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Research paper

Enhanced particle swarm optimization based on weighted least square method

Mothafer A. Hussein [1] *, Asst. Prof Ahmed Jasim Sultan [2]

[1] *Department of Electrical power engineering techniques, Electrical Engineering Technical College, Middle Technical University*
[2]*Asst. Prof Ahmed Jasim Sultan Department of Electrical power engineering techniques, Electrical Engineering Technical College, Middle Technical University [3]Affiliation of the third author*
**Corresponding author E-mail:*

Abstract

with the increase of population, electrical power systems have grown with more complexity. This complexity leads to increase the focusing on the monitoring and control system of power systems. State estimation on of the recent techniques that are used to enhance the monitoring of the power system, however traditional state estimation is one of the methods that are not enough by themselves, though optimization methods are needed to enhance the results of state estimation. PSO algorithm is an artificial intelligence optimization method which can be used to enhance the WLS estimation method. Traditional PSO-WLS has showed its efficiency however in this paper an enhancement is done to PSO method to utilize the same number of iterations to achieve better estimation. The proposed method is proved by using MATLAB simulation and applied on standard IEEE-14 bus.

Keywords: *PSSE; WLS; PSO; State Estimation; Power System; Optimization; Artificial Intelligence.*

1. Introduction

Power System State Estimation (PSSE) is defined as "A data processing algorithm for converting redundant meter reading and other available information into an estimate of the state of an electric power system". Until four decade ago, researchers where believed that the measurement that driven from control systems (normally SCADA) are accurate, however recently they found that these measurements are not accurate and redundant due to the accuracy of meters used, the placement of meters are not everywhere and the noise due to transmission devices. These aspects make the measurement are not accurate and needed to be estimated to their accurate value and considering the accuracy of measurements. The most popular method that used for power system state estimation is Weighted Least Square (WLS) [1-7] which minimize the residual error of measurements to achieve the state vector of the electrical system. Although WLS is an accurate state estimation method, an optimization method can be used to obtain more accurate state vector of the system. Many optimization methods have been introduced and utilized with WLS method in [1-4]. The most efficient method of optimization that can be utilized is Particle Swarm Optimization (PSO) [9-10]. This method is considered as artificial intelligence technique and baes on the behaviour of birds swarm. PSO is mainly depends on two essential variable which are Position (X) and Velocity (V), the position is a vector of variables that need to be estimated, Voltage and Voltage Angle in our problem, and the velocity is the change that is added to the position. The velocity (V) depends on constant variables (c_1, c_2), random variables between 0 and (r_1, r_2), P_{best} and g_{best}, where last two variables are the top set of state vector and top state vector respectively. PSO method has been studied on IEEE standard and showed its efficiency in [5-9], however it needs multiple adjustment and high number of iterations to achieve the best estimation result. In this paper an enhancement is done on the PSO method to utilize the same number of iterations to achieve better estimation. The enhancement is done by dividing the total number of iterations to subdivisions and with each subdivision reinitialization is taken for the X and V, while keeping P_{best} and g_{best} as it was in last subdivision of iterations. In this method the state vector will obtain better results with each subdivision until it reaches the required tolerance. The proposed method is applied on standard IEEE 14 bus using MATLAB simulation and the results showed smaller objective function compared with WLS and traditional PSO.

2. Weighted least square (WLS)

WLS is a state estimation method which computing the state vector x using set of actual redundant measurements z which have residual error r using set of non-liner equations. The state vector equation can be expressed as follows:

$$r_i = z_i - h_i(x) \qquad (1)$$

Where $i = 1,2 \ldots\ldots m$, m total number of measurements r_i is the residual error of the i_{th} measurement. z_i is the i_{th} measurement. h_i in the state vector of the i_{th} measurement, which is computed using liner and non-liner equations of voltage, power flow, power injection and current flow. x are the variables that needs to be estimated.
State estimation is built on minimizing the sum of residual errors between the measured and estimated values that considered by the nonlinear equation $h(x)$. Since the main objective is minimizing the residual error which can be expressed as follows for WLS method [1-4], [10], [11]

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

Where w_i is the weight of the measurement. σ_i^2 is the tolerance of the measurement device.
Although WLS is very popular and efficient but still more improvement can be done using optimization methods built on WLS.

3. Traditional particle swarm optimization (PSO)

3.1. Overview

PSO is one of the Artificial Intelligence optimization method which is used for minimization or maximization purposes. PSO algorithm has been introduced in 1995 by Kennedy And Eberhart as an alternative algorithm for Genetic Algorithm (GA). This technique is derived from the behaviour of Birds Flock and consists of random state vector population that is used to estimate the state vector of the problem Originally PSO was used to estimate the graphical position of the flock of birds by discovering different paths and diagnose the estimated path to converge to the best particle by changing the velocity and position of the birds with every iteration. By utilizing this technique, researchers found that it is an efficient method that can be used as minimization algorithm for various types of problems [5-9,12-14].
The main aspect of PSO is based on two variables, the first one is a set of random initialized particles which is called Position and the change of these particles which is called Velocity. These two variables are used to explore number of possibilities that adjusted with each iteration to achieve the best particle that leads to optimal fitness function. The adjustment that is done to the particles is the Velocity which depend on constants, random numbers, local best particle and global best particle. Local best particles are set of particles that make the fitness function the lowest among other possibilities until the current iteration, while global best particle is the particle that make the fitness function the lowest among all possibilities. The position will be updated with each iteration and the velocity as well, the equations below show the formulation of Position (X) and Velocity (V):

$$V_i^{t+1} = WV_i^t + c_1 r_1 \big(X_i^{best} - X_i^t\big) + C_2 r_2 (X^{Gbest} - X_i^t) \quad (3)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (4)$$

Where X_i^{t+1} and V_i^{t+1} are updated position and velocity respectively, W is the inertia of the particles, c_1 & c_2 are constant number and r_1 & r_2 are random numbers between (0, 1). This algorithm can be summarized in the flowchart shown in Fig.1.

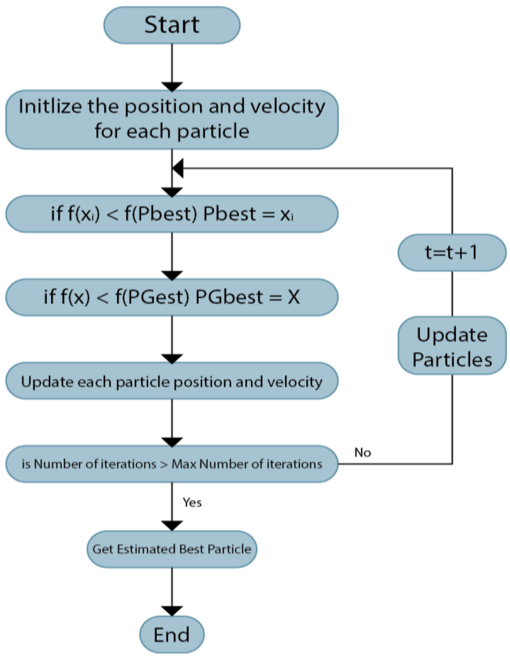

Fig. 1: Traditional PSO Algorithm.

3.2. Fitness function and workflow

The fitness function is the function that needs to be minimized with the addition to the penalty that deals with the constraints. The fitness function and penalty are given by:

$$F(x) = J(x) + P(x) \quad (5)$$

$$P(x) = \lambda \sum_{i=1}^{NV} \{\max(0, x_i - x_i^{max})\}^2 + \lambda \sum_{i=1}^{NV} \{\max\big(0, x_i^{min} - x_i\big)\}^2 \quad (6)$$

Where P(x) is the penalty term that constraint all the state variable within their limit, $x_i, x_i^{max}, x_i^{min}$ are the estimated variable of current set of population, upper limit of the variable and lower limit of the variable respectively. λ is the penalty factor [9]. NV is total number of variables.
The workflow of the algorithm is given as follows:

1) Initialize the position and velocity for each particle (variables) within their limits.
2) For each particle, compute the fitness function given by equation (5)
3) Compare each result of fitness value with the previous P_{best}, if the value of the new result is less than the previous, replace the particle of the P_{best} with the new particle, other wise keep the old particle.
4) Compare the current global best particle G_{best} with the old G_{best} if the new particle has lower fitness value set G_{best} to the new particle.
5) Update the position and velocity for each particle.
6) If maximum number of iterations is not reached, return to step number (2).

4. Proposed PSO algorithm

The traditional algorithm of PSO runs for number of iterations and update the Local Best Particle X_{best} and Global Best Particle X_{Gbest}, despite its high efficiency to converge to the best particle, the number of iteration that result in low fitness function can be minimized by utilizing the last combination of X_{best} and X_{Gbest} for number of iteration and repeat the algorithm with new initialization for the position and velocity of the problem. This will lead in faster convergence to the lowest fitness function with a smaller number of iterations. The main benefit of this way is reducing the computational time compared with traditional PSO algorithm. Fig.2 illustrates the algorithm in flow chart.

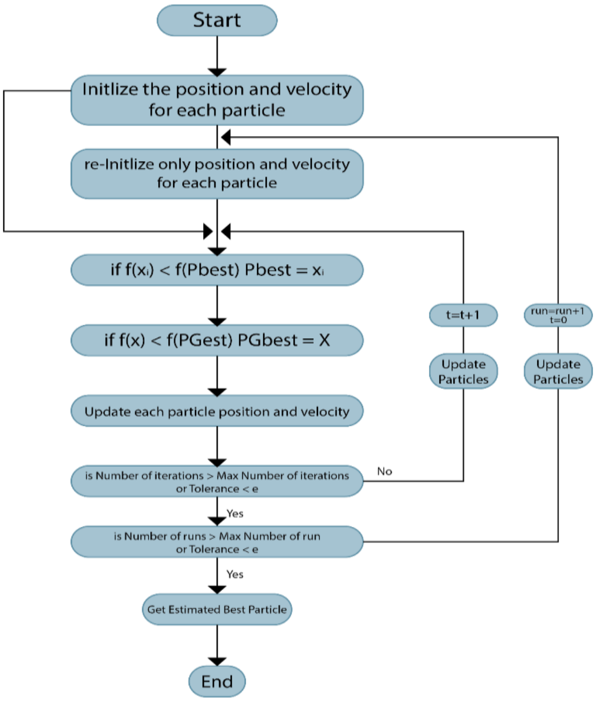

Fig. 2: Proposed PSO Algorithm.

5. Data presentation

In order to evaluate the performance of the proposed method, simulation has been done using MATLAB software and applied on IEEE 14 bus standard system. The line data, bus data and measurements are shown in table 1,2 and 3 respectively [15-16].

Table 1: Line Data

From Bsu	To Bus	R pu	X pu	B/2 pu	Tap(a)
1	2	0.0194	0.0592	0.0264	1.0000
1	5	0.0540	0.2230	0.0219	1.0000
2	3	0.0470	0.1980	0.0187	1.0000
2	4	0.0581	0.1763	0.0246	1.0000
2	5	0.0570	0.1739	0.0170	1.0000
3	4	0.0670	0.1710	0.0173	1.0000
4	5	0.0134	0.0421	0.0064	1.0000
4	7	0	0.2091	0	0.9780
4	9	0	0.5562	0	0.9690
5	6	0	0.2520	0	0.9320
6	11	0.0950	0.1989	0	1.0000
6	12	0.1229	0.2558	0	1.0000
6	13	0.0662	0.1303	0	1.0000
7	8	0	0.1762	0	1.0000
7	9	0	0.1100	0	1.0000
9	10	0.0318	0.0845	0	1.0000
9	14	0.1271	0.2704	0	1.0000
10	11	0.0820	0.1921	0	1.0000
12	13	0.2209	0.1999	0	1.0000
13	14	0.1709	0.3480	0	1.0000

Table 2: Bus Data

Bus NO.	Type	V	Theta	PGi	QGi	PLi	QLi
1	1	1.06	0	0	0	0	0
2	2	1.0450	0	40	42.4	21.7000	12.7000
3	2	1.01	0	0	23.4	94.2000	19.0000
4	3	1	0	0	0	47.8000	-3.9000
5	3	1	0	0	0	7.6000	1.6000
6	2	1	0	0	12.2	11.2000	7.5000
7	3	1	0	0	0	0	0
8	2	1	0	0	17.4	0	0
9	3	1	0	0	0	29.5000	16.6000
10	3	1	0	0	0	9.0000	5.8000
11	3	1	0	0	0	3.5000	1.8000
12	3	1	0	0	0	6.1000	1.6000
13	3	1	0	0	0	13.5000	5.8000
14	3	1	0	0	0	14.9000	5.0000

Table 3: Measurements

Measurement No.	Type	Value	From Bus	To Bus	σ
1	1	1.0500	1	0	9e-4
2	1	1.0000	3	0	9e-4
3	1	1.0400	5	0	9e-4
4	1	1.0900	8	0	9e-4
5	1	1.0500	9	0	9e-4
6	1	1.0570	11	0	9e-4
7	1	1.0300	13	0	9e-4
8	2	0.1647	2	0	1e-4
9	2	-0.4763	4	0	1e-4
10	2	-0.1021	6	0	1e-4
11	2	-0.2939	9	0	1e-4
12	2	-0.0833	10	0	1e-4
13	2	-0.0601	12	0	1e-4
14	3	0.3042	2	0	1e-4
15	3	0.0571	3	0	1e-4
16	3	0.0510	6	0	1e-4
17	3	-0.1660	9	0	1e-4
18	3	-0.0480	14	0	1e-4
19	4	1.4276	1	2	64e-4
20	4	0.4072	2	5	64e-4
21	4	0.4076	5	6	64e-4
22	4	0.1714	6	13	64e-4
23	4	0	7	8	64e-4
24	4	0.0158	12	13	64e-4
25	4	0.0518	13	14	64e-4
26	4	-0.6648	3	2	64e-4
27	4	-0.5043	4	2	64e-4
28	4	-0.2581	7	4	64e-4
29	4	-0.1597	9	4	64e-4
30	4	-0.0661	11	6	64e-4
31	4	-0.0495	10	9	64e-4
32	5	0.0108	2	5	64e-4
33	5	-0.0150	10	11	64e-4
34	5	0.0160	13	14	64e-4
35	5	0.0220	5	1	64e-4
36	5	0.0288	4	2	64e-4
37	5	-0.1332	5	4	64e-4
38	5	0.1032	7	4	64e-4
39	5	0.0159	9	4	64e-4
40	5	-0.0313	11	6	64e-4
41	5	-0.0221	12	6	64e-4
42	5	-0.0316	14	9	64e-4

6. Results & discussion

IEEE 14 bus standard has been used to test the proposed algorithm, WLS, Traditional methods has been tested to be compared with the proposed method. Newton Raphson power flow is applied to get the true values of voltage and voltage angle to compare the efficiency of the mentioned methods. The same constants has been used for both traditional PSO and proposed algorithm and the total number of iteration is the same except in the proposed algorithm the total number of iterations has been divided into five runs in each run the same local best particle and global best particle is taken of the last run is taken to be used in the new run, while in the traditional PSO the total number of iterations are run as one run. The variables of PSO are set as follows, c1 & c2 = 1, r1 & r2 = (0,1), total number of iterations that was used is 2000 while in the enhanced method this number of iterations was divided to five runs to be 400 iterations in each run, number of population = 200, w_{max} = 0.9 and w_{min} = 0.4. Tables 4 and 5 show the voltage and voltage angle of 14 buses of each method.

Table 4: Voltage for 14 Bus Bar

True Value by NR Power Flow	WLS	Traditional PSO-WLS	Modified PSO-WLS
1.06	1.0768	1.0421	1.0522
1.045	1.0661	1.0289	1.0413
1.06	1.0359	0.9967	1.0106
1.069	1.0410	1.0016	1.0164

1.063	1.0427	1.0033	1.0178
1.12	1.0737	0.9878	1.0777
1.108	1.0596	1.0202	1.0354
1.09	1.0000	0.9218	1.1579
1.127	1.0499	0.9793	1.0444
1.133	1.0546	0.9605	1.0639
1.130	1.0612	0.9683	1.0691
1.133	1.0577	0.9661	1.0657
1.137	1.0442	0.9435	1.0581
1.147	1.0315	0.9409	1.0351

Table 5: Voltage Angle for 14 Bus Bar

True Value by NR Power Flow	WLS	Traditional PSO-WLS	Modified PSO-WLS
0	0	0	0
-4.98	-4.4606	-4.6927	-4.6982
-12.353	-11.2514	-11.9496	-11.81
-9.854	-9.2338	-9.7387	-9.7659
-8.516	-7.8640	-8.2761	-8.3335
-13.362	-12.8599	-13.9667	-13.5295
-12.633	-11.9400	-12.4851	-12.6713
-12.633	-11.9400	-12.4542	-12.6832
-14.051	-13.4357	-14.564	-14.1218
-14.183	-13.7504	-14.4809	-14.7194
-13.898	-13.3684	-14.3447	-14.1959
-14.126	-13.7663	-15.0762	-14.4547
-14.199	-13.4303	-14.2685	-14.3897
-14.957	-14.2632	-16.0526	-14.9806

Figure 2: Voltage Angle for 14 Bus Bar

To evaluate the accuracy of the results Mean Square Error (MSE) equation is be used and calculated as follows:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(|x_i^{true} - x_i^{est}|^2)}{N} \tag{7}$$

Where x_i^{true} is the true measurement that is computed by NR power flow, x_i^{est} is the estimated value by sate estimation methods and N is the total number of variables [4], [6-7], [18].

Table 6: Shows the MSE FOT the Used Methods

Method	Voltage MSE	Angle MSE	Overall MSE
WLS	0.0021	0.1983	0.2005
Traditional PSO-WLS	0.0209	0.1213	0.1422
Modified PSO-WLS	0.0091	0.0348	0.0439

From Table 6 noticed that PSO-WLS is efficient technique that achieve better results over WLS and the modified PSO-WLS showed lower MSE for the same total number of iterations.

7. Conclusion

This paper is focused on enhancing artificial intelligence technique of Particle Swarm Optimization by achieve better estimation for the same configuration used for traditional PSO. IEEE 14 bus has been tested using WLS, PSO-WLS and Modified PSO-WLS, the later proved its high efficiency to obtain the state vector. The proposed method utilizes the local best particle and global best particle for the nest set of iterations, in this method the algorithm will converge to the true value in lest number of iteration compared to traditional PSO-WLS. However, optimization techniques neef multiple adjustment to obtain the optimum estimated state.

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