary limits on state variables. The objective of SE is to find best estimated state variables for the considered power system by optimizing all the errors in measurements. This problem is solved by enforcing the equality and limit constraints by using teaching-learning based optimization (TLBO) technique. TLBO is formulated by considering two methods of learning (i.e., teacher and learner phases) in a classroom. Teacher phase consists the interaction between learner and teacher, whereas learners phase consists the interaction among the learners. This paper is presented as follows. The problem formulation of SE is described in section 2. The solution algorithm, i.e., TLBO algorithm is presented in section 3. Results and discussions on standard IEEE 14 bus system are presented in section 4. conclusions are presented in section 5.

2. PROBLEM FORMULATION

Load flow calculations indeed are an inevitable tool for off-line studies and planning exercises, but incomplete and erroneous measurement is a real time proposition. Solution for such situation has been provided by static state estimator, which ignores the slow changes in the system and utilizes redundant set of measurements for cross checking and approximating the most reliable estimates of system state [19]. State estimator should estimate the system states as quickly as possible, but conventional computer-based methods are almost reaching a limit in terms of speed. Figure 1 depicts the description of state estimator/SE. In this figure, *m* is number of measurements, *n* is number of state variables.

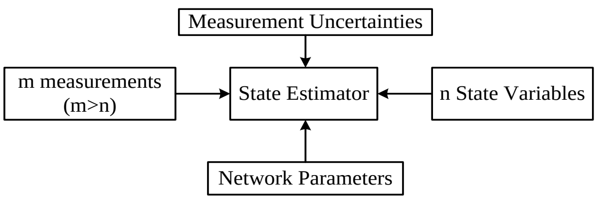

Figure 1. Schematic diagram of state estimator

The state vector (x) has voltage magnitudes and angles at buses [20]. Power system with N number of buses can be expressed as $x=[\delta, V]^T$ with size n=2N-1, includes (N-1) bus voltage angles (δ_i). General static SE model is expressed by using [21],

$$z = h(x) + \epsilon \tag{1}$$

where z is all measurements, and h(.) represents nonlinear measurement functions. Here, meta-heuristic based optimization technique is used for solving nonlinear programming problem [22]. It is often desirable to put different weightings on different components of measurements as some of the measurements may be more reliable and accurate than the others and should be given more importance. In power network there are some nodes with zero injections i.e., switching substations as constant load. Such buses are called constrained buses and can be included in the cost function by assigning large weighting factors [23]. The estimate of x can be obtained by minimizing the function of weighted least square (WLS), and it is expressed as [24],

$$J(x) = [z - h(x)]^T \omega [z - h(x)] \tag{2}$$

where ω is a diagonal matrix. The estimate is solved by an iterative method, which determines corrections (Δx) by solving the following function [25],

$$G(x)\Delta x = H(x)^T \omega \Delta z \tag{3}$$

where Δz = z-h(x), and H(x)=$\frac{\partial h(x)}{\partial x}$=Jacobian matrix.

$$G(x) = H(x)^T \omega H(x) \tag{4}$$

where $x=x^k$ at the k^{th} iteration. In view of fact that power systems nowadays are becoming more openly accessible; maneuverability of their power flow continues to be a general concern in the coming decade [26].

2.1. SE: objective function

The objective of SE is to minimize the weighted squared error between calculated and measured quantities. Where R^{-1} is the weights of individual measurements, and it is solved subject to following inequality and equality constraints and it is expressed as,

$$minimize \quad \frac{1}{2}[z - h(x)]^T R^{-1} [z - h(x)] \tag{5}$$

2.2. Equality constraints

These are the active and reactive power balance equations at all buses, which can be expressed as [27],

$$P_i = \sum_{m=1}^{N} V_i V_m (G_{im} cos\delta_{im} + B_{im} sin\delta_{im}) = 0 \tag{6}$$

$$Q_i = \sum_{m=1}^{N} V_i V_m (G_{im} sin\delta_{im} - B_{im} cos\delta_{im}) = 0 \tag{7}$$

2.3. Inequality constraints

2.3.1. Voltage constraints

They include minimum and maximum limits on bus voltage magnitudes, and they are expressed as,

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{8}$$

2.3.2. Phase angle constraints

At each bus, the phase angle must be between minimum and maximum limits, and they are expressed as,

$$\delta_i^{min} \leq \delta_i \leq \delta_i^{max} \tag{9}$$

2.3.3. Line flow constraints

This constraint can be expressed as [28],

$$P_{li}^{max} \geq P_{li} \tag{10}$$

2.3.4. Generator reactive power constrsint

The reactive power limits of generator are expressed as,

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \tag{11}$$

3. TLBO ALGORITHM

The SE problem proposed in this paper is solved by using TLBO. It is a population based meta-heuristic technique developed to get global solution. TLBO takes the advantage of two approaches of learning in a classroom. First method is through the interaction between the learner and the teacher, and this is termed as teacher phase. The second one is through the interaction among learners, and this is termed as learner phase [29]. The flowchart of TLBO is depicted in Figure 2. The reader may refer references [29, 30] for more details of TLBO algorithm.

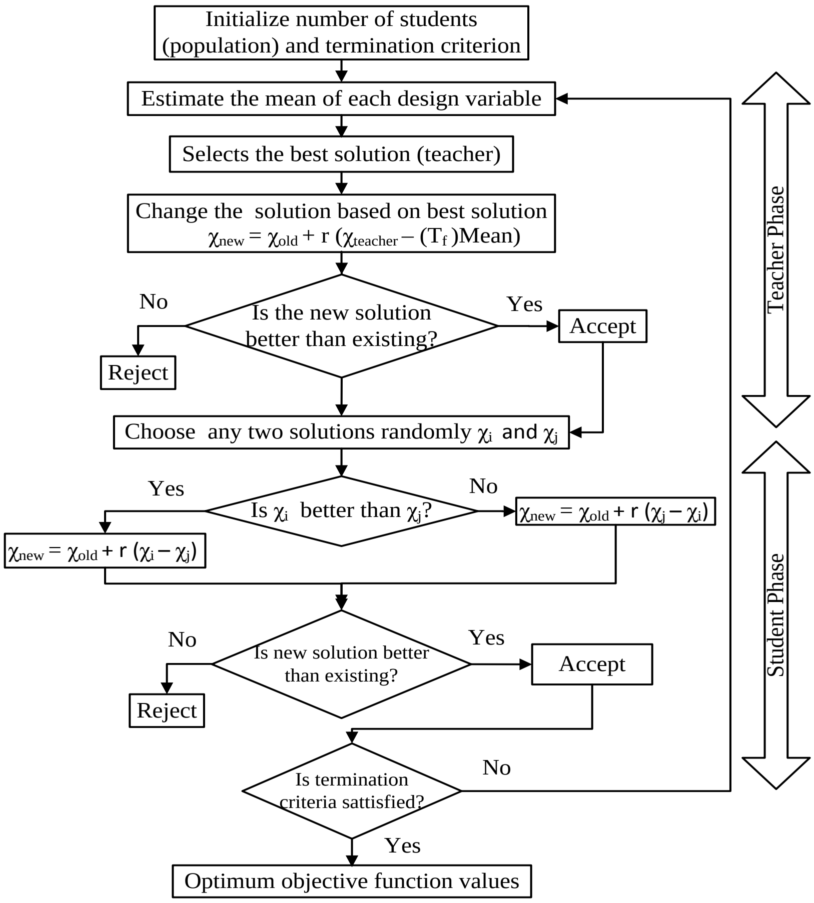

Figure 2. Flow chart of TLBO algorithm

4. SIMULATION RESULT AND DISCUSSION

In this work, standard IEEE 14 bus [31] system is considered for solving the proposed SE problem. For this problem, the voltage magnitudes at each bus and the phase angles at all buses except reference bus are selected as the state variables. Load flow solution is used for obtaining the true values, and measurements were made by adding errors to the true values. Zero power injection at nodes with no generation and no load are considered as equality constraints. Proposed SE problem is solved by using TLBO algorithm. The data required for solving the SE problem on standard IEEE 14 bus system is taken from [31]. The measurement set data of IEEE 14 bus system is depicted in Figure 3 and in Table 1. The bus numbers 5 and 7 are considered as zero injection buses. In this test system, total 32 measurements are considered, in that 12 are considered as the bus injection type measurements and 20 are considered as the line flow type measurements [32]. With this data, the SE problem is solved by using TLBO algorithm.

The estimated state variables by solving the SE with equality constraints are presented in Table 2. Errors of estimate values (i.e., ΔP and ΔQ) obtained by solving the SE using TLBO are reported in Table 3. The errors of estimated values obtained using the TLBO algorithm are also compared with WLS technique and the evolutionary based PSO algorithm. From the obtained results, it is clear that by solving SE problem by using teaching-learning based optimization (TLBO) has better results when compared to conventional WLS technique and the evolutionary based PSO algorithm.

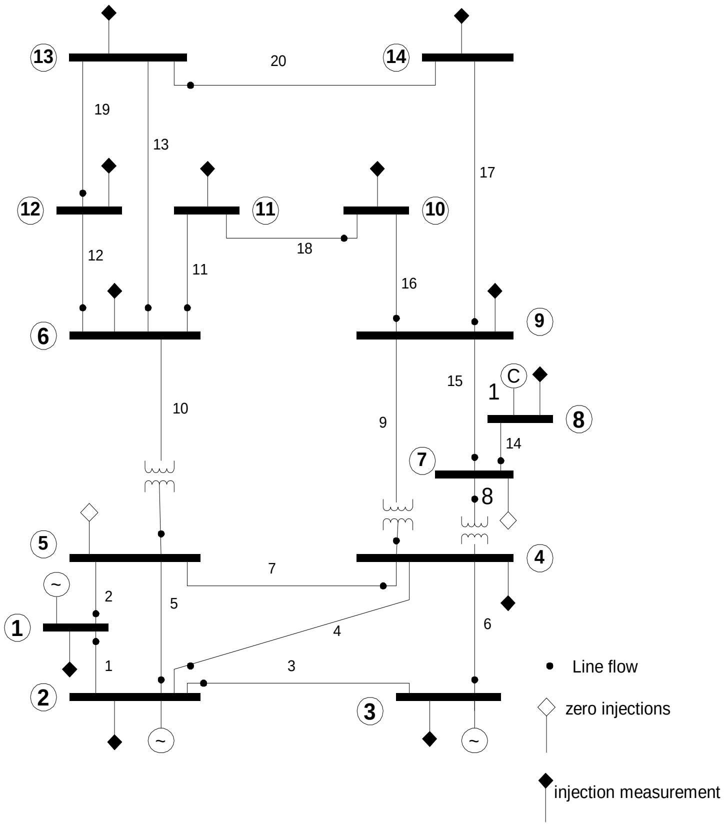

Figure 3. Measurement data set for IEEE 14 bus system

Table 1. Measurement data set for IEEE 14 bus system

Measurements	Measurement Type	Buses	P (MW)	Q (MW)
z_1	Injection	1	224.62	-17.22
z_2	Injection	2	18.23	25.35
z_3	Injection	3	-94.53	4.26
z_4	Injection	4	-47.83	7.04
z_5	Injection	6	-11.29	3.44
z_6	Injection	8	0.00	17.33
z_7	Injection	9	-29.55	2.34
z_8	Injection	10	-9.22	-6.35
z_9	Injection	11	-3.27	-1.25
z_{10}	Injection	12	-6.1	-1.6
z_{11}	Injection	13	-13.66	-6.05
z_{12}	Injection	14	-14.87	-4.89
z_{13}	Line flow	1-2	151.96	-16.28
z_{14}	Line flow	1-5	72.65	4.79
z_{15}	Line flow	2-3	72.43	6.03
z_{16}	Line flow	2-4	54.47	-1.23
z_{17}	Line flow	2-5	39.26	0.99
z_{18}	Line flow	3-4	-24.37	3.6
z_{19}	Line flow	4-5	-63.84	13.9
z_{20}	Line flow	4-7	28.06	-19.72
z_{21}	Line flow	4-9	16.07	-5.79
z_{22}	Line flow	5-6	44.4	-17.94
z_{23}	Line flow	6-11	7.37	3.5
z_{24}	Line flow	6-12	7.84	2.56
z_{25}	Line flow	6-13	17.91	7.45
z_{26}	Line flow	7-8	0.00	-16.88
z_{27}	Line flow	7-9	28.05	7.14
z_{28}	Line flow	9-10	5.21	4.28
z_{29}	Line flow	9-14	9.36	3.48
z_{30}	Line flow	10-11	-4.02	-2.1
z_{31}	Line flow	12-13	1.66	0.8
z_{32}	Line flow	13-14	5.68	1.77

Table 2. Estimated state variables after solving the SE for IEEE 14 bus system

Bus No.	V	δ	Bus No.	V	δ	Bus No.	V	δ
1	1.060	0	6	1.071	-12.68	11	1.058	-13.167
2	1.045	-4.731	7	1.062	-12.080	12	1.057	-13.296
3	1.010	-12.309	8	1.090	-11.922	13	1.051	-13.443
4	1.022	-9.615	9	1.055	-13.481	14	1.037	-14.258
5	1.024	-8.046	10	1.051	-13.553			

Table 3. Errors of estimated values obtained by using WLS technique, PSO and AFSOA

Measurements	SE Using WLS		SE Using PSO		SE Using TLBO	
	ΔP	ΔQ	ΔP	ΔQ	ΔP	ΔQ
z1	0.0037	-0.0019	0.0052	-0.0034	0.0061	-0.0046
z2	-0.0018	-0.0061	0.0019	-0.0069	0.0042	-0.0066
z3	-0.0028	0.0028	0.0025	-0.0028	0.0018	-0.0025
z4	-0.0014	0.0024	-0.0009	0.0025	0.0017	0.0023
z5	-0.0016	-0.0022	-0.0015	-0.0034	-0.0017	-0.0051
z6	-0.0012	-0.0081	-0.0015	-0.0039	-0.0018	0.0021
z7	-0.0082	0.0126	-0.0056	0.0092	-0.0017	-0.0014
z8	-0.0028	-0.0155	-0.0030	0.0010	-0.0011	0.0012
z9	0.0019	0.0657	-0.0014	0.0021	-0.0016	0.0022
z10	0.0001	0.0509	0.0001	0.0052	-0.0021	0.0055
z11	0.0083	0.0852	0.0072	0.0012	-0.0017	0.0016
z12	-0.0405	-0.0067	-0.0105	-0.0050	-0.0023	0.0066
z13	0.0329	-0.0087	0.0311	-0.0016	0.0275	-0.0025
z14	0.0161	-0.0433	0.0253	-0.0015	0.0329	-0.0021
z15	0.0173	-0.0147	0.0114	-0.0012	0.0063	-0.0016
z16	0.0128	-0.0046	0.0196	-0.0035	0.0316	-0.0037
z17	0.0085	-0.0054	0.0082	-0.0061	0.0305	-0.0082
z18	-0.0058	0.0013	0.0315	-0.0047	0.0237	-0.0057
z19	-0.0018	0.0129	-0.0034	0.0135	-0.0063	-0.0138
z20	0.0096	-0.0276	0.0089	0.0019	0.0522	0.0021
z21	0.0525	-0.0058	0.0452	0.0010	0.0256	0.0015
z22	0.0148	0.0499	0.0511	0.0053	0.0666	0.0095
z23	-0.0012	-0.0057	0.0067	-0.0025	0.0086	-0.0012
z24	0.0003	-0.0046	0.0032	-0.0019	0.0173	-0.0027
z25	-0.0001	-0.0086	0.0016	-0.0052	0.0239	-0.0045
z26	0.0126	0.0074	0.0151	-0.0017	0.0181	-0.0061
z27	0.0083	0.0016	0.0092	0.0008	0.0308	-0.0008
z28	0.0243	0.0081	0.0195	0.0079	0.0194	-0.0019
z29	0.0298	0.0043	0.0211	0.0042	0.0204	-0.0043
z30	0.0047	-0.0075	0.0059	-0.0019	0.0079	-0.0011
z31	0.0022	0.0032	0.0032	0.0026	-0.0034	0.0023
z32	0.0011	0.0041	0.0010	0.0037	0.0029	-0.0014

5. CONCLUSIONS

Power system state estimation (SE) problem in this paper is solved as a constrained nonlinear programming problem with various constraints and boundary limits on state variables. The proposed power system SE problem is solved by using teaching leaning based optimization (TLBO) technique. The major difference between TLBO and conventional optimization methods is that TLBO gives global optimal solution for this proposed problem. The effectiveness and suitability of TLBO algorithm for solving SE problem has been examined on IEEE 14 bus system. Results obtained with TLBO algorithm are also compared with conventional WLS technique and evolutionary based PSO algorithm.

ACKNOWLEDGEMENTS

This research work has been carried out based on the support of “Woosong University's Academic Research Funding – (2019-2020)”.

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