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# Chaotic particle swarm optimization based robust load flow

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ABSTRACT

A reliable load flow algorithm based on chaotic particle swarm optimization (CPSO) technique has been developed. To obtain optimum solution efficiently and accurately, an innovative formula for adaptive inertia weight factor (AIWF) has been introduced. Novel formulae for constriction factors have been designed for the load flow problems which are also adaptive. In addition to that, chaotic local search (CLS) is used with PSO to get rid of the local optima. To the best of our knowledge, it is the first report of applying CPSO to solve load flow problems. The efficiency and effectiveness of the proposed algorithm has been tested on different standard and ill-conditioned test systems. The proposed method shows its robustness under critical conditions when conventional load flow methods fail.



## 1. Introduction

Load flow is the most extensively used analytical tool in any power industry. General purpose conventional load flow methods [1–5] face difficulties in solving systems having high $R/X$ ratios or when the system loading approach their loadability limits. Modified load flow algorithms based on conventional approaches are developed for critical or ill-conditioned power systems [6,7]. The load flow problem was first solved using the genetic algorithm by Wong et al. [8]. Later on in [9], Wong et al. have applied the evolutionary programming technique in solving the load flow problem for systems having FACTS devices. The authors of [10] have reported several constraint enforcement techniques that involve complex and lengthy equations. Moreover, convergence reliability in 40% of test cases have been reported. Karami and Mohammadi developed radial basis neural network method to solve the power flow problems [11]. In the recent years particle swarm optimization (PSO) has gained much popularity in different kind of applications because of its simplicity, easy implementation and reliable convergence [11–14]. PSO is computationally inexpensive in terms of memory requirement and CPU times [15]. PSO has been found to be robust in solving continuous non-linear optimization problems [12,13]. However, the traditional PSO highly depends on its parameter and often suffers the problem of being trapped in local optima [16]. To overcome this drawback, the chaotic particle swarm optimization (CPSO) method has been introduced.

PSO is a population-based swarm intelligence algorithm that shares many similarities with evolutionary computation techniques. The field of swarm intelligence is an emerging research area that presents features of self-organization and cooperation principles among group members [15–18]. CPSO is an optimization approach based on the PSO with adaptive inertia weight factor (AIWF) and chaotic local search [19–21]. Unique formulae have been designed for weighting factor and constriction factors in the proposed method. Parameter estimation for the load flow problem is formulated as a multi-dimensional optimization problem and a chaotic PSO approach is implemented to solve it.

Chaos is a kind of characteristics of non-linear system that demonstrates sensitive dependence on initial conditions and also includes infinite unstable periodic motions [22,23]. Due to non-repetitive nature of chaos, it can carry out overall searches at higher speeds than stochastic ergodic searches that is probabilistic in nature [24]. The combination of optimization methods and chaotic systems are important issues in non-linear science and has attracted increased interests from various fields in recent years [22–26]. As power flow is a complex, non-linear system, the authors use chaotic local search (CLS) to overcome the local optima and speed up the convergence.

The authors' endeavour in the present paper is to develop general purpose power flow using CPSO technique that is robust, reliable and versatile enough to be applicable to all possible analytical applications. The proposed method shows its reliability under critical conditions like high $R/X$ ratios and heavy loading situations when conventional methods fail. The proposed method is first described and its performances on standard and ill-conditioned test systems are then presented along with the comparative analysis with other conventional load flow technique.

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## 2. Load flow problem

The problem in load flow is to determine the voltages at $(n-g)$ nodes and phase angles of the voltages at $(n-1)$ nodes when the real power at $(n-1)$ nodes and the reactive power at $(n-g)$ nodes are specified. The reactive power limits of the $g$ number of generator nodes and the active power balances at all the nodes are to be satisfied. Since the number of variables goes on increasing with the size of the system, the load flow problem becomes increasingly difficult as the size of the system increases. If maintaining the power balances at the nodes is set as the objective function, the load flow may be formulated as,

$$SSE = \sum_{i=1}^{n-1}(P_{sp} - P_i)^2 + \sum_{i=1}^{l}(Q_{sp} - Q_i)^2 \tag{1}$$

Subject to,

$$Q_{gen,i}^{\min} \leqslant Q_i \leqslant Q_{gen,i}^{\max}, \quad i = 1 \ldots g \tag{2}$$

$$V_i^{\min} \leqslant V_i \leqslant V_i^{\max} \quad \text{and} \quad \delta_i^{\min} \leqslant \delta_i \leqslant \delta_i^{\max} \tag{3}$$

where

$$P_i + jQ_i = V_i . e^{j\delta_i} \sum Y_{im} \cdot e^{-j\theta_{im}} \cdot V_m \cdot e^{-j\delta_m} \tag{4}$$

$V_i$, $V_m$, voltage magnitude of $i$th and $m$th bus; $\delta_i$, $\delta_m$, phase angle of $i$th and $m$th bus; $Y_{im}$, $\theta_{im}$, admittance matrix element and its corresponding phase angle; $P_i$, $Q_i$, active and reactive power, respectively, of $i$th bus; $\Delta P_i$, $\Delta Q_i$, active and reactive power mismatches of the $i$th bus

$$\max\_E = \max([(P_{sp} - P_i)|_{i=1\ldots(n-1)}(Q_{sp} - Q_i)|_{i=1\ldots l}]) \tag{5}$$

'SSE' and 'max_E' represent the sum square error and maximum error of the power mismatches, respectively. In the above $g$ is the number of generator buses except the slack bus, l is the number of load buses and $n$ is the total number of buses in the system. $P$, $Q$, $V$ and $\delta$ represent active power, reactive power, voltage and phase angle, respectively. Subscripts '$sp$' represents the specified value and 'gen' represents the quantity associated with the generator bus. Superscripts 'min' and 'max' are used to indicate the corresponding minimum and maximum limits. It may be noted here that when load flow problem is solved using conventional approach the constraint given in (3) becomes redundant, as the flat start is the accepted starting values of the load flow iterative solutions. In the non-conventional approach during random initialization, flat start cannot be adhered to. Thus, constraint (3) has been included such that acceptable starting values are generated and during the course of search procedure variable values do not cross the boundary of the feasible limits. Generally max_E is reduced in each iteration for the desired convergence [1–5]. In meta-heuristic/evolutionary methods [8–10], SSE is the limiting constrain for achieving convergence. In the proposed method, if the maximum error (max_E) of the best solution is less than the specified tolerance i.e. 0.001, the solution is converged.

## 3. Chaotic particle swarm optimization

### 3.1. General PSO method

Inspired by the social behavior of organisms like bird flocking and fish schooling, Kennedy and Eberhart first introduced PSO in 1995 [17]. PSO randomly initializes the population (swarm) of individuals (particles) in the search space. Each particle in PSO has a randomized velocity associated to it, which moves through the space of the problem. The particle velocity is constantly adjusted according to the experience of the particles and its companions. In a $D$-dimensional space the velocity $v_{id}$ and position $x_{id}$ of particle $i$ are adjusted as:

$$\begin{aligned} v_{id} &= w_i * v_{id} + c1 * rand() * (p_{id} - x_{id}) + c2 * Rand() * (p_{gd} - x_{id}) \\ x_{id} &= x_{id} + v_{id} \end{aligned} \tag{6}$$

where $c1$ and $c2$ are the positive constant parameters called learning factors or constriction factors and $rand()$ and $Rand()$ are two random functions in the range of [0, 1]. $p_{id}$ represents *pbest* position of particle $i$, i.e., the best position of the particle in the current iteration, and $p_{gd}$ denotes the *gbest* position of the particle $i$, i.e., the best position of the particle upto the present iteration. $w_i$ is weight function or inertia weight for velocity of particle $i$.

### 3.2. Proposed CPSO method

The load flow using simple PSO does not give satisfactory results as the simple PSO highly depends on its parameter-settings. While solving the load flow problem using simple PSO, it is noticed that after certain iterations, the population-sets are almost identical and no further improvements is observed. The convergence characteristics of the general PSO based load flow problem with 500 population size has been shown in Fig. 1.

The parameters of CPSO method are made adaptive [16,19–21] and it has wider applications in different fields [22–26]. The authors have designed two sets of formulae for inertia weight and constriction factors for load flow problems. To the best of our knowledge, the unique formulae are not proposed in any earlier publications.

#### 3.2.1. Adaptive inertia weight factor (AIWF)

PSO finds the optimum solution by efficiently controlling the global exploration and local exploitation. The inertia weight ($w$) is the modulus that controls the impact of the previous velocity of the particle on its current one. So it is important to make balance between exploration and exploitation in PSO by properly adjusting the value of '$w$'. Considering this, the authors have introduced a novel formula of $w$ depending on the sum square error (SSE) of the current one, *pbest* solution and *gbest* solution. The AIWF is obtained as follows:

$$w_p^k = w_{\min} + \frac{SSE_{pbest}^k * |SSE_p^k - SSE_{pbest}^k|}{SSE_p^k * |SSE_p^k - SSE_{gbest}^k|} \tag{7}$$

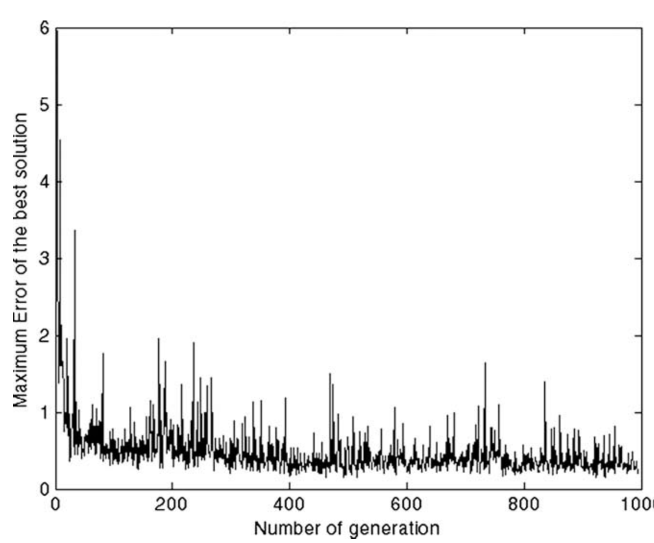


**Fig. 1.** Convergence characteristic of simple PSO based load flow for IEEE 14 bus test system with 500 population size.