Optimal Power Flow Problem Analysis Incorporating TCSC using Multi-Swarm Optimization Algorithm

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ABSTRACT : *This paper presents optimal power flow technique namely multi swarm optimization with FACTS device. This method is used to solve the nonlinear and non-convex optimization problem. The proposed method has been examined and tested on the standard IEEE 30-bus test system with and without TCSC. The results are promising and show the effectiveness and robustness of the method.*

Keywords *-Cost Minimization, Optimization Techniques, Optimal Power Flow, Multi Swarm Optimization Algorithm, Thyristor-controlled series compensation.*

I. INTRODUCTION

Optimal power flow (OPF) is an operating condition in which the power flow in an electrical system occurs optimally. OPF was first introduced by Carpentier in 1962[1]. the OPF problem solution aims to optimize a selected objective function such as fuel cost via optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. The equality constrains are the power flow equations while the inequality constraints are the limits on control variables and the operation limits are power system dependent variables. The control variables include the generator real powers, the generator bus voltages, the transformer tap settings and the reactive power of switchable VAR sources. The dependent variables include the load bus voltages ,generator reactive powers, and the line flows .Generally ,the OPF problem is a large scale highly constraint nonlinear non-convex optimization problem[2-3].

Scanning through the literature, it will be observed that there are many classic OPF algorithms to describe, define, formulate and solve the optimal Power flow problems such as Newton's method, gradient method, linear programming as well as latest methods such as artificial intelligence techniques, evolutionary algorithms, swarm intelligence [4-10]. Thus, in the subsequent sections great emphasis will be placed on a thorough formulation of the OPF problem and on techniques which lend themselves to an application of proven optimization methods. Furthermore, most previous methods had tendency to get stuck in a near optimal solution and may find it difficult to improve solution accuracy by fine tuning. Similarly, the original Particle Swam Optimization(PSO) frequently get the local solution, particularly the problem size is middle or large .Recently, a Multi-Swarm Optimization(MSO) Algorithm have been undertaken to improve the performance of original PSO[11-15].

This technique combines social psychology principles in socio-cognition human agents and evolutionary computation.MSO has been motivated by the behavior of organisms such as fish schooling and bird flocking. It is characterized as simple in concept to implement and computationally efficient. Unlike the other heuristic techniques, MSO has a flexible and well balanced mechanism to enhance and adapted to the global and local exploration abilities.

In this paper, MSO based method incorporating TCSC is discussed to solve the OPF problem. the problem is formulated as an optimization problem with mild constraints. In this study, minimization of the fuel cost has been considered as an objective function. This approach has been examined and tested on IEEE 30-bus standard system [16]. The potential and effectiveness of the method is demonstrated and the results are reported.

II. THYRISTOR-CONTROLLED SERIES COMPENSATION

There are significant activities and achievements in the research and application of flexible AC transmission systems (FACTS). Thyristor-controlled series compensation (TCSC) is an important device in the FACTS family. It can have various roles in the operation and control of power systems such as scheduling power flow, decreasing unsymmetrical components, reducing net loss, providing voltage support, limiting short-circuit currents, mitigating sub synchronous resonance (SSR), damping the power oscillation and enhancing transient stability. Advances in high-power, high-efficiency power electronics have led to the development of thyristor-controlled series compensators in power systems [17].

In contrast to capacitors switched by circuit breakers, TCSC will be more effective because thyristors can offer flexible adjustment and more advanced control theories can be easily applied. Series capacitor is used in a long distance EHV lines for increasing power transfer. Series capacitor is commonly used for the most economic enhancing power flow though it has a problem of SSR. Series is only used for power transfer as compared to shunt. Shunt has the main problem of location not of SSR. The first demo project of TCSC was done at west Virginia USA. In 1991, it was installed at Arizona substation and then in 1993 at Oregon. Series compensation can be achieved in two ways discrete and continues.

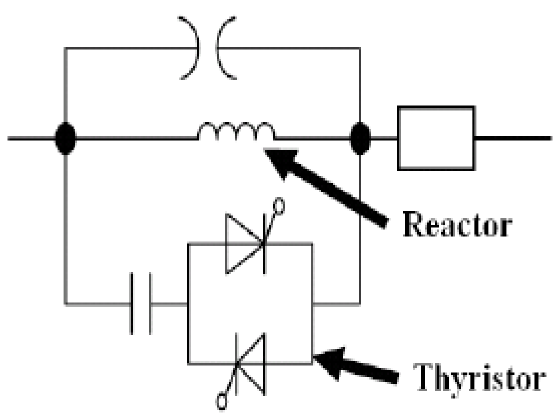

Fig.1 Block diagram of TCSC

Fig.1 shows the simple diagram of TCSC comprised of a series capacitor bank, shunted by a Thyristor Controlled Reactor (TCR) to provide a smoothly variable series capacitive reactance. It is a one-port circuit in series with transmission line. It uses natural commutation and its switching frequency is low. It contains insignificant energy storage and has no DC port. Incorporation of a capacitive reactance in series with the line lowers the total effective impedance of the line and thus virtually reduces its length. As a result, both angular and voltage stability gets improved.

III.OPF PROBLEM FORMULATION WITH TCSC

The idea of OPF is to find the optimal settings of a given power system network that is to optimize the steady state performance of a power system in terms of an objective function while satisfying several equality and inequality constraints .Mathematically the OPF problem can be formulated as follows

$$\text{Min } J(x,u) \quad (1)$$

Subject to

$$g(x,u) = 0 \quad (2)$$

$$h(x,u) < 0 \quad (3)$$

Where J is the objective function to be minimized, X is the vector of dependent variable consisting of slack bus power P_{G1}, load bus voltages V_L, generator reactive power outputs $Q_{G,}$ and transmission loadings $S_{1.}$ Hence, X can be expressed as

$$x^T = [P_{G1}, V_{L1}..V_{LNL}, Q_{G1}..Q_{GNG}, S_1..S_{xti}] \quad (4)$$

$$u^T = [V_{G1}..V_{GN}, P_{G2}..P_{GNG}, T_1..T_{NT}, Q_{C1}..Q_{CNC}] (5)$$

Where NT and NC are the number of the regulating transformers and shunt compensators respectively. g is the equality constraints represent typical load flow equations and h is the system operating constraints that include[18-19].

(a) Limitations of Generation: Generator voltages, real power outputs and reactive power outputs are restricted by their lower and upper limits as follows:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i = 1, \dots NG \quad (6)$$

$$P_{Gi}^{min} \le P_{Gi} \le P_{G\,i}^{max}, i = 1, \dots NG \quad (7)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i = 1, \dots NG \quad (8)$$

(b).Limitations of Transformer: Transformer tap settings are bounded as follows:

$$T_i^{min} \le T_i \le T_i^{max}, i = 1, \dots NT \quad (9)$$

(c).Limitations of Shunt VAR: Shunt VAR compensations are restricted by their limits as follows:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i = 1, \dots, NC \quad (10)$$

The TCSC device constraints are as follows

$$X_{tcsc}^{min} \le X_{tcsc} \le X_{tcsc}^{max} \quad (11)$$

The power flow limits in i th transmission line are

$$S_{ti} \leq S_{ti}^{max} \qquad ti = 1,2,3..xti \qquad (12)$$

xti is the number of transmission lines

The Objective Functions of the generator cost for any turbo generator is obtained from the following equation.

J is considered as the Total fuel cost

$$\mathrm{J} = \sum_{i=1}^{NG} f_{Gi} \quad \$/h \qquad (13)$$

$$f_{Gi} = (p_i + q_i P_{Gi} + r_i P_{Gi}^2) \quad \$/h \qquad (14)$$

Where f_{Gi} is the generation cost of i^{th} generator , NG is the number of participating generators, P_{Gi} is the generation of i^{th} generator, p_i, q_i and r_i are cost coefficients of i^{th} generator.

IV. MULTI-SWARM OPTIMIZATION ALGORITHM

A. Overview

Multi-swarm optimization (MSO) is a technique for estimating the solution to difficult or impossible numerical problems. It's a variation of particle swarm optimization. Regular particle swarm optimization models flocking behavior, such as that seen in groups of birds and schools of fish. MSO extends particle swarm optimization by using several swarms of simulated particles rather than a single swarm.

The proposed MSO algorithm consists of a main swarm and some sub-swarms. The main swarm is responsible for finding promising area in the search space upon which a sub-swarm is created to exploit the newly found promising area. The proposed algorithm adapts the idea of hibernation of animals to prevent the unproductive search of a sub- swarm in order to save the precious fitness evaluations for more efficient searches. In the proposed algorithm, each sub- swarm is considered as an animal searching for food.

As long as it finds a better solution, it remains active and continues searching if it cannot find a better solution because its particles have converged to a solution and that solution is not as good as the best solution found by the whole swarm, the sub-swarm considers its activity unproductive. Therefore, it will hibernate until it can be useful again that is the moment a change is detected in the environment, similar to the change of the season in the nature, which awaken the hibernating animals. So the population is not trapped by local optimum position easily. So the possibility of capturing the real global optimum increases greatly.

MSO can be applied to several machine-learning scenarios, such as estimating the weights and bias values for an artificial neural network or estimating the weights of weak learners in ensemble classification and prediction. MSO is a meta-heuristic, meaning that the technique is really a set of design principles and guidelines that can be used to construct a specific algorithm to solve a specific optimization problem.

Velocity Updating: The key operation in MSO is computing a new velocity for a particle. A new velocity for a given particle is influenced by the current velocity, the current position, the best-known position of the particle, the best-known position of any particle in the same swarm as the particle, and the best-known position of any particle in any swarm. In math terms, the new velocity is

$$V(t+1) = W \times V(t) + (c1 \times r1) \times$$

$$\big(P(t) - x(t)\big) + (c2 \times r2) \times \big(\mathrm{S}(\mathrm{t}) - x(\mathrm{t})\big)$$

$$+(\mathrm{c}3 \times \mathrm{r}3) \times \big(\mathrm{M}(\mathrm{t}) - x(\mathrm{t})\big). \qquad (15)$$

Position Updating: After a new velocity has been computed, a particle's new position is:

$$x(\mathrm{t}+1) = x(\mathrm{t}) + \mathrm{V}(\mathrm{t}+1) \qquad (16)$$

The term V (t+1) mean the velocity at time t+1, in other words, the new velocity. Term V (t) is the current velocity. Term x(t) is the current position.

P (t) is a particle's best-known position; S (t) is the best position of any particle in the particle's swarm. ;M (t) is the best position of any particle in any swarm; W is a constant called the inertia factor; *c1*, *c2* and *c3* are constants that establish a maximum change for each component of the new velocity; r1, r2, and r3 are random values between 0 and 1 that provide a randomization effect to each velocity update.

Death and Immigration:

There are various ways to modify the basic MSO algorithm. One possibility is to essentially kill a randomly selected particle every now and then and give birth to a new particle. Thus it generates a random value between 0 and 1 and stores it into p. If the random value is less than 0.005, the current particle is re-instantiated by calling the Particle constructor, effectively killing the current particle and giving birth to a new particle at a random location.

Another MSO option is to model immigration by periodically taking two particles in different swarms and exchanging them. One particle effectively immigrates into the current swarm and another particle emigrates out of the swarm. The method is simple and allows the undesirable possibility that a particle might be exchanged with itself.

The procedure of the Multi-Swarm optimization algorithm is as follows

1) Initialize the population of particles and the population size n

2) Divide the population of particles into h swarms and number of particles in each swarm randomly

3) Begin with the first swarm and $i = 1$;

4) For i^{th} swarm, let iteration number $t = 1$;

5) Calculate every particle's fitness value. According to the fitness values, m positions with best fitness values are selected from all positions tracked by the particle as pbests of the particle. m pbests with best fitness values are selected from all particles' pbests from which the best fitness value is taken as the swarm best of the i^{th} group; if $t = m$, only take t pbests and t swam bests.

6) If $i = h$, go on to step 7).Otherwise $i = i + 1$ and turn to step 4);

7) Combine all swarm best of h swarms. According to the fitness values, best fitness value is selected from all swarms tracked by the particle as pbests of the particle. m pbests with best fitness value is selected from all swarm best as the multi swarm best of the population;

8) Update each particle's velocity and position

9) If the stop condition is satisfied, the iteration stops and the best multi swarm best are outputted. Otherwise $t = t + 1$ and turn to step 5).

Form the procedure we can see that if $h = 1, m = 1$, the MSO is basic PSO. So the MSO is a generalization of the basic PSO and the basic PSO is a special example of the MSO.

V. RESULTS

The proposed MSO based approach with OPF model incorporating TCSC for enhancement of system performance has been tested on the standard IEEE 30-bus system. The system has six generators at buses 1,2,5,8,11 and 13 and four transformers with off-nominal tap ratio in lines 6-9,6-10,4-12 and 28-27.In addition ,buses 10,12,15,17,20,21,23,24,and 29 have shunt VAR compensation. The method of investigating the effects of the TCSC on the power system is carried out with simulation using MATLAB software package. The MSO parameters used for the simulation are shown in Table.1

Table 1 MSO parameters

S.No	Control variables	values
1	Number of Swarms	5
2	Number of Particles in each Swarm	5
3	Initial inertia factor	1
4	Acceleration constants	2
5	Number of iterations	25

Table 2 Optimal settings of control variables for IEEE-30 bus test system

S.No	Parameters	Case 1	Case 2
1	P_{G1}	168.845	163.561
2	P_{G2}	48.484	50.833
3	P_{G5}	20.591	22.851
4	P_{G8}	18.549	23.488
5	P_{G11}	19.475	15.616
6	P_{G13}	17.260	16.249
7	V_{G1}	1.017	1.038
8	V_{G2}	1.046	1.028
9	V_{G5}	0.990	1.008
10	V_{G8}	0.964	0.995
11	V_{G11}	1.037	1.020
12	V_{G13}	0.999	1.004
13	T_{6-9}	0.957	0.994
14	T_{6-10}	0.969	1.001
15	T_{4-12}	0.994	0.984
16	T_{28-27}	0.941	0.960
17	Q_{c10}	3.919	1.894

18	Q_{c12}	3.113	3.554
19	Q_{c15}	2.684	0.733
20	Q_{c17}	3.646	2.141
21	Q_{c20}	2.400	2.170
22	Q_{c21}	0.676	2.266
23	Q_{c23}	1.701	1.231
24	Q_{c24}	3.007	1.384
25	Q_{c29}	1.470	3.800
26	Total real power generation(MW)	293.207	292.670
27	Total Cost($/h)	807.972	806.349
28	Real power loss(MW)	9.807	9.270
29	X_{tcsc} (p.u)	---	-0.336

The optimal settings of the control variables are given in Table 2.In order to demonstrate the effectiveness and robustness of the technique, cost objective function has been considered with and without TCSC and both the cases are discussed.

Table 3 Bus voltage of IEEE -30 bus test system

Bus No.	Case 1		Case 2	
	Voltage magnitude (p.u)	Voltage angle (deg.)	Voltage magnitude (p.u)	Voltage angle (deg.)
1	1.017	0	1.038	0
2	0.999	-3.592	1.028	-3.419
3	0.988	-5.385	1.008	-5.019
4	0.981	-6.604	1.000	-6.150
5	0.989	-11.081	1.008	-10.248
6	0.972	-7.762	0.992	-7.186
7	0.971	-9.638	0.982	-8.980
8	0.964	-8.005	0.995	-7.279
9	1.012	-9.296	0.987	-8.945
10	0.999	-11.335	1.011	-10.885
11	1.037	-7.085	1.020	-7.097
12	1.013	-10.564	1.055	-10.347
13	1.046	-9.258	1.004	-9.137
14	0.999	-11.575	0.998	-11.322
15	0.996	-11.762	0.999	-11.410
16	1.000	-11.209	0.987	-10.838
17	0.996	-11.577	0.983	-11.151
18	0.986	-12.413	0.977	-12.028
19	0.983	-12.592	0.980	-12.187
20	0.988	-12.373	0.977	-11.954
21	0.987	-11.866	0.978	-11.436
22	0.988	-11.862	0.985	-11.424
23	0.987	-12.276	0.974	-11.859
24	0.980	-12.458	0.986	-11.990
25	0.987	-12.472	0.968	-12.015
26	0.969	-12.918	1.003	-12.462
27	1.000	-12.193	0.985	-11.735
28	0.965	-8.281	0.997	-7.679
29	0.984	-13.613	0.984	-13.318
30	0.970	-14.475	0.974	-14.039

In case1 OPF model without incorporating TCSC is considered. The cost characteristics without the TCSC are shown in Fig.2. In case2 OPF model incorporating TCSC is considered, the variation in the total cost is shown in Fig.3. The total fuel cost was 807.972 $/h without the TCSC and the total cost obtained with TCSC is 806.345$/h. It is clear that the total cost is reduced. From the results, it is obvious that the installation of TCSC in network gives good performance of the system in terms of reduction of cost in generation, power loss reduction and better voltages.

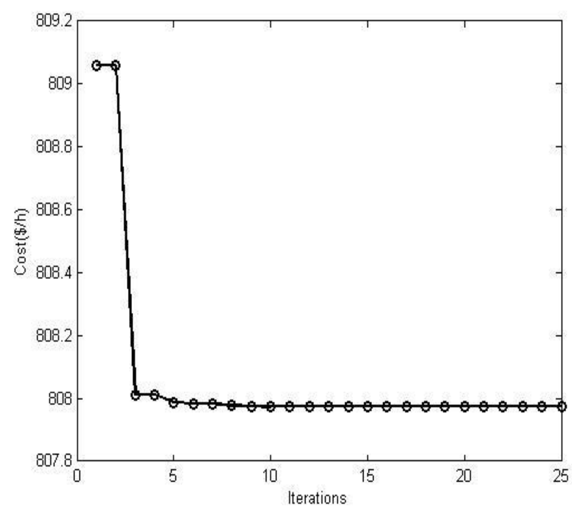

Fig.2. Convergence Characteristics of case 1.

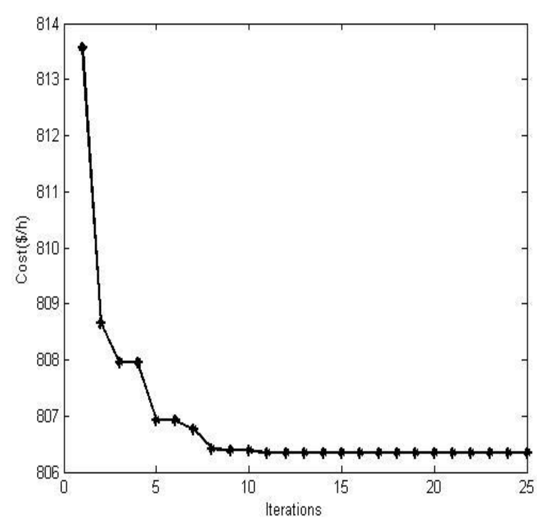

Fig.3. Convergence Characteristics of case 2.

VI. CONCLUSION

In this paper MSO based approach Incorporating TCSC to OPF problem has been presented. The proposed method utilizes the global and local exploration capabilities of MSO to search for the optimal settings of control variables. The proposed approach has been tested and examined on IEEE 30 bus system to demonstrate its effectiveness and robustness. The results of the MSO algorithm were compared with and without TCSC. From the two cases, it is obvious that TCSC in network gives the less fuel cost of generation, power loss reduction as well as voltage improvements. The results confirm the potential of approach and show its effectiveness.

REFERENCES

[1] J. Carpentier; Optimal Power Flows; Electrical Power & Energy Systems, Butterworths; Vol. 1 , April 1979.

[2] A.V.Naresh Babu and S.Sivanagaraju, "A solution to the optimal power flow problem: A new approach based on two step initialization," Proc. of IEEE India International Conference (INDICON) on Engineering Sustainable Solutions, BITS, Hyderabad, India, Dec. 2011.

[3] H.W. Dommel, W.F. Tinney; Optimal Power Flow Solutions; IEEE Transactions on Power Apparatus and Systems, Vol. 8, pp. 1866-1867,Oct. 1968.

[4] Salgado.R, Brameller.A, Optimal power flow solutions using the gradient projection method. II. Modelling of the power system equations , Generation Transmission and Distribution, IEE Proceedings C , Vol.137 , Issue. 6,pp.429-435,Nov.1990.

[5] D.I. Sun, B. Ashley, B. Brewer, A. Hughes, W.F. Tinney; Optimal Power Flow by Newton Method; IEEE Transactions on Power Apparatus Vol 42,pp-256-260,2007 .

[6] R.Gnanadass, P.Venkatesh and Narayana Prasad Padhy, "Evolutionary programming based optimal power flow for units with non-smooth fuel cost functions," Electric Power Components and Systems, vol.33, pp.349-361, 2005.

[7] Zhiwen Yu, Hau-San Wong, Knowledge learning based evolutionary algorithm for unconstrained optimization problem, IEEE World Congress**,** pp.572-579, June. 2008.

[8] Bangia, S. Sharma, P.R, Comparison of artificial intelligence techniques for the enhancement of power quality , Power Energy and Control (ICPEC) International Conference ,pp.537-541,Feb.2013.

[9] Ah King, R.T.F , Using artificial intelligence techniques for solving power systems problems at undergraduate level, IEEE International Conference, Vol.1 , Issue. 6,pp.42-47,Dec.2003.

[10] Salgado.R, Brameller.A, Optimal power flow solutions using the gradient projection method. II. Modelling of the power system equations , Generation Transmission and Distribution, IEE Proceedings C , Vol.137 , Issue. 6,pp.429-435,Nov.1990.

[11] J. Kennedy and R. Eberhart , " Particle swarm optimization , " in *Proc. IEEE Int. Conf. Neural Networks* , Perth, Australia, vol. 4, pp. 1942 – 1948, 1995.

[12] Antonio Bolufé Röhler and Stephen Chen, "An Analysis of Sub-swarms in Multi-swarm Systems", in Lecture Notes in Artificial Intelligence, Vol. 7106, pp. 271–280,2011.

[13] S. Z. Zhao, J. J. Liang, P. N. Suganthan, and M. F. Tasgetiren, "Dynamic Multi-Swarm Particle Swarm Optimizer with Local Search for Large Scale Global Optimization," in Proceedings IEEE Congress on Evolutionary Computation, pp. 3845–3852,2008.

[14] T. Hendtlass, "WoSP: A Multi-Optima Particle Swarm Algorithm," in Proceedings IEEE Congress on Evolutionary Computation, pp. 727–734,2003.

[15] S. Chen, "Locust Swarms – A New Multi-Optima Search Technique", in Proceedings of the IEEE Congress on Evolutionary Computation, pp. 1745–1752,2009.

[16] Totonchi. I, Al Akash.H, the IEEE 30 bus system using load-flow studies , Electric Power and Energy Conversion Systems (EPECS) 3rd International Conference,pp.1-6,oct.2013.

[17] Wu Shouyuan, Zhou Xiaoxin, Design and simulation on TCSC analog model and controller, Power System Technology POWERCON International Conference , Vol.1,pp .430 – 435,aug 1998.

[18] Al.Rashidi, M.R, El-Hawary, Approach for Solving the Discrete OPF Problem Considering the Valve Loading Effects **,** IEEE Transactions**,** Vol.22 , Issue. 4 ,pp.2030-2038, Nov. 2007.

[19] Abido MA. "Optimal power flow using particle swarm optimization," Electr Power Energy Syst, Vol.24, pp.563–71, 2002.