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A Modified PSO Based Solution Approach for Economic Load Dispatch Problem in Power Systems

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Abstract: This paper presents a new algorithm that utilizes the PSO with double chaotic maps to solve the economic load dispatch problem with different cost functions. In proposed approach, we employ the PSO method that involves the alternating use of chaotic maps in estimating the velocity of the particle. Presently the PSO method has been widely used in complex designs problems with multiple variables where the optimization of a cost function is required. The use of the PSO method for the economic load dispatch problem is widely studies however the best solution may require higher number of iterations and at the worst it fails to achieve global best solution, hence to overcome the problem irregular velocity updates are performed by some kind of random function which force the particles to search greater space for best global solution. However the random function itself derived from a well-defined mathematical expression which limits its redundancy hence in the paper we are utilizing the two different chaotic maps which are used alternatively this mathematically increased the randomness of the function. The simulation of the algorithm verifies the effectiveness and superiority of the algorithm over standard PSO and single chaotic map based PSO.

Keywords: Economic Load dispatch (ELD) problem, PSO, Chaotic Maps, Logistic Map, Lozi Map.

1. INTRODUCTION

The economic load dispatch (ELD) in power system is the key aspect of powers system and plays a crucial role in power systems. The ELD problem is considered as optimization problem in which minimization of the total operating cost is set as main objective which should be found within the equality and inequality constraints (operational constrains) limitations. The operational constraints are referred as generation limitations, ramp rate limits, and network loss are considered for practical operation. Moreover the valve-point effects may also be considered. These considerations make the ELD problem a large-scale highly non-linear constrained optimization problem.

Another aspect other than cost which force to use the ELD is the new clean air policies and regulations who have instruct electricity generating plants and power producers to consider the environmental impact of the operation of plant. Under these circumstances, demand optimization is not only governed by the unit's capability of minimizing the total fuel cost of system generation, but also their capability of satisfying the emission requirements. Because of the importance of the problem, a number of conventional and non-conventional approaches have been developed for solving the ELD problem like lambda iteration method, quadratic linear programming [3], mathematical linear programming [4], non-linear programming [5], dynamic programming [6][7], In these numerical methods for solving the ELD problem, the incremental cost curves are considered as piecewise-linear monotonically increasing functions. However, the input-output characteristics of modern power generating units are inherently highly non-linear because of valve-point loadings, multi-fuel effects, etc. this lead to multiple local minimum points of the cost function. Classical dispatch algorithms require that these characteristics be approximated, even though such approximations are not desirable as they may lead to sub optimal solutions and hence huge revenue losses over time. In order to overcome these limitations artificial intelligence techniques, such as swarm intelligence, genetic algorithm has been used and found much better than the former one although these techniques also suffers from some inherent limitations for which many improvements have been already proposed this paper is also falls in such category here the PSO techniques is improved with alternative use of two different chaotic maps. The rest of the paper is arranged as second section presents a brief review of the related literatures in third section discusses the problem formulation while fourth section explains the PSO and the variants used in the paper fifth section explain chaotic maps six section explain the implementation algorithm finally in chapter seventh and eight respectively presents the simulation result and conclusion or future scope.

2. LITERATURE REVIEW

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The economic dispatch problem with non-smooth cost function using PSO is discussed in [8] this paper presented a modified PSO (MPSO) mechanism is suggested to deal with the equality and inequality constraints in the ED problem. A constraint treatment mechanism is devised in such a way that the dynamic process inherent in the conventional PSO is preserved. Moreover, a dynamic search-space reduction strategy is devised. The quantum-inspired particle swarm optimization (QPSO)is proposed by KeMeng et al [9] the algorithm has stronger search ability and quicker convergence speed, not only because of the introduction of quantum computing theory, but also due to two special implementations: self-adaptive probability selection and chaotic sequences mutation. XuJian et al [10] proposed an improved algorithm of PSO (Particle Swarm Optimization). The main contribution of the improved algorithm includes: new migration strategy was proposed and the velocity update strategy was replaced by a new one. A Hybrid PSO (HPSO) proposed in [11] which is a blend of binary particle swarm optimization (BPSO) and real coded particle swarm optimization (RCPSO). Michal Pluhacek et al [12] proposed a new approach for chaos driven PSO algorithm is proposed. Two different chaotic maps are alternately used as pseudorandom number generators and switched over during the run of chaos driven PSO algorithm. For solving economic dispatch (ED) problems with non-convex cost functions an improved particle swarm optimization (IPSO) is proposed in [13]. They proposed an improved PSO framework employing chaotic sequences combined with the conventional linearly decreasing inertia weights and adopting a crossover operation scheme to increase both exploration and exploitation capability of the PSO. In addition, an effective constraint handling framework is employed for considering equality and inequality constraints.

3. PROBLEM FORMULATION

The objective of an ELD problem is to minimize the total operating cost which should be found within the equality and inequality constraints (operational constrains) limitations. The simplified cost function of each generating unit can be represented as described in (2)

$$F_T = \sum_{i=1}^{n} F_i(P_i) \dots\dots\dots\dots\dots\dots\dots. (1)$$

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 \dots\dots\dots. (2)$$

$where$

$$F_T = Total\ Generation\ Cost$$

$$F_i = Cost\ Function\ of\ Generator\ i$$

$$a_i, b_i, c_i = Cost\ Coefficient\ of\ Generation\ i$$

$$P_i = Power\ Output\ of\ Generator\ i$$

3.1.1 ELD Problem Considering Valve-Point Effects: The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost function. Since the valve point results in the ripples, a cost function contains higher order nonlinearity. Therefore, the cost function (2) should be replaced by the following to consider the valve-point effects:

$$F_i(P_i) = a_i + b_iP_i + c_iP_i^2 + |e_i * sin\left(f_i * \left(P_{i,min} - P_i\right)\right)| \dots. (3)$$

$where$

$e_i\ and\ f_i are\ the\ cost\ coefficient\ of\ generator\ i,$ $reflecting\ valve\ point\ effect$ [14]

3.1.2 ELD Problem Considering Multi-Fuels with Valve-Point Effects: Since the dispatching units can be supplied with multi-fuel sources, each unit can be represented with several piecewise quadratic functions reflecting the effects of different fuel types. In general, a piecewise quadratic function is used to represent the input-output curve of a generator with multiple fuels [15] and described as

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2, & fuel\ 1, \quad P_{i,min} \le P_i \le P_{i,1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2, & fuel\ 2, \quad P_{i,1} \le P_i \le P_{i,2} \\ & \dots\dots. \\ & \dots\dots. \\ a_{ik} + b_{ik}P_i + c_{ik}P_i^2, & fuel\ k, \quad P_{ik-1} \le P_i \le P_{i,max} \end{cases} \dots\dots\dots\dots\dots (4)$$

$where$

$a_{ik}, b_{ik}\ and\ c_{ik}\ are\ the\ cost\ coefficients\ of\ generator\ i,$

$for\ fuel\ type\ k.$

In general, fuels are supplied by fuel suppliers under a multitude of contracts between the suppliers and the utility. Determining the selection of fuels for each unit is dictated by the contracts, and can be solved by economic fuel dispatch [16]. This paper assumes that such selection is given a-priori. Therefore, to obtain an accurate and practical ELD solution, the fuel cost function should be considered with both multi-fuels and valve-point effects simultaneously [17]. Thus, the fuel cost function (3) should be combined with (4), and can be represented as follows:

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$$F_i(P_i) = \begin{cases} F_{i1}(P_i), & fuel\ 1, \quad P_{i,min} \le P_i \le P_{i,1} \\ F_{i2}(P_i), & fuel\ 2, \quad P_{i,1} \le P_i \le P_{i,2} \\ & \dots\dots \\ & \dots\dots \\ F_{i3}(P_i), & fuel\ k, \quad P_{ik-1} \le P_i \le P_{i,max} \end{cases} \dots\dots\dots\dots\dots(5)$$

$Where$

$$F_{ik}(P_i) = a_{ik} + b_{ik}P_i + c_{ik}P_i^2 + |e_{ik} * \sin\left(f_{ik} * \left(P_{ik,min} - P_i\right)\right) \dots\dots(6)$$

$and\ e_{ik}\ and\ f_{ik}\ are\ the\ cost\ coefficients\ of\ generator\ i,\ reflecting\ valve\ point\ effects\ for\ fuel\ type\ k\ ,and\ P_{ik,min}\ is\ the\ minimum\ output\ of\ generator\ i, using\ fuel\ type\ k.$

3.2. Equality and Inequality Constraints

3.2.1 Active Power Balance Equation: For power balance, an equality constraint should be satisfied. The total generated power should be the same as the total load demand plus the total line loss. However, the network loss is not considered in this paper for simplicity.

$$\sum_{i=1}^{n} P_{load} + P_{loss} \dots\dots\dots\dots\dots(7)$$

$where\ P_{load}\ is\ the\ total\ system\ load. The\ total\ transmission\ network\ loss, P_{loss}\ ,is\ a\ function\ of\ the\ unit\ power\ outputs\ that\ can\ be\ represented\ using\ B\ coefficients\ [18]\ as\ follows:$

$$\sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i}P_i + B_{00} \dots\dots\dots\dots(8)$$

3.2.2 Minimum and Maximum Power Limits: Power output of each generator should be within its minimum and maximum limits. Corresponding inequality constraint for each generator is

$$P_{i,min} \le P_i \le P_{i,max} \dots\dots\dots\dots\dots(9)$$

$where\ P_{i,min}\ and\ P_{i,max}\ are\ the\ minimum\ and\ maximum\ output\ of\ generator\ i, respectively.$

3.2.3 Ramp Rate Limits: The actual operating range of all the online units is restricted by their corresponding ramp rate limits. The ramp-up and ramp-down constraints can be written as follows:

$$P_i - P_i^0 \le UR_i\ and\ P_i^0 - P_i \le DR_i \dots\dots\dots\dots(10)$$

$where\ P_i^0\ is\ the\ previous\ power\ output\ of\ the\ i\ th\ generating\ unit. UR_i\ and\ DR_i\ are\ the\ up\ ramp\ and\ down\ ramp\ limits\ of\ generator\ ,respectively.$

To consider the ramp rate limits and power output limits constraints at the same time, (10) and (9) can be rewritten as an inequality constraint as follows:

$$\max\{P_{i,min}, P_i^0 - DR_i\} \le P_i \le \min\{P_{i,max}, P_i^0 + UR_i\}. (11)$$

3.2.4 ELD Problem Considering Prohibited Operating Zones: In some cases, the entire operating range of a generating unit is not always available due to physical operation limitations. Units may have prohibited operating zones due to faults in machines themselves or associated auxiliaries. Such faults may lead to instability in certain ranges of generator power output [19]. Therefore, for units with prohibited operating zones, there are additional constraints on the unit operating range as follows:

$$P_i \in \begin{cases} P_{i,min} \le P_i \le P_{i,1}^l \\ P_{i,k-1}^u \le P_i \le P_{i,k}^l \\ P_{i,pz_i}^u \le P_i \le P_{i,max} \end{cases}, \quad k = 2,3,\dots pz_i$$

$$i = 1,2,\dots n_{PZ} \dots\dots\dots(12)$$

$where\ P_{i,k}^l\ and\ P_{i,k}^u\ are, respectively, the\ lower\ and\ upper\ bounds\ of\ prohibited\ operating\ zone\ of\ unit\ i. Here\ pz_i,\ is\ the\ number\ of\ prohibited\ zones\ of\ unit\ i\ and\ n_{PZ}\ is\ the\ number\ of\ units\ which\ have\ prohibited\ operating\ zones.$

4. PARTICLE SWARM OPTIMIZATION (PSO)

Kennedy and Eberhart developed a PSO algorithm based on the behaviour of individual (i.e., particles or agents) of a swarm [1]. Its roots are in zoologist's modelling of the movement of individual (e.g., fish, birds, and insects) within a group. It has been noticed that members of the group seem to share information among them, a fact that leads to increased efficiency of the group, The PSO algorithm, search in parallel using a group of individual similar to other AI- based heuristic optimization techniques [20]. Each individual corresponds to a candidate solution to the problem. Individuals in a swarm approach to the optimum through its present velocity, previous experience, and the experience of its neighbours.

In a physical n-dimensional search space, the position and velocity of individual i are represented as the vectors $X_i = (X_{i1},.....X_{in})$ and $V_i = (V_{i1},......V_{in})$ in the PSO algorithm. Let $Pbest_i = (X_{i1}^{Pbest},......,X_{in}^{Pbest})$ and $Gbest_i = (X_{i1}^{Gbest},......,X_{in}^{Gbest})$ be the best position of individual i and its neighbours' best position so far, respectively. Using the information .the updated velocity of individual i is modified under the following equation in the PSO algorithm.

$$V_i^{k+1} = \omega V_i^k + c_1 rand_1 \text{ X } (Pbest_i^k - X_i^k) + c_2 rand_2 \text{ X } (Gbest^k - X_i^k) \ldots\ldots\ldots\ldots(13)$$

Where,

V_i^k : velocity of individual i at iteration k,

ω : weight parameter,

c_1, c_2 : weight factors,

$rand_1$, $rand_2$: random number between 0 and 1,

X_i^k : position of individual i at iteration k,

$Pbest_i^k$: best position of individual a until iteration k,

$Gbest^k$: best position of the group until iteration k,

In this velocity updating process, the value of parameters such as ω , c_1, and c_2 should be determined in advance. In general, the weight ω is set according to the following equation [2],[8]:

$$\omega = \omega_{max} - [\, \omega_{max} - \omega_{min} / Iter_{max} \,] \text{ X } Iter \quad \ldots\ldots.(14)$$

where,

ω_{max} , ω_{min} : initial, final weight,

$Iter_{max}$: maximum iteration number,

Iter : current iteration number.

Each individual moves from the current position to the next one by the modified velocity in (13) using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad \ldots\ldots\ldots\ldots\ldots(15)$$

Fig. 1 shows the concept of the searching mechanism of PSO using the modified velocity and position of individual i based on (13) and (15) if the values of ω , c_1, c_2, $rand_1$, $rand_2$ are 1.

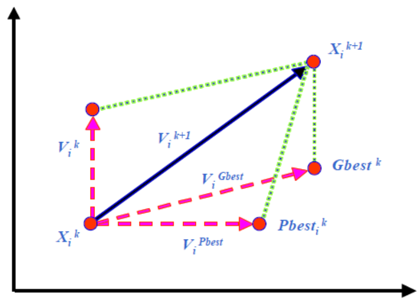

Fig. 1. Concept of modification of a searching point by PSO

5. CHAOTIC MAPS

This section contains the description of discrete chaotic maps used as the chaotic pseudorandom generator for PSO. In this research, direct output iterations of the chaotic map were used for the generation of real numbers for the main PSO formula that determines new velocity, thus the position of each particle in the next iteration. The initial concept of embedding chaotic dynamics into evolutionary algorithms is given in [21].

5.1 Dissipative standard map

The Dissipative standard map is a two-dimensional chaotic map [22]. The parameters used in this work are b = 0.6 and k = 8.8 based on previous experiments [23] and suggestions in literature [21,22]. The Dissipative standard map is given in Fig.2. The map equations are given in (16).

$$X_{n+1} = X_n + Y_{n+1}(mod 2\pi)$$

$$Y_{n+1} = bY_n + k sin X_n (mod 2\pi) \ldots\ldots\ldots\ldots\ldots.(16)$$

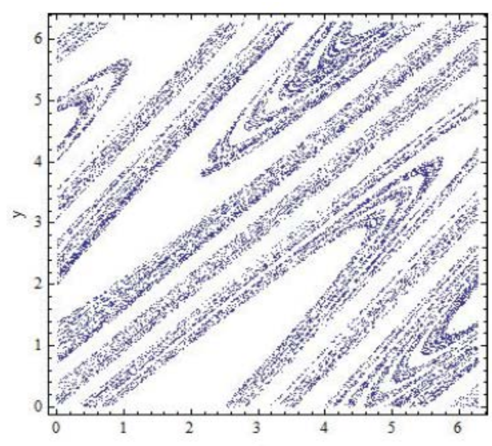

Fig. 2. Fig. 1. x, y plot of Dissipative standard map

5.2. Lozi map

The Lozi map is a simple discrete two-dimensional chaotic map. The Lozi map is depicted in Fig. 3. The map equations are given in (17). The parameters used in this work are: $a = 1.7$ and $b = 0.5$ with respect to [21, 22,24].

$$X_{n+1} = 1 - x|X_n| + bY_n$$

$$Y_{n+1} = X_n \dots\dots\dots\dots\dots\dots. (17)$$

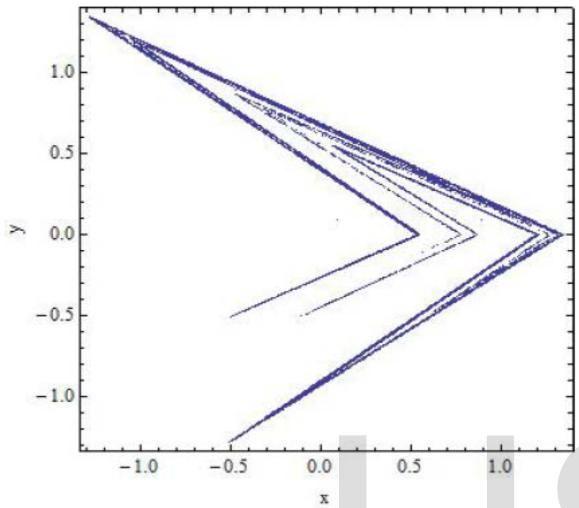

Fig. 3. x, y plot of Lozi map

The new proposed algorithm utilizes Lozi map for the first part of the optimization process. When pre-defined number of iterations is achieved, the Lozi map is switched over to Dissipative standard map.

6. IMPLEMENTATION OF MODIFIED PSO ALGORITHM FOR ECONOMIC LOAD DISPATCH PROBLEMS

Since the decision variables in ELD problems are real power outputs, the structure of a particle is composed of a set of elements corresponding to the generator outputs. Therefore, particle's position at iteration k can be represented as the vector $X_i^k = \left(P_{i1}^k, P_{i2}^k \dots\dots.., P_{im}^k\right)$ where n is the number of generators, The velocity of particle i corresponds to the generation updates for all generators. The process of the proposed MPSO algorithm can be summarized as in the following steps.

1. Initialize the position and velocity of a population at random while satisfying the constraints.

2. Update the velocity of particles.

3. Modify the position of particles to satisfy the constraints, if iteration is odd use logistic map to calculate modified coefficient else lozi map.

4. Generate the trial vector through alternative chaotic coefficient operation process.

5. Update and Pbest and Gbest.

6. Go to Step 2 until the stopping criteria is satisfied.

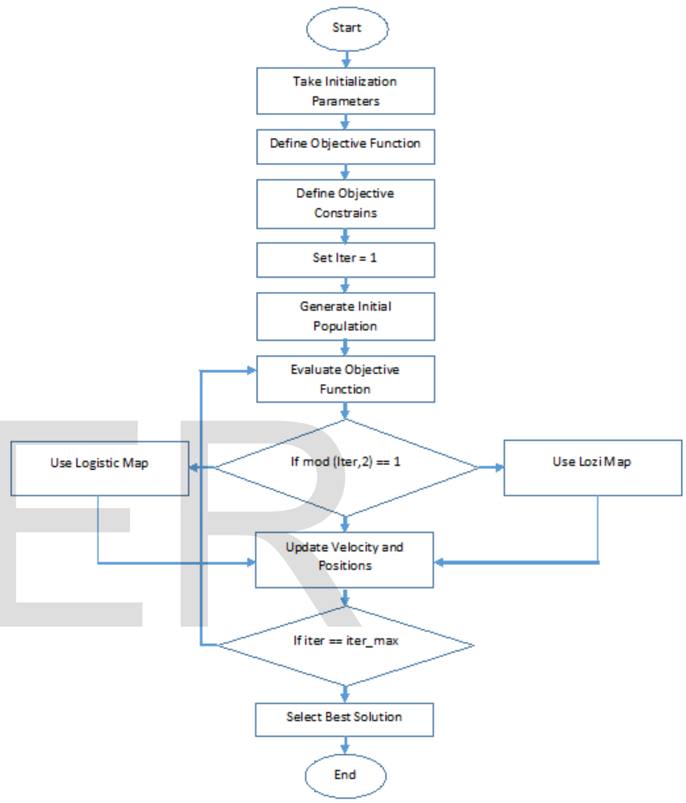

Figure 4: Flow Chart of the Proposed Algorithm.

7. SIMULATION RESULTS

The proposed MPSO approach is applied to three different power systems problems: 1) 3-unit system with valve-point effects; 2) 40-unit system with valve point effect; 3) 10-unit system considering multiple fuels with valve-point effects; For each case 50 independent trials are conducted to compare the solution quality and convergence characteristics. For each ELD problem, three strategies are applied and compared:

• The conventional PSO

• The PSO with chaotic sequences

• The PSO with alternative chaotic operation

The proposed MPSOs have been executed on Intel I3 2.0-GHz computer. The population size N_P and maximum iteration number $iter_{max}$ are set as 100 and 50, respectively. Since the performance of PSO-based approach depends on the parameters such as inertia weight factor and the two acceleration coefficients, it is important to determine suitable values of these parameters. As for the inertia weight, the starting value (i.e,w_{max}) is set as 0.9 and the ending value (i.e.,) as 0.1 because these values are widely accepted in solving various optimization problems [26],[27],[28]. Two acceleration coefficients of each ELD problem are determined through the experiments without employing the suggested framework such as the chaotic sequences and alternative chaotic map. In chaotic sequences, the control parameter is set to 0.1 and initial value of is determined by a random number between [2] except the values 0, 0.25, 0.5, 0.75, and 1. In the alternative chaotic map operation, estimating the velocity of the particle, and increased the randomness of the function.

A. Test System 1: This system comprises of 3 generating unit and the input data of 3-generating system are given in [25]. Here, the total demand for the system is set to 850MW.

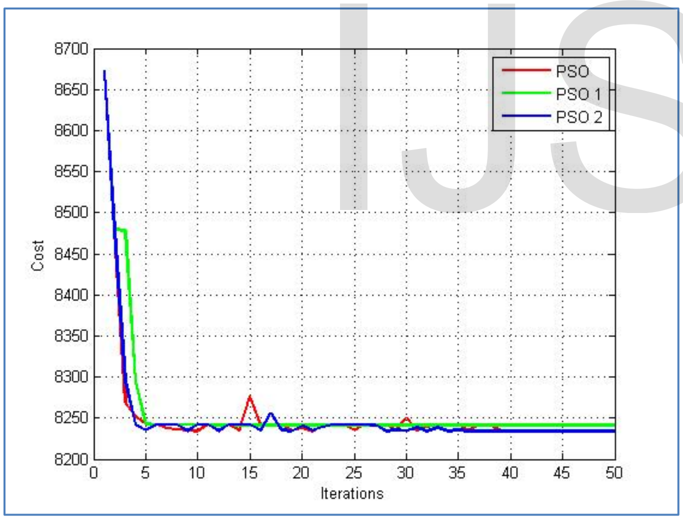

Figure 5: Comparison of cost minimization vs. iterations for PSO, PSO with chaotic map (PSO 1) and Proposed PSO (PSO 2) with 2 chaotic maps.

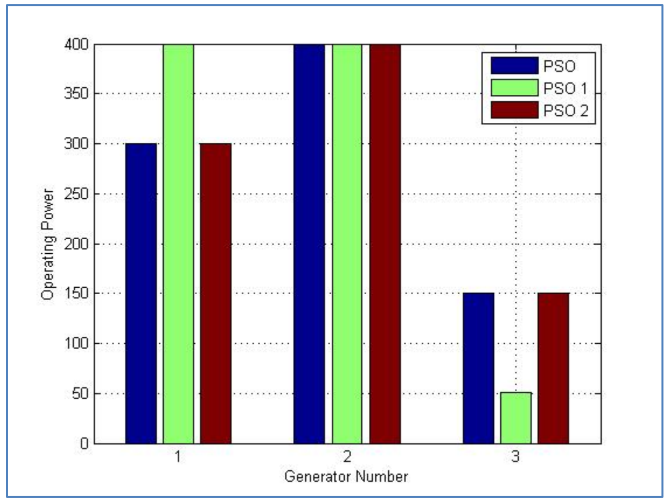

Figure 6: Comparison of optimum operational condition for all generator units for PSO, PSO with chaotic map (PSO 1) and Proposed PSO (PSO 2) with 2 chaotic maps.

Table 1: Minimum Operational Cost by all Three Techniques

Technique	Minimum cost
PSO	8.2441e3
PSO 1	8.2416e3
PSO 2	8.2302e3

B. Test System 2: In this case the test system consists of 40-generating units and the input data are described in [14]. The total demand is set to 10500 MW.

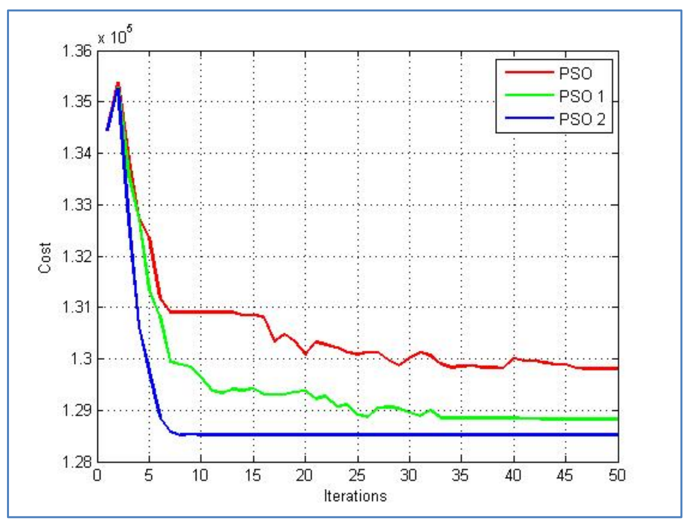

Figure 7: Comparison of cost minimization vs. iterations for PSO, PSO with chaotic map (PSO 1) and Proposed PSO (PSO 2) with 2 chaotic maps.

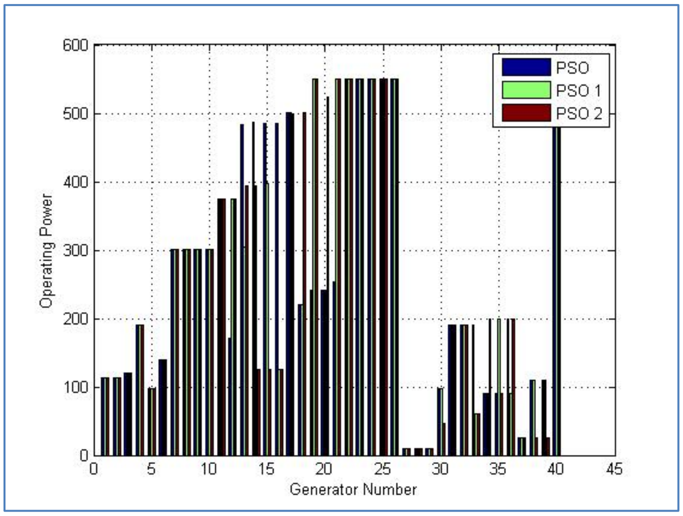

Figure 8: Comparison of optimum operational condition for all generator units for PSO, PSO with chaotic map (PSO 1) and Proposed PSO (PSO 2) with 2 chaotic maps.

Table 2: Minimum Operational Cost by all Three Techniques

Technique	Minimum Cost
PSO	1.3015e5
PSO 1	1.3112e5
PSO 2	1.2733e5

C. Test System 3: Multi-Fuels with Valve-Point Effect The test system consists of 10-generating units considering multi-fuels with valve-point effects. The input data and related constraints of the test system are given in [17]. The total system demand is set to 2700 MW.

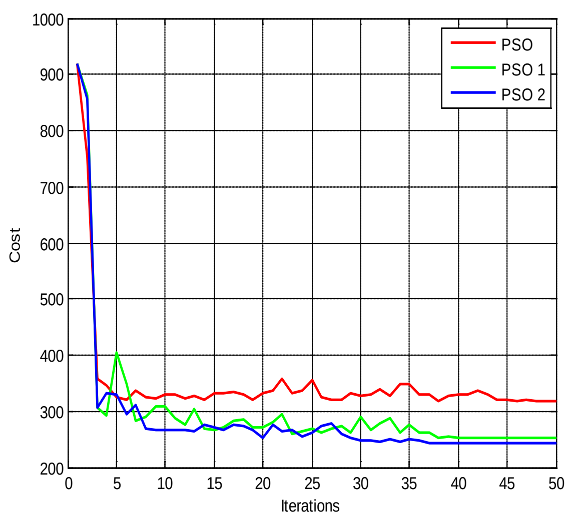

Figure 9: Comparison of cost minimization vs. iterations for PSO, PSO with chaotic map (PSO 1) and Proposed PSO (PSO 2) with 2 chaotic maps.

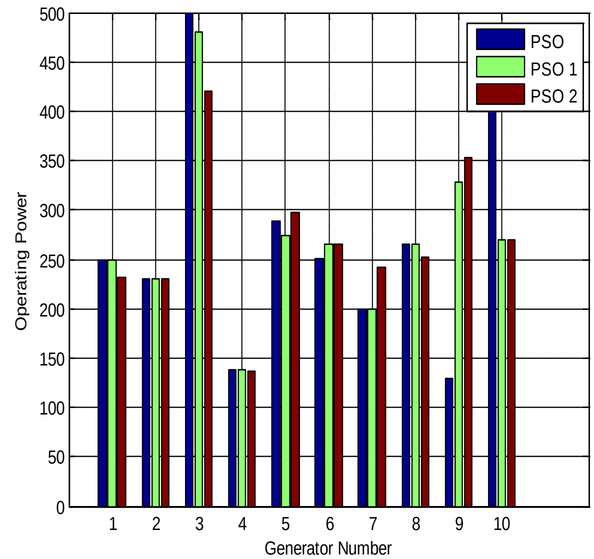

Figure 10: Comparison of optimum operational condition for all generator units for PSO, PSO with chaotic map (PSO 1) and Proposed PSO (PSO 2) with 2 chaotic maps.

Table 3: Minimum Operational Cost by all Three Techniques

Technique	Minimum Cost
PSO	319.0602
PSO 1	251.7066
PSO 2	244.0730

8. CONCLUSION AND FUTURE SCOPE

In this paper presents an efficient approach for enhancing the performance of standard PSO algorithm by alternative use of two different chaotic maps for velocity updation and applied to the ELD problem and tested for three different systems and objectives. The simulation results shows the superiority of the proposed algorithm over the previously proposed single chaotic map based PSO algorithm and support the idea that switching over of chaotic pseudorandom number generators in the PSO algorithm improves its performance and the optimization process. The results for three different experiments are collected with different settings and results compared with other methods which shows that the proposed algorithm improves the results by at least 10% for all three cases. Although the results has improved we can further develop the algorithm by utilizing multiple maps and optimizing the chaotic maps parameters however these considerations are leaved for future enhancements.

REFERENCES

[1] J. Kennedy, R. Eberhart, "Particle swarm optimization," in Proceedings of IEEE International Conference on Neural Networks. IV., 1995, pp. 1942-1948.

[2] K. Y. Lee and M. A. EI-Sharkawi (Editors), Modern Heuristic Optimization Techniques with Application to Power Syatems, IEEE Power Engineering Society (02TP160), 2002.

[3] Reid,G.F.;Hasdorff,L; Economic Dispatch using Quadratic programming" IEEE transaction on power apparatus & system, 1973, vol:PAS-92, Page 2015-2023.

[4] Farag,A.;Albhiyat,s.;cheng,T.C.;"Economic load dispatch multiobjective optimization procedure using linear programming technique" IEEE transaction on power system, 1995, page 731-738.

[5] Sasoon,A.M.; "Non-linear programming solutions for load flow, minimum loss & economic dispatching problem" IEEE transaction on power apparatus & system, 1973, vol:PAS-88, Page 399-409.

[6] R. R. Shoults et al., "A dynamic programming based method for developing dispatch for developing dispatch curves when incremental heat rate curves are non-monotonically increasing", IEEE Trans. Power Syst., vol. 1, no. 1, pp. 10–16, Feb. 1986.

[7] Z. X. Liang and J. D. Glover, "A zoom feature for a dynamic programming solution to economic dispatch including transmission losses," IEEE Trans. Power Syst., vol. 7, no. 2, pp. 544–550, May 1992.

[8] J. B. Park, K. S. Lee, J. R. Shin, and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions," IEEE Trans. Power Syst., vol. 20, no. 1, pp. 34–42, Feb. 2005.

[9] Ke Meng, Hong Gang Wang, Zhao Yang Dong, and Kit Po Wong, "Quantum- Inspired Particle Swarm Optimization for Valve-Point Economic Load Dispatch," IEEE Trans. Power Syst., Vol.25,no. 1 pp.215-222,Feb.2010.

[10] Xu Jian, Liu Zhao,"An improved particle swarm optimization algorithm for MINLP problem," Global congress on intelligent systems, IEEE computer society 2009. Pp.159-162.

[11] T.O. Ting, M. V. C. Rao, and C.K. Loo, "A Novel Approach for Unit Commitment Problem via an Effective Hybrid Particle Swarm Optimization", IEEE Trans. Power System., vol. 21, no. 1, pp.411-418, Feb. 2006.

[12] Michal Pluhacek, Roman Senkerik and Ivan Zelinka,Donald Davendra, "Chaos PSO Algorithm Driven Alternately by two Different Chaotic Map – an Initial Study", Congress on Evolutionary Computation Cancun Mexico, IEEE 2013, June 20-23, pp. 2444-2449.

[13] Jong-Bae Park, Yun-Won Jeong, Joong-Rin Shin,Kwang Y.Lee, "An Improved Particle Swarm Optimization for Non-convex Economic Dispatch Problems," IEEE Trans. Power System, Vol.25, no.1, pp. 156-166, Feb.2010.

[14] N.Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Trans. On Evolutionary Computations*, Vol. 7, No. 1, pp. 83-94, Feb. 2003.

[15] C. E. Lin and G. L. Viviani, "Hierarchical economic dispatch for piece-wise quadratic cost functions," *IEEE Trans. Power App. Syst.*, vol. 17,pp. PAS-103, no.6, pp. 1170-1175, June 1984.

[16] F.J. Trefny and K.Y.Lee, "Economic fuel dispatch," IEEE Trans. Power App. Syst., vol. PAS-100, pp. 3468-3477, Jul./Aug. 1981.

[17] C.L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels." IEEE Trans. Power Syst., vol. 20. no.4, pp. 1690-1699, Nov. 2005.

[18] A. J. Wood and B.F. Wollenberg, Power Generation, Operation, and Control, New York, NY: John Wiley & Sons, Inc., 1984.

[19] S. O. Orero and M. R. Irving, "Economic dispatch of generators with prohibited operating zones: a genetic algorithm approach," proc. Inst. Elect. Eng., Gen., Transm., Distrib., Vol. 143, no. 6, pp. 529-534, Nov. 1996.

[20] J. Kennedy and R. C. Eberhart, Swarm Intelligence, San Francisco, CA Morgan Kaufmann Publishers, 2001.

[21] R. Caponetto, L. Fortuna, S. Fazzino, M.G. Xibilia, Chaotic sequences to improve the performance of evolutionary algorithms, Evolutionary Computation, IEEE Transactions on , vol.7, no.3, pp. 289- 304. June 2003

[22] J. C. Sprott, Chaos and Time-Series Analysis, Oxford University Press, 2003.

[23] M. Pluhacek, R. Senkerik, D. Davendra, Z. Kominkova Oplatkova, I. Zelinka, On the behavior and performance of chaos driven PSO algorithm with inertia weight, Computers

and Mathematics with Applications (2013) doi: 10.1016/j.camwa.2013.01.016. Article in press

[24] M. A. Aziz-Alaoui, C. Robert, C. Grebogi, Dynamics of a Hénon–Lozi-type map, Chaos, Solitons & Fractals, Volume 12, Issue 12, September 2001, Pages 2323-2341, ISSN 0960-0779.

[25] Jong-Bae Park, Yun-Won Jeong, Woo-Nam Lee, Joong-Rin Shin power engineering society general meeting, 2006 IEEE.

[26] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," in Proc, 1999 Congr. Evolutionary Computation, 1999, pp. 1945-1950.

[27] H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, and Y. Nakanishi, "A particle swarm optimization for reactive power and voltage control considering voltage security assessment," IEEE Trans. Power Syst., vol.15, no. 4, pp. 1232-1239, Nov. 2000.

[28] S. Naka, T. Genji, T. Yura, and Y. Fukuyama, "A hybrid particle swarm optimization for distribution state estimation," IEEE Trans. Power Syst., vol. 18, no. 1, pp. 60-68, Feb.2003.