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Iraqi Super Grid Network State Estimation Using PSO Technique

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Assist. Prof. Dr. Afaneen A. Abood
Department of Electrical Engineering
Engineering
University of Technology
Baghdad-Iraq
afaneenalkazragy@yahoo.com

Anmar Jasim Hameed
Department of Electrical
University of Technology
Baghdad -Iraq
an_ch2009@yahoo.com

Abstract

Power System State Estimation (PSSE) became a main subject in the operation of power systems through its important role in ensuring the secure and economical operation of the power system. In this work, two approaches were proposed and implemented in order to search for the optimal solution of state estimation in power systems, the first approach used a conventional state estimation program based on Weighted Least Square (WLS) method, and the second one used an intelligent technique based on Particle Swarm Optimization (PSO). All programs were implemented using MATLAB and developed to solve the state estimation problem of the Iraqi Super Grid network (400kV). The results showed that the PSO is more accurate and it convergence close to the optimal solution.

Keywords: Power System State Estimation (PSSE), Particle Swarm Optimization (PSO). Weighted Least Square (WLS)

تخمين حالة منظومة الشبكة العراقية استناداً الى تقنية امثلية الحشد الجزيئي

الخلاصة

يُعتبر تخمين حالة منظومات القدرة الكهربائية من الأمور المهمة في تشغيل منظومات القدرة وخصوصا في حالة الحمل الزائد على شبكة الطاقة الكهربائية من خلال دوره في ضمان تشغيل أكثر اقتصادية وأمان. تم اعداد واقتراح برنامجين للتغلب على سلبيات الطرق التقليدية وللبحث عن الحل الأمثل في تخمين حالة منظومات القدرة, البرنامج الأول هو برنامج تقليدي لتخمين حالة القدرة يستخدم طريقة التربيعات الموزونة (WLS), والأخر برنامج يستخدم تقنية امثلية الحشد الجزيئي (PSO). تم اعداد وتنفيذ البرامجيات بأستخدام الماتلاب وتم تطويره لحل مشكلة تخمين حالة الشبكة العراقية. كما أظهرت نتائج طريقة تقنية امثلية الحشد الجزيئي (PSO) دقيقة واقرب الى الحل الأمثل.

1. Introduction

The problem of monitoring the power flows and voltages on a transmission system is very important in maintaining system security, By simply checking each measured value against its limit, the power system operators can tell where problems exist in the transmission system and can take corrective actions to relieve overloaded lines or out of limit voltages [1, 2].

Power system state estimation is the process in which a best estimate of the state of the system is obtained based on a set of real-time system measurements for a pre-determined system model. It plays an important role in modern Energy Management Systems (EMS) by providing a complete, consistent, accurate and reliable database as an input to other key functions of the EMS system, such as Contingency Analysis, Optimal Power Flow (OPF), Security Monitoring, Automatic Voltage Control (AGC) and Economic Dispatch (ED),...etc. [3].

Studies of Power System State Estimation (PSSE) have been attempted by many researchers and papers. C. Venkatesh [4] presented an Interline power flow controller based on the conventional power system state estimation model, Hee-Myung [5] considered a binary PSO for identifying multiple bad data in the framework of the least squares state estimation, Jiaxiong [6] proposed state estimation method based on the extended weighted least squares (WLS) method for considering both measurement errors and model inaccuracy, Efthymios' s work [7] presents an ANN-based approach to pseudo measurement modeling for distribution system state estimation (DSSE). The proposed methodology uses load profiles and offline load flow analysis or historical data to train two ANNs, Ab. Halim[8] presented Weight least Square (WLS) method based on Particle Swarm Optimization (PSO) to identify the optimal measurement placement of power system state estimation, D.H. Tungadio [9] proposed the PSO algorithm for the power system state estimation (PSSE) problem. Two different approaches have been used to model the objective function of PSSE, that is, weighted least squares (WLS) and weighted absolute value (IRLS).

In this work two approaches were used and tested on the Iraqi Super Grid, those are: the conventional Weighted Least Square (WLS) method and the Particle Swarm Optimization (PSO) technique.

2. The Weighted Least Square (WLS) mathematical representation

Due to noise or random error, the true value of any physical quantity is not known; hence, a suitable procedure has to be followed to calculate the best estimate of the unknown quantity [1]. The method of least squares is often used to "best fit" measured data relating to two or more quantities.

The true but unknown measurement vector $[z]$ is related to the true but unknown state vector $[x]$ and the error vector $[e]$ by the relation [10]:

$$[\boldsymbol{z}] = \left[\boldsymbol{z}_{(x)}\right] + [\boldsymbol{e}] \tag{1}$$

$$z=\begin{bmatrix} z_1 \\ z_2 \\ . \\ . \\ . \\ z_m \end{bmatrix}=\begin{bmatrix} h_1(x_1,x_2,\ldots\ldots,x_n) \\ h_2(x_1,x_2,\ldots\ldots,x_n) \\ . \\ . \\ . \\ h_m(x_1,x_2,\ldots\ldots,x_n) \end{bmatrix}=\begin{bmatrix} e_1 \\ e_2 \\ . \\ . \\ . \\ e_m \end{bmatrix}=h(x)+e \tag{2}$$

Where**:**

[z] : the measurements vector.

$h^T = [\, h_1(x), h_2(x), \ldots , h_m(x) \,]$

$h_1(x)$: The nonlinear function relating measurement z_i to the state vector x.

$x^T = [\, x_1, x_2, \ldots , x_m \,]$, the system state vector**.**

$e^T = [\, e_1, e_2, \ldots , e_m \,]$, the vector of measurement errors.

m : no. of measurements

n : no. of state variables

$$E(e_i) = 0, \quad i = 1,2,3, \ldots , m. \tag{3}$$

Measurement errors are independent, i.e. $E\left[e_i e_j\right] = 0$ Hence**,**

$$cov(e) = E[e.e^T] = R = \begin{bmatrix} \sigma_1^2 & & & & \\ & \sigma_2^2 & & & \\ & & . & & \\ & & & . & \\ & & & & \sigma_m^2 \end{bmatrix} \tag{4}$$

The standard deviation σ_i of each measurement, i is calculated to reflect the expected accuracy of the corresponding meter used .The actual error [e] is given by:

$$[e] = [z] - [h(\, x \,)\,] \tag{5}$$

The actual (true) error cannot he determined because the true state vector value [x] is unknown, but their estimates can be calculated.

The estimated error is:

$$[\hat{e}] = [z] - [\hat{z}] \tag{6}$$

$$[\hat{e}] = [z] - [h(\hat{x})] \tag{7}$$

Where ^ indicate estimated values.

The criterion for calculating the best estimates of state vector $[\hat{x}]^T$ is to minimize the sum of the squares of the errors. To ensure that measurements from meters of known accuracy are treated more famously than less accurate measurements, each term in the sum of squares is multiplied by weight factor w. The weight factors are chosen as a reciprocal of the corresponding variance δ_i^2.

The WLS formulation can be expressed with the following minimization function, which is the sum of the squared normalized residuals

$$J(\hat{x}) = \sum_{j=}^{m} w_i\, e_i^2 \tag{8}$$

Where:

$$w_i = \frac{1}{\delta_{ii}^2} = \frac{1}{R_{ii}} \text{ i s the weighting factor}$$

$$J(\hat{x}) = \sum_{i=1}^{m} \frac{(z_i - h_i(\hat{x}))^2}{R_{ii}} \tag{9}$$

Can be expressed Equation (9) in matrix form as:

$$J(\hat{x}) = [z - h(\hat{x})]^T R^{-1} [z - h(\hat{x})] \tag{10}$$

At the minimum, the first order optimality conditions will have to be satisfied. These can be expressed in compact form as follows:

$$g(x) = \frac{\partial J(x)}{\partial x} = H^T(x) R^{-1} [z - h(x)] = 0 \tag{11}$$

$$Where: \; H(x) = \left[\frac{\partial h(x)}{\partial x}\right]$$

Expanding the nonlinear function $g(x)$ into its Taylor series around the state vector x^k yields**:**

$$g(x) = g(x^k) + G(x^k)(x - x^k) + \ldots = 0 \tag{12}$$

Neglecting the higher order terms leads to an iterative solution scheme known as the Gauss-Newton method as shown below:

$$x^{k+1} = x^k - [G(x^k)]^{-1} . g(x^k) \tag{13}$$

Where: k is the iteration index.

x^k Is the solution vector at iteration k.

$$G(x^k) = \frac{\partial g(x^k)}{\partial x} = H^T(x^k) R^{-1} [z - h(x^k)] \tag{14}$$

$$g(x^k) = -H^T(x^k)\, R^{-1} [z - h(x^k)] \tag{15}$$

$G(x)$ is called the gain matrix. It is sparse, positive definite and symmetric provided that the system is fully observable. The matrix G(x) is typically not inverted, but instead it is decomposed into its triangular factors and the following sparse linear set of equations are solved using forward/ back substitution at each iteration,

3. Weighted Least Squares (WLS) Algorithm [11]

Weighted Least Squares (WLS) state estimation involves the iterative solution of the normal equations. An initial guess has to be made for the state vector x^0. As in the case of the power flow solution, this guess typically corresponds to the flat voltage profile, where all bus voltages are assumed to be 1.0 per unit and in phase with each other.

The iterative solution algorithm for WLS state estimation problem can be outlined as follows:

1. Begin the iteration by setting the iteration index k=0, then, set flat start values1and 0 to bus voltage magnitudes and bus phase angles respectively. Finally, ε is set to a certain value.
2. Calculate, $h(x^k)$.
3. Calculate the gain matrix $G(x^k)$ and Jacobin matrix $H(x^k)$
4. Decompose $G(x^k)$ and solve for Δx^k.
5. Test for convergence, max $|\Delta x^k| \leq \varepsilon$.
6. If max $|\Delta x^k| > \varepsilon$, update $x^{k+1} = x^k + \Delta x^k$, $k = k + 1$,and go to step2 . Else, stop.

The algorithm flowchart is shown in the Appendix.

4. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is based on the behavior of a colony or swarm of insects, such as ants, termites, bees, and wasps; a flock of birds; or a school of fish. The particle swarm optimization algorithm mimics the behavior of these social organisms [12]. Each particle is assumed to have two characteristics: a position and a velocity. Each particle wanders around in the design space and remembers the best position (in terms of the food source or objective function value) it has discovered. The particles communicate information or good positions to each other and adjust their individual positions and velocities based on the information received on the good positions [13]

Basic algorithm as proposed by Kennedy and Eberhart (in 1995), introduced to calculate the velocity and position of each particle and it is used to find the optimal solution

Where
x_j^i : Particle position
v_j^i : Particle velocity
p_j^i : Best position found by jth particle (personal best)
p_j^g : Best position found by swarm (global best, best of personal bests)

Position of individual particles updated as follows:

$$x_{j+1}^{i} = x_{j}^{i} + v_{j+1}^{i} \qquad j=1,\ldots,n \tag{16}$$

With the velocity calculated as follows:

$$v_{j+1}^{i} = v_{j}^{i} + c_1\, r_1\, (p_{j}^{i} - x_{j}^{i}) + c_2\, r_2\, (p_{j}^{g} - x_{j}^{i}) \qquad j=1,\ldots,n \tag{17}$$

Where c_1 and c_2 are the cognitive (individual) and social (group) learning rates, respectively, and r_1 and r_2 are uniformly distributed random numbers in the range 0 and 1. The parameters c_1 and c_2 denote the relative importance of the memory (position) of the particle itself to the memory (position) of the swarm. The values of c_1 and c_2 are usually assumed to be 2.

The particle velocities build up too fast and the minimum of the objective function is skipped. Hence an inertia term, w, is added to reduce the velocity. Usually, the value of w is assumed to vary linearly from 0.9 to 0.4 as the iterative process progresses. The velocity of the jth particle, with the inertia term, is assumed as:

$$v_{j+1}^{i} = w_i\, v_{j}^{i} + c_1\, r_1\, (p_{j}^{i} - x_{j}^{i}) + c_2 r_2\, (p_{j}^{g} - x_{j}^{i}) \qquad j=1,\ldots,n \tag{18}$$

To achieve a balance between global and local exploration to speed up convergence to the true optimum, an inertia weight whose value decreases linearly with the iteration number has been used as:

$$w_i = w_{max} - \left(\frac{w_{max} - w_{min}}{imax}\right) * i \tag{19}$$

Where w_{max} and w_{min} are the initial and final values of the inertia weight, respectively, and imax is the maximum number of iterations used in PSO [12, 13].

5. Power System State Estimation using PSO

The non – linear equations relating the measurements vector $[z]$ and the true state variable $[x]$:

$$[z] = [h(x)] + [e] \tag{20}$$

Because of noise, the true values of the state vector x are never known, and the best possible estimates of the state vector is calculated based on Particle Swarm Optimization method (PSO). The usual state variables are the voltage magnitude and angle, while the measurements are the real and reactive power flows, node injections and voltage magnitudes.

The objective function of the state estimation is the same as that of conventional state estimation as follows: The PSO estimator will minimize the objective function $J[\hat{x}]$ given by Equation (10) and rewritten as follows:

$$J[\hat{x}] = [z - h(\hat{x})]^{T}\, R^{-1}\, [z - h(\hat{x})] \tag{21}$$

The PSO Algorithm can be described as follows [15]:

A) State variable: The bus voltage phase angles and magnitudes are considered to be state variables. The state variable particles are: $\theta_2, \theta_3 \ldots \theta_n, V_1, V_2 \ldots V_n$

B) Proposed State estimation algorithm: 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

i. Calculation of initial values of state variables: Using measurement data and state variables, initial load-flow calculation is performed.
ii. 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 PSO algorithm

Step 4 Converge criteria: The algorithm stops looking for a solution if the maximum of a variation of the state variable Δx, is smaller than 0.0001 and the iterations have reached the maximum number of iterations specified.

Step 5 Bad data detection and identification

i. Detection: The method used for bad data detection is the Chi-squares test.
ii. 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 (LNR) test [14, 15].

The flowchart of the PSO program is shown in the Appendix.

6. Simulation Results

The aim of this work is solving the State Estimation problem of the Iraqi Super Grid Network (400kv). To Do so, Two methods were used those are, the conventional (WLS) estimator and bad data detection and identification algorithms and the Particle Swarm Optimization (PSO) state estimation algorithm.

The Iraqi Super Grid network contains (29) bus bars, (16) generating plant and (38) transmission lines. The measured data for Iraqi network was taken from the Iraqi National Dispatch Center. The components of the Iraqi power system were modeled using MATLAB programming language.

In order to evaluate the performance of the state estimator, a base case or a reference case of the system is required. Hence, the system is solved using the power flow using Newton Raphson method which was assumed to be the actual or true power flow values of this system.

The effectiveness of the proposed approach is demonstrated. Additionally, the performance of the proposed estimator with the conventional one is compared in terms of accuracy. The Mean Square Error (MSE) was used to clarify the accuracy of the algorithms.

Tables (1) and (2) show a comparison between the actual and the estimated values variables (bus voltage magnitude and buses voltage angle) using both algorithms with their MSE error.

The estimated values are compared against the actual values using a bar chart. Figure (1) and (2) show a plot of state variables (buses voltage magnitudes and buses voltage angles) respectively.

While the estimated values of the real/reactive power flow and real/reactive power injection illustrated in Tables (3) – (6) respectively.

The estimated (both real and reactive) bus power injection and line power flows values are also plotted against the actual values, for both methods (WLS and PSO), as shown in Figures (4) – (7).

Table (1): Actual and estimated Voltage magnitudes

Bus No.	Bus Name	Voltage Actual (P.u)	Voltage (WLS) (P.u)	Voltage (PSO) (P.u)	Abs. error (WLS)	Abs. error (PSO)
1	BAJP	0.952	0.8749	0.9196	0.0771	0.0324
2	MMDH	0.9656	0.8688	0.9242	0.0968	0.0414
3	GNENW	0.9489	0.8628	0.9104	0.0861	0.0385
4	MSL4	0.9478	0.8591	0.9167	0.0887	0.0311
5	BAJG	0.9522	0.8750	0.9198	0.0772	0.0324
6	KAK4	0.9493	0.8810	0.9305	0.0683	0.0188
7	BGW4	0.8988	0.8481	0.8924	0.0507	0.0064
8	BGS4	0.9039	0.8613	0.9060	0.0426	0.0021
9	BGE4	0.8989	0.8416	0.8906	0.0573	0.0083
10	BGN4	0.8983	0.8403	0.8899	0.0580	0.0084
11	QDSG	0.9001	0.8414	0.8907	0.0587	0.0094
12	AMN4	0.8978	0.8404	0.8890	0.0574	0.0088
13	BGC4	0.8923	0.8419	0.8862	0.0504	0.0061
14	DAL4	0.929	0.8419	0.8897	0.0871	0.0393
15	KUT4	0.904	0.8338	0.9087	0.0702	0.0047
16	KUTP	0.9103	0.8393	0.9013	0.0710	0.0090
17	HDTH	0.9457	0.9029	0.9457	0.0428	0
18	QIM4	0.9502	0.8783	0.9220	0.0719	0.0282
19	MUSP	0.9146	0.8694	0.9087	0.0452	0.0059
20	MUSG	0.9144	0.8671	0.9064	0.0473	0.0080
21	BAB4	0.9173	0.8738	0.9095	0.0435	0.0078
22	GKHER	0.935	0.9309	0.9300	0.0041	0.0043
23	KDS4	0.8971	0.8686	0.9813	0.0285	0.0842
24	NSRP	0.8982	0.9064	0.9804	0.0082	0.0822
25	AMR4	0.9029	0.9312	0.9816	0.0283	0.0787
26	HRTP	0.8971	0.9832	1.0041	0861 0.	0.1070
27	KAZG	0.8906	0.9421	1.0004	0.0515	0.1098
28	RMULG	0.8978	0.9919	0.9997	0.1012	0.1019
29	BSR4	0.919	0.8921	1.0001	0.0269	0.0811
MSE					0.0092	0.0030

Table (2): Actual and estimated Bus angles

Bus No.	Bus Name	Angle Actual (rad.)	Angle (WLS) (rad.)	Angle (PSO) (rad.)	Abs. error (WLS)	Abs. error (PSO)
1	BAJP	0	0	0	0	0
2	MMDH	-0.4709	-0.4075	-0.4597	0.0634	0.0112
3	GNENW	-0.4950	-0.4470	-0.4699	0.0480	0.0251
4	MSL4	-0.4946	-0.4584	-0.4772	0.0362	0.0174
5	BAJG	-0.4615	-0.4218	-0.4439	0.0397	0.0176
6	KAK4	-0.4585	-0.4032	-0.4278	0.0553	0.0307
7	BGW4	-0.4576	-0.3998	-0.4190	0.0578	0.0386
8	BGS4	-0.3725	-0.3174	-0.3332	0.0551	0.0393
9	BGE4	-0.4046	-0.3592	-0.3634	0.0454	0.0412
10	BGN4	-0.4156	-0.3670	-0.3741	0.0486	0.0415
11	QDSG	-0.4107	-0.3624	-0.3829	0.0483	0.0278
12	AMN4	-0.3829	-0.3567	-0.3522	0.0262	0.0307
13	BGC4	-0.4327	-0.4032	-0.4109	0.0295	0.0218
14	DAL4	-0.4492	-0.4045	-0.4312	0.0447	0.0180
15	KUT4	-0.2754	-0.2332	-0.2322	0.0422	0.0432
16	KUTP	-0.2676	-0.2183	-0.2211	0.0493	0.0465
17	HDTH	-0.4814	-0.4376	-0.4693	0.0438	0.0121
18	QIM4	-0.5072	-0.4731	-0.4880	0.0341	0.0192
19	MUSP	-0.3252	-0.3012	-0.3100	0.0240	0.0152
20	MUSG	-0.3283	-0.2832	-0.2809	0.0451	0.0474
21	BAB4	-0.3101	-0.2480	-0.2532	0.0621	0.0569
22	GKHER	-0.2649	-0.1897	-0.1996	0.0752	0.0653
23	KDS4	-0.3164	-0.2670	-0.2752	0.0494	0.0412
24	NSRP	-0.2618	-0.2095	-0.2097	0.0523	0.0521
25	AMR4	-0.2180	-0.1841	-0.1807	0.0339	0.0373
26	HRTP	-0.1763	-0.1184	-0.1380	0.0579	0.0383
27	KAZG	-0.1815	-0.14085	-0.1463	0.0406	0.0352
28	RMULG	-0.2063	-0.1832	-0.1924	0.0231	0.0139
29	BSR4	-0.2862	-0.2259	-0.2291	0.0603	0.0571
MSE					0.0021	0.0013

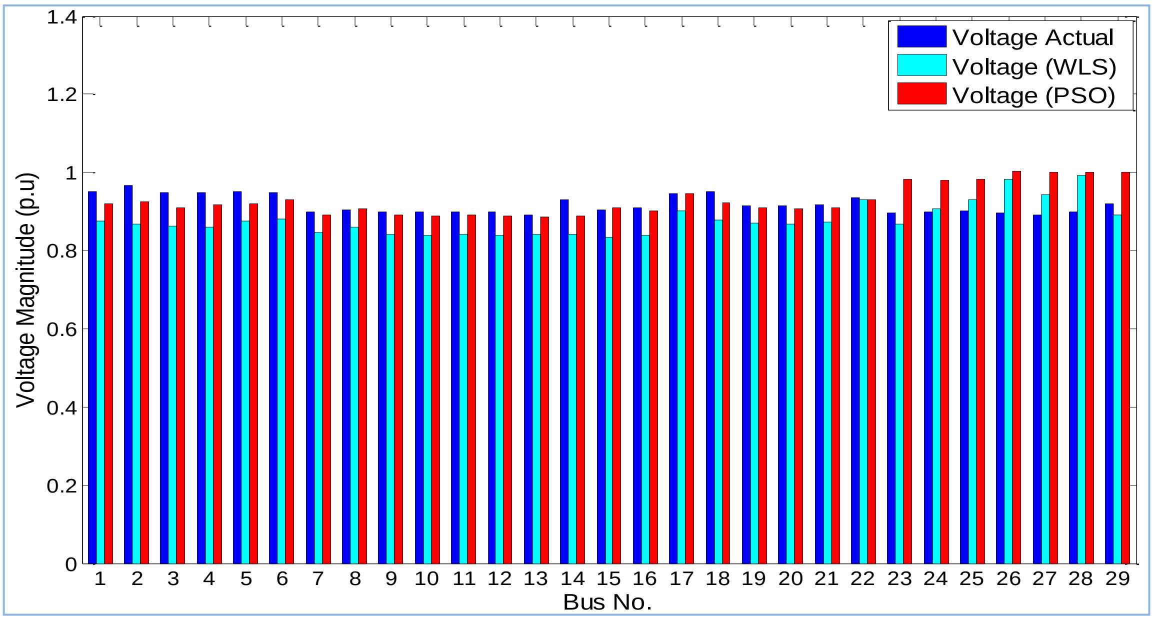

Figure (1): Comparison between actual and estimated values of the bus voltage magnitude

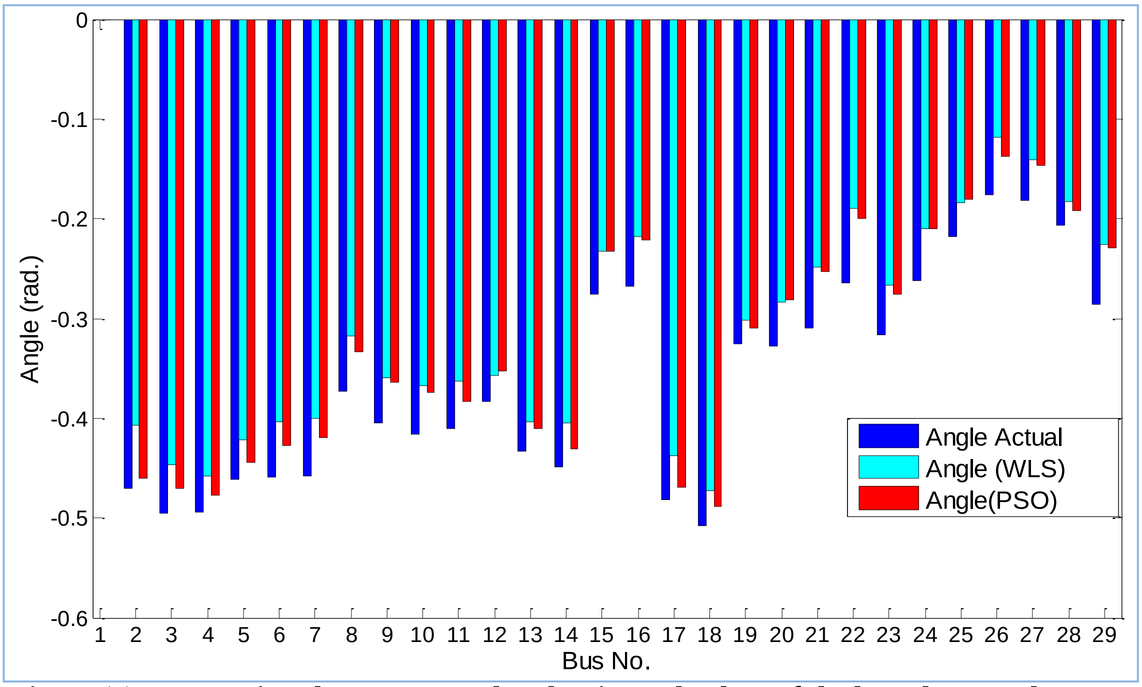

Figure (2): Comparison between actual and estimated values of the bus phase angle

Table (3): Actual and estimated active bus power injection

Bus No.	Bus Name	P Actual (P.u)	P estimation (WLS) (P.u)	P estimation (PSO) (P.u)	Abs. error (WLS)	Abs. error (PSO)
3	GNENW	-0.9930	-0.9428	-0.9498	0.0502	0.0432
4	MSL4	-4.5420	-4.3229	-4.4039	0.2191	0.1381
6	KRK4	-2.5000	-2.3995	-2.4280	0.1005	0.0720
8	BGS4	-1.5010	-1.4168	-1.4189	0.0842	0.0821
9	BGE4	-0.0340	-0.0220	-0.0242	0.0120	0.0098
10	BGN4	-4.5380	-4.2563	-4.3625	0.2817	0.1755
12	AMN4	-2.2550	-2.2065	-2.2121	0.0485	0.0429
13	BGC4	-2.1610	-2.0050	-2.0931	0.1560	0.0679
15	KUT4	-1.7640	-1.5027	-1.5061	0.2613	0.2579
16	KUTP	-3.7340	-3.8795	-3.9632	0.1455	0.2292
17	HDTH	-0.3970	-0.3135	-0.3329	0.0835	0.0641
20	MUSG	1.6000	1.4532	11.498	0.1468	0.1020
21	BAB4	-1.2830	-1.3931	-1.3689	0.1101	0.0859
22	GKHER	5.1000	5.3214	5.4030	0.2214	0.3030
23	KDS4	-2.5270	-2.3429	-2.4528	0.1841	0.0742
25	AMR4	0.1780	0.2002	0.0212	0.0222	0.1568
26	HRTP	1.6920	1.8645	1.8646	0.1725	0.1726
28	RMULG	0	-0.0588	-0.0598	0.0588	0.0598

Table (4): Actual and estimated reactive bus power injection

Bus No.	Bus Name	Q Actual (P.u)	Q estimation (WLS) (P.u)	Q estimation (PSO) (P.u)	Abs. error (WLS)	Abs. error (PSO)
3	GNENW	-0.5270	-0.5011	-0.5163	0.0259	0.0107
4	MSL4	-2.9250	-3.1110	-3.2320	0.1860	0.3070
6	KRK4	-0.4190	-0.3832	-0.4017	0.0358	0.0173
8	BGS4	-0.6940	-0.6232	-0.6409	0.0708	0.0531
9	BGE4	-1.2942	-1.2590	-1.2884	0.0352	0.0058
10	BGN4	-1.5322	-1.4275	-1.4524	0.1047	0.0798
12	AMN4	-2.1580	-2.2864	-2.2327	0.1284	0.0747

13	BGC4	-1.9580	-1.8783	-1.7580	0.0797	0.2000
15	KUT4	-1.3732	-1.3674	-1.3093	0.0058	0.0639
16	KUTP	0.0298	0.3521	0.3456	0.3223	0.3158
17	HDTH	-0.7200	-0.8924	-0.9326	0.1694	0.2096
20	MUSG	0.6550	0.5733	0.5982	0.0817	0.0568
21	BAB4	-0.4041	-0.4233	-0.4206	0.0192	0.0165
22	GKHER	2.0000	1.6170	1.7695	0.3830	0.2305
23	KDS4	-3.7880	-3.5247	-3.5093	0.2633	0.2787
25	AMR4	-0.5900	-0.6547	-0.7599	0.0647	0.1699
26	HRTP	-0.4432	-0.4085	-0.4215	0.0347	0.0217
28	RMULG	0	-0.0063	-0.0067	0.0063	0.0067

Table (5): The actual and estimated active power flow

Bus bar		P Flow Actual (P.u)	P Flow estimation (WLS) (P.u)	P Flow estimation (PSO) (P.u)	Abs. error (WLS)	Abs. error (PSO)
From	To					
BAJP	GNNW	0.9800	1.0101	1.0109	0.0301	0.0309
BAJP	BAJG	-3.1400	-3.1368	-3.1368	0.0032	0.0032
BAJP	BGW4	0.3800	0.3176	0.3276	0.0624	0.0524
BAJP	BGW4	0.2853	0.2429	0.2437	0.0424	0.0416
BAJP	HDTH	0.9024	0.7924	0.7935	0.1100	0.1089
MSL4	MMDH	-1.9900	-2.1539	-2.1536	0.1639	0.1636
MSL4	MMDH	-1.9900	-2.1539	-2.1536	0.1639	0.1636
MSL4	BAJP	-0.9382	-1.0365	-1.0375	0.0983	0.0993
MSL4	GNNW	0.8983	0.9652	0.9892	0.0669	0.0909
KRK4	MSL4	0.5932	0.5112	0.5320	0.0820	0.0612
KRK4	BAJG	0.1400	0.1298	0.1166	0.0102	0.0234
KRK4	BGE4	-0.8900	-1.0212	-1.0211	0.1312	0.1311
QIM4	HDTH	-1.0400	-0.9378	-0.9404	0.1022	0.0996
HDTH	BGW4	-0.3300	0.400-	-0.4005	0.0700	0.0705
QDSG	BGN4	3.4324	3.3066	3.3063	0.1258	0.1261
QDSG	BGN4	3.4324	3.3066	3.3063	0.1258	0.1261
BGN4	BGW4	3.9600	3.8709	3.8935	0.0891	0.0665
BGN4	BGE4	-3.7032	-3.6994	-3.6987	0.0038	0.0045
BGC4	BGW4	3.4700	3.6483	3.6497	0.1783	0.1797
BGC4	BGS4	-5.6400	-5.7943	-5.6698	0.1543	0.0298
AMN4	BGE4	4.3500	4.3783	4.3775	0.0283	0.0275
AMN4	BGS4	-1.1800	-1.0425	-1.1179	0.1375	0.0621
AMN4	BGS4	-1.0181	--0.9756	-0.9782	0.0425	0.0399
AMN4	KUTP	-2.0221	-1.8410	-1.9215	0.1811	0.1006
BGS4	MUSP	-3.9100	-3.0802	-3.8424	0.8298	0.0676

MUSP	BAB4	-1.8800	2.0010	-2.0020	3.8810	0.1220
MUSP	BAB4	-1.8800	-2.0010	-2.0020	0.1210	0.1220
MUSG	MUSP	-2.2099	-2.1247	-2.1223	0.0852	0.0876
MUSG	BGS4	4.0000	3.8739	3.9878	0.1261	0.0122
BAB4	GKHER	-3.2200	-3.3762	-3.2087	0.1562	0.0113
BAB4	KDS4	-5.4400	-5.3256	-5.3961	0.1144	0.0439
GKHER	KDS4	2.5200	2.4021	2.4329	0.1179	0.0871
NSRP	KDS4	-1.2500	-1.2280	-1.2082	0.0220	0.0418
KUTP	KUT4	0.4400	0.4679	0.4552	0.0279	0.0152
NSRP	KUT4	0.2600	0.2439	0.2499	0.0161	0.0101
NSRP	RMLG	-1.1219	-1.1157	-1.1140	0.0062	0.0079
KUT4	AMR4	-1.0500	-1.0664	-1.0693	0.0164	0.0193
AMR4	HRTP	-01.400	-1.4721	-1.4713	0.0721	0.0713
RMLG	KAZG	-1.4100	-1.2361	-1.2349	0.1739	0.1751
HRTP	KAZG	0.4400	0.3792	0.3920	0.0608	0.0480
BSR4	KAZG	0	0.0929	0.0930	0.0929	0.0930

Table (6): The actual and estimated reactive power flow

Bus bar		Q Flow actual (P.u)	Q Flow estimation (WLS) (P.u)	Q Flow estimation (PSO) (P.u)	Abs. error (WLS)	Abs. error (PSO)
From	To					
BAJP	GNNW	-0.3900	-0.3652	-0.3720	0.0248	0.0180
BAJP	BAJG	-0.4400	-0.4452	-0.4453	0.0052	0.0053
BAJP	BGW4	-0.6400	-0.5414	-0.5595	0.0986	0.0805
BAJP	BGW4	0.0380	0.04237	0.04139	0.0044	0.0034
BAJP	HDTH	-0.2850	-0.2732	-0.2801	0.0118	0.0049
MSL4	MMDH	-1.1320	-1.0404	-1.0302	0.0916	0.1018
MSL4	MMDH	-1.1320	-1.0404	-1.0302	0.0916	0.1018
MSL4	BAJP	-0.8729	-0.8230	-0.8463	0.0499	0.0266
MSL4	GNNW	-0.0292	-0.0219	0.0240	0.0073	0.0532
KRK4	MSL4	-0.9400	-0.9304	-0.9654	0.0096	0.0254
KRK4	BAJG	-0.4000	-0.3921	-0.3991	0.0079	0.0008
KRK4	BGE4	0.5800	0.5729	0.5796	0.0071	0.0004
QIM4	HDTH	-0.5508	-0.3796	-0.4060	0.1712	0.1448
HDTH	BGW4	1.4900	1.3689	1.3984	0.1211	0.0916
QDSG	BGN4	0.8600	0.7700	0.7700	0.0900	0.0900
QDSG	BGN4	0.6800	0.7700	0.7700	0.0900	0.0900
BGN4	BGW4	-0.5000	-0.5680	-0.5748	0.0680	0.0748
BGN4	BGE4	0.1600	0.1282	0.1114	0.0318	0.0486
BGC4	BGW4	-1.4400	-1.4750	-1.4754	0.0350	0.0354
BGC4	BGS4	-0.5000	-0.5442	-0.5258	0.0442	0.0258

AMN4	BGE4	-0.7200	-0.8806	-0.9015	0.1606	0.1815
AMN4	BGS4	-0.6800	-0.7147	-0.7180	0.0347	0.0380
AMN4	BGS4	-0.6800	-0.7147	-0.7180	0.0347	0.0380
AMN4	KUTP	-0.0600	-0.0744	-0.0754	0.0145	0.0155
BGS4	MUSP	-0.5200	-0.5029	-0.5128	0.0171	0.0072
MUSP	BAB4	0.2000	0.1765	0.17880	0.0235	0.0212
MUSP	BAB4	0.2100	0.1765	0.17880	0.0335	0.0312
MUSG	MUSP	-0.5000	-0.5291	-0.5501	0.0291	0.0501
MUSG	BGS4	0.1200	0.1829	0.1928	0.0629	0.0728
BAB4	GKHER	-1.5100	-1.5892	-1.5090	0.0792	0.0010
BAB4	KDS4	-0.6500	-0.6054	-0.5900	0.0446	0.0600
GKHER	KDS4	1.4000	1.0050	1.0111	0.3950	0.3889
NSRP	KDS4	-0.2200	-0.2471	-0.2389	0.0271	0.0189
KUTP	KUT4	-0.4900	-0.6089	-0.6199	0.1189	0.1299
NSRP	KUT4	-0.6200	-0.5892	-0.5987	0.0308	0.0213
NSRP	RMLG	-0.1600	-0.2095	-0.2071	0.0495	0.0471
KUT4	AMR4	-0.3500	-0.7255	-0.7410	0.3755	0.3910
AMR4	HRTP	-0.0400	0.0927	0.0780	0.1327	0.1180
RMLG	KAZG	0.5000	0.5794	0.6960	0.0794	0.1960
HRTP	KAZG	0.3600	0.5078	0.5220	0.1478	0.1620
BSR4	KAZG	0	-0.0834	-0.0904	0.0834	0.0904

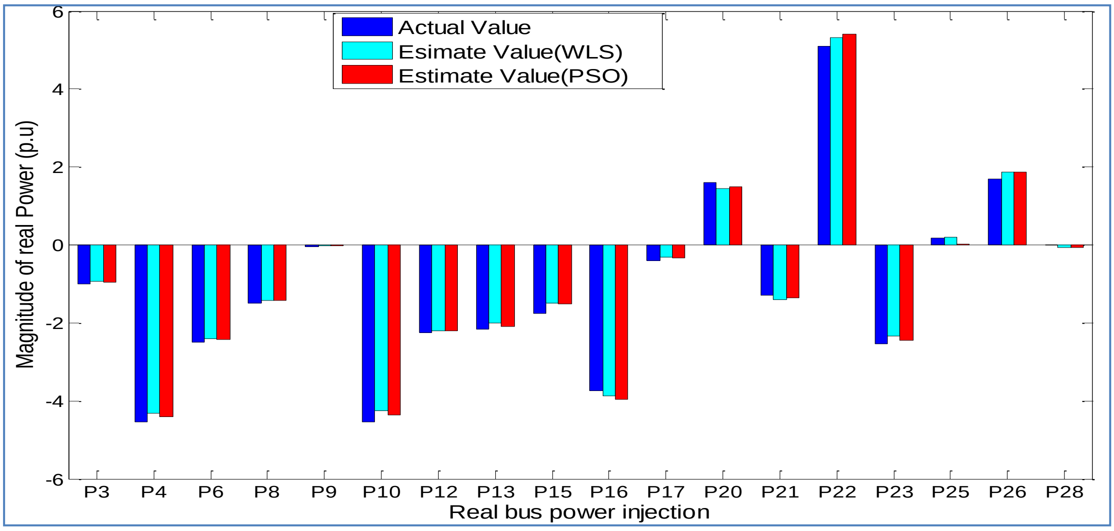

Figure (3): Comparison between actual and estimated bus real power injection

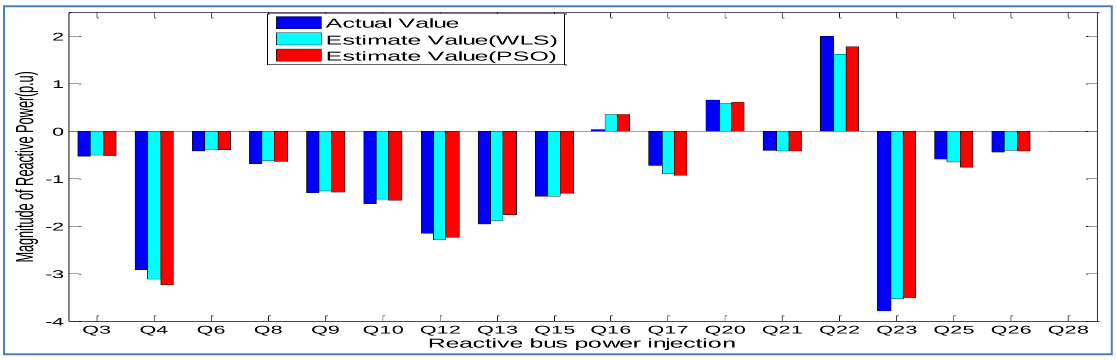

Figure (4): Comparison between actual and estimated reactive bus power injection

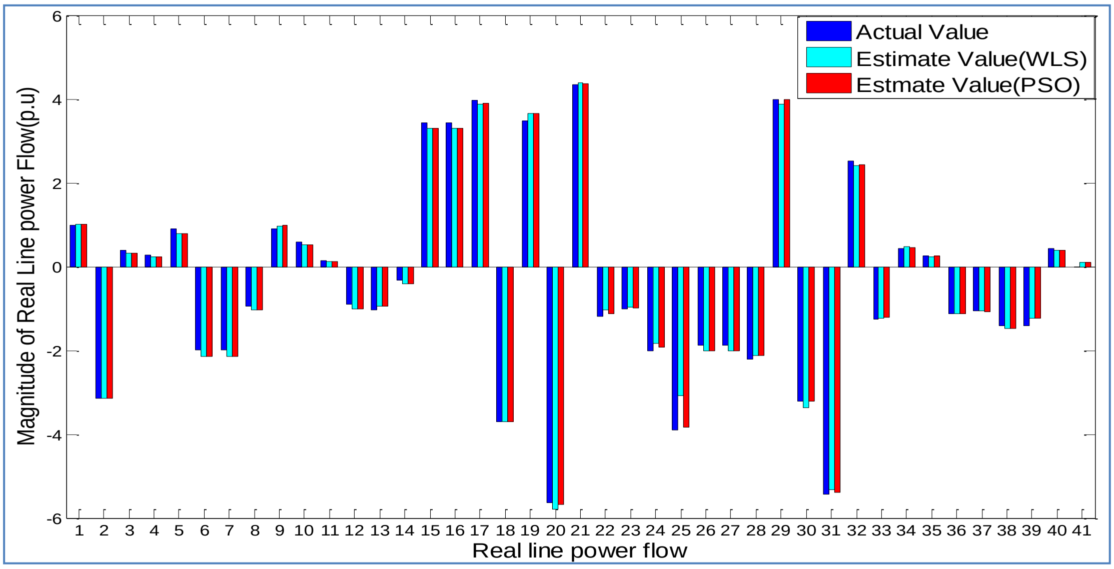

Figure (5): Comparison between actual and estimated reactive line power flow

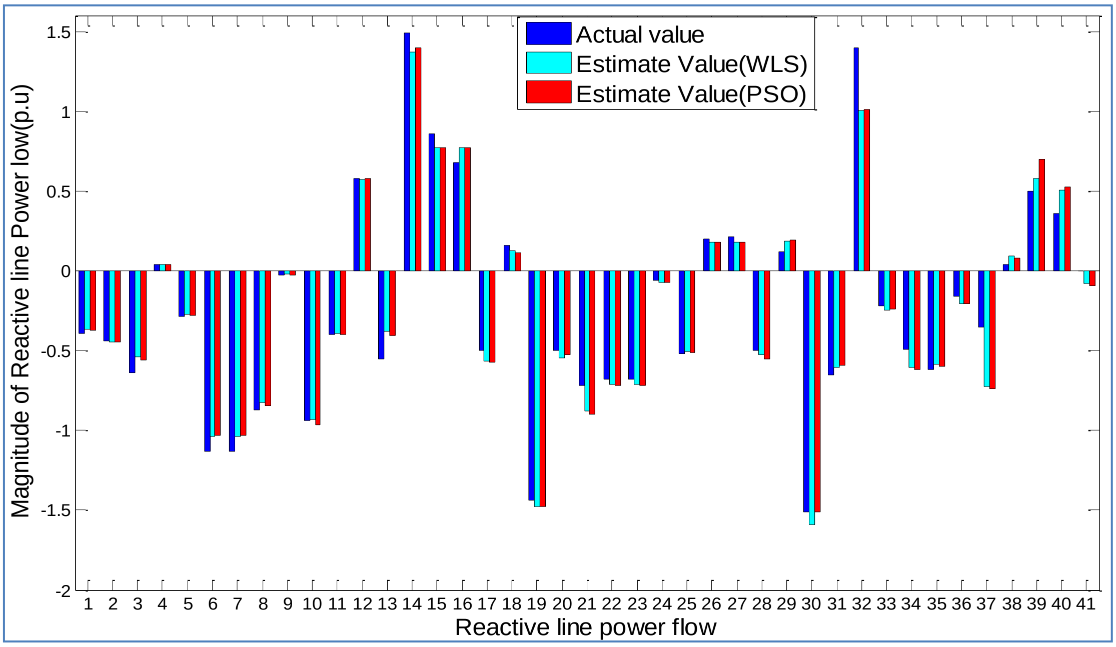

Figure (6): Comparison between actual and estimated reactive line power flow

From the obtained results and from the analysis of the results in Tables (1 to 6), it is observe that the accuracy of (PSO) method was preferable when compared to the (WLS) method, the accuracy of the (PSO) algorithm is preferable when compared with the (WLS) algorithm on account of (MSE), from Table (1) we can see that MSE in voltage estimates in case of PSO (0.0030) is less than (0.0092) for WLS. For bus angle in Table (2) the MSE is (0.0021) for WLS and (0.0013) for PSO.

From the obtained results, it was clear that the values of the buses voltage magnitude, buses phase angle, the power injection, and line power flow, show a closer estimation to the actual value by using the two methods (WLS and PSO), but the proposed PSO estimator outperformed the conventional WLS.

Conclusions

A Particle Swarm Optimization (PSO) based approach to Power System State Estimation (PSSE) problem was presented in this work. The obtained results using the proposed approach were compared with the conventional method the Weighted Least Square method (WLS). By summarizing all results of the estimated values in the two methods, it can be seen that they are very close to the actual case values and differ only by a few degrees in both methods when no bad data are presented and the PSO is more efficient and accurate than Weight Least Square (WLS) method, therefore, the Particle Swarm Optimization (PSO) may consider as a successful technique in Power System State Estimation problem, since it has an effective and robust performance for solving state estimation through its ability to detect and identify bad data location correctly by identifying the largest normalized residual.

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Appendix:

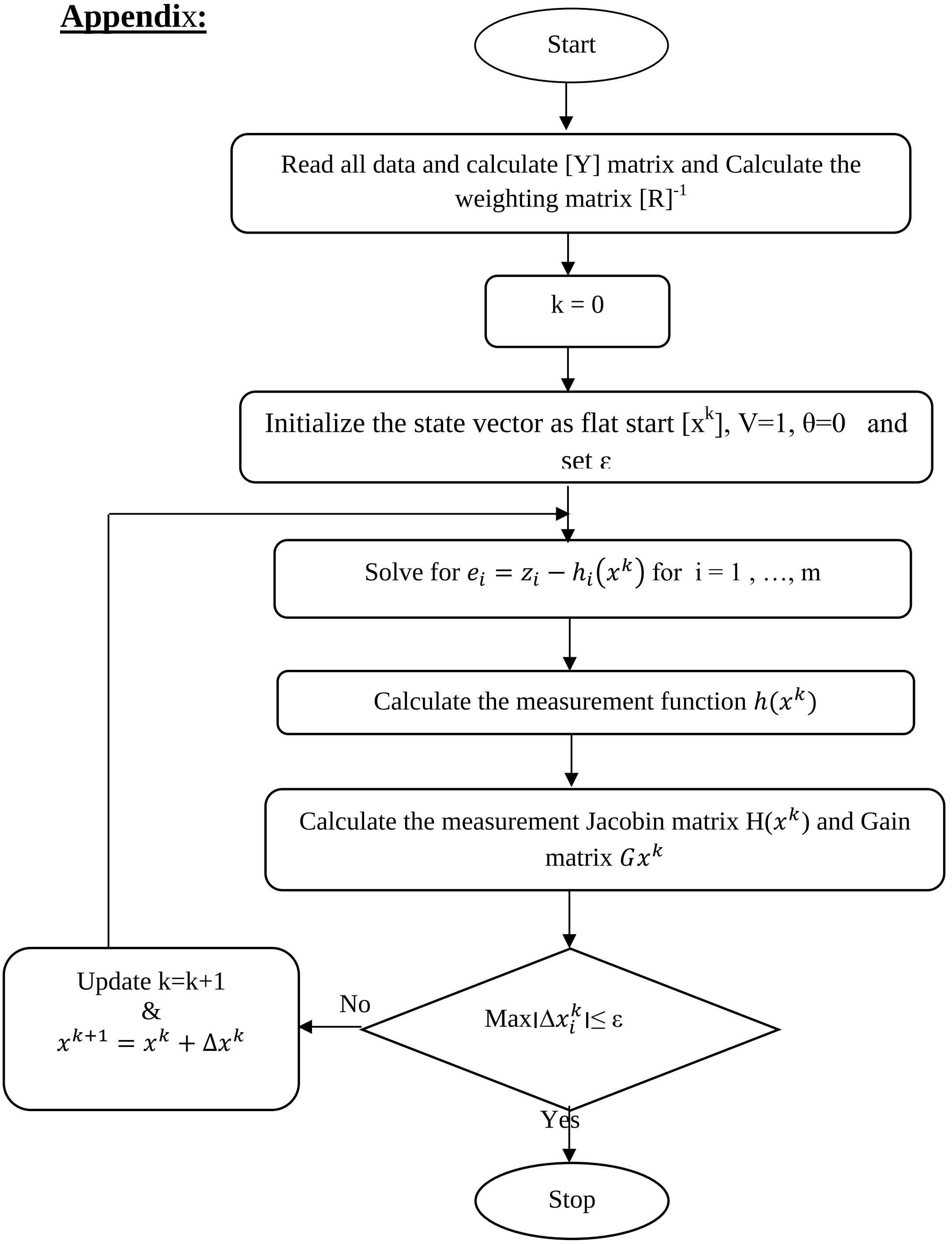
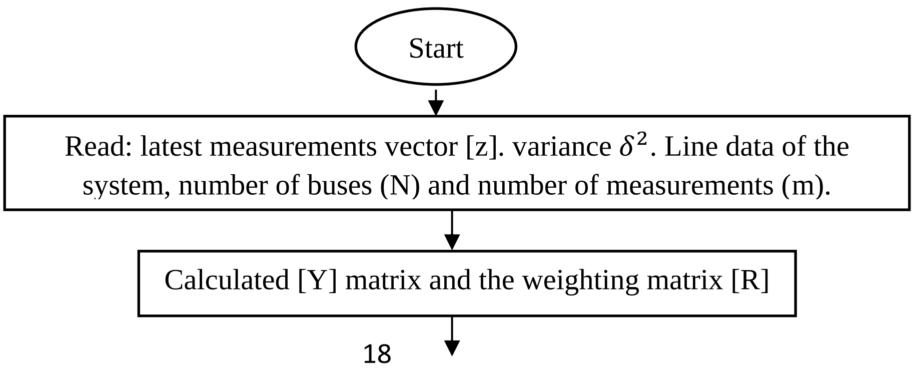


Figure (A): Flowchart Weighted Least Square (WLS) technique



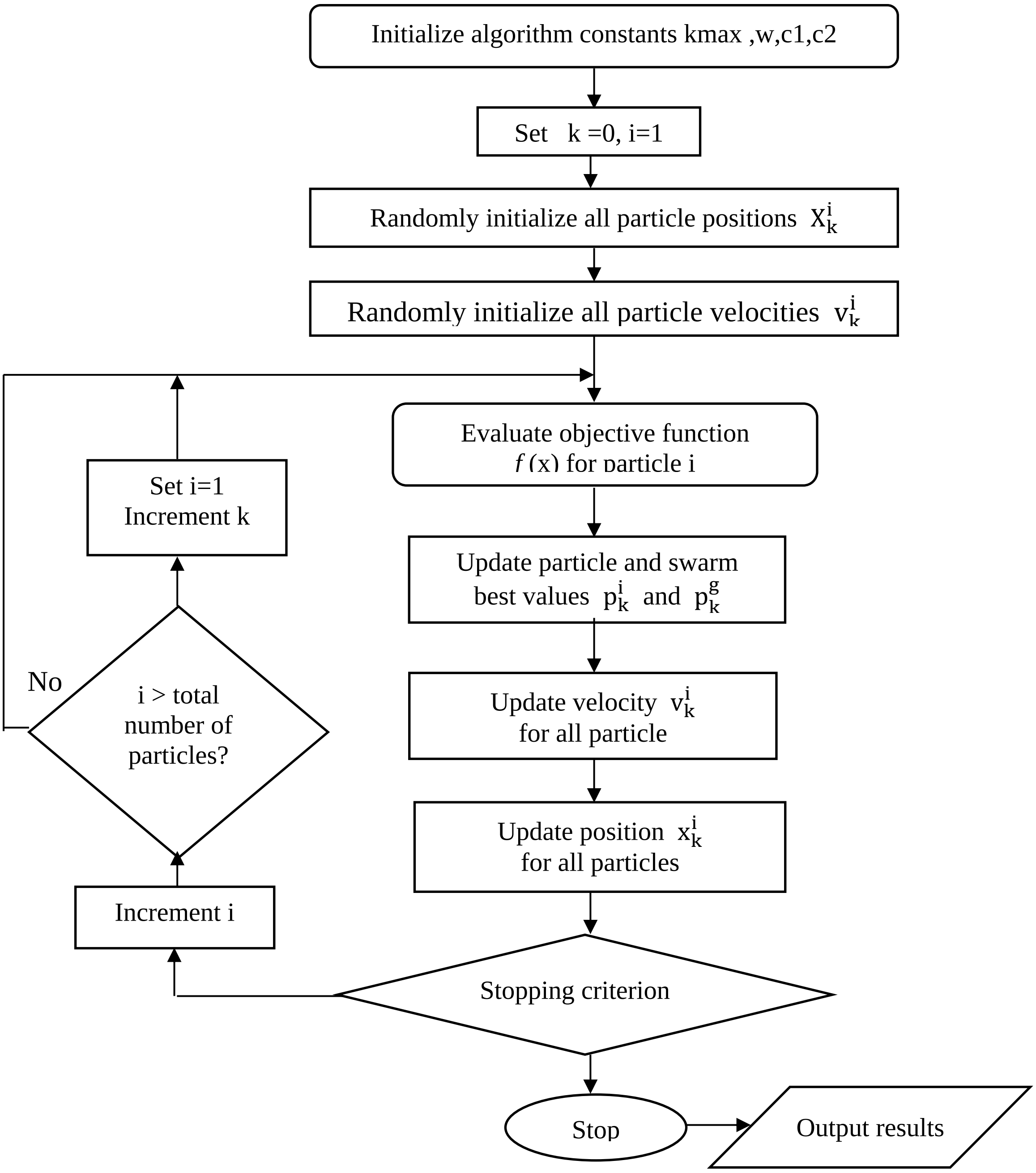


Figure (B) Flowchart of state estimation by use Particle Swarm Optimization (PSO)