A Novel Multi agent based PSO approaches for security Constrained Optimal Power Flows using smooth and non-smooth cost functions

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ABSTRACT

This paper puts forward two new evolutionary multi agent based particle swarm optimization algorithms for solving security constrained (line flows and bus voltages) optimal power flows. These two methods combine the multi agents in two dimensional and cubic lattice structures with particle swarm optimization (PSO). All agents occupy in a cubic and square lattice like environments, with agents fixed on a lattice point in the ascending order of their fitness values. To obtain the optimal solution, each agent in cubic and square lattice competes and cooperates with its neighbor. Making use of these agent-agent interactions, CLSMAPSO and TDLSMAPSO accomplish the purpose of minimizing the Fuel cost value while maintaining all the constraints. In this paper, a Variable constriction factor has been considered for TDLSMAPSO and CLSMAPSO. Both the smooth and non-smooth cost functions were considered to take the effect of multiple fuels and multiple valves effects in to consideration. The outcomes are compared with many other methods like Genetic Algorithms, Differential Evolution, Normal PSO and Ant Colony optimization etc., The OPF problem has been considered with three different cost functions to realize Optimal Power Flow using CLSMAPSO and TDLSMAPSO applied to IEEE 30 bus system. This unique method has the advantage of more agent interactions in case of CLSMAPSO which improved the convergence drastically compared to the Two dimensional structure used in paper by sivasubramani and Shanti swarup in reference[2]. It is found that the proposed method is found to be computationally fast, robust, superior and promising from its convergence characteristics.

General Terms

Newton-Raphson(NR) algorithm, Lattice, Agent, Smooth and Non-smooth cost functions.

Keywords

Multi agent systems, Optimization techniques, Particle swarm optimization, Optimal power flows, security constraints.

1. INTRODUCTION

Optimal Power Flows was first setup in the early 1960's by Carpentier[1] as an extension of conventional economic dispatch. Nowadays, utilities are facing rapid growth in the Electricity demand with slow fortification projects due to financial and political issues. Proper operation and planning requires consideration of different factors such as reduction of generation cost, losses, pollution, security of power system, and FACTS allocation etc…. In this regard Optimal power Flows (OPF) have been widely used in planning and real time operation of power systems for Reactive and active power

dispatch to minimize generation costs and system losses and to improve profiles of the voltages. The OPF generally meant to optimize set of objectives under set of constraints under consideration.

A vast variety of optimization techniques have been applied in solving the OPF problem such as non-linear programming, Quadratic Programming, Linear Programming, Newton based methods, Sequential unconstrained minimization technique, interior point methods, Genetic Algorithm, Evolutionary Programming. Heuristic algorithms such as Genetic Algorithms (GA) and Evolutionary programming which have been reported as show promising results for further research in this direction.

Recently, a new novel evolutionary computation technique, called Multi agent based Particle Swarm Optimization (MAPSO)[2], has been proposed. Particle Swarm Optimization (PSO) is one of the evolutionary computation techniques. In PSO, search for an optimal solution is conducted using a population of particles, each of which represents a candidate solution to the optimization problem. It was developed through the simulation of flock of birds to search for food in an optimal manner through their velocity and position up gradation. The PSO technique has been widely used for the solving the optimization of various power system problems. However, the major drawback with PSO is that, it may need several iterations and may get trapped in local optima. Therefore, several strategies have been developed to overcome the limitations of PSO, such as modified PSO, and attractive and Repulsive PSO. These all were proved to be effective and boosted the development of MAPSO.

Agent based computation has been introduced recently by Wooldridge[11] and applied for various optimization problems. In this paper, Multi agent based lattice structure and PSO have been integrated to obtain optimal Power Flows. In TDLSMAPSO, each agent in square lattice structure represents a particle to PSO and a candidate solution to the optimization problem. In CLSMAPSO, each agent in cubic lattice structure represents a particle to PSO and a candidate solution to the optimization problem. All agents live in a cubic and square lattice structured environments, with each agent fixed on a lattice point. TO obtain optimal solution quickly, competition and cooperation operators have been used with their neighbor counterparts, and they can also use their own knowledge. With the search mechanism of PSO and agent-agent interactions, TDLSMAPSO and CLSMAPSO can obtain global solution with faster convergence characteristics.

This paper is organized as follows: Problem formulation in section 2. Different cost functions were discussed in section 3. Two dimensional and Cubic lattice structured Multi agent based PSO approaches in section 4. Implementation of

TDLSMAPSO and CLSMAPSO for OPF is discussed in section 5. The simulation results with different methods comparison are discussed in section 6. Finally, brief conclusions are deduced in section 7. References were given in section 8 and biographies were given in section 9.

2. PROBLEM FORMULATION OPTIMAL POWER FLOW

All The OPF problem is a static constrained non-linear optimization problem, the solution of which determines the optimal settings of control variables in a power system network satisfying different constraints. Hence, the problem is to obtain the solution for a set of non-linear equations describing the optimal solution of power system. It is expressed as

$$\text{Min } F(x,u) \qquad (1)$$
$$\text{Subject to } g(x, u)=0$$
$$h(x, u) \leq 0$$

The objective function F is fuel cost of thermal generating units of the test system. g(x,u) is a set of non-linear equality constraints to represent power flow and h(x,u) is a set of non-linear inequality constraints(i.e., bus voltage limits, line MVA limits etc..). Vector x consists of dependent variables and u consists of control variables.

In most of the non-linear optimization problems, the constraints are being handled by generalizing the objective function using penalty terms. In this OPF problem, slack bus power P_{G1}, bus voltages V_L and line flows I_j are constrained by adding them as penalty terms to objective function. Hence, the problem is generalized and can be written as follows.

$$F_T^* = F_{T+} \lambda \left[\sum_{i \in N_L} (I_i - I_{max})^2 + (P_{G1} - P_{G1}^{lim})^2 \right.$$
$$+ \sum_{i \in N_{PQ}} (V_i - V_i^{lim})^2$$
$$+ \sum_{i \in N_{PV}} \left(Q_{Gi} - Q_{Gi}^{lim} \right)^2$$
$$\left. + \sum_{i \in N_{line}} (loss_i)^2 \right] \qquad (2)$$

Where λ, the penalty factor, is given as

$$\lambda = \frac{\sum c_i}{Number\ of\ generator\ buses}$$

V_i^{lim} and P_{G1}^{lim} are defined as

$$V_i^{lim} = \begin{cases} V_i^{max} \ ; \ V_i > V_i^{max} \\ V_i^{min} \ ; \ V_i < V_i^{min} \end{cases} \qquad (3)$$

$$P_{G1}^{lim} = \begin{cases} P_{G1}^{max} \ ; \ P_{G1} > P_{G1}^{max} \\ P_{G1}^{min} \ ; \ P_{G1} < P_{G1}^{min} \end{cases} \qquad (4)$$

3. DIFFERENT COST FUNCTIONS

3.1 OPF Problem With Smooth Cost Function

The OPF problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying an equality constraint and inequality constraints. The most simplified cost function of each generator can be represented as a quadratic function as given in eq (5) whose solution can be obtained by the conventional mathematical methods

$$F_T = \sum_{i \in NG} (a_i P_{Gi}^2 + b_i P_{Gi} + C_i) \qquad (5)$$

While minimizing the total generation cost, the total generation should be equal to the total system demand plus the transmission network loss.

3.2 OPF Problem with Non-smooth Cost Functions

In reality, the objective function of an ED problem has non-differentiable points according to valve-point effects and change of fuels; therefore, the objective function should be composed of a set of non-smooth cost functions. In this paper, two cases of non-smooth cost functions are considered. One is the case with the valve-point loading problem where the objective function is generally described as the superposition of sinusoidal functions and quadratic functions. The other is the case with the multiple fuel problem where the objective function is expressed as the piecewise quadratic cost functions. In both cases, the problems have multiple minima, therefore, the task of finding the global solution still remains to be tackled.

3.2.1 Non-smooth Cost Function With Valve-Point Effects

The generator with multi-valve steam turbines has very different input-output curve compared with the smooth cost function. Typically, the valve point results in, as each steam valve starts to open, the ripples like in Fig. 1, To take account for the valve-point effects, sinusoidal functions are added to the quadratic cost functions as follows:
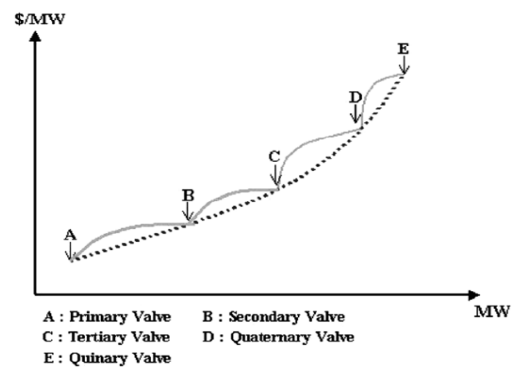

A : Primary Valve   B : Secondary Valve
C : Tertiary Valve   D : Quaternary Valve
E : Quinary Valve

Fig1. Non-smooth cost function curve with   valve-point effects

$$F_T = \sum_{i \in NG} ((a_i P_{Gi}^2 + b_i P_{Gi} + C_i) + \left| e_i X \sin(f_i X(P_{imin} - P_i)) \right| \qquad (6)$$

where e_i and e_j are the coefficients of generator reflecting valve-point effects.

3.2.2 Non-smooth Cost Function With Multiple Effects

Generally, a piecewise quadratic function is used to represent the input-output curve of a generator with multiple fuels . The piecewise quadratic function is described as (7) and the cost and the incremental cost functions are illustrated in Fig. 2
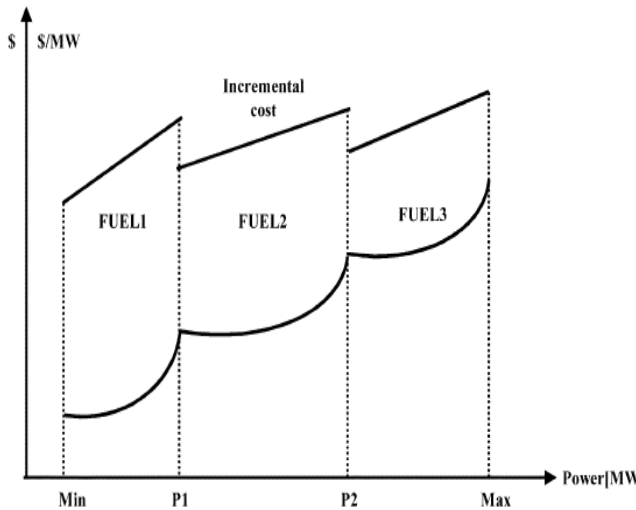
Fig2. Non-smooth cost functions curve with multiple fuels

$$F_i(P_i) = \begin{cases} \sum_{i \in NG} ((a_{i1}P_{Gi}^2 + b_{i1}P_{Gi} + C_{i1}) \text{ if } P_{imin} \leq P_i \leq P_{i1} \\ \sum_{i \in NG} ((a_{i2}P_{Gi}^2 + b_{i2}P_{Gi} + C_{i2}) \text{ if } P_{i1} \leq P_i \leq P_{i2} \\ \quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad . \\ \sum_{i \in NG} ((a_{in}P_{Gi}^2 + b_{in}P_{Gi} + C_{in}) \text{ if } P_{in-1} \leq P_i \leq P_{imax} \end{cases}$$

$$(7)$$

where a_{i1}, b_{i1} and c_{i1} are the cost coefficients of generator for the pth power level.

4. TWO DIMENSIONAL AND CUBIC LATTICE STRUCTURED MULTI AGENT BASED PSO APPROACHES

4.1 PSO

The intrinsic rule adhered by the members of birds and fishes in the swarm, enables them to move, synchronize, without colliding, resulting in an amazing choreography which is the basic idea of PSO technique. PSO is a similar Evolutionary computation technique in which, a population of promising solutions to the problem under consideration, is used to probe the search space. The main difference between the other Evolutionary Computation (EC) techniques and Swarm intelligence (SI) techniques is that the other EC techniques make use of genetic operators whereas SI techniques use the physical movements of the individuals in the swarm. PSO is developed through the bird flock simulation in two-dimensional space with their position, x and velocity, v.

The optimization of the objective function is done iteratively through the bird flocking. In every iteration, every agent knows its best so far, called 'P$_{best}$', which shows the position and velocity information. This information is analogous to its own personal experience of each agent. Moreover, each agent knows the best value so far in the group, 'G$_{best}$' among all 'P$_{best}$'. This information is analogous to the knowledge, as to how the other neighboring agents have excelled. Each agent

tries to update its position by considering current positions, current velocities, the individual intelligence (P$_{best}$), and the group intelligence (G$_{best}$).

To ensure the best convergence to PSO, Eberhart and Shi prompted the use of constriction factor. The modified velocity and position of each particle can be found as follows.

$$v_{d+1} = k_1 \times (\omega \times v_d) + k_2(C_1 \times \text{rand} \times (P_{best} - X_d) + C_2 \times \text{rand} \times (G_{best} - X_d)) \quad (8)$$

$$x_{d+1} = x_d + v_{d+1} \quad (9)$$

Where d indicates the generation number, x_d is the current position of the particle in d_{th} generation, v_d is the velocity of the particle in the d_{th} generation, ω is the inertia weight, C_1 and C_2 are acceleration constants, and k_1 and k_2 are the constriction factors. The constriction factor is been updated by the following equations for PSO, TDLSMAPSO and CLSMAPSO respectively. By making use of this updating, variable constriction factor can be adapted so that the convergence can be achieved quickly.

$$k_1 = k_2 = (\frac{error}{Initial\ error})^{0.009}) \text{ for PSO} \quad (10)$$

$$k_1 = k_2 = (\frac{error}{Initial\ error})^{0.95} \times 0.8 \text{ for}$$

TDLSMAPSO and CLSMAPSO $\quad (11)$

Here, the values of k_1 and k_2 vary with respect to iteration. The "Initial error" is the maximum deviation between the fitness values of the agents in the first iteration and "error" is the maximum deviation between the agents at n^{th} iteration. In case of normal PSO the position vector is updated only by velocity vector. In case of TDLSMAPSO and CLSMAPSO, the position vector is updated by both velocity and competition and cooperation operators. Hence k_1 and k_2 cannot be equal for both inertial and dynamic terms of velocity if we have to get CLSMAPSO converged faster. The velocity of every agent must be updated in such a way that it decreases as the agent converges and increase as the agent diverges. The values of exponents and multipliers are selected randomly in the equations (10) and (11) as with these values the algorithm converges faster.

In PSO, the particle velocity is limited by some maximum value V$_{max}$. If V$_{max}$ is too high, particles may fly past good solutions. If V$_{max}$ is too small, particles may not cross local solutions. Normally V$_{max}$ is taken as 10% - 20% of dynamic range and V$_{min}$ is selected as - V$_{max}$.

$$V_{max} = \frac{(Max\ position\ limit - Min\ position\ limit)}{10} \quad (12)$$

4.2 Multi Agent Systems

According to Wooldridge, an agent is a physical or virtual entity that has the following properties.

i. It lives in and acts in the environment.
ii. It senses its local environment through its interaction with the other agents.
iii. It will attempt to achieve some goals and execute certain tasks.
iv. It will respond to the environment through the self learning.

Multi agent systems are computation based systems in which several agents interact and work in coordination with one another to achieve some targets and perform certain tasks. In general, there are four things need to be defined when we are solving problems using multi agent systems.

i. Meaning and purpose of the agent.
ii. Agent Environment where all agents live.
iii. Definition of the local environment to know the local understanding.

Set of governing or behavioural rules for interaction between the agents.

4.3 TDLSMAPSO

In TDLSMAPSO, multi agents are being arranged in a square lattice structure and is been integrated with PSO to form a new approach called as TDLSMAPSO. Each agent represents a particle to PSO and a candidate solution to OPF problem. Since all the agents live in square lattice structured environment as in Fig.1, each agent can interact with all the neighbors. Using the competition, cooperation and PSO operators, the global solution is achieved.

4.4 CLSMAPSO

In CLSMAPSO, multi agents are being arranged in a cubic lattice structure and is been integrated with PSO to form a new approach called as CLSMAPSO. Each agent represents a particle to PSO and a candidate solution to OPF problem. Since all the agents live in cubic lattice structured environment as in Fig.2, each agent can interact with all the neighbors. Using the competition, cooperation and PSO operators, the global solution is achieved.

The following items are essential before realizing the actual algorithms of TDLSMAPSO and CLSMAPSO.

4.4.1 Agent For OPF Problem

In CLSMAPSO, each agent is a particle to PSO and a candidate solution to OPF problem. Therefore, every agent λ has a fitness value to the OPF problem. The fitness value is the value of generation cost, i.e., F_T .

$$F_T(\lambda) = \sum_{i \in NG}(a_i P_{Gi}^2 + b_i P_{Gi} + C_i) \qquad (13)$$

4.4.1.1 Definition Of an Environment

In TDLSMAPSO, all agents live in square lattice-like structured environment as in Fig. 3. In the environment L, each agent is placed on a lattice-point and each circle represents an agent. The size of L is $L_{size} \times L_{size}$ where L_{size} is an integer number. In TDLSMAPSO, number of particles and L should be same.

In CLSMAPSO, all agents live in cubic lattice-like structured environment as in Fig. 4. In the environment L, each agent is placed on a lattice-point and each circle represents an agent. The size of L is $L_{size} \times L_{size} \times L_{size}$ where L_{size} is an integer. In CLSMAPSO, number of particles and L should be same.
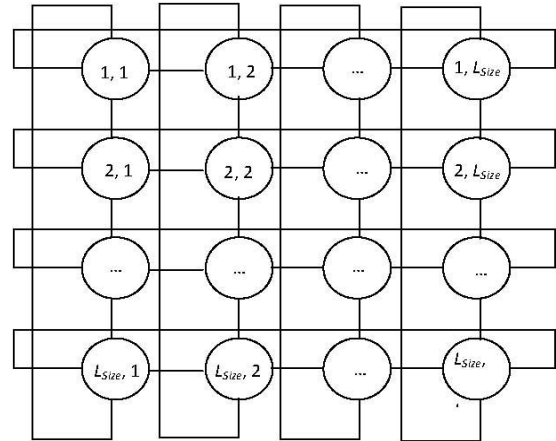

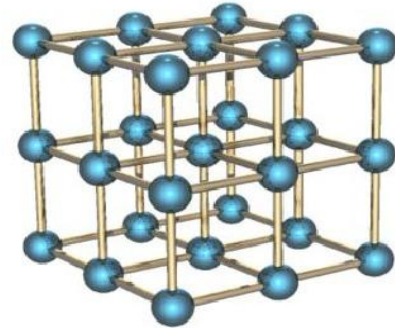**Fig 3. Square Lattice structure of Multi agent system for TDLSMAPSO**

Fig 4. Cubic lattice structure of multi agent system for CLSMAPSO

4.4.1.2 Definition of the Local Environment

Since each agent can only sense its neighbours, it is very essential to define the local environment. In this paper, in TDLSMAPSO, an agent λ located at (i,j) can have 8 neighbours (including agents at 4 sides and 4 corners) as it can be seen from the lattice and in CLSMAPSO, an agent λ located at (i,j) can have 26 neighbours (including agents at 6 sides, 8 corners and 12 edges) as it can be seen from the lattice.

4.4.1.3 Behavioural rules for Agent

In TDLSMAPSO and CLSMAPSO, every agent competes and cooperates among its neighbours and makes use of evolution mechanism and knowledge of PSO and hence it diffuses all its information to whole environment. Based on the behaviours, the competition and cooperation operator were designed and are as follows.

4.5 Competition and Cooperation Operator

Suppose that competition and cooperation operator ios performed on the agent λ located at (i,j) and $\lambda_{i,j}=(\lambda_1 , \lambda_2 , ...\lambda_n)$ and $Min_{i,j}=(m_1 , m_2 , ...m_n)$ is the agent with minimum fitness value among its neighbours, namely $Min_{i,j} \epsilon Neighbours_{i,j}$. If agent $\lambda_{i,j}$ satisfies the following equation it is a winner otherwise it is a loser.

$$f(\lambda_{i,j}) = f(Min_{i,j}) \qquad (14)$$

If $\lambda_{i,j}$ is victorious, it can still live in the agent lattice. If $\lambda_{i,j}$ is a loser, it must die and its lattice-point will be occupied by $New_{i,j}$. The new agent $New_{i,j} = (\lambda'_1, \lambda'_2, ..., \lambda'_n)$ is determined by the following strategy

$$\lambda'_k = \begin{cases} x_{\min,k} & \text{if } (m_k + rand(0,2.5*(\text{error/initial\_error})) \times (m_k - \lambda_k)) \leq x_{\min,k} \\ x_{\max,k} & \text{if } (m_k + rand(0,2.5*(\text{error/initial\_error})) \times (m_k - \lambda_k)) \geq x_{\max,k} \\ (m_k + rand(0,2.5*(\text{error/initial\_error})) \times (m_k - \lambda_k)) & \text{otherwise} \\ k = 1,2,......n \end{cases}$$

(15)

5. IMPLEMENTATION OF CLSMAPSO FOR OPF PROBLEM

In TDLSMAPSO and CLSMAPSO, mainly the operators like competition and cooperation operators along with PSO operators were used to obtain the optimal solution in quick time with accuracy. The detailed algorithm of TDLSMAPSO and CLSMAPSO for OPF problem is as given below:

1. Input the required parameters and specify lower and upper limits of variables. In OPF problem, P_{Gi}, $i \in NG$ except for slack bus are the variables.
2. Determine the fitness value of each agent i.e., Production cost or total Fuel cost, by Newton-Raphson power flow analysis results.
3. Sort the particles.
4. Create a lattice like environment L, and assign each agent (which is essentially a particle) on lattice point in the ascending order. Here each agent carries generation values of generators except slack bus power.
5. Increment the iteration counter
6. Carryout competition and cooperation operator on each agent and modify it.
7. Apply PSO mechanism to each agent and adjust its position using the equations related to velocity and position.
8. Determine the fitness value of each agent i.e., production cost, by Newton-Raphson power flow analysis results
9. Determine the best agent with minimum fitness value.
10. Sort the particles in ascending order.
11. Check for stopping condition (all the agents converge to a fitness value), if yes go to next step, else go to step (4).

Print the agent and its fitness value.

6. RESULTS AND DISCUSION

The algorithm is implemented in C programming language and executed on Intel Core 2 Duo system with 1GB RAM running on linux. To verify the performance of the CLSMAPSO algorithm, a standard representative system, i.e., IEEE30 bus systems has been taken as shown in Fig 5. The table 2 shows comparison of the results for CLSMAPSO, tdlsmapso and original PSO algorithm with constriction factor with different methods in the literature. For all the algorithms c1=0.6, c2=0.4, r1=0.6, r2=0.4 and inertia,ω=0.8. The number of particles for CLSMAPSO is 27 and for PSO it is 25.
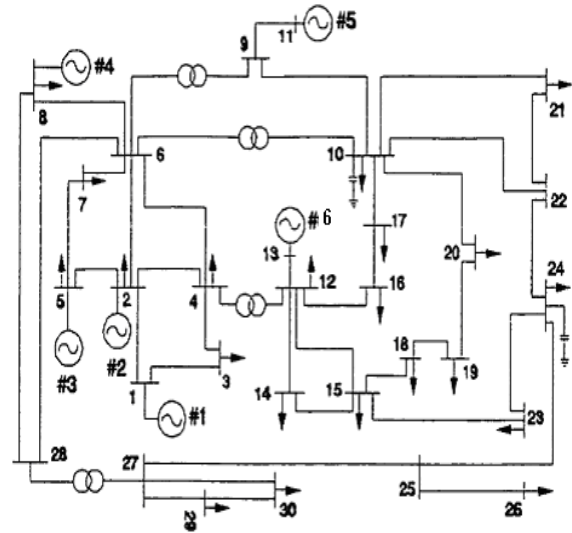

Fig 5. Single line diagram of standard IEEE 30 bus system

Table1. Generator data with quadratic cost functions considered for IEEE 30 bus system

Bus No	$P_G^{\min}$ MW	$P_G^{\max}$ MW	$Q_G^{\min}$ MVAR	$Q_G^{\max}$ MVAR	a $/hr	b $/MW hr	C $/MW² hr
1	50	200	-20	200	0	2.0	0.00375
2	20	80	-20	100	0	1.75	0.0175
5	15	50	-15	80	0	1.0	0.0625
8	10	35	-15	60	0	3.25	0.00834
11	10	30	-10	50	0	3.0	0.0250
13	12	40	-15	60	0	3.0	0.0250

Table2.Comparison of results with PSO, TDLSMAPSO and CLSMAPSO with other methods for obtaining optimal fuel cost.

Algorithm	Best Cost ($/Hr)	Average Cost ($/hr)	Worst Cost ($/hr)
TS	802.502	803.632	802.746
TS/SA	802.788	803.032	803.291
ITS	804.556	805.812	8060856
EP	802.907	803.231	803.474
IEP	802.465	802.521	802.581
DE	802.230	802.31	802.35
PSO	802.31	802.351	802.31
TDLSMAPSO	802.11	802.31	802.11
CLSMAPSO	802.011	802.101	802.011

Table 3. Comparison of results with PSO, TDLSMAPSO and CLSMAPSO for obtaining optimal fuel cost

Algorithm	Number of partic-les	Error for conve-rgence	Processing time (sec)	Number of itera-tions	Optimal cost achieved $/hr
PSO	25	0.0001	4.74	54	802.31
TDLSMAPSO	27	0.0001	1.51	16	802.11
CLSMAPSO	27	0.0001	1.19	12	802.011

Table4. Optimum generation of generators obtained using basic PSO, TDLSMAPSO and CLSMAPSO algorithms.

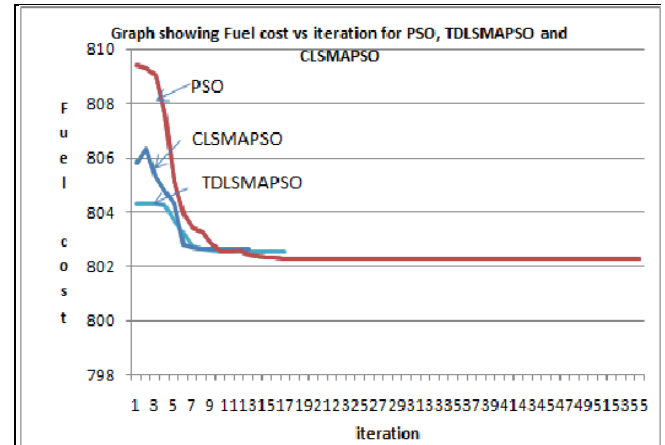| Test System	Method	Optimum Generation (pu)	Optimal Total Cost ($/hr)
IEEE 30	PSO	P_1=1.759677	802.31
		P_2=0.486338	
		P_5=0.216260	
		P_8=0.224147	
		P_{11}=0.126091	
		P_{13}=0.120000	
IEEE 30	TDLSMAPSO	P_1=1.738939	802.11
		P_2=0.509450	
		P_5=0.215397	
		P_8=0.235106	
		P_{11}=0.106875	
		P_{13}=0.126268	
IEEE 30	CLSMAPSO	P_1=1.740471	802.011
		P_2=0.482508	
		P_5=0.216090	
		P_8=0.222844	
		P_{11}=0.125147	
		P_{13}=0.144271	

Fig 6. Comparison Plot Of Fuel Cost Vs Iterations For Basic PSO, TDLSMAPSO and CLSMAPSO.
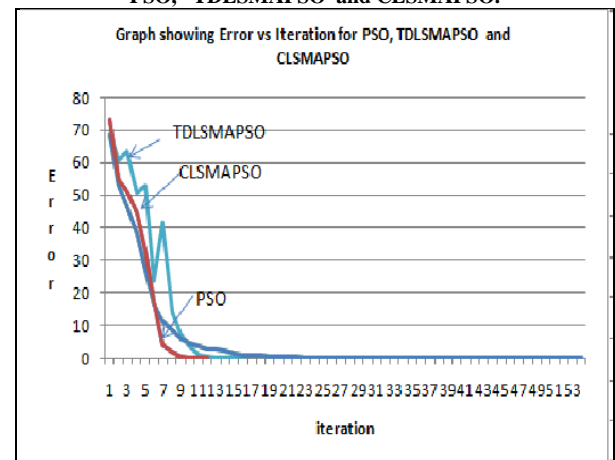

Fig 7: Plot of Error vs iterations for Basic PSO and CLSMAPSO.

Table5. Generator data with piecewise linear quadratic cost functions considered for IEEE 30 bus system.

Generator	From (MW)	To (MW)	Cost Coefficients		
			A	b	C
1	50	140	55.0	0.70	0.0050
	140	200	82.5	1.05	0.0075
2	20	55	40.0	0.30	0.0100
	55	80	80.0	0.60	0.02

Table 6. Comparison of results with pso, TDLSMAPSO and CLSMAPSO for obtaining optimal fuel cost by considering generator data with piecewise linear quadratic cost functions.

Algorithm	Number of particles	Error for conve-rgence	Proce ssing time (sec)	Number of itera-tions	Optimal cost achieved $/hr
PSO	25	0.0001	27.89	376	652.43485
TDLSMAPSO	27	0.0001	1.29	18	652.071003
CLSMAPSO	27	0.0001	1.21	13	650.723427

Table7. Generator data with quadratic cost functions with multiple valve point loading effects considered for IEEE 30 bus system.

Gen	P_G^{min}	P_G^{max}	a	B	C	d	e
1	50	200	150.0	2.0	0.0016	50.0	0.063
2	20	80	25.0	2.5	0.0010	40.0	0.098

Table8. Comparison of results with PSO, TDLSMAPSO and CLSMAPSO for obtaining optimal fuel cost by considering generator data with quadratic cost functions by considering mulltiple valvepoint loading effects.

Algorithm	Number of particles	Error for convergence	Processing time (sec)	Number of iterations	Optimal cost achieved $/hr
PSO	25	0.0001	11.125	147	919.707134
TDLSMAPSO	27	0.0001	1.12	13	919.624804
CLSMAPSO	27	0.0001	0.99	11	919.08384

7. CONCLUSION

Based on multi agent systems, TDLSMAPSO and CLSMAPSO have been developed for solving Optimal power Flow problem (OPF) with security constraints. To the best of our knowledge, OPF problem has been solved by several methods in the literacy but these unique TDLSMAPSO and CLSMAPSO methods integrates the square and Cubic Lattice Structured multi agents respectively for TDLSMAPSO and CLSMAPSO with PSO using variable constriction factor to find the global or near global optimum point for OPF problem. IEEE 30 bus with different cost functions has been tested with PSO, TDLSMAPSO and CLSMAPSO methods and results are compared. From the results, TDLSMAPSO and CLSMAPSO converges to global optimum with more accuracy and within less time. From the results, CLSMAPSO converges to global optimum with an accuracy of 0.0001 and within less time. It can be observed that PSO is consuming more time and iterations to converge, where as TDLSMAPSO and CLSMAPSO were consuming less time and less number of iterations to obtain near optimum solution. Hence, we can say that TDLSMAPSO and CLSMAPSO algorithms were very fast and accurate. Moreover, from the literature it is observed that we have got the best optimal cost with PSO,TDLSMAPSO and CLSMAPSO. These algorithms are general and can be applied to other power system optimization problems.

8. REFERENCES

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