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A HYBRID PARTICLE SWARM OPTIMIZATION APPROACH FOR LOAD-FLOW COMPUTATION

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Abstract. *This paper presents a hybrid particle swarm based methodology for solving load flow in electrical power systems. Load flow is an electrical engineering well-known problem which provides the system status in the steady-state and is required by several functions performed in power system control centers. The proposed approach for load flow computation is based on the minimization of the power mismatches in the system buses and applies a hybrid particle swarm optimization with mutation operation to achieve this. The presented model searches for a greater convergence and a wider application in comparison with traditional methods. As the proposed method is not a tangent method, it is able to solve even non convex problems, unlike traditional methods. Numerical results of the proposed methodology are presented for two different power system case studies.*
Keywords: Particle swarm optimization, Load flow, Artificial intelligence, Electrical power system, Computational intelligence

1. **Introduction.** Load flow studies are required by most functions performed in power system control centers [1]. Load flow is an electrical engineering well-known problem which provides the power system operation point in the steady-state [2,3]. This problem is modeled by a set of non-linear equations, which is commonly solved by the application of numerical methods [4,5]. Newton-Raphson approach – and its variants – is highlighted as a numerical method to solve load flow, because of its good and quick convergence. However, this method includes some difficulties or limitations because of the complex Jacobian matrix calculation and inversion and also the dependence on good initial estimated values to guarantee the convergence. Moreover, some current changes in the power system characteristics, such as an occurrence of a higher resistance-to-reactance ratio (R/X), may complicate the load flow convergence [6,7]. Finally, Newton-Raphson is a tangent method, so it cannot solve non convex problems. For example, if part of the power system is lost, because of a contingency, Newton-Raphson method cannot find the load flow solution properly.

In [8] it is pointed out that the Newton-Raphson based approaches to solve the load flow problem do not work well when the power system becomes highly stressed and when there are nonlinear elements in the power network, which may occur because of the employment of flexible AC transmission systems (FACTS) devices [9]. [10] also highlights that the Newton-Raphson method is highly sensitive to the initial settings of the variables. Other problems in convergence are related in [11], which remarks that the Newton-Raphson based methods do not behave well when the system is heavy loaded and when the Jacobian matrix is ill-conditioned. Moreover, [12] observes that conventional methods have difficulty to converge if the R/X ratio is high, and they indeed can fail to converge due to an inappropriate choice of starting values.

Thus, researchers have been attempting new methods to solve the load flow equations, looking for an easier and a more efficient implementation, as well as overcoming the aforementioned limitations and convergence problems. Many of these new methods have applied artificial intelligence techniques.

In the area of artificial intelligence, computational intelligence based algorithms have been applied successfully to electrical engineering problems, and Particle Swarm Optimization (PSO) is pointed out among these techniques. PSO algorithms are applied in function optimization and they are based on the behavior of birds' flocks searching for food [13]. PSO applications have provided good convergence properties, ease of implementation and low computational time [14]. The PSO based methodologies have potential to overcome limitations of the conventional methods for solving load flow because of the technique nature and the algorithm structure, and they are powerful alternatives when conventional methods fail to find the load flow solution [4]. An important characteristic of PSO is that it is not a tangent method, it does not depend on so good initial estimative values to converge to a best solution and so it is able to solve even non convex problems.

Ref. [15] proposed an adaptive PSO based method for normal and low voltage multiple load flow solutions, which is important to the purpose of voltage stability assessment, highlighting the potential of PSO to do this job, while standard methods are not suitable to do this. In [14,16,17], the authors propose the PSO application to the optimal power flow problem. In [18], the authors propose a PSO methodology for power system restoration. In [19], it is presented PSO applied to voltage and reactive power control. Several researches have also been implementing hybrid models, putting PSO together with other techniques, for instance the Genetic Algorithm (GA) operators. In [20], it is proposed a Hybrid PSO with Mutation applied to loss power minimization. In [21], it presents the particle swarm optimization algorithm for solving the optimal distribution system reconfiguration problem for power loss minimization, and in [6] it is presented a chaotic PSO algorithm with local search to the load flow calculation. Finally, in [22], it is proposed a hybrid algorithm based on combining fuzzy adaptive PSO and Differential Evolution for nonconvex economic dispatch.

This paper proposes the application of a hybrid particle swarm optimization approach for load flow computation, combining PSO with a mutation operation. This methodology is based on the minimization of the apparent power mismatches in the system buses. The variables are continuous and must stay within the specified boundaries defined in the system input data. Numerical results were obtained for 6-bus and 9-bus power system case studies [23,24].

2. Load Flow Analysis in Electrical Power Systems.

Load flow – or power flow – provides the system status in the steady-state; it means the determination of the power system operation point based on the previous knowledge of system parameters and some variables of the system buses. The purpose of this study is to obtain the system buses voltages in order to determine later the power adjustments in the generation buses and the power flow in the system branches. Therefore, it is possible to obtain the amount of power generation necessary to supply the power demand plus the power losses in the system branches. Besides, the voltage levels must comply with the predetermined boundaries and overloaded operations added to those in the stability limit must be prevented [4].

Each power system bus is associated with four variables, where two of them can be controlled and the other two are results of the system conditions. These variables are: real power (P), reactive power (Q), voltage magnitude ($|V|$) and voltage phase angle (δ). The power system buses are classified according to these mentioned variables. Type 1 Bus or PQ Bus: P_i and Q_i are specified, and $|V_i|$ and δ_i are calculated; Type 2 Bus or PV Bus: P_i and $|V_i|$ are specified, and Q_i and δ_i are calculated; Type 3 Bus or Vδ Bus ("Slack Bus"): $|V_i|$ and δ_i are specified, and P_i and Q_i are calculated.

The equation general form that represents the system power flow computation is given by (1).

$$P_i - jQ_i - y_{i1}V_1V_i^* - y_{i2}V_2V_i^* - \ldots - y_{in}V_nV_i^* = 0 \tag{1}$$

where $i = 1, \ldots, n$, bus number; P_i = real power generated or injected in the bus i; Q_i = reactive power generated or injected in the bus i; $|V_i|$ = voltage magnitude of the bus i; δ_i = voltage phase angle of the bus i; $V_i = |V_i|e^{j\delta i}$, i.e., the voltage in the polar form; $V_i^* = |V_i|e^{-j\delta i}$, i.e., the conjugate voltage; y_{ik} = element of the nodal admittance matrix Y_{bus}.

The nodal admittance matrix can be computed as follows: if $i = k$, y_{ik} is the sum of the admittances that come out from the bus i; else y_{ik} is the admittance between the buses i and k, multiplied by -1.

Equation (1) represents a complex and non-linear equations system, and its solution is usually obtained through approximations adopting numerical methods.

3. Overview on Particle Swarm Optimization and Mutation Operation.

3.1. Particle swarm optimization.

Swarm Intelligence is a kind of Artificial Intelligence based on social behavior. An intelligent swarm relates to a population of interacting individuals able to optimize a function or goal by collectively adapting to the environment in which they are inserted. PSO has roots in artificial life and evolutionary computation; it consists of an optimization procedure developed through the simulation of simplified social models as bird flocks flying randomly in search for food [14,25].

PSO is applied to function optimization by using a population of individuals, i.e., a set of particles, where each one is a candidate to the approached problem solution. These particles are distributed in the search space, each one having position and velocity parameters at each time instant. Moreover, such particles have cognition about their own performances and also about their neighbors' performances. The best individual position of a particle is called personal best, and the best position of all the particles is called global best. The particles are assessed through a specific rule function at each time instant. The rule function performs the interaction between the particles and the environment in which they are inserted, and it is related to the problem modeling.

The PSO algorithm analyzes, at each time step, the particles displacement in search for the global best and updating their parameters through defined equations. This process is iterative and it proceeds until all the particles converge to the achieved global best, which is adopted as the problem solution.

3.2. Mutation operation in genetic algorithms.

Genetic Algorithm (GA) is a search heuristic iterative procedure inspired by natural evolution and useful to optimization and search problems [26]. GA uses a population of individuals, in which each one represents a possible solution to the treated problem [27,28]. The GA accumulated information is applied to decrease the search space and create new good solutions to the problem domain [29].

Mutation is a genetic operator applied in order to cover better the problem search space, maintaining genetic diversity and also preventing the convergence to a local best. The mutation operation is performed by altering one or more gene values in a chromosome, randomly and with an associated probability to occur [20].

4. **A Hybrid Particle Swarm Optimization Approach for Load Flow Computation.** The proposed algorithm for solving load flow computation is named Hybrid Particle Swarm Optimization with Biased Mutation (HPSOBM) [30]. This methodology is based on the minimization of the power mismatches in the system buses. The particles positions are defined as the buses voltages, – the voltage phase angles and magnitudes, – as depicted in (2), so they assume continuous values within the boundaries specified in the input data.

$$x_i = \{\delta_2, \delta_3, \ldots, \delta_k, \ldots, \delta_n, V_2, V_3, \ldots, V_k, \ldots, V_n\} \tag{2}$$

where i = particle index; x_i = particle i position; k = bus index; n = total number of buses; δ_k = voltage phase angle at bus k; V_k = voltage magnitude at bus k. Note that bus 1 is defined as the slack bus, so the particle position does not comprise it.

The rule function parameters are defined as *scores* and they must be minimized in the HPSOBM algorithm. The scores are computed as the arithmetic mean of the buses apparent power mismatch, ΔS. So the arithmetic mean of ΔS's is the parameter to be minimized by the algorithm rule function. Each particle has a *personal score*, i.e., the value obtained by its personal best. The *global score* is the score associated to the global best. The *current score* is the score obtained by a particle at the current iteration of the process.

4.1. **Algorithm startup.** The algorithm begins generating the initial estimate value to the particles positions, velocities, personal best values and global best values. The initial estimation procedure is explained as follows. The voltage phase angles, which are one kind of parameters of the particles positions, begin as random values within the specified boundary. The voltage magnitudes, which are the other kind of parameters of the particles positions, require an analysis on the bus type before the initial estimation. In the case of a PQ bus, the voltage magnitude begins as a random value within the specified boundary; in the case of a PV bus, the voltage magnitude is the rated value specified in the input data. The initial velocities are null. The personal best parameters start as the associated particle position values and the global best parameter starts as an arbitrary particle value. The scores begin with large values in order to be minimized later.

4.2. **Rule function.** The iterations are initialized and then the rule function is successively applied. The procedure explained as follows is executed for each particle of the population. Firstly, the buses voltages receive the particle position values. Thus, the unknown power values of PV buses and $V\delta$ bus are computed using (1). The power flow in the system branches is calculated using (3).

$$S_{ij} = P_{ij} + jQ_{ij} = V_i(V_i^* - V_j^*)Y_{ij}^* + V_iV_i^*Y_{sh,i} \tag{3}$$

where S_{ij} = complex apparent power between the buses i and j; P_{ij} = real power between the buses i and j; Q_{ij} = reactive power between the buses i and j; V_i = bus i voltage; V_j = bus j voltage; $V_i^* = |V_i|e^{-j\delta i}$, i.e., the conjugate voltage; $V_j^* = |V_j|e^{-j\delta j}$, i.e., the conjugate voltage; Y_{ij} = admittance between the buses i and j; $Y_{sh,i}$ = shunt admittance of the bus i.

The real and reactive power mismatches of each bus are calculated as the sum of the injected power in the approached bus. The apparent power mismatches arithmetic mean is obtained and associated to the particle current score. It is also obtained the particle position which has the biggest score until that instant time. This particle index is kept and it is used in the mutation operation. The personal best updating verification is made, and after all the particles pass through the described routine, the global best updating verification is accomplished.

4.3. **Particle parameters updating.** The velocities as well as the position of the particles are updated according to (4), (5) and (6) [13,21,22].

$$v(t+1) = w.v(t) + c_1.r_1.(p(t) - x(t)) + c_2.r_2.(g(t) - x(t)) \tag{4}$$

$$x(t+1) = x(t) + v(t+1) \tag{5}$$

$$w = w_{\max} - \frac{(w_{\max} - w_{\min}).t}{ni} \tag{6}$$

where i = particle index; t = iterations counter; ni = total number of iterations; $v(t)$ = particle i velocity at iteration t; $x(t)$ = particle i position at iteration t; r_1, r_2 = random numbers between 0 and 1; c_1, c_2 = acceleration coefficients, both set to a value of 2.0; $p(t)$ = particle i personal best found at iteration t; $g(t)$ = global best found at iteration t; w = velocity equation's inertia weight; $w_{\max}$ = inertia weight maximum value, set to a value of 0.7; $w_{\min}$ = inertia weight minimum value, set to a value of 0.2.

Then the mutation operation is applied to the worst particle of the current iteration, i.e., the particle which has the biggest score, and because of this principle it is named as Biased Mutation [30]. The procedure consists in adding a random value to the particle position, according to (7) [22].

$$mx(k) = x(k) + 0.1.[(x_{\max} - x_{\min}).r + x_{\min}] \tag{7}$$

where k = mutated particle index; $x(k)$ = particle position before the mutation operation; $mx(k)$ = particle position after the mutation operation; r = random number between 0 and 1; $x_{\max}$ = maximum value of the position, related to the specified boundary in the input data; $x_{\min}$ = minimum value of the position, related to the specified boundary in the input data.

4.4. **Problem solution.** The stop criterion is defined by iterations groups and by the required accuracy for the global score. This tolerance was adopted as 10^{-5} (pu). The simulation runs a group of a fixed number of iterations. In the end of the iterations group, if the global score is bigger than the tolerance, so the algorithm runs another group of iterations. The process continues until a maximum number of iterations groups it can run. So the final global best is adopted as the load flow solution.

Note that the proposed methodology can provide several acceptable results for the same load flow study, depending on the simulation. The reason is because each particle has a random initial estimate value and the HPSOBM equations also employ random values, so several solutions can be achieved for the same initial estimative [30]. However, numerical traditional methods, starting with the same initial estimative values, achieve the same final results, regardless of the program simulation.

Finally, in order to illustrate the proposed methodology and to compare with the conventional one, Figures 1 and 2 present flowcharts of the Newton-Raphson method and the HPSOBM method, respectively.

Regarding the flowchart presented in Figure 1, it is important to point out that the mismatches equationing is a matrix equation which relates the voltage mismatches $\Delta\theta$'s and ΔV's with the power mismatches ΔP's and ΔQ's.

Analyzing the flowcharts depicted in Figures 1 and 2, and comparing the techniques nature, it can be noted the main differences between them. HPSOBM is a stochastic method based on a population of individuals searching for the global best. Because of this stochastic nature, HPSOBM does not require gradient information, it utilizes the rule function information and works in a random oriented way. HPSOBM is not a tangent

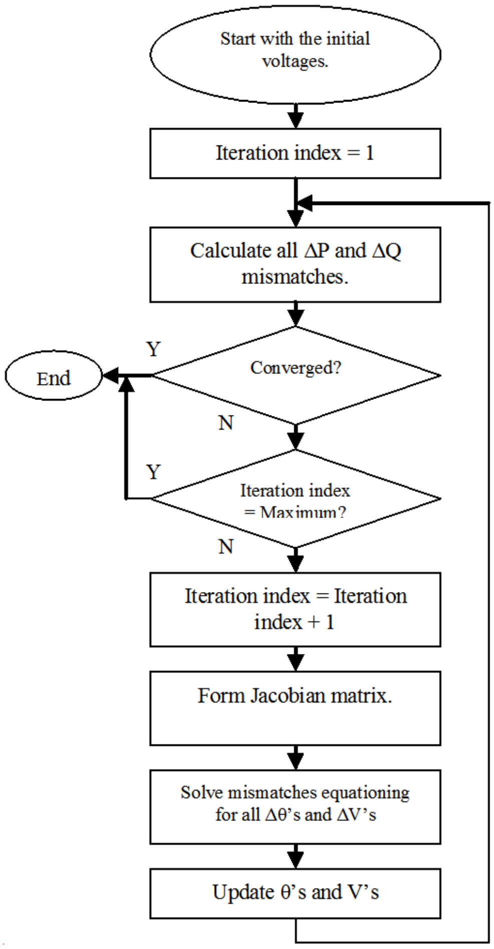

FIGURE 1. Flowchart of the Newton-Raphson based load flow

method, so it can find the solution for non convex problems. On the other hand, Newton-Raphson is a deterministic method, based on derivative calculation and provides good results when the functions are continuous, convex and unimodal. Newton-Raphson also depends on good initial estimative values to guarantee the convergence to an optimal solution. In the HPSOBM algorithms, the individuals have the ability to adapt to the environment in which they are inserted and to learn individually and with their neighbors, through the rule function assessment and Equations (4)-(7). Moreover, the mutation operation aids the particles to search along the search space, preventing a convergence to a local best. These characteristics are not present in conventional numerical methods and help HPSOBM method to obtain a better convergence and work even when these conventional methods can fail. Therefore, the aforementioned HPSOBM characteristics indicate its inherent potential to overcome some limitations found in the conventional deterministic methods, including Newton-Raphson based algorithms to solve load flow.

As mentioned previously, a practical application for HPSOBM to solve load flow when traditional methods have difficulty to converge could be when part of the power system is lost, because of a contingency. In such situation, traditional tangent methods, as Newton-Raphson and its variants, cannot converge to an optimal solution properly, because the initial estimative values, normally 1 (pu) for voltage magnitudes and 0 (rad) for voltage phase angles, are far away from the system current status. On the other hand, because of the aforementioned characteristics, HPSOBM can find the load flow solution even in this case.

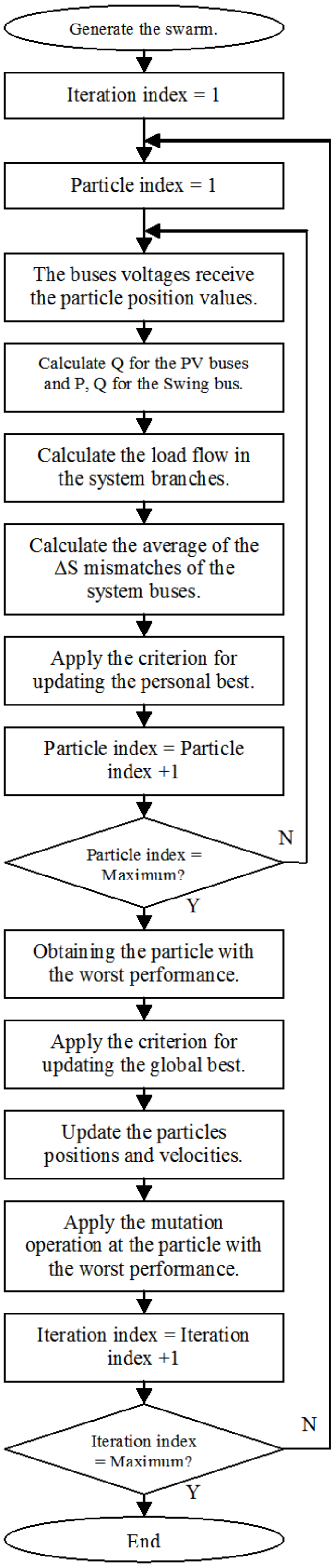

Figure 2. Flowchart of the HPSOBM load flow

5. **Numerical Results.** In this section, the proposed methodology for load flow computation is evaluated on two case studies: the 6-bus power system case study [23] and the 9-bus power system case study [24]. A computational procedure has been developed based on the HPSOBM methodology for solving the load flow. The software simulations have been run on a 1.66-GHz Intel(R) T1600 PC. Five runs have been performed for each test system study case. The selected results are the best solution over these five runs. The obtained results of the proposed methodology for each case study are compared with those obtained using a Newton-Raphson based computational method, which is a traditional method applied to find the load flow solution, as mentioned in the last sections.

5.1. **6-bus power system case study.** The first test system is a 6-bus power system proposed in [23], as shown in Figure 3. This test system comprises six buses, including three generation buses and three load buses, and 11 branches, composed by transmission lines.

The simulations for this system held a population of 15 particles. The maximum number of iterations was 4000, arranged into 40 groups of 100 iterations per group. Figure 4 shows the global score decreasing along the iterations. The global score starts with 0.541057 (pu) at the first iteration and reaches 9.750141E-06 (pu) at the end of the iterations.

Tables 1 and 2 present the load flow results for the six bus power system obtained through the application of a Newton-Raphson based method. Tables 3 and 4 present the results obtained with the proposed methodology.

5.2. **9-bus power system case study.** The second test system is a 9-bus power system proposed in [24], as shown in Figure 5. This test system comprises nine buses, including

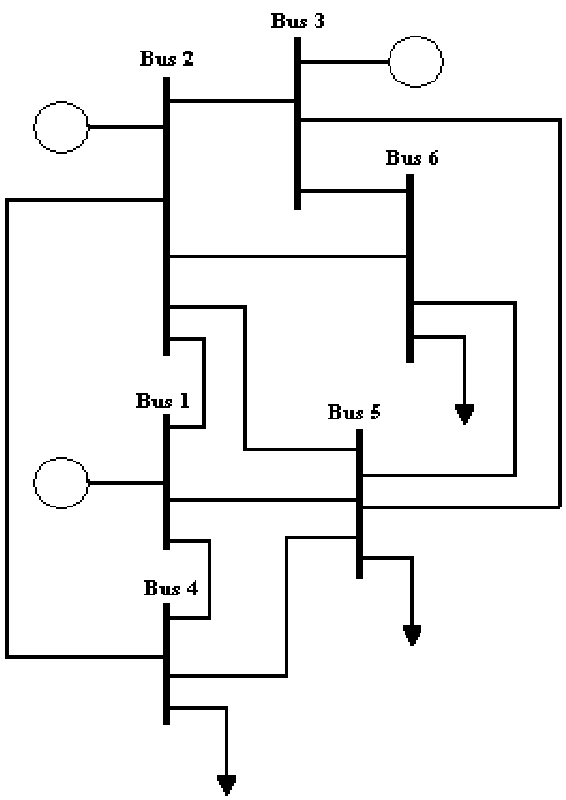

FIGURE 3. 6-bus power system, with all buses and branches

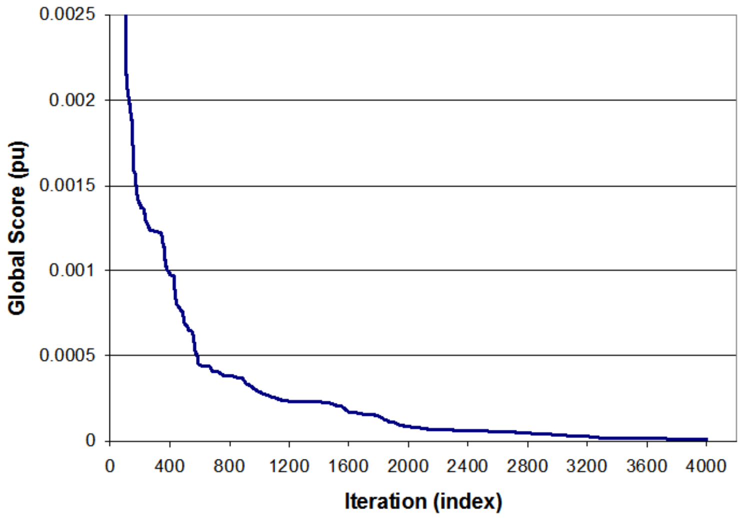

FIGURE 4. Simulation with 6-bus power system, global score vs. iterations

TABLE 1. 6-bus simulation applying a Newton-Raphson based method: buses parameters results

k	V_k	δ_k	P_k	Q_k	ΔP_k	ΔQ_k	ΔS_k
1	1.050000	0.000000	1.078688	0.159554	8.881784E-16	2.775558E-16	9.305365E-16
2	1.050000	−0.064068	0.500000	0.743507	1.403889E-05	2.428613E-15	1.403889E-05
3	1.070000	−0.074576	0.600000	0.896237	5.474126E-06	−3.330669E-16	5.474126E-06
4	0.989375	−0.073227	−0.700000	−0.700000	1.174903E-05	2.788370E-05	3.025790E-05
5	0.985449	−0.092085	−0.700000	−0.700000	2.679193E-05	3.770603E-05	4.625530E-05
6	1.004427	−0.103796	−0.700000	−0.700000	1.916657E-06	9.151917E-06	9.350463E-06

k = bus index, V_k = bus voltage module k, δ_k = bus voltage angle k, P_k = real power generated at bus k, Q_k = reactive power generated at bus k, ΔP_k = real power mismatch at bus k, ΔQ_k = reactive power mismatch at bus k, ΔS_k = apparent power mismatch at bus k.

TABLE 2. 6-bus simulation applying a Newton-Raphson based method: load flow in the system branches

i	j	P_{ij}	Q_{ij}	P_{ji}	Q_{ji}
1	2	0.286872	−0.154176	−0.277824	0.128172
1	4	0.435828	0.201193	−0.424953	−0.199322
1	5	0.355989	0.112537	−0.345254	−0.134492
2	3	0.029298	−0.122687	−0.028895	0.057280
2	4	0.330913	0.460513	−0.315863	−0.451227
2	5	0.155142	0.153519	−0.150163	−0.180054
2	6	0.262484	0.123989	−0.256652	−0.160109
3	5	0.191167	0.231729	−0.180232	−0.260937
3	6	0.437734	0.607227	−0.427701	−0.578597
4	5	0.040828	−0.049423	−0.040466	−0.027852
5	6	0.016142	−0.096627	−0.015646	0.038715

$P_{ij(ji)}$ = real power in the branch composed by the buses $i-j$ $(j-i)$,
$Q_{ij(ji)}$ = reactive power in the branch composed by the buses $i-j$ $(j-i)$.

Table 3. 6-bus simulation applying the proposed methodology: buses parameters results

k	V_k	δ_k	P_k	Q_k	ΔP_k	ΔQ_k	ΔS_k
1	1.050000	0.000000	1.084409	0.231199	−4.440892E-16	−3.989864E-16	5.969970E-16
2	1.050000	−0.065011	0.500000	0.868622	−7.189685E-08	−4.822531E-15	7.189685E-08
3	1.070000	−0.075641	0.600000	0.988291	−5.389207E-07	3.122502E-16	5.389207E-07
4	0.986424	−0.072934	−0.700000	−0.700000	−2.561847E-07	−1.599371E-08	2.566835E-07
5	0.979661	−0.091177	−0.700000	−0.700000	−6.881101E-07	−1.618395E-07	7.068858E-07
6	1.001443	−0.104203	−0.700000	−0.700000	−5.672482E-05	−4.787121E-06	5.692646E-05

Table 4. 6-bus simulation applying the proposed methodology: load flow in the system branches

i	j	P_{ij}	Q_{ij}	P_{ji}	Q_{ji}
1	2	0.291155	−0.133932	−0.281839	0.152565
1	4	0.436949	0.238303	−0.425715	−0.193367
1	5	0.356305	0.165415	−0.345108	−0.123425
2	3	0.029829	−0.089712	−0.029424	0.091739
2	4	0.332800	0.501470	−0.316373	−0.468615
2	5	0.154944	0.195713	−0.149292	−0.178758
2	6	0.264266	0.166467	−0.258072	−0.148772
3	5	0.193275	0.283064	−0.180962	−0.256385
3	6	0.436149	0.650698	−0.425430	−0.597101
4	5	0.042088	−0.003962	−0.041720	0.004697
5	6	0.017082	−0.076549	−0.016442	0.078471

Table 5. 9-bus simulation applying a Newton-Raphson based method: buses parameters results

k	V_k	δ_k	P_k	Q_k	ΔP_k	ΔQ_k	ΔS_k
1	1.000000	0.000000	1.736411	−0.464677	0.000000E+00	−3.330669E-16	3.330669E-16
2	1.035000	−0.008727	1.500000	0.189550	−1.961729E-03	−5.551115E-17	1.961729E-03
3	1.029000	−0.090234	0.000000	0.600000	−5.090027E-02	2.199547E-02	5.544942E-02
4	1.027000	−0.117461	0.000000	0.000000	1.907532E-03	−1.109605E-02	1.125882E-02
5	1.012000	−0.155509	−0.550000	−0.270000	5.276012E-04	−2.922534E-03	2.969776E-03
6	1.022000	−0.157254	−0.370000	−0.180000	1.885152E-03	1.150218E-02	1.165564E-02
7	1.007000	−0.186052	−0.680000	−0.450000	−6.588536E-04	4.953215E-03	4.996842E-03
8	1.019000	−0.173835	−0.900000	−0.350000	−2.206755E-03	−4.251948E-03	4.790493E-03
9	1.003000	−0.228289	−0.750000	−0.280000	3.624526E-04	−3.718384E-03	3.736008E-03

two generation buses and five load buses, and 10 branches, composed by eight transmission lines and two power transformers.

The simulations for this system held a population of 15 particles. The maximum number of iterations was 8000, arranged into 40 groups of 200 iterations per group. Figure 6 shows the decrease of the global score along the procedure iterations. The global score starts with 1.405300 (pu) at the first iteration and achieves 8.653121E-04 (pu) at the end of the iterations.

Tables 5 and 6 present the load flow results for the 9-bus power system obtained through the application of a Newton-Raphson based method. Tables 7 and 8 present the results obtained applying the proposed methodology.

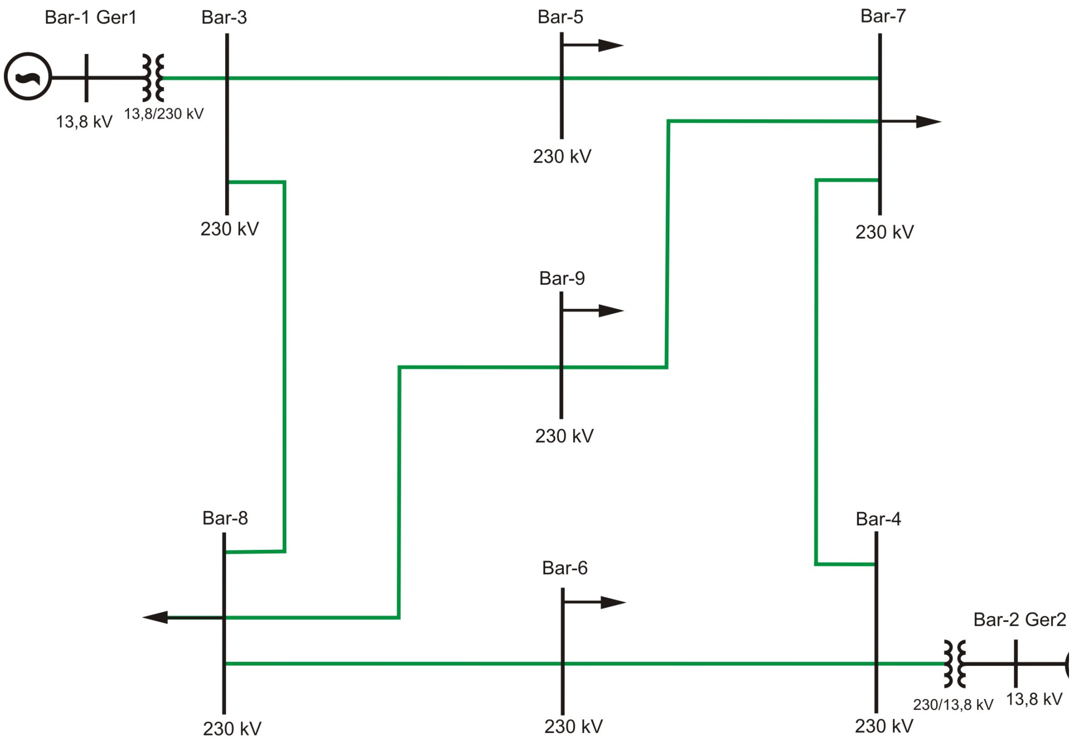

FIGURE 5. 9-bus power system, with all buses and branches

TABLE 6. 9-bus simulation applying a Newton-Raphson based method: load flow in the system branches

i	j	P_{ij}	Q_{ij}	P_{ji}	Q_{ji}
1	3	1.736411	−0.464677	−1.736411	0.637215
2	4	1.501962	0.189550	−1.501962	−0.025241
3	5	0.752231	0.075248	−0.743055	−0.025590
3	8	1.035080	0.042368	−1.024945	0.043783
4	6	0.581620	0.014196	−0.578893	0.008910
4	7	0.918434	0.186151	−0.910940	−0.120376
5	7	0.192528	−0.003886	−0.191369	0.009715
6	8	0.207007	0.011096	−0.206555	−0.007640
7	9	0.422968	−0.001037	−0.420869	0.018821
8	9	0.333706	0.028261	−0.329494	−0.009899

It is possible to verify the effectiveness of the proposed methodology analyzing how small the obtained power mismatches are. A remark must be made at this point. The 9-bus test system voltage magnitudes obtained through the Newton-Raphson based method have accuracy until the third decimal place, smaller than the proposed methodology accuracy, so it obscures a direct comparison between the power mismatches obtained through these two techniques. However, one can note that in both of the case studies the proposed hybrid particle swarm optimization approach provides voltage modules and angles very similar to those obtained through Newton-Raphson based methods. Moreover, the power mismatches are properly minimized, most of them are smaller than the tolerance usually accepted, which is about 10^{-4} (pu). So the aforementioned facts prove the effectiveness

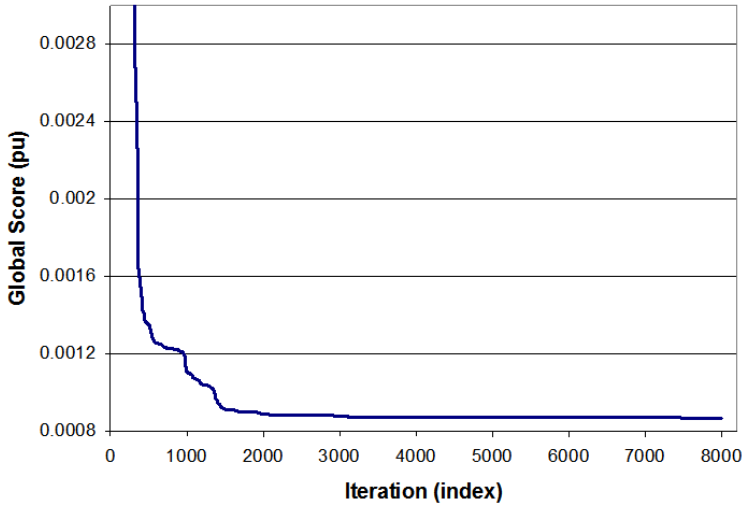

Figure 6. Simulation with 9-bus power system, global score vs. iterations

Table 7. 9-bus simulation applying the proposed methodology: buses parameters results

k	V_k	δ_k	P_k	Q_k	ΔP_k	ΔQ_k	ΔS_k
1	1.000000	0.000000	1.790318	−0.466095	0.000000E+00	−1.720846E-15	1.720846E-15
2	1.035000	−0.011652	1.500000	0.193644	2.402975E-08	−2.997602E-15	2.402975E-08
3	1.029339	−0.093012	0.000000	0.600000	5.968895E-09	3.948885E-08	3.993742E-08
4	1.026682	−0.120277	0.000000	0.000000	1.056733E-06	1.195302E-06	1.595441E-06
5	1.011912	−0.158256	−0.550000	−0.270000	7.443516E-06	1.767402E-05	1.917751E-05
6	1.022208	−0.160093	−0.370000	−0.180000	4.100075E-06	1.469834E-05	1.525948E-05
7	1.006626	−0.188952	−0.680000	−0.450000	1.492413E-05	2.406256E-05	2.831495E-05
8	1.018853	−0.176731	−0.900000	−0.350000	−2.056931E-06	1.553391E-05	1.566951E-05
9	1.001943	−0.231275	−0.750000	−0.280000	2.681026E-03	7.226422E-03	7.707728E-03

Table 8. 9-bus simulation applying the proposed methodology: load flow in the system branches

i	j	P_{ij}	Q_{ij}	P_{ji}	Q_{ji}
1	3	1.790318	−0.466095	−1.790318	0.648855
2	4	1.500000	0.193644	−1.500000	−0.029645
3	5	0.752925	0.079939	−0.743727	−0.030161
3	8	1.037393	0.048148	−1.027214	0.038373
4	6	0.581006	0.006756	−0.578284	0.016305
4	7	0.918993	0.186797	−0.911484	−0.120885
5	7	0.193720	−0.002297	−0.192547	0.008198
6	8	0.208280	0.015274	−0.207821	−0.011768
7	9	0.424016	0.005664	−0.421904	0.012225
8	9	0.335036	0.033414	−0.330777	−0.014848

of HPSOBM methodology to find optimal solutions for the load flow problem minimizing the power mismatches on the system buses.

6. **Conclusions.** This paper proposes a hybrid particle swarm optimization approach for load flow computation. The methodology was evaluated on 6-bus and 9-bus power

system case studies through the developed computational program. In both of the case studies, the simulations results indicates that the proposed methodology presents acceptable solutions for the buses power mismatches and the results are also better or as good as those obtained through Newton-Raphson based methods.

The main advantages of this presented methodology are the ease and flexibility of implementation, and its better convergence. The proposed HPSOBM method is not a tangent method, so it is able to solve even non convex problems, unlike traditional methods as Newton-Raphson and its variants. It is suggested for future works an improvement in the procedure in order to achieve lower mismatches in the cases which they are larger than 10^{-4} and also to evaluate its applicability in cases where the traditional methods have limitations or fail to solve load flow.

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