*Journal of Engg. Research* **Vol. 5 No. (3) September 2017 pp.** *110-124*

# حل مشكلة إيفاد الحمل الاقتصادية باستخدام سرب الجسيمات الأمثل مع ثوابت التسارع الموزعة

**ناريش كومار ياداف**
قسم الهندسة الكهربائية، كلية الهندسة والتكنولوجيا
جامعة دينباندهو تشوتو رام للعلوم والتكنولوجيا، مورثال (سونيبات) -هاريانا، الهند
مراسلة المؤلف: *nareshyadhavdr@gmail.com*

## الخلاصة

مشكلة إرساء الحمولة الاقتصادية هي واحدة من التحديات الكبيرة في أنظمة توليد الطاقة في ظل بيئة خالية من الضوابط. وبما أن المشكلة غير محدبة ومتعددة الوسائط بطبيعتها، فإن نماذج البرمجة التقليدية ليست مناسبة لحلها. خوارزميات التحسين التقليدية، ولكن المعروفة مثل الخوارزمية الجينية (GA)، تحسين سرب الجسيمات (PSO) ومتغيراتها بحاجة إلى مزيد من التطوير للوصول إلى الحل الامثل المطلق في وقت محدد.

الخوارزمية التي تهمنا تكمن في (PSO)، بسبب تطبيقها على نطاق واسع والزكاء الواسع. ومع ذلك، فإن الخوارزمية لديها عيب التسارع المستمر من الجسيمات نحو الحل الامثل المطلق. ونتيجة لذلك، والالتصاق مع بالحل الامثل المحلي، فإن التعقيد الحسابي العالي وتحديد فقط الحل القريب من الحل الأمثل غالبا ما يحدث باستعمال (PSO). تحاول هذه الورقة إدخال تحسين على (PSO) التي تتم فيها عمل ثوابت التسارع متكيفة.

فهي تميل إلى التغيير ديناميكيا على أساس موقف الجسيمات وعدد تقييمات الوظائف. هذا يوجه الجسيمات للبحث في بيئة موزعة منهجية، وبالتالي نحن نطلق مصطلح الخوارزمية كما (PSO) مع التسارع الموزع الثابت (PSODAC). تم اعتماد ثلاثة أنظمة اختبار للدراسة التجريبية من خلالها يتم إثبات أداء (PSODAC على (PSO). ويكشف التحقيق التجريبي أيضا أن (PSODAC) يظهر ديناميكية الجسيمات أعلى من (PSO).

# Solving economic load dispatch problem using particle swarm optimization with distributed acceleration constants

Naresh Kumar Yadav

*Department of Electrical Engineering, Faculty of Engineering and Technology*

*Deenbandhu Chhotu Ram University of Science & Technology, Murthal (Sonepat)-Haryana, India*

*Corresponding author: nareshyadhavdr@gmail.com*

## ABSTRACT

Economic load dispatch problem is one of the significant challenges in power generation systems under deregulated environment. Since the problem is non-convex and multimodal in nature, conventional programming models are not suitable to solve it. Traditional, but renowned optimization algorithms such as Genetic algorithm (GA), Particle Swarm optimization (PSO) and their variants need further development to reach global optima in a defined time. Our algorithm of interest lies on PSO, because of its wide application and swarming intelligence. However, the algorithm has a drawback of constant acceleration of particles towards global optima. As a result, sticking with local optima, high computational complexity and identifying only near-optimal solution often happens with PSO. This paper attempts to introduce an improved PSO in which the acceleration constants are made adaptive. They tend to change dynamically based on the position of the particle and the number of function evaluations. This directs the particles to search in a systematic distributed environment, and hence we term the algorithm as PSO with Distributed Acceleration Constant (PSODAC). Three test systems are adopted for experimental study through which the performance of PSODAC over PSO is proved. The experimental investigation also reveals that PSODAC exhibits higher particle dynamics than PSO.

## 1- INTRODUCTION

Economic load dispatch (ELD) is a significant methodology to determine cost efficient and reliable power generation to meet the power demand (Bhattacharjee et al., 2014). The challenge towards ELD has increased due to evolution of smart grid, which is often included with renewable energy sources, electricity conveyors (Gungor et al., 2011; Gungor et al., 2013; Yao et al., 2012; Zhao et al., 2012; Su et al., 2012; Siano et al., 2012). The primary objective of an ELD problem is to minimize the total cost of a power generation unit without power scarcity and no compromise on the operating constraints (Wood & Wollenberg, 1996; Ding et al., 2014; Somasundaram et al., 2004). However, the multimodal property of ELD problem poses a great challenge to analysts and experts on determining the optimal generation strategy. In other words, ELD problem has numerous local optima, because of nonlinear fuel cost coefficients (Rabiee et al., 2014). Hence, the probability of converging to local optimal strategy is higher than the converging towards global optimal strategy (Panigrahi et al., 2006).

Despite the literature has been reported by ample number of optimization algorithms, they do have sufficient enhancements to handle the aforesaid characteristics of ELD. For instance, classical calculus – based methods are able to handle only smooth and differentiable objective functions (El-Keib et al., 1994). Linear programming models lag while handling piecewise linear cost approximations (Fanshel & Lynes, 1964), whereas, dynamic programming models suffer due to curse of dimensionality and high computational complexity (Wood & Wollenberg, 1984).

Few centralized approaches such as lambda iteration method and interior point method can solve only convex optimization methods (Lin & Viviani, 1984; Lin & Chen, 2002). However, ELD problems are practical problems and they are non-convex optimization problems (Wood & Wollenberg, 1984; Yang et al., 1996).

In solving ELD problem, population based stochastic search algorithms have gained more attention in the recent days. In fact, they are well known for its ability to handle non – convex problems (Binetti et al., 2014). Genetic Algorithm (GA) (Chiang et al., 2009; Amjady & Nasiri-Rad, 2009a; Amjady & Nasiri-Rad, 2009b; Walters & Sheble, 1993) and Differential Evolution (DE) (Nomana & Iba, 2008) are the two of the popular evolutionary algorithms (Jayabharathi et al., 2005; Hou et al., 2002; Nomana & Iba, 2008; Panigrahi et al., 2007) that are well known for their specific computational intelligence on handling non-convex ELD problems, whereas Particle Swarm Optimization (PSO) (Gaing, Z.-L. 2003; Kennedy & Eberhart, 1995; Selvakumar & Thanushkodi, 2007; Chaturvedi et al., 2008; Panigrahi et al., 2008; Selvakumar & Thanushkodi, 2009; Sun et al.,2014) is one of the most popular swarm intelligent algorithms (Sun et al.,2014; Panigrahi & Pandi, 2008; Bhattacharya & Chattopadhyay, 2010) to handle the problem effectively (Binetti et al., 2014). Despite they enable fast searching of near global optimal generation strategies, achieving global best remains open ended challenge in this platform.

### *1.1. Motivation*

To handle the open ended challenge, numerous variants such as improved GA and PSO have been reported in the literature (Gaing, Z.-L. 2003; Kennedy & Eberhart, 1995; Selvakumar & Thanushkodi, 2007; Chaturvedi et al., 2008; Panigrahi et al., 2008; Selvakumar & Thanushkodi, 2009; Sun et al., 2014). Since the proposed algorithm of interest relies on around PSO, this paper has studied various improved version of PSO that have been attempted to solve the various non-convex optimization problems (Vlachogiannis & Lee, 2009; Park et al., 2010). Selvakumar and Thanushkodi have introduced an improved PSO in which the particle movement has been exhibited not only based on the particle and global best positions but also based on the worst position. Further, a simplified local random search (LRS) has also been employed in the improved version (Selvakumar & Thanushkodi, 2007).

In (Panigrahi et al., 2008), the inertia weight has been made adaptive based on the particle rank rather than iteration ratio. In (Chaturvedi et al., 2008), self – organizing hierarchical PSO has been introduced. It has also been recommended to use adaptive acceleration constants to further improve self – organizing PSO (Chaturvedi et al., 2008). The earlier two algorithms are complexity oriented, whereas the latter embeds the process that coincides with regular PSO operation and so the searching complexity will not be increased. Being motivated by the conclusion, this paper attempts to introduce an improved PSO based on adaptive acceleration constants.

1.2. ***Contributions***

This paper intends to solve the ELD problem using a robust optimization algorithm.

The algorithm is an improved version of PSO in which the acceleration constants are made adaptive.

**Contribution 1**: *This paper formulates the acceleration constant as a function of number of evaluations made on the particles generated till the instant*.

The improved PSO is used to solve ELD problems and the performance comparison is made with traditional PSO.

**Contribution 2**: *This paper investigates the dynamics of the particle throughout the swarming iteration and the performance is correlated with them*

Since each particle is allowed to search with systematic distribution, this paper embodies the PSO as PSO with distributed acceleration constant (PSODAC). Due to this property, PSODAC exhibits wide particle dynamics. This results in evading from local optima and finding the global optima efficiently.

The rest of the paper is organized as follows. Section 2 formulates the ELD problem and Section 3 describes PSODAC and the procedure to solve ELD problem. Section 4 discusses the experimental results. Section 5 investigates the particle dynamics and Section 6 concludes the paper.

## 2- PROBLEM FORMULATION

Let $f(P_n): 0 \le n \le N_g$ be the cost $n^{th}$ of generation unit to generate $P_n$ MW of power, where $N_g$ is the number of generation units in the system. Since the objective of ELD problem is to minimize the total cost of the generation system, the ELD problem can be formulated as :

$$G^* = \underset{P_n \forall n}{\arg\min} \sum_{n=1}^{N_g} f(P_n) \tag{1}$$

Eq. (1) is subjected to the following constraints:

(i) Generation capacity constraint:

$$P_n^{\min} \le P_n \le P_n^{\max} \tag{2}$$

(ii) Real power balance constraint:

$$\sum_{n=1}^{N_g} P_n - (P_D + P_L) = 0 \tag{3}$$

In Eq. (3), $P_D$ refers to the total power demand in MW and $P_L$ refers to transmission losses, which can be represented as:

$$P_L = \sum_{m=1}^{N_g}\sum_{n=1}^{N_g} (P_m B_{mn} P_n) + \sum_{n=1}^{N_g} (B_{0n} P_n) + B_{00} \tag{4}$$

where, $B_{mn}$, $B_{0n}$ and $B_{00}$ are the loss coefficients, which are statically defined for bus systems as given in Table 2 and 4. In Eq. (1), is obtained. which is the optimal generation schedule for the given generation system. This paper attempts to solve Eq. (1) using traditional PSO and PSODAC and further investigates the obtained generation schedule.

## 3 - PSODAC FOR ELD PROBLEM

### *3.1. Traditional PSO*

Eberhart has introduced PSO based on swarming behavior of bird flocks and fish schools (Kennedy & Eberhart, 1995). The basic steps reside in the standard PSO are given below.

**Step 1:** Initialize Iteration count $N_I$ and Number of function evaluations $N_F$ as 0 and 0, respectively

**Step 2:** Initialize arbitrary particles $[P_n]_k : 0 \le k \le P_{size}$, where $P_{size}$ is the size of particle set. The particles are subjected to the constraints given in Eq. (2) and (3).

**Step 3:** Initialize arbitrary velocities $[v_n]_k$ in the interval $[-1,1]$

**Step 4:** Determine fitness of each particle using Eq. (1)

**Step 5:** Save $P_{best}$, $G_{best}$ and the associated fitness values, where size of $P_{best}$ is $P_{size} \times n$ and size of $G_{best}$ is $1 \times n$

**Set** $N_I$ and $N_F$ to zero
**Set** $P_{best}$ and $G_{best}$ as null vector
**Set** $f(P_{best})$ and $f(G_{best})$ to a Large number, say $10^{10}$
**Initialize** $[P_n]_k$ and $[v_n]_k$
**Calculate** fitness of every particle $P_n$, i.e. $f(P_n)\forall k = f_k(P_n)$
**Update** $P_{best}$
  **For** every $k^{th}$ particle,
  $$P_{best}(k) = \begin{cases} [P_n]_k ; f_k(P_n) < f(P_{best}(k)) \\ P_{best}(k); otherwise \end{cases}$$
  **For End**
**Update** $G_{best}$: $G_{best} = \begin{cases} [P_n]_{j;\, j\in(0,P_{size})} : \min(f(P_{best} \mid \forall k)) = f_j(P_n); \min(f(P_{best} \mid \forall k)) < f(G_{best}) \\ G_{best};\ otherwise \end{cases}$
**Increase** $N_I$ and $N_F$ by 1 and $P_{size}$, respectively
**While** sufficient number of function evaluations are not met, i.e., $N_F < N_F^{\max}$
  **Do** for each particle
    Calculate $c_{1k}$ and $c_{2k}$ using Eq. (7)
    Update velocity using Eq. (6)
    Update particle using Eq. (5)
    Calculate Fitness
    Update $P_{best}$
    Increase $N_F$ by 1
  **End Do**
  Increase $N_I$ by 1
  **Update** $G_{best}$
**End While**
**Return** $G_{best}$ and $f(G_{best})$

**Fig. 1.** Pseudo code of PSODAC

**Step 6:** Increase $N_I$ and $N_F$ by 1 and $P_{size}$, respectively

**Step 7:** If termination criteria is met, go to Step 12

**Step 8:** Update particle set using Eq. (5)

**Step 9:** Determine fitness of updated particle set using Eq. (1)

**Step 10:** Update $P_{best}$, $G_{best}$ and the associated fitness values, when they undergo any improvement due to the particle updates

**Step 11:** Go to Step 7

**Step 12:** Return $G_{best}$ and the fitness value

The termination of the process, as mentioned in Step 7, can be done, when either the algorithms satisfies $N_I > N_I^{\max}$ or $N_F > N_F^{\max}$ or combinations of both, where $N_I^{\max}$ and $N_F^{\max}$ are maximum number of iterations and function evaluations, respectively.

### *3.2. PSODAC*

PSODAC differs from PSO in the particle update process by introducing adaptive acceleration constants. The pseudo code of PSODAC is presented in Fig. 1.

Traditionally, the updating process on particles in PSO (Kennedy & Eberhart, 1995; Shi, Y. & Eberhart, R. 1998) is performed as follows:

$$[P_n]_k^{updated} = [P_n]_k + [v_n]_k^{updated} \tag{5}$$

$$\begin{aligned}[v_n]_k^{updated} &= w[v_n]_k + c_1 r_1 [P_n]_k - [P_{best}(n)]_k \\ &+ c_2 r_2 [P_n]_k - [G_{best}(n)]\end{aligned} \tag{6}$$

In Eq. (6), $w$ refers to an inertia weight, $c_1$ and $c_2$ refer to acceleration constants and refer to arbitrary integers at $[0,1]$. Here, $c_1$ and $c_2$ are set as constant, usually set at 2, whereas $r_1$ and $r_2$ are generated for each particle update throughout the iterations. However, the significance of these parameters is high because they define the amount of deviation of particle with respect to $P_{best}$ and $G_{best}$ to be considered for updating the particles. In this work, these parameters are varied based on the position of each particle and the number of function evaluations that are made till the current iteration. They can be given as

$$c_{1k} = c_{2k} = c^{\min} + \left[c^{\max} - c^{\min}\right] \frac{N_F}{N_F^{\max}} \tag{7}$$

whereas, $c^{\min}$ and $c^{\max}$ are minimum and maximum limits of the acceleration constants, say 0 and 2, respectively, within which the $c_{1k}$ and $c_{2k}$ are dynamically varied, $N_F$ is the number of evaluations of particles made till the current iteration and $N_F^{\max}$ is the maximum number of iterations. Hence by eq. (7), the $c_{1k}$ and $c_{2k}$ are gradually increased from $c^{\min}$ and $c^{\max}$ based on the position of the particle that is determined from the place where the evaluation of the particle takes place. While the parameters the $c_{1k}$ and $c_{2k}$ are made adaptive, the rest of the parameters such as $w$ has to be tuned properly because of its sensitivity towards problem domain, system characteristics and relation between the independent and its dependent variables. Even though the $r_1$ and $r_2$ are arbitrary integers, as per the basics of PSO, they can also be tuned to a definite and systematically varying parameters for better convergence.

**Table 1.** Generation limits and cost coefficients of Test System A

| Generation Units | Generation limits | | Cost coefficients | | |
|---|---|---|---|---|---|
| | $P^{min}$ *(MW)* | $P_{max}$ *(MW)* | *a ($/MWhr)* | *b ($/MWhr)* | *c ($)* |
| Unit 1 | 10 | 85 | 0.008 | 7 | 200 |
| Unit 2 | 10 | 80 | 0.009 | 6.3 | 180 |
| Unit 3 | 10 | 70 | 0.007 | 6.8 | 140 |

**Table 2.** Transmission loss coefficients of Test System A

| Loss Coefficients | $B_{mn}$ | | | $B_{on}$ | $B_{oo}$ |
|---|---|---|---|---|---|
| *Generation units* | *1* | *2* | *3* | | |
| *1* | .00218 | .00093 | .00028 | .0003 | .030523 |
| *2* | .00093 | .00028 | .00017 | .0031 | |
| *3* | .00028 | .00017 | .00179 | .0015 | |

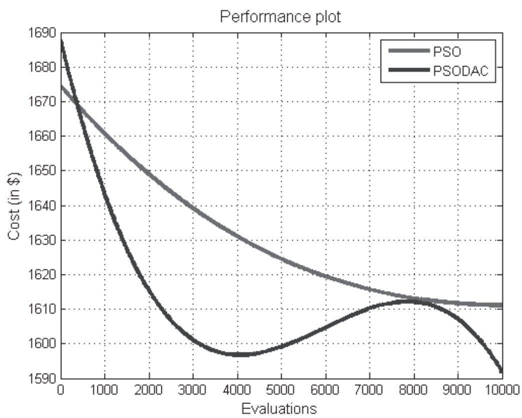


**Fig. 2.** Performance illustration between PSO and PSODAC (Convergence plot of Test System A)

# 4 - RESULTS AND DISCUSSION

## *4.1. Test System A*

In system A, this paper attempts to connect three generation units and the experimentation is carried out. The power demand is set to 150MW. The generation limits, cost coefficients and loss coefficients are given in Table 1 and 2, respectively. Both the algorithms are executed and the obtained generation strategies are tabulated in Table 5. Table 6 gives the solution quality of both the algorithms, while solving ELD problem in System A and Fig. 2 illustrates the convergence performance of PSO and PSODAC. To ensure fair results, each algorithm is initiated with 10 particles and executed for 10000 number of function evaluations. Similar set of experiments have been conducted for 100 rounds and the results are collected to determine the statistical metrics such as best value, worst value, mean, median and standard deviation of performance from the mean value.

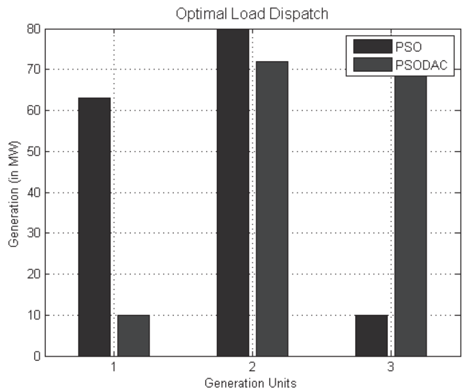


**Fig. 3.** Strategic variations between PSO and PSODAC under the environment of Test System A

**Table 3.** Generation limits and cost coefficients of Test System B

| Generation Units | Generation limits | | Cost coefficients | | |
|---|---|---|---|---|---|
| | $P^{min}$ *(MW)* | $P_{max}$ *(MW)* | *a ($/MWhr)* | *b ($/MWhr)* | *c ($)* |
| Unit 1 | 100 | 500 | 0.007 | 7 | 240 |
| Unit 2 | 50 | 200 | 0.0095 | 10 | 200 |
| Unit 3 | 80 | 300 | 0.009 | 8.5 | 220 |
| Unit 4 | 50 | 150 | 0.009 | 11 | 200 |
| Unit 5 | 50 | 200 | 0.008 | 10.5 | 220 |
| Unit 6 | 50 | 120 | 0.0075 | 12 | 120 |

As a best case performance, PSO derives a generation strategy of $1626, whereas PSODAC derives a generation strategy of $1607. The cost proposed by PSODAC is 2% lesser than the cost proposed by PSO. The similar ratio has been maintained in the worst case performance and statistical metrics such as mean and median costs. The convergence plot given in Fig. 2 is acquired from one of the experiments. Despite the initial particles are same for both PSO and PSODAC, the updating operator produces varying solutions, which are considered as initial solutions in the convergence analysis (in all the test systems). The polynomial fitting exhibits varying visualization on the initial conditions. It has been shown in the plot that PSODAC has been initialized by strategy with higher cost than PSO, but it converges better than PSO. A raise at 8000th function evaluation is due to polynomial fitting exhibited by the plot. Yet, it has been observed from Fig. 2 that there is a potential evading from local optima after 4000 evaluations. Similar kind of evading property can be observed for other test systems as per Fig. 4 and 7, which are discussed in the subsequent sections. Hence, the optimal number of evaluations can be determined as 4000 - 5000. For better illustration, the strategic variation is plotted between PSO and PSODAC in Fig. 3. Here, PSO proposes to generation around 60MW, 80MW and 10MW using unit 1, 2 and 3, respectively, to meet 150MW demand, whereas PSODAC strategizes to generate 10MW using unit 1, 70MW using unit 2 and 70MW using unit 3. This strategic variation has reduced around 2% of total fuel cost.

### *4.2. Test System B*

In system B, there are six generation units that are operated to meet the demand of 700MW.

The generation limits, cost coefficients and loss coefficients are given in Table 3 and 4, respectively. The generation strategies obtained using both the algorithms is given in Table 5, whereas Table 6 details the quality of the solutions provided by the algorithms. Under best case environment, PSODAC has incurred 95.6% of total cost incurred by PSO. It has been slightly varied to 95.9% under worst case environment.

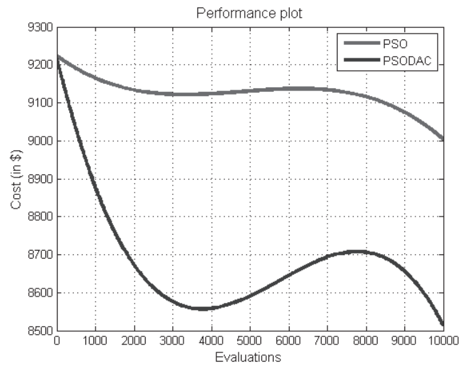


**Fig. 4.** Performance illustration between PSO and PSODAC (Convergence plot of Test System B)

**Table 4.** Transmission loss coefficients of Test System B

| **Loss Coefficients** | **$B_{mn}$ ($10^{-4}$)** | | | | | |
|---|---|---|---|---|---|---|
| ***Generation units*** | ***1*** | ***2*** | ***3*** | ***4*** | ***5*** | ***6*** |
| 1 | 0.14 | 0.17 | 0.15 | 0.19 | 0.26 | 0.22 |
| 2 | 0.17 | 0.6 | 0.13 | 0.16 | 0.15 | 0.2 |
| 3 | 0.15 | 0.13 | 0.65 | 0.17 | 0.24 | 0.19 |
| 4 | 0.19 | 0.16 | 0.17 | 0.71 | 0.3 | 0.25 |
| 5 | 0.26 | 0.15 | 0.24 | 0.3 | 0.69 | 0.32 |
| 6 | 0.22 | 0.2 | 0.19 | 0.25 | 0.32 | 0.85 |

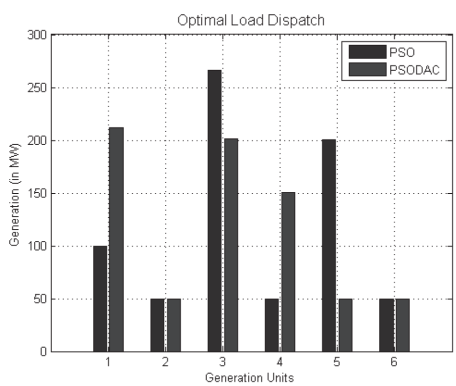


**Fig. 5.** Strategic variations between PSO and PSODAC under the environment of Test System B

On average, PSODAC incurs 95.9% of the total cost incurred by PSO. The performance plot of both the algorithms given in Fig. 4 illustrates the gradual convergence of PSO and steep convergence of PSODAC. Fig. 5 represents the generation strategy proposed by PSO and PSODAC. PSO proposes to generate 100MW from unit 1, whereas PSODAC almost doubles the generation of unit 1. Unit 3 generates around 260MW as per PSO strategy, but it is allowed to generate only 200MW by PSODAC. PSO generates only 50MW from unit 4, but PSODAC generates three times of the generation quantity proposed by PSO. In unit 5, PSODAC recommends just 25% of the power generated by PSO strategy. In unit 2 and unit 6, both the algorithms recommend 50MW generation. As a result, PSODAC reduces nearly 5% of the cost incurred by PSO strategy.

### *4.3. Test System C*

In Test System C, IEEE 24 bus RTS system is utilized in which 12 generation units are connected. 24 hour load profile is used to investigate the performance of PSODAC and PSO. The simulated load profile is depicted in Fig. 6. The system is experimented under no transmission loss constraints. Table 5 and 6 give the details of the generation strategy and solution quality, respectively. The performance plot is illustrated in Fig. 7, where the PSODAC potentially dominates PSO by exhibiting early convergence and converging to near-optimal solution. Despite there is degradation on convergence over PSO, when 8000 particles have undergone evaluation, the PSODAC further improves its searching ability and attempts to minimize the cost far better than PSO. Moreover, the PSO has almost reached a saturation point after 8000 function evaluations have been done, while the PSODAC sill improves the solution to minimize the gap between the ideal and converged solution. In the best case scenario, both the algorithms are found to be equivalent to each other. However, the performance of PSODAC is better than PSO in worst case scenario. As a result, the mean and median performance of PSODAC is better than PSO. Since best case scenario is considered to define the strategic variations between PSO and PSODAC, they exhibit similar generation strategies.

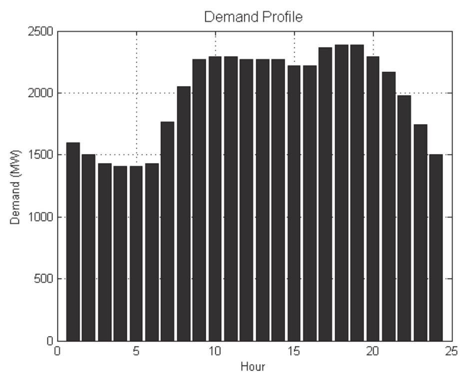


**Fig. 6.** 24 hour load profile of IEEE 24 bus RTS system

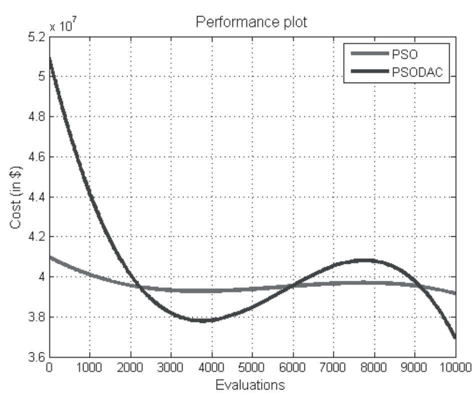


**Fig. 7.** Performance illustration between PSO and PSODAC (Convergence plot of Test System C)

## 5 - Investigation on particle dynamics

Investigating the particle dynamics can effectively illustrate the movement of a particle towards global minima/optima. The particle dynamics of the proposed PSODAC is better than the PSO because the proposed PSODAC uses adaptive acceleration coefficients. To observe the property, fitness of each particle at all iteration levels are obtained. The unique set of fitness values are plotted against iteration in Fig. 8. The illustration represents test system C. If the particle dynamics are high, then more number of unique number particle fitness values, i.e. more number of $N_p$, shall be obtained. In other words, high particle dynamics means (higher value of $N_p$) each particle varies its position at wide range for obtaining global optima. Few number of unique particles represent the particle is finding difficult to skip from its current position. The current position may be either global optima or local optima. Since ELD is multimodal in nature, there is more number of local optima. Hence, the probability of identifying global optima through PSO becomes less, say $\frac{1}{N}$; if there is one global optima and $N-1$ local optima. Increased $N$ often leads PSO to find difficulty in evading from local optima. From Fig. 8, it can be observed that traditional PSO exhibits particle dynamics only at few initial iterations and lags to search widely at the end of the iterations, despite the converged cost is not the least cost. However, PSODAC is active in searching till the end of the iterations and hence the possibility of evading from local optima and finding global optima is higher than PSO. Moreover, the effect of DAC on the intermittent generation and the performance can also be studied using Fig. 8. Since the constant acceleration coefficients in PSO enable a constant search space, the updated solution can be either drastically improved or deteriorated. In contrast, the PSODAC enables a gradual increase in the search space for exploration and hence the strength of searching in a huge dimension can be increased gradually. This results in a gradual improvement on the updated solution. Since the number of accomplished improvements are mapped to dynamics of the particle, $N_p$ of PSODAC is said to be higher than PSO.

**Table 5.** Comparison between PSO and PSODAC in terms of generation strategies and minimizing cost

| Test Case | Algorithms | Generator IDs | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* |
| A | PSO | 63 | 80 | 10 | | | | | | | | | |
| | PSODAC | 10 | 72 | 70 | | | | | | | | | |
| B | PSO | 100 | 50 | 266 | 50 | 200 | 50 | | | | | | |
| | PSODAC | 212 | 50 | 201 | 150 | 50 | 50 | | | | | | |
| C | PSO | 100 | 400 | 30 | 30 | 54 | 54 | 109 | 140 | 75 | 207 | 12 | 300 |
| | PSODAC | 100 | 100 | 30 | 30 | 54 | 54 | 109 | 140 | 75 | 207 | 12 | 300 |

**Table 6.** Quality of solutions obtained from PSO and PSODAC: statistical measurement of total generation cost

| Test Case | Algorithms | Cost (in $) | | | | | Execution time (seconds) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *Best* | *Worst* | *Mean* | *Median* | *SD* | *Best* | *Worst* | *Mean* | *Median* | *SD* |
| A | PSO | 1626.54 | 1634.51 | 1630.50 | 1630.44 | 2.36 | 1.62 | 1.62 | 1.62 | 1.62 | 0.00 |
| | PSODAC | 1607.98 | 1615.74 | 1611.83 | 1611.89 | 2.32 | 1.83 | 1.84 | 1.84 | 1.84 | 0.002 |
| B | PSO | 9007.29 | 9053.06 | 9029.41 | 9029.77 | 13.33 | 1.63 | 1.64 | 1.64 | 1.63 | 0.002 |
| | PSODAC | 8644.66 | 8686.26 | 8666.52 | 8665.86 | 12.62 | 1.64 | 1.65 | 1.64 | 1.64 | 0.002 |
| C | PSO | 3951.7e4 | 3973.3e4 | 3962.1e4 | 3962.1e4 | 6.21e4 | 4.049 | 4.070 | 4.059 | 4.059 | 0.006 |
| | PSODAC | 3951.7e4 | 3970.7e4 | 3961.1e4 | 3960.9e4 | 5.35e4 | 3.603 | 3.621 | 3.611 | 3.611 | 0.005 |

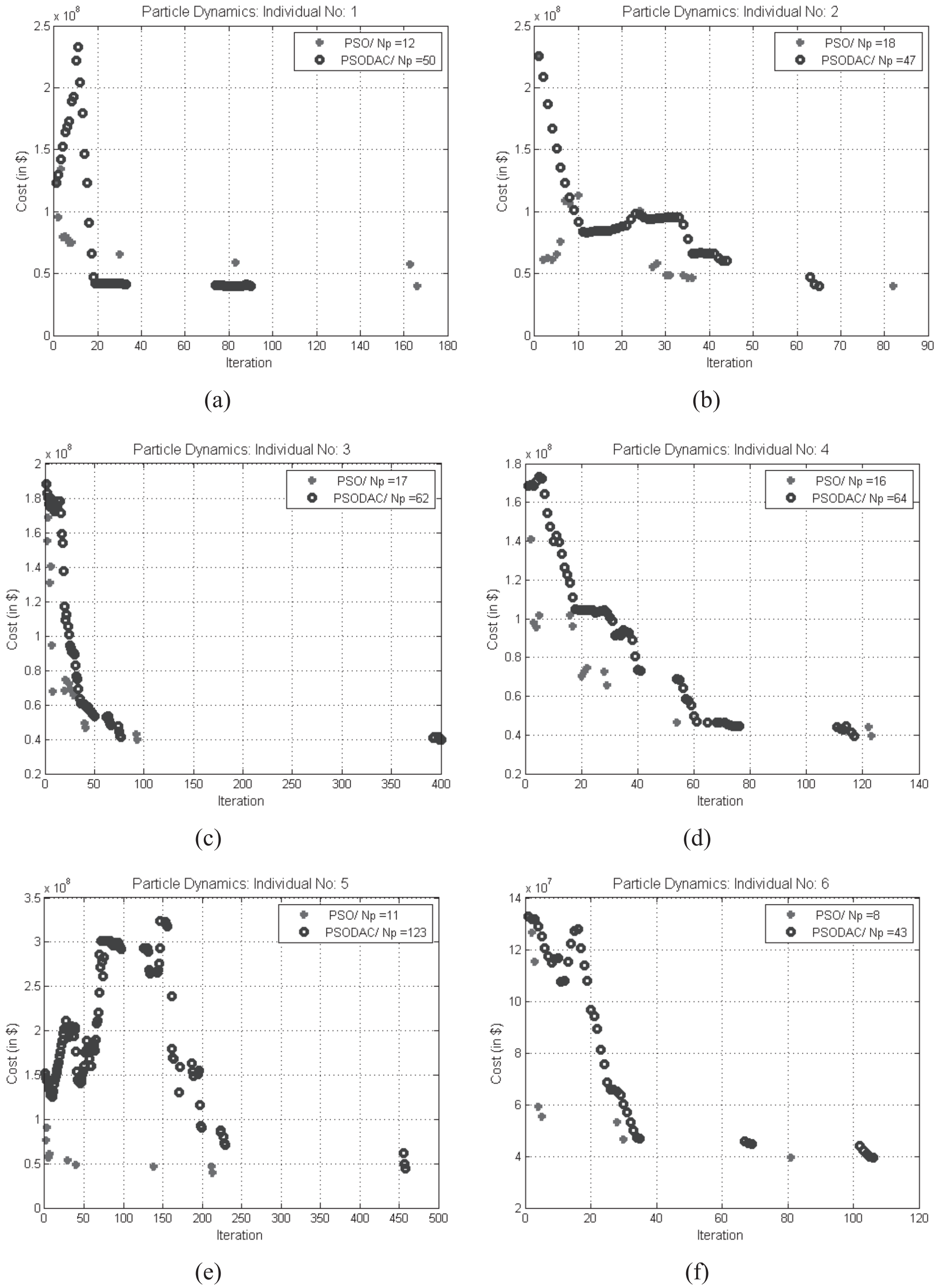


**Fig. 8.** Dynamics of Particles (Individuals) at every iteration.
(The graphs are acquired for IEEE24 bus RTS system;
here $N_p$ refers to the number of unique particles that exhibited varying fitness)

## 6 - Conclusion and Future scope

This paper introduced an improved version of PSO, termed as PSODAC, to solve ELD problem in deregulated electricity generation system. The proposed PSODAC has recommended adaptive acceleration coefficients for particle updates phenomenon. As a result, each particle is accelerated in accordance to its position to reach the global optima. The efficacy of solving ELD problem is experimented under three cases. First case is a generation system with three generation units, second case has six generation units and third case is an IEEE24 benchmark RTS system with 12 generation units. The experimental results have demonstrated that the performance of PSODAC is better than PSO. Further, this paper has investigated the dynamics of particle movement exhibited by PSO and PSODAC. The investigation has resulted in higher particle dynamics in PSODAC and lower particle dynamics in PSO. The results are encouraging and hence, this paper define the future research to focus. on solving dynamic ELD problem using PSODAC under wide constrained environment that includes systems with hybrid renewable energy sources such as wind turbine, photovoltaic panels and hydro units.

***Compliance with Ethical Standards:***

- **CONFLICT OF INTEREST**:The author of this article declares that he has no conflict of interest.
- **ETHICAL APPROVAL**:This article does not contain any studies with human participants or animals performed by any of the authors.
- **FUNDING INFORMATION**:There are no funders associated with this article.

## References

**Amjady, N. & Nasiri-Rad, H. 2009.** Economic dispatch using an efficient real-coded genetic algorithm. IET Gener., Transm. Distrib. **3**(3): 266–278.

**Amjady, N. & Nasiri-Rad, H. 2009.** Nonconvex economic dispatch with ac constraints by a new real coded genetic algorithm. IEEE Trans. Power Syst. **24**(3): 1489–1502.

**Bhattacharjee, K., Bhattacharya, A. & Halder, S. 2014.** Chemical reaction optimisation for different economic dispatch problems. IET Generation, Transmission & Distribution **8**(3): 530 – 541.

**Bhattacharya, A. & Chattopadhyay, P.K. 2010.** Biogeography-based optimization for different economic load dispatch problems. IEEE Trans. Power Syst. **25**(2): 1064–1077.

**Binetti, G., Davoudi, A., Naso, D., Turchiano, B. & Lewis, F.L. 2014.** A Distributed Auction-Based Algorithm for the Nonconvex Economic Dispatch Problem. IEEE Transactions on Industrial Informatics. **10**(2): 1124- 1132.

**Chaturvedi, K. T., Pandit, M. & Srivastava, L. 2008.** Self-organizing hierarchical particle swarm optimization for non-convex economic dispatch. IEEE Trans. Power Syst. **23**(3): 1079–1087.

**Chiang, C.L. 2005.** Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels. IEEE Trans. Power Syst. **20**(4): 1690–1699.

**Ding, T., Bo, R., Gu,W. & Sun, H. 2014.** Big-M Based MIQP Method for Economic Dispatch with Disjoint Prohibited Zones. IEEE Transactions on Power Systems. **29**(2): 976- 977.

**El-Keib, A.A., Ma, H. & Hart, J.L. 1994.** Environmentally constrained economic dispatch using the Lagrangian relaxation method, IEEE Trans. Power Syst. **9**(4): 1723–1729.

**Fanshel, S. & Lynes, E.S. 1964.** Economic power generation using linear programming. IEEE Trans. Power Appar. Syst. (4): 347–356

**Gaing, Z.-L. 2003.** Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Trans. Power Syst., **18**(3): 1187–1195.

**Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C. & Hancke, G. P. 2011.** Smart grid technologies Communication technologies and standards. IEEE Trans. Ind. Inf. **7**(4): 529–539.

**Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C. & Hancke, G. P. 2013.** A survey on smart grid potential applications and communication requirements. IEEE Trans. Ind. Inf. **9**(1): 28–42.

**Hou, Y.H., Wu, Y.W., Lu, L.J. & Xiong, X.Y. 2002.** Generalized ant colony optimization for economic dispatch of power systems. Proc. Int. Conf. Power System Technology, Power-Con. **1**: 225–229.

**Jayabharathi, T., Jayaprakash, K., Jeyakumar, N. & Raghunathan, T. 2005.** Evolutionary programming techniques for different kinds of economic dispatch problems. Electr. Power Syst. Res. **73**(2):169–176.

**Kennedy, J. & Eberhart, R. 1995.** Particle swarm optimization.Proceedings of IEEE International Conference on Neural Networks 1942–1948.

**Lin, C. E. & Viviani, G. L. 1984.** Hierarchical economic dispatch for piecewise quadratic cost functions, IEEE Trans. Power A Syst. **6**:1170–1175.

**Lin, W.M. & Chen, S.J. 2002.** Bid-based dynamic economic dispatch with an efficient interior point algorithm. Int. J. Electr. Power Energy Syst. **24**(1): 51–57.

**Moeini-Aghtaie, M., Dehghanian, P., Fotuhi-Firuzabad, M. & Abbaspour, A. 2014.** Multiagent Genetic Algorithm an Online Probabilistic View on Economic Dispatch of Energy Hubs Constrained by Wind Availability. IEEE Transactions on Sustainable Energy. **5**(2): 699 – 708.

**Nomana, N. & Iba, H. 2008.**Differential evolution for economic load dispatch problems., Electr. Power Syst. Res. **78**(3): 1322–133.

**Panigrahi, B. K., Pandi, V. R. & Das, S. 2008.**Adaptive particle swarm optimization approach for static and dynamic economic load dispatch. Energy Convers. Manag. **49**(6): 1407–1415.

**Panigrahi, B.K. & Pandi, V.R. 2008.** Bacterial foraging optimization Nelder-Mead hybrid algorithm for economic load dispatch. IET Gener. Transm. Distrib. **2**(4): 556–565.

**Panigrahi, B.K., Yadav, S.R., Agrawal, S. & Tiwari, M.K. 2007.** A clonal algorithm to solve economic load dispatch., Electr. Power Syst. Res. **77**(10): 1381–1389.

**Panigrahi, C.K., Chattopadhyay, P.K., Chakrabarti, R.N. & Basu, M. 2006.**Simulated annealing technique for dynamic economic dispatch. Electr. Power Compon. Syst. **34**(5): 577–586

**Park, J.B., Jeong, Y.W., Shin, J.R. & Lee, K.Y. 2010.**An improved particle swarm optimization for nonconvex economic dispatch problems. IEEE Trans. Power Syst. **25**(1):156–166

**Rabiee, A., Mohammadi-Ivatloo, B. & Moradi-Dalvand, M. 2014.** Fast Dynamic Economic Power Dispatch Problems Solution Via Optimality Condition Decomposition. IEEE Transactions on Power Systems **29**(2): 982 - 983.

**Selvakumar, A. I. & K. Thanushkodi 2007.** A new particle swarm optimization solution to nonconvex economic dispatch problems. IEEE Trans. Power Syst. **22**(1): 42–51.

**Selvakumar, A.I. & Thanushkodi 2009.** Optimization using civilized swarm Solution to economic dispatch with multiple minima. Electr. Power Syst. Res., **79**(1): 8–16.

**Shi, Y. & Eberhart, R. 1998.** A modified particle swarm optimizer. IEEE World Congress on Computational Intelligence 69-73.

**Siano, P., Cecati, C., Yu, H. & Kolbusz, J. 2012.** Real time operation of smart grids via FCN networks and optimal power flow. IEEE Trans. Ind. Inf. **8**(4): 944–952.

**Somasundaram, P., Kuppusamy, K. & Kumudini Devi, R.P. 2004.** Economic dispatch with prohibited operating zones using fast computation evolutionary programming algorithm. Electric Power Systems Research **70**: 245–252.

**Su, W., Eichi, H. R., Zeng, W. & Chow, M.Y. 2012.** A survey on the electrification of transportation in a smart grid environment. IEEE Trans. Ind. Inf. **8**(1): 1–10.

**Sun, J., Palade, V., Wu, X.-J., Fang, W. & Wang, Z. 2014.** Solving the power economic dispatch problem with generator constraints by random drift particle swarm optimization. IEEE Trans. Ind. Inf. **10**(1): 222-232.

**Vlachogiannis, J.K. & Lee, K.Y. 2009.** Economic load dispatch – a comparative study on heuristic optimization techniques with an improved coordinated aggregation-based PSO. IEEE Trans. Power Syst. **24**(2): 991–1001.

**Walters, D.C. & Sheble, G.B. 1993.** Genetic algorithm solution of economic dispatch with valve point loadings. IEEE Trans. Power Syst. **8**(3): 1325–1331.

**Wood, A. J. & Wollenberg, B. F. 1996.** Power Generation, Operation, Control. New York, NY, USA Wiley.

**Wood, J. & Wollenberg, B.F. 1984.** Power generation, operation, and control (John Wiley and Sons, 1984, 2nd edn.)

**Yang, H.T., Yang, P.C. & Huang, C.L. 1996.** Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions. IEEE Trans. Power Syst. **11**(1): 112–118.

**Yao, F., Dong, Z. Y., Meng, K., Xu, Z., Iu, H. H.C. & Wong, K. P. 2012.** Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia. IEEE Trans. Ind. Inf. **8**(4): 880–888.

**Zhao, J., Wen, F., Dong, Z. Y., Xue, Y. & Wong, K. P. 2012.** Optimal dispatch of electric vehicles and wind power using enhanced particle swarm optimization. IEEE Trans. Ind. Inf. **8**(4): 889–899.

***Submitted:*** 04/05/2016
***Accepted :*** 22/12/2016