Optimal Power Flows with Security Constraints Using Cubic Lattice Structured Multi-agent Based PSO Algorithm by Optimal Placement of Multiple Thyristor Controlled Series Capacitors

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Received: December 2013 Revised: March 2014 Accepted: June 2014

ABSTRACT
This paper puts forward the implementation of cubic lattice structured multi-agent based PSO algorithm (CLSMAPSO) to obtain the optimal power flows by optimally placing Thyristor Controlled Series Capacitor (TCSC) devices. The TCSC is modeled using susceptance model with modifications in the Y bus of the Newton Raphson Algorithm. The constraints related to violation limits, minimization of line overload factor, and line loss are dealt using penalty factor approach. The new multi-agent based cubic lattice structured PSO algorithm was considered for optimizing power flows while satisfying all the constraints mentioned above. This algorithm was tested on IEEE14, IEEE30 and IEEE57-bus systems to identify the suitable location, its reactance value and firing angle. The results obtained were quite encouraging and will be useful in electrical restructuring.

KEYWORDS: Multi-Agent Systems, Optimization Techniques, Particle Swarm Optimization, Optimal Power Flows, Security Constraints, Thyristor Controlled Series Capacitor (TCSC), Flexible AC Transmission Systems (FACTS).

1. INTRODUCTION

Nowadays, utilities are facing rapid increase in electricity demand with slow reinforcement projects due to financial and political issues. Proper operation and planning requires consideration of various factors such as reduction of generation cost, losses, security of power system, and FACTS application etc. In this aspect, the optimal power flows has become the leading research field with potential applications for both planning and operation of power system. An operational point of a power system not only is a stable equilibrium of differential and algebraic equations (DAE), but also must satisfy all of the static constraints of the equilibrium such as upper and lower bounds of generations, voltages of all buses and line flow units of all the transmission lines. This operation point in the power system is solved by OPF. In other words, OPF is to minimize the operating costs of the power system, transmission losses or other appropriate objective functions at the specified time instance subject to equality and inequality constraints, by determining an equilibrium operating state variables corresponding to power output of generators, transformer tap positions, phase shifter angle positions, shunt capacitors / reactors values, voltage values etc. Conventionally, OPF is used to solve security and economic operation of the power system.

A wide 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 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 birds' flock to search for food in an optimal manner through their velocity and position up gradation. The PSO technique has been widely used for 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 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 lattice structured environments, with each agent located on a lattice point. To obtain optimal solution quickly, competition and cooperation operators have been used with their neighbors, and they can also use their own knowledge. With the search mechanism of PSO and agent-agent interactions, CLSMAPSO can obtain global solution with faster convergence characteristics.

Today technologies which are developed as a part of flexible AC Transmission system (FACTS), can be handy to corrective methods, so that the system operates smoothly and consistently without violating thermal and operational limits. FACTS devices, which permit to achieve many objectives in an electric power system [5, 8, 9, and 10] can be used to reduce the power flow on the overloaded lines and to increase the utilization of the existing transmission lines. This allows increasing the transfer capability in existing transmission and distribution systems under normal conditions, obtaining the possibility to load lines much closer to their thermal limits.

Series FACTS devices such as TCSCs will reduce the net reactance of the transmission line so that it improves the power transfer capability of the power system's transmission lines. While placing the devices we need to identify the best location based on various factors such as line overload factor, reduction of total fuel cost, reduction of losses etc.

This paper is organized as follows: FACTS device modeling and Problem formulation were discussed in section 2. Cubic lattice structured Multi-agent based PSO approach in section 3. Implementation of CLSMAPSO for optimal placement of TCSCs along with OPF is discussed in section 4. In section 5 the simulation results are discussed. Finally, brief conclusions are deduced in section 6 and references in section 7.

2. PROBLEM FORMULATION

2.1. TCSC Model

According to IEEE definition, the TCSC can be represented as a capacitive reactance compensator which consists of three main components: capacitor bank C, bypass inductor L and bidirectional thyristors SCR1 and SCR2. The Series capacitive compensation has been used to increase line power transfer capability as well as to enhance system stability. Figure 1 shows the main circuit of a TCSC.

The firing angles of the thyristors are controlled simultaneously to adjust the TCSC reactance according to the system control algorithm, normally in response to some system parameter variations. According to the variation of the thyristor firing angle or conduction angle, this process can be simulated as a fast switch between corresponding reactance offered to the power system. Assuming that the total current passing through the TCSC is sinusoidal, the equivalent reactance at the fundamental frequency can be represented as a variable reactance X_{TCSC}. The TCSC can be controlled to work either in the capacitive or the inductive zones avoiding steady state resonance. There will be a steady state relationship between the firing angle α and the reactance X_{TCSC}. This relationship can be described by the following equation [8]:

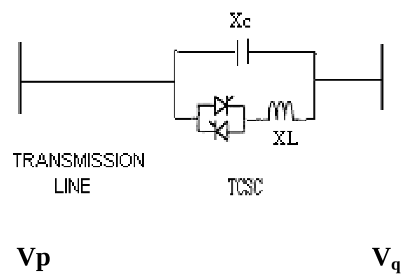

Fig . 1. TCSC model in series with a transmission line

$$X_{TCSC}(\alpha) = \frac{X_C X_l(\alpha)}{X_l(\alpha) - X_C}$$

Where $X_l(\alpha) = X_L \frac{\pi}{\pi - 2\alpha - sin\alpha}$, α is the firing angle, X_L is the reactance of the inductor and $X_l(\alpha)$ is the effective reactance of the inductor at firing angle.

2.2. Objective Function:

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 various constraints. Hence, the problem is to solve a set of non-linear equations describing the optimal solution of power system. It is expressed as

Min F(x,u)
Subject to g(x, u)=0 (1)

$h(x, u) \leq 0$

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 considered 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 can be generalized and written as follows.

$$F_T^* = F_{T+}\,\lambda\left[\sum_{i\in N_L}(P_{Gi}-P_{Gi}^{lim})^2 + \sum_{i\epsilon N_{PQ}}(V_i-V_i^{lim})^2 + \sum_{i\epsilon N_{PV}}\left(Q_{Gi}-Q_{Gi}^{lim}\right)^2 + \sum_{i\epsilon N_{line}}(loss_i)^2 + IC^2\right] \quad (2)$$

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

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

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

Where IC is the Installation cost of the device given by

$$IC = C \times S \times 1000 + PF \times \|J-1\| \quad (5)$$

Where C = Cost of installation of FACTS devices in US $/KVAR;
PF = Penalty Factor, value ranges from 10^{30} to 10^{35};
S = Operating range of FACTS devices in MVAR;
$C_{TCSC}=0.0015S^2-0.7130S+153.75$

$$J = \prod OVL_{Line} \prod VS_{Bus}$$

Where

OVL= Line overload factor for a line;
VS = Voltage Stability index of a bus

$$OVL = \begin{cases} 1 & ; if\ P_{PQ} \leq P_{PQ}^{max} \\ \exp\left(\lambda\left|1-\frac{P_{PQ}}{}P_{PQ}^{max}\right|\right) & ; if\ P_{PQ} > P_{PQ}^{max} \end{cases}$$

$$VS = \begin{cases} 1 & ; if\ 0.9 \leq V_b \leq 1.1 \\ \exp(\mu|1-V_b|) & ; otherwise \end{cases}$$

P_{PQ} is the Real Power flow between buses P and Q;
P_{PQ}^{max} *is the Thermal limit for the line between buses P and Q*
Vb is the voltage at bus b and
μ *is the small positive constant equal to* 0.1

3. CUBIC LATTICE STRUCTURED MULTI-AGENT BASED PSO

3.1 PSO

The inherent 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 potential 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 personal experience of each agent. Moreover, each agent knows the best value so far in the group, 'best' among all 'P_{best}'. This information is analogous to the knowledge, as to how the other neighbouring agents have performed. Each agent tries to modify 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 indicate that use of constriction factor may be necessary. The modified velocity and position of each particle can be found as follows.

$$v_{d+1} = k_1 \times (\omega \times \mathrm{v_d}) + k_2\big(\mathrm{C_1} \times \mathrm{rand} \times (\mathrm{P_{best}} - \mathrm{X_d}) + \mathrm{C_2} \times \mathrm{rand} \times (\mathrm{G_{best}} - \mathrm{X_d})\big) \quad (6)$$

$$x_{d+1} = x_d + v_{d+1} \quad (7)$$

Where d indicates the generation, 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 and CLSMAPSO respectively. By making use of this updating, variable constriction factor can be adapted so that the convergence can be achieved quickly.

$$k_1 = k_2 = (\frac{error}{Initial\ error})^{0.009}) \text{ for PSO} \quad (8)$$

$$k_1 = k_2 = \left(\frac{error}{Initial\ error}\right)^{0.95} \times 0.8 \quad (9)$$

For CLSMAPSO

Here, the values of k_1 and k_2 vary from iteration 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 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 increases as the agent diverges. The exponents and multipliers are selected randomly in the equations (7) and (8) 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}..

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

3.2. 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 goals 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. Environment where all agents live.

iii. Definition of the local environment to know the local perceptivity.

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

3.3. CLSMAPSO

In CLSMAPSO, multi-agents are being arranged in a cubic lattice structure and are being integrated with PSO to form a new approach called 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 neighbours. Using the competition, cooperation and PSO operators, the global solution is achieved.

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

3.3.1. 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 .

$$FT(\lambda) = \sum_{i \in NG} (a_i P_{Gi}^2 + b_i P_{Gi} + C_i) \quad (11)$$

3.3.2. Definition of an Environment

In CLSMAPSO, all agents live in an environment which is of cubic lattice-like structure 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 Lsize ×Lsize ×Lsize where Lsize is an integer. In CLSMAPSO, number of particles and L should be similar.

3.3.3. Definition of the Local Environment

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

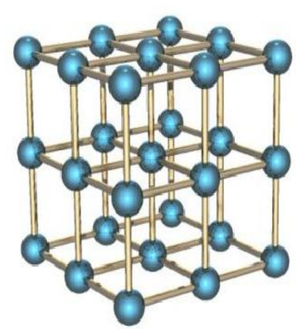

Fig . 2. Cubic Lattice structure of Multi-agent system for PSO

3.3.4. Behavioral Rules for Agent

In 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.

3.4. Competition and Cooperation Operator

Suppose that competition and cooperation operator ios performed on the agent λ located at (i,j) and $\lambda_{i,j}$=(λ_1 ,λ_2 , ...λ_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.

$$f(\lambda_{i,j}) = f(Min_{i,j}) \tag{12}$$

If $\lambda_{i,j}$is a winner, 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 $New_{i,j}$ =($\lambda'_1, \lambda'_2, \dots \dots, \lambda'_n$) is determined by the following strategy

$$\lambda'_k = \begin{cases} x_{\min,k} & \text{if } (m_k + rand(0{,}2.5 * (\text{error/initial\_error})) \text{ x} (m_k - \lambda_k)) \le x_{\min,k} \\ x_{\max,k} & \text{if } (m_k + rand(0{,}2.5 * (\text{error/initial\_error})) \text{ x } (m_k - \lambda_k)) \ge x_{\max,k} \\ (m_k + rand(0{,}2.5 * (\text{error/initial\_error})) \text{ x } (m_k - \lambda_k)) & \text{otherwise} \\ k = 1,2,\dots\dots,n \end{cases} \tag{13}$$

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

4. IMPLEMENTATION

4.1. Algorithm for TCSC Placement

The step by step algorithm for the proposed optimal placement of TCSCs for optimal power flows is given below:

1. Read data from file
2. Formulate Y_{bus} without FACTS devices
3. Initialize PSO algorithm with PSO parameters c,r1,c2,r2,inertia.
4. Set position and velocity limits for a position vector.
5. Call PSO algorithm that internally calls objective function for fitness value.
6. After PSO execution is completed, output the Position vector to console.

4.2. Algorithm for Objective Function Evaluation

1. Get the pgi values from the position vector for each pv bus
2. Get the position (Line number for TCSC device) And Firing angle for each FACTS Device.
3. With the position and firing angles for each FACTS device, find the effective values of reactance for each FACTS device.
4. Modify the originally calculated Y bus with the reactance calculated above.
5. Find the load flow solution by calling NR algorithm.
6. From the N- R Algorithm solution, using security constraints, compute the penalties.
7. From the PGis of PV buses and from the solution of NR, Find PGi of slack bus.
8. Find the operating cost & FACTS device costs.
9. Output the fitness value as the sum of operating cost, FACTS device costs and the penalties.

In CLSMAPSO, mainly the operators were used to obtain the optimal solution in quick time with accuracy. Among them competition and cooperation operators along with PSO operators were used.

4.3. CLSMAPSO Algorithm for OPF Problem

1. Input the parameters and specify lower and upper Limits of variables. In OPF problem, P_{Gi}, i ϵ NG except for slack bus are the variables.
2. Determine the fitness value of each agent i.e., Production 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 velocity and position equations.
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).
12. Print the agent and its fitness value.

Table 1 gives the details about various parameters of CLSMAPSO algorithm and parameters of TCSC.

Table 1. Parameters for CLSMAPSO and TCSC

S.No	Parameter	Value
1.	c1	0.6

2.	c2	0.4
3.	r1	0.6
4.	r2	0.4
5.	No. of	64
6.	TCSC	X_L=2.5 p.u and

Table 2 indicates the generator data with quadratic cost function of IEEE14-bus system.

Table 2. Generator Data With Quadratic Cost Functions Considered for IEEE14-Bus System

Bus No	P_G^{min} MW	P_G^{max} MW	Q_G^{min} MVAR	Q_G^{max} MVAR	a $/hr	b $/MWhr	C $/MW²hr
1	0	200	40	50	100	1.083	0.074
2	0	140	40	50	70	1.033	0.089
3	0	100	0	40	100	1.083	0.074
6	0	100	6	24	70	1.033	0.089
8	0	100	6	25	40	1.17	0.053

Table 3 indicates the generator data with quadratic cost function of IEEE30-bus system.

Table 3. Generator Data With Quadratic Cost Functions Considered for IEEE30-Bus System

Bus No	P_G^{min} MW	P_G^{max} MW	Q_G^{min} MVAR	Q_G^{max} MVAR	a $/hr	b $/MWhr	C $/MW²hr
1	50	200	-20	200	0	2.0	0.00375
2	20	80	-20	100	0	1.7	0.0175
5	15	50	-15	80	0	1.0	0.0625
8	10	35	-15	60	0	3.2	0.00834
1	10	30	-10	50	0	3.0	0.0250
1	12	40	-15	60	0	3.0	0.0250

Table 4 indicates the generator data with quadratic cost function of IEEE57-bus system.

Table 4. Generator Data With Quadratic Cost Functions Considered for IEEE57-Bus System

Bus No	P_G^{min}	P_G^{max}	Q_G^{min}	Q_G^{max}	a $/	b $/M	C $/MW²hr
2	0	100	71	138	0	2	0.007757 95
3	0	140	11	81	0	4	0.001
6	0	100	-6	27	0	2	0.0025
8	0	100	-118	222	0	2	0.002222 22
9	0	100	23	35	0	4	0.001
12	0	100	-26	179	0	2	0.003225 81

5. RESULTS AND DISCUSION

The IEEE14, IEEE30 and IEEE57-bus systems have been tested to assess the correctness of proposed model of TCSC, algorithm and implementation. The TCSCs were set to be placed optimally with a goal that the power flow and generation should be optimal. To verify as well as to compare the effectiveness of the algorithms the results obtained were compared with the literature. Table 5 summarizes the line flow results for IEEE14, 30 and IEEE57-bus systems.

The algorithm is implemented in C programming language and executed on Intel Core 2 Duo system with 1GB RAM running on Linux. The solutions for optimal location of TCSCs to minimize the generation cost subject to minimize the cost of installation and line overload factor so that it improves the line flows of the IEEE14, 30 and 57-bus systems. The simulation studies were carried out on Pentium IV, 2.4 GHz system in LINUX environment.

CLSMAPSO was applied for optimal power flows and also to identify the optimal location of TCSCs. Initially the algorithm was tested with one TCSC, later with two TCSCs and finally tested with three TCSCs. The results were listed in the tables below. Fig.3,4 and 5 shows the Comparison plots of Line flows without TCSC, with 1TCSC, with 2TCSCs and 3 TCSCs for IEEE14, IEEE30 and IEEE57-bus systems respectively. Fig.6,7 and 8 shows the Comparison plots of Line flows without TCSC, with 1TCSC, with 2TCSCs and 3 TCSCs for IEEE14, IEEE30 and IEEE57-bus systems respectively. Fig.9,10 and 11 shows the Comparison plots of Line flows without TCSC, with 1TCSC, with 2TCSCs and 3 TCSCs for IEEE14, IEEE30 and IEEE57-bus systems respectively.

From the results, it is evident that, after the placement of TCSC devices, the line flows have been improved. It is also observed that, the line losses of the system have also been reduced. From the results, it is also observed that, the optimal fuel cost, best efficiency and lowest losses were obtained with the placement of two TCSC devices which is economical from the device cost point of view. Due to the limitation of cost, we have limited our investigation only up to three devices.

It is quite evident from the results shown in the tables that, the line losses were reduced and the line flows were improved. With the optimal location of TCSCs the optimal generation schedule was obtained.

Table 5. Line Flows results for IEEE14, 30 and 57-bus systems with TCSCs placement

		Line Flow in MW
IEEE14	Without TCSC in Line 13	5.9404
	With 1 TCSC at Line 13	5.967
	Without TCSCs in Lines 10 &19	60.2569
		1.4951
	With 2 TCSCs in Lines 10 &19	64.2841
		1.4959
	Without TCSCs in Lines 6,8 &13	15.909
		0.7671
		5.9404
	With 3 TCSCs in Lines 6,8 &13	16.4641
		0.9077
		6.9803
IEEE30	Without TCSC in Line 39	3.7054
	With 1 TCSC at Line 39	3.7808
	Without TCSCs in Lines 35 &38	3.5464
		3.9155
	With 2 TCSCs in Lines 35 &38	7.099
		7.1495
	Without TCSCs in Lines 27,28 &36	9.0606
		2.1007
		17.1311
	With TCSCs in Lines 27,28 &36	19.9491
		2.7995
		18.4414
IEEE57	Without TCSC in Line 31	1.5597
	With 1 TCSC at Line 31	
	Without TCSCs in Lines 27 & 45	121.0014
		3.8081
	With 2 TCSCs in Lines 27 &45	115.3521
		3.8135
	Without TCSCs in Lines 2,31 &48	156.8194
		1.5597
		8.3178
	With TCSCs in Lines 2,31 & 48	152.9805
		2.4674
		8.4129

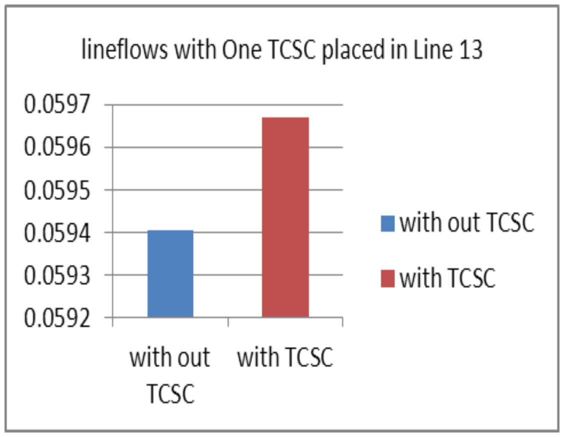

Fig . 3. Comparison plot of Line flows without TCSC and with TCSC placed in Line 13 for IEEE14-bus system

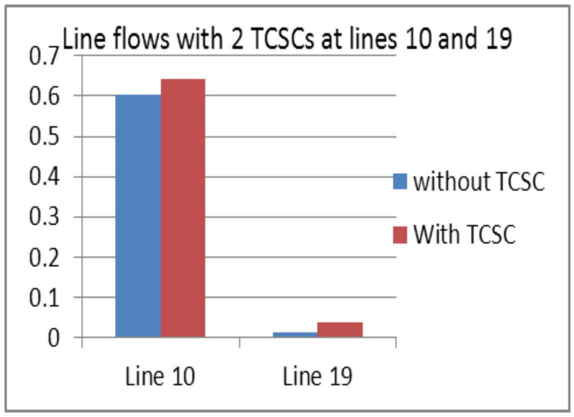

Fig . 4. Comparison plot of Line flows without TCSC and with 2 TCSCs placed at Line 10 and 19 for IEEE14-bus system

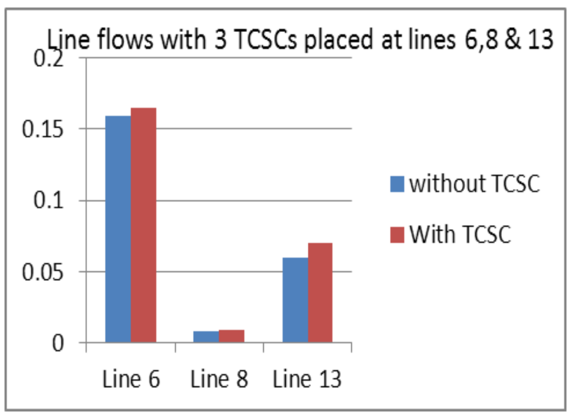

Fig . 5. Comparison plot of Line flows without TCSC and with 2 TCSCs placed at Lines 6,8 and 13 for IEEE14-bus system

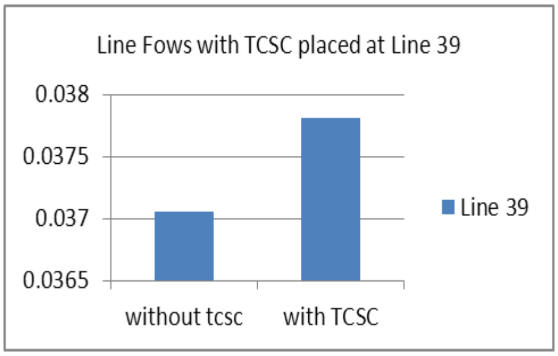

Fig . 6. Comparison plot of Line flows without TCSC and with 1 TCSC placed at Line 39 for IEEE30-bus system

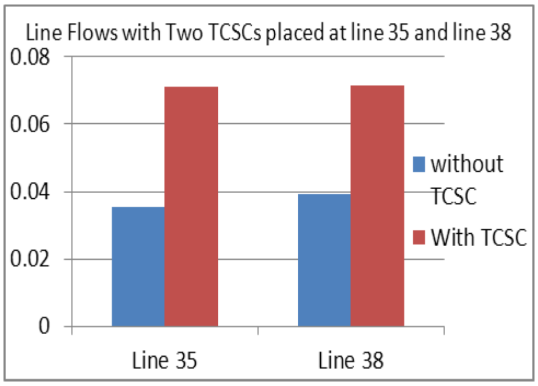

Fig . 7. Comparison plot of Line flows without TCSC and with 2 TCSCs placed at Line 35 and line 38 for IEEE30-bus system

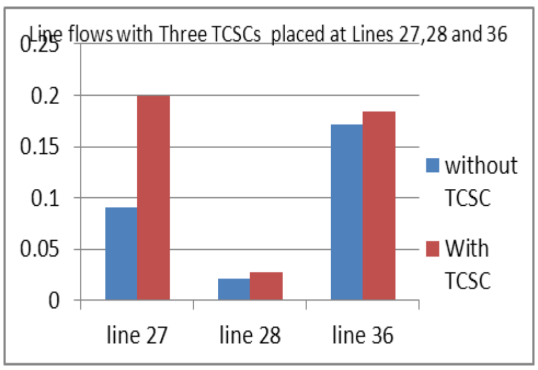

Fig . 8. Comparison plot of Line flows without TCSC and with 3 TCSCs placed at Lines 27,28 and 36 for IEEE30-bus system

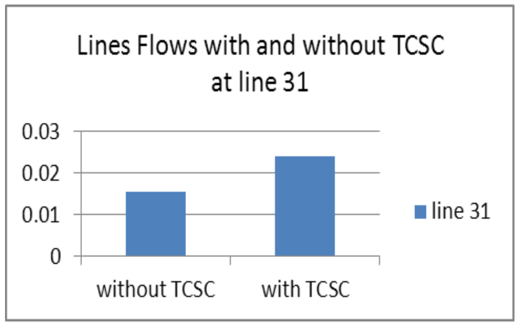

Fig . 9. Comparison plot of Line flows without TCSC and with 1 TCSC placed at Line 31 for IEEE57-bus system

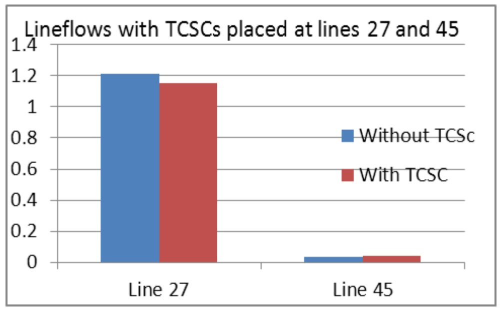

Fig . 10. Comparison plot of Line flows without TCSC and with 2 TCSCs placed at Line 27 and 45 for IEEE57-bus system

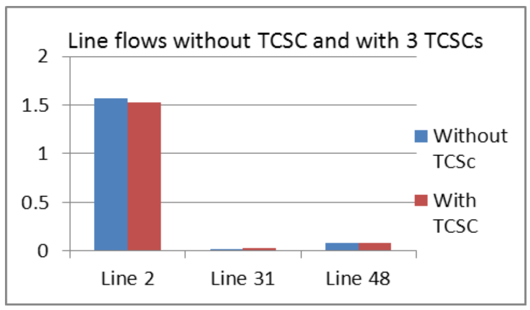

Fig . 11. Comparison plot of Line flows without TCSC and with 3 TCSCs placed at Line 2,31 and 48 for IEEE57-bus system

From the above figures (Fig .4 to Fig.11), for both of the IEEE14 and IEEE30-bus systems, it is evident that, after the placement of TCSC devices, the line flows have been improved. Whereas for IEEE57-bus system, since there are no line limits on the system, it is observed that, line flows have been reduced after the placement of TCSC devices where there is line flow is above 100%. It is also observed that, the Line losses have also been reduced. Due to the limitation of cost, we have limited our investigation only up to three devices. It is also been observed that, the optimal cost has been attained with the placement of devices along the reduction in the losses.

Table 6. Results showing Optimal Fuel cost, generation, losses and TCSC settings for IEEE14-bus system

	Without TCSC	With 1 TCSC	With 2 TCSCs	With 3 TCSCs
Optimal Fuel Cost in $/hr	1660.927759	1660.028273	1659.754728	1658.958797
Total Generation in MW	0.944860 pu	0.944834 pu	0.943566 pu	0.944443
Losses	0.013694 pu	0.013503 pu	0.013 pu	0.012759 pu
% Efficiency	98.550731	98.65074	98.753649	98.843182
TCSC Effective Reactance in pu	-	11.58038(C)	9.88362(C) 2.215909(L)	10.86366(C) 2.215909(L) 2.215909(C)
TCSC Firing Angle	-	2.0733rad	125.21^0 180^0	121.44^0 180^0 180^0

Table 7. Results showing Optimal Fuel cost, generation, losses and TCSC settings for IEEE30-bus system

	Without TCSC	With 1 TCSC	With 2 TCSCs	With 3 TCSCs
Optimal Fuel Cost in $/hr	802.281407	802.200376	802.030179	802.0003343
Total Generation	3.279300 pu	3.269461 pu	3.258607	3.249559
Losses	0.088535 pu	0.088520 pu	0.087432 pu	0.087032
Efficiency	97.300182	97.6300763	97.7302748	97.897452
TCSC Effective X	-	14.9973(C)	2.385998(C) 2.21591(L)	14.99925(C) 2.21591(L) 14.793775(C)
TCSC Firing Angle	-	92.45^0	176.23^0 180^0	91.59^0 180^0 100.25^0

Table 8. Results showing Optimal Fuel cost, generation, losses and TCSC settings for IEEE57-bus system

	Without TCSC	With 1 TCSC	With 2 TCSCs	With 3 TCSCs
Optimal Fuel Cost in $/hr	7018.239068	7017.823799	7002.496677	7000.199496
Total Generation	14.845671	14.835342	14.830189	14.820885
Losses	0.668128	0.666981	0.656067	0.623481
Efficiency	95.499511	95.500403	95.577033	95.829370
TCSC Effective X	-	2.21591(C)	11.710699(C) 2.21591(L)	2.21591(C) 2.21591(L) 4.619727(C)
TCSC Firing Angle	-	180^0	118.3^0 180^0	180^0 180^0 150^0

6. CONCLUSION

Based on Cubic Lattice structured multi-agent based PSO, CLSMAPSO has been developed for solving optimal power Flow problem (OPF) with optimal placement of TCSCs along with security constraints. To the best of our knowledge, OPF problem has been solved by several methods in the literacy but this unique CLSMAPSO method integrates the Cubic Lattice Structured multi-agents with PSO using variable constriction factor to find the global or near global optimum point for OPF problem along with the optimal location of TCSCs. IEEE14, IEEE30 and IEEE57-bus systems have been tested and results are compared. From the results, CLSMAPSO converges to global optimum with more accuracy and within less time. From the results, CLSMAPSO converges to global optimum with accuracy of 0.0001 and within less time.

Another unique feature of this paper was the TCSC variable reactance model with the modifications in the Y_{bus} which are considered. The result also suggests that, with the optimal location of TCSC devices, the Line flows are improved as well as losses were also reduced quite significantly and efficiency has been improved. Moreover, from the literature it is observed that we have got the best optimal cost and best optimal location with CLSMAPSO [5]. These algorithms are general and can be applied to other power system optimization problems.

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