

# Application of Modified Particle Swarm Optimization for Load Flow Problem

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## **Abstract :**

*This paper presents an evolutionary computation approach, based on the Modified Particle Swarm Optimization method, for solving the load flow problem. The proposed method combines the Particle Swarm Optimization algorithm with modified velocity in order to eliminate the local minima. The objective of the load flow problem is to minimize the voltage and power mismatch and also constraining the power loss to a minimum value. The proposed method has been tested on the Ward Hale Six Bus and Nine Bus test systems. The results obtained shows the effectiveness and the improvements in the solutions.*

## **Keyword :**

*Load Flow Problem (LFP) , Particle Swarm Optimization (PSO) , Fitness Function(FF), Gauss Siedel (GS) , Newton-Raphson (NR) , Fast Decoupled Load Flow (FDLF) ,Modified Particle Swarm Optimization (MPSO),Genetic Algorithm(GA).*

## **I Introduction**

Load Flow Analysis, leading to the solution of the steady state operating conditions of an electric power transmission system, is the starting step for the solutions of a number of power system problems. Results of the solutions of load flow equations are required for the system planning, the operational planning and control, for large system estimation and outage security assessment and also for the more complicated stability and optimization computations. The increasing availability of high speed digital computers has brought about a dramatic change in the techniques used to solve the power system load problems. Since the load flow equations are algebraic non linear, many numerical methods have been developed for finding the designed normal solution. Among these, the GS method using the nodal admittance matrix, which requires minimal computer storage but the GS method is slow, unsuitable for solving large systems and has poor reliability [3]. The NR method is superior to GS approach provided that good estimates of the initial nodal voltages are available. The major disadvantage of this method is the requirement of increased computer memory due to the jacobian matrix needed to direct the iterations [1][12]. The FDLF method is generally efficient but has disadvantage of poor reliability for ill conditioned systems [3]. All the conventional methods need an initial guess value to start. A careless or random selection of initial values may cause the methods to miss the normal solution, either by divergence or by convergence to an abnormal solution [2]. Another drawback in these methods are derivative based techniques[10]. The results obtained from these methods are not reliable. Particle Swarm Optimization(PSO) is suggested by Eberhart and Kennedy based on the analogy of swarm of birds and

school of fish[4][9]. PSO mimics the behaviour of individuals in a swarm to maximize the survival of the species. In PSO, each individuals makes his decision using his own experience together with other individuals' experiences. The algorithm, which is based on a metaphor of social interaction, searches a space by adjusting the trajectories of moving points in a multidimensional space. The individual particles are drawn stochastically towards the position of present velocity of each individual, their own previous best performance and the best previous performance of their neighbours [9],[4]. The main advantages of the PSO algorithm are summarized as:

Simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithms and other heuristic optimization techniques[4]. PSO can be easily applied to nonlinear and non continuous optimization problems.

In this paper, the LFP is solved by the proposed Modified PSO algorithm. This will improve the global searching capability and prevent the premature convergence to local minima. The MPSO method is tested for two different systems and the results are compared with NR method and GA in order to demonstrate its performance.

## **II Overview of PSO.**

PSO is a stochastic global optimization method which is based on simulation of social behavior[4]. Kennedy and Eberhart developed a PSO algorithm based on the individuals ( i.e., particles or agents) of a swarm[5]. The features of the method are as follows[6]:

1. The method is based on researchers about swarms such as fish schooling and a flock of birds.
2. It is based on a simple concept. Therefore, the computation time is short and it requires few memories.
3. It was originally developed for non linear optimization problems.

The original PSO formulae, as described in[7], are:

$$V_i^{k+1} = V_i^k + c_1 r_1 \times (Pbest_i^k - X_i^k) + c_2 r_2 \times (Gbest^k - X_i^k) \quad (1)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2)$$

Shi and Eberhart devised an inertia weight  $\omega$ , to improve the accuracy of PSO by damping the velocities overtime, allowing the swarm to converge with greater precision[7][4][6]. Integrating  $\omega$  into the algorithm, the formulae for computing the new velocities are

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \times (Pbest_i^k - X_i^k) + c_2 r_2 \times (Gbest^k - X_i^k) \quad (3)$$

where

$V_i^k$  - Velocity of individual i at iteration k

$\omega$  - Inertia weight parameter

$c_1, c_2$  - acceleration coefficients

$r_1, r_2$  - random numbers between 0 and 1

$X_i^k$  - position of individual i at iteration k

$Pbest_i^k$  - best position of individual i until Iteration k

$Gbest^k$  - best position of the group until Iteration k

The role of inertia weight  $\omega$  is considered important for the PSO's convergence behavior. The inertia weight is employed to control the impact of the previous history of velocities on the current velocity. Thus, the parameter  $\omega$  regulates the trade-off between the global (wide-ranging) and the local (nearby) exploration abilities of the swarm. A large inertia weight facilitates exploration, while a small one tends to facilitate exploitation, i.e., fine tuning the current search area. A proper value for the inertia weight  $\omega$  provides balance between the global and local exploration ability of this swarm, and, thus results in better solutions.

In this velocity updating process, the values of parameters such as  $\omega, c_1$  and  $c_2$  should be determined in advance. In general, the weight  $\omega$  is set according to the following equation[6],[4],[8]:

$$\omega = \omega_{\max} - \left( \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \right) \times iter \quad (4)$$

Where

$\omega_{\max}, \omega_{\min}$  - initial and final weights

$iter_{\max}$  - maximum iteration number

$iter$  - current iteration number

With the constriction factor, the PSO formula for computing the new velocity is[7]

$$V_i^{k+1} = k \left( V_i^k + c_1 r_1 \times (Pbest_i^k - X_i^k) + c_2 r_2 \times (Gbest^k - X_i^k) \right) \quad (5)$$

Where

$$k = \frac{2}{\left| 2 - \phi - \sqrt{\phi^2 - 4\phi} \right|} \quad (6)$$

This modified PSO was very successful in finding changing optimal solutions, even at significant rate of change.

The algorithm for the PSO method is as follows

For each particle

Initialize particle

End

Do

For each particle

Calculate fitness value

If the fitness value is better than the best fitness value(Pbest) in history, set current value as the new Pbest

End

Choose the particle with the best fitness

Value of all the particles as the Gbest

For each particle

Calculate particle velocity according to equation (1) or (3) or (5)

Update particle position according to equation (2)

End

While maximum iteration (or convergence criteria) is not attained.

### III Problem Formulation

In this work, the problem formulation is in rectangular co-ordinates and the variables are in per unit. Consider an interconnected n-node power system where there are  $n_{pq}$  load nodes,  $n_{pv}$  voltage controlled nodes and one slack node. In the rectangular there are  $2(n-1)$  unknowns to solve. The load flow equations are

$$P_i^{sp} = E_i \sum_{j=1}^n (G_{ij} E_j + B_{ij} F_j) + F_i \sum_{j=1}^n (G_{ij} F_j - B_{ij} E_j) \quad (7)$$

$$i\epsilon n_{PQ} + n_{PV}$$

$$Q_i^{sp} = F_i \sum_{j=1}^n (G_{ij} E_j + B_{ij} F_j) - E_i \sum_{j=1}^n (G_{ij} F_j - B_{ij} E_j) \quad (8)$$

$$i\epsilon n_{PQ}$$

$$(V_i^{sp})^2 = E_i^2 + F_i^2 \quad i\epsilon n_{PV} \quad (9)$$

Where,  $V_i = E_i + jF_i$  and  $Y_{ij} = G_{ij} - jB_{ij}$

The objective function results from the summation of squares of the power mismatch, the voltage mismatch and the real power loss whose minimum coincides with the load flow solution [2][11].

$$\text{ming}(E,F) = \sum_{i \in \text{PQ} + \text{PV}} \Delta P_i^2 + \sum_{i \in \text{PQ}} \Delta Q_i^2 + \sum_{i \in \text{PV}} \Delta V_i^2 + W P_{loss}^2 \quad (10)$$

Where,

$$\Delta P_i = P_i^{sp} - E_i \sum_{j=1}^n (G_{ij} E_j + B_{ij} F_j) - F_i \sum_{j=1}^n (G_{ij} F_j - B_{ij} E_j) \quad (11)$$

$$i\epsilon n_{PQ} + n_{PV}$$

$$\Delta Q_i = Q_i^{sp} - F_i \sum_{j=1}^n (G_{ij} E_j + B_{ij} F_j) + E_i \sum_{j=1}^n (G_{ij} F_j - B_{ij} E_j) \quad (12)$$

$$i\epsilon n_{PQ}$$

$$\Delta V_i = |V_i^{sp}| - (E_i^2 + F_i^2)^{\frac{1}{2}} \quad i\epsilon n_{PV} \quad (13)$$

$$P_{loss} = \sum_{i=1}^n \sum_{j=1}^n G_{ij} (E_i E_j + F_i F_j) \quad (14)$$

W= Penalty factor

#### IV Results and Discussion

The proposed MPSO is tested on Ward Hale Six bus system [13] including the half line charging admittance and off-nominal turns ratio and on 9 bus systems. For the 6 bus system, there are ten variables to solve and for the 9 bus system there are 16 variables to solve. The variables are  $E_i$  and  $F_i$  except the slack bus. On the PQ nodes, the variables were specified in the intervals [0.9,1.0] for E and [-0.2,0.2] for F on the PV nodes, the variables were specified in the intervals [0.9,1.2] and [-0.3,0.3]. The test problems are solved using simple PSO and MPSO. The parameters selected for the solution of above problems are given in table I. Both algorithms are implemented using MATLAB software on a Pentium-4 PC. Case a shows the voltage

profile according to equation(1). Case b shows the voltage profiles according to equation(3). Case c shows the voltage profile according to equation(4).

TABLE I Parameters for PSO

| Parameter        | Six bus | Nine bus |
|------------------|---------|----------|
| no. of particles | 30      | 30       |
| no. of iteration | 100     | 100      |
| $C_1$            | 2       | 2        |
| $C_2$            | 2       | 2        |
| $\omega_{min}$   | 0.4     | 0.4      |
| $\omega_{max}$   | 0.9     | 0.9      |
| $\phi$           | 4.1     | 4.1      |
| W                | 50      | 0.1      |

The voltage profile corresponds to the Gbest from different runs for six bus and nine system without real power loss are tabulated in table-II and table-III respectively.

Table II Voltage profile for six bus system without loss

|       | NR     | Case a  | Case b  | Case c  |
|-------|--------|---------|---------|---------|
| Conv. | 0.0001 | 0.5     | 0.1     | 0.1     |
| loss  | 0.1044 | 0.0712  | 0.0867  | 0.0264  |
| E1    | 1.0500 | 1.0500  | 1.0500  | 1.0500  |
| E2    | 1.1047 | 1.0248  | 0.8738  | 1.0005  |
| E3    | 0.9715 | 0.9825  | 1.0551  | 1.0305  |
| E4    | 0.9109 | 0.9413  | 0.9894  | 0.9512  |
| E5    | 0.8963 | 0.8903  | 0.9887  | 0.9451  |
| E6    | 0.8926 | 0.9226  | 0.9808  | 0.9224  |
| F1    | 0.0000 | 0.0000  | 0.0000  | 0.0000  |
| F2    | -0.072 | -0.2186 | -0.3794 | -0.1449 |
| F3    | -0.220 | -0.1881 | -0.1945 | -0.0658 |
| F4    | -0.157 | -0.1149 | -0.1244 | -0.0146 |
| F5    | -0.197 | 0.1152  | -0.0179 | 0.1267  |
| F6    | -0.194 | 0.0863  | 0.0249  | 0.1244  |

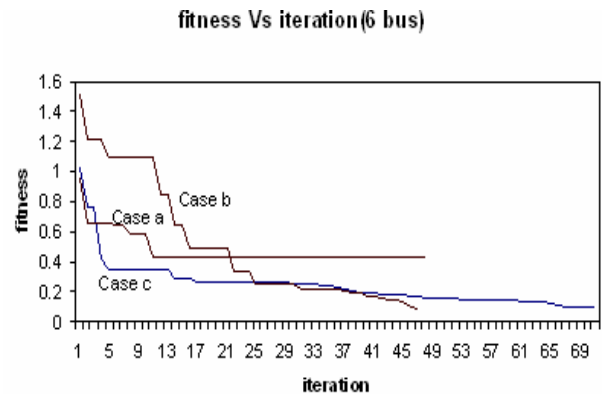


Fig.1 fitness Vs iteration for Six bus

Table III Voltage profile for Nine bus system without loss

|       | NR          | Case a  | Case b  | Case c  |
|-------|-------------|---------|---------|---------|
| Conv. | Conv. It 10 | 5       | 3       | 3       |
| loss  | 8.3396      | 8.1818  | 8.1304  | 8.0501  |
| E1    | 1.0000      | 1.0000  | 1.0000  | 1.0000  |
| E2    | 0.9857      | 1.1070  | 1.0201  | 1.0338  |
| E3    | 0.9965      | 0.9986  | 1.0130  | 1.0189  |
| E4    | 0.9861      | 0.9657  | 0.9659  | 0.9736  |
| E5    | 0.9726      | 0.9785  | 0.9564  | 0.9533  |
| E6    | 1.0024      | 0.9551  | 0.9835  | 0.9719  |
| E7    | 0.9859      | 0.9685  | 0.9709  | 0.9523  |
| E8    | 0.9938      | 0.9898  | 0.9778  | 0.9815  |
| E9    | 0.9552      | 0.9759  | 0.9753  | 0.9688  |
| F1    | 0.0000      | 0.0000  | 0.0000  | 0.0000  |
| F2    | 0.1679      | -0.0777 | -0.2168 | -0.1888 |
| F3    | 0.0831      | -0.0035 | -0.0182 | -0.0494 |
| F4    | -0.0414     | 0.0500  | 0.0126  | 0.0100  |
| F5    | -0.0683     | 0.1132  | 0.0816  | 0.0558  |
| F6    | 0.0337      | 0.0616  | 0.0222  | -0.0152 |
| F7    | 0.0170      | 0.0408  | 0.0076  | -0.0088 |
| F8    | 0.0659      | -0.0346 | -0.0905 | -0.0826 |
| F9    | -0.0726     | 0.0793  | 0.0020  | 0.0137  |

fitness Vs iteration(9 bus)

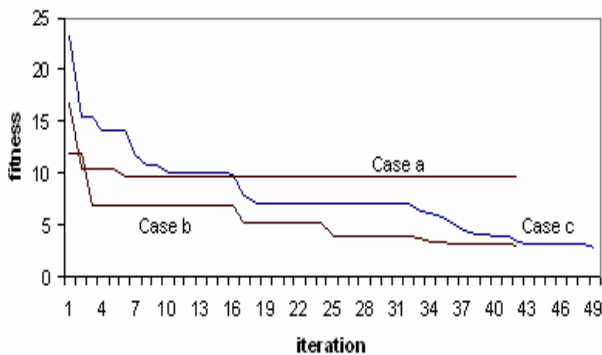


Fig.2 fitness Vs iteration for Nine bus

The objective function for the NR method, Case a, Case b and Case c is, the power and the voltage mismatch. Here the termination of the program is based on the convergence criteria. From the Table II and Table III, the voltage profiles for the MPSO is better than the NR method results. The losses also gets reduced in MPSO. Simple PSO results better voltages and less losses. PSO with inertia weight gives further improvements in the results. PSO with constriction factor produces quality solutions than other methods. Fig.1. and Fig.2. shows the convergence characteristics of Six bus and Nine bus systems respectively.

Table IV Voltage profile for six bus system with loss

|         | Case 1  | Case 2  | Case 3  |
|---------|---------|---------|---------|
| fitness | 0.3701  | 0.1391  | 0.0820  |
| E1      | 1.0500  | 1.0500  | 1.0500  |
| E2      | 1.0259  | 0.9279  | 0.9452  |
| E3      | 1.0012  | 1.0030  | 1.0568  |
| E4      | 0.9241  | 0.9345  | 0.9768  |
| E5      | 0.9906  | 0.9263  | 0.9489  |
| E6      | 0.9986  | 0.9219  | 0.9475  |
| F1      | 0.0000  | 0.0000  | 0.0000  |
| F2      | -0.2273 | -0.1628 | -0.2167 |
| F3      | -0.1456 | -0.0719 | -0.1243 |
| F4      | -0.0877 | -0.0277 | -0.0611 |
| F5      | 0.0222  | 0.0921  | 0.0483  |
| F6      | 0.0460  | 0.0980  | 0.0636  |

fitness Vs iteration

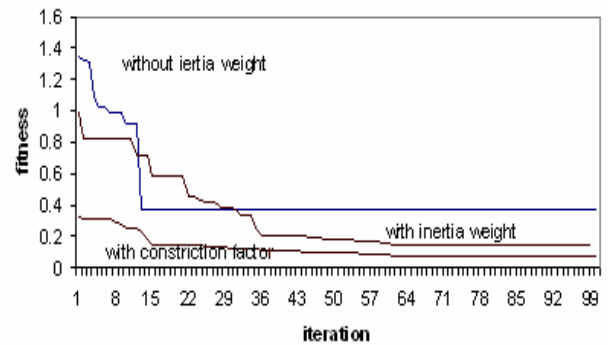


Fig.3 fitness Vs iteration for Six bus with loss

TABLE V Voltage profile for Nine bus system with loss

|         | Case 1  | Case 2  | Case 3  |
|---------|---------|---------|---------|
| fitness | 12.4377 | 7.5565  | 6.3855  |
| E1      | 1.0000  | 1.0000  | 1.0000  |
| E2      | 0.9813  | 0.9477  | 0.8603  |
| E3      | 0.8426  | 0.9898  | 0.8719  |
| E4      | 0.9397  | 0.9728  | 0.9489  |
| E5      | 0.8797  | 0.9518  | 0.9335  |
| E6      | 0.9307  | 0.9739  | 0.9110  |
| E7      | 0.9901  | 0.9646  | 0.9315  |
| E8      | 0.9822  | 0.9639  | 0.9016  |
| E9      | 0.9821  | 0.9546  | 0.8822  |
| F1      | 0.0000  | 0.0000  | 0.0000  |
| F2      | -0.1259 | -0.1784 | -0.1892 |
| F3      | -0.2287 | -0.0828 | -0.0865 |
| F4      | 0.0243  | 0.0370  | 0.0596  |
| F5      | -0.0165 | 0.0521  | 0.0834  |
| F6      | -0.1157 | -0.0376 | -0.0400 |
| F7      | -0.0477 | -0.0107 | -0.0112 |
| F8      | -0.0689 | -0.0692 | -0.0702 |
| F9      | 0.0704  | 0.0953  | 0.1431  |

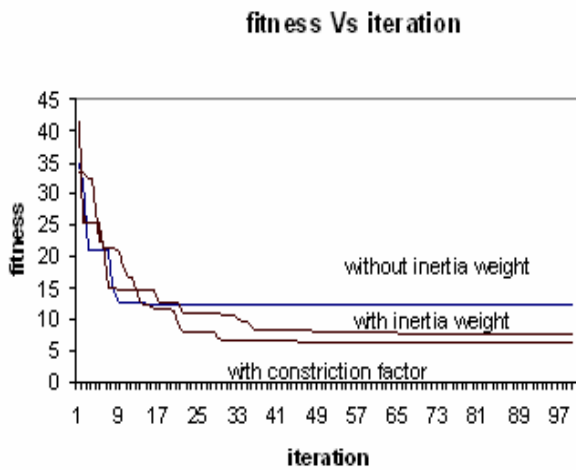


Fig.4 fitness Vs iteration for Nine bus with loss

The real power loss is added as a penalty to the objective. Here the termination of the program is based on the maximum iteration. The best solution from different run is given in Table IV and Table V for Six bus and Nine bus system respectively. The convergence characteristics of fitness Vs iteration for Six bus and for Nine bus system with power loss is shown in fig.3 and fig.4 respectively. From the Table IV and Table V, the voltage profiles are improved from case a to case b to case c.

From the above discussion, the objective value for the LPF gets reduced due to inertia weight and also further reduced due to constriction factor. The addition of real power loss into the objective gives precise solutions. It shows that the MPSO gives better solutions and less computation than the conventional method.

#### V Conclusions

This paper presents modified particle swarm optimization to solve the load flow problem. Without any requirements for auxiliary information and calculation of derivatives, a simple and efficient algorithm is proposed. The memory requirement for this approach is very less when compared to the conventional method and the complexity of calculation is less. The PSO results better solutions than the conventional method. The addition of inertia weight results improved solutions. Constriction factor approach has possibility to generate accurate solutions. The addition of power loss will give the precise solution.

#### VI Appendix

Load Flow Data for Nine Bus System(100 MVA base)

TABLE VII BUS DATA(IN P.U)

| Bus | Type  | $P_d$ | $Q_d$ | $P_g$ | $Q_g$ | $V_m$ |
|-----|-------|-------|-------|-------|-------|-------|
| 1   | Slack | 0     | 0     | 0     | 0     | 1.0   |

|   |    |      |      |      |   |     |
|---|----|------|------|------|---|-----|
| 2 | PV | 0    | 0    | 1.63 | 0 | 1.0 |
| 3 | PV | 0    | 0    | 0.85 | 0 | 1.0 |
| 4 | PQ | 0    | 0    | 0    | 0 | 1.0 |
| 5 | PQ | 0.9  | 0.3  | 0    | 0 |     |
| 6 | PQ | 0    | 0    | 0    | 0 |     |
| 7 | PQ | 1.0  | 0.35 | 0    | 0 |     |
| 8 | PQ | 0    | 0    | 0    | 0 |     |
| 9 | PQ | 1.25 | 0.5  | 0    | 0 |     |

TABLE VI LINE IMPEDANCE( IN P.U)

| Between buses |   | R      | X      |
|---------------|---|--------|--------|
| 1             | 4 | 0      | 0.0576 |
| 4             | 5 | 0.017  | 0.092  |
| 5             | 6 | 0.039  | 0.17   |
| 3             | 6 | 0      | 0.0586 |
| 6             | 7 | 0.0119 | 0.1008 |
| 7             | 8 | 0.0085 | 0.072  |
| 8             | 2 | 0      | 0.0625 |
| 8             | 9 | 0.032  | 0.161  |
| 9             | 4 | 0.01   | 0.085  |

#### VII Acknowledgement

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