Optimal Placement of TCSC for Congestion Management using Modified Particle Swarm Optimization

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ABSTRACT
In a competitive power market, the task of an independent system operator (ISO) is to ensure full dispatches of the contracted power are carried out reliably. However, if it threatens the system security then ISO makes decision on the re-dispatch of the contracted power i.e., Congestion Management (CM). This paper proposes an optimal congestion management approach in a deregulated electricity market with optimal location of TCSC under Combined Economic Emission Dispatch Environment (CEED) using Particle Swarm optimization with Time Varying Acceleration Co-efficient (PSO-TVAC). Sensitivity factors are used to find the optimal location TCSC. After placing TCSC the investment cost of TCSC and generator rescheduling cost is minimized using Particle Swarm Optimization (PSO) and PSO-TVAC. Numerical results on test system, IEEE 30 bus and IEEE 118 bus systems are presented for illustration purpose and the results are compared with Particle swarm optimization (PSO) in terms of solution quality. The comprehensive experimental results prove that the PSO-TVAC is one among the challenging optimization methods which is indeed capable of obtaining higher quality solutions for the proposed problem.

Keywords
Congestion Management; Cost of TCSC, Voltage stability, Particle Swarm optimization (PSO), Particle Swarm optimization with Time Varying Acceleration Co-efficient (PSO-TVAC).

1. INTRODUCTION
In a deregulated electricity market, the task of the independent system operator (ISO) is to ensure that contracted power transactions are carried out reliably. However, due to the large number of transactions that take place simultaneously, transmission networks may easily get congested. Electricity markets will not be able to operate at its competitive equilibrium with congestion in the system. Congestion in transmission systems is a major problem and may lead to electricity price spikes in restructured power systems. Transmission congestion occurs when there is inadequate transmission capacity to meet the demands of all customers and more expensive generating units may have to be brought on-line, hereupon electricity markets will not be able to operate at its competitive equilibrium and also imperil system security. Therefore congestion management is one of the key issues for secure and reliable system operations in electric power markets.

Congestion occurrence can be experienced in various forms as reported by Besharat et. al [1] which describes that the congestion can be caused by transmission line outages, generator outages, changes in demand and uncoordinated transactions. Subsequent events led by congestion in power system can cause price spike in certain regions and component damages. As a glimpse, the occurrence of congestion is depending on the capacity and management of the market facilities. Another effect resulted from the congestion is the failure of the system to operate within the competitive equilibrium as highlighted by N. Acharya et. al [2]. The impact resulted from congestion is very significant in power system operation because it can also depreciate the performance of the system. One of the issues is the failure of transmission network establishment. This has been highlighted by Pandey et. al in [3] which several transmission network cannot be established due to the congestion such as regulated monopolistic power system and deregulated competitive power market.

The location of FACTs devices can be based on static or dynamic performances of the system. The sensitivity factor methods are generally used to find the best location to enhance the static performance of the system. In [4], an overload sensitivity factor (power flow index) is used for optimal location of series FACTs devices (i.e. TCSC and TCPAR) for static congestion management. A loss sensitivity factor method is used in [5] to determine the suitable location for FACTS devices. The disadvantage of these methods is that it may not capture the non-linearity associated with the system. The enumerative procedures combined with sensitivity analysis have been studied in [6], with the location decision made after evaluating all possibilities. For large systems, the enumerative approach is not practical given the large number of combinations that have to be examined.

Numerous methods have been reported for social welfare maximization and congestion management, which are based on particle swarm optimization (for generation rescheduling and/or load shedding) [7] and sensitivity analysis using transmission line susceptances [8]. Recent solutions for managing power flow in transmission lines are based on flexible AC transmission systems (FACTs) [9]. Different approaches, based on sensitivity method, have been proposed for optimal locating of FACTs devices in both vertically integrated and unbundled power systems [6]. Application of series FACTs for congestion management in deregulated electricity markets is discussed in [10]. For congestion issue, Methods based on Optimal Power Flow (OPF) provide the most efficient solutions in locating and sizing FACTS devices. The sensitivity based method has been used to find optimal placement of TCSC to reduce congestion in [1]. Although, these methods have good performance to locate TCSC, they may not capture the nonlinearity associated with the system. The effect of congestion on spot prices or Local Marginal Prices (LMP) can be used to obtain TCSC optimal location. In [11] a novel method has been introduced in which differences between local marginal prices (LMP) are used to make a priority list to find suitable placement to install TCSC. In [12], a type of Security-Constrained OPF (SCOPF) is proposed for minimizing total generation costs with the decision variables of FACTs devices. In [13] the Tabu search method and in [9] the Genetic algorithm is used to solve the combinatorial (i.e. to determine number and location) problem of FACTs device allocation. However, these methods are computationally demanding and less reliable.

Mixed Integer Linear and Nonlinear Programming based Optimal Power Flow (OPF) methods were used to determine the maximum loadability using FACTs devices in pool and hybrid electricity markets [14-15]. EP was proposed to obtain optimal placement of multi-type FACTS devices for simultaneously maximizing the Total Transfer Capability whereas minimizing the total system real power loss and the results are better when compared to loss sensitivity index method [16]. The optimal location for single and multi-type FACTs devices to improve system loadability with minimum cost of installation was determined using PSO [17] and further modifications were carried out in [18-20]. An Ordinal Optimization (OO) technique which uses Guaranteed Convergence Particle Swarm Optimization (GCPSO) was also proposed to enhance system loadability with FACTS devices to reduce computational effort [21]. GA and SQP [22] techniques are used to find the optimal number of FACTs devices for congestion management. These methods have the advantage of searching the solution space more thoroughly, but have limitations of their sensitivity to the choice of parameters such as the crossover and mutation probabilities, instable convergence, slow and easy to premature exist in GA, scaling factor in EP and inertia weight and learning factors in PSO. The PSO technique can generate better optimal solution in less calculation time with stable convergence characteristic compared to other population-based methods.

The PSO algorithm was introduced by Kennedy and Eberhart [23] and further modifications in PSO algorithm were carried out [24-27]. It has been observed by most researchers that in PSO, problem based tuning of parameters is a key factor to find the optimum solution accurately and efficiently. Various researchers [23-25] have found that the PSO is beset by a premature convergence issue, as the particles tend to be trapped in the local optima solution, which is attributed to the rapid convergence of PSO and the loss of swarm diversity. Another major concern in the application of PSO is the algorithm's capability in balancing exploration/exploitation searches. Excessive exploration or exploitation searches are undesirable, as the former prevents swarm convergence, whereas the latter has a high tendency to cause premature swarm convergence. In PSO, particles move around in the search space with the help of two accelerating components. One component, known as the cognitive component, controls the local exploration of the particles, while the second component, known as the social component, guides the global search capability of the particles. In population-based optimization methods, the policy is significant to encourage individuals to roam through the entire search space during the initial parts without clustering around local optima, and during the latter stages, to encourage convergence towards the global optima to find the optimal solution efficiently. But, in PSO high value of the cognitive component will result in excessive exploration of the particles through the search space while a high value of the social component will result in a premature convergence of the particles [21]. In order to overcome these problems, Ratnaweera et al. [18] introduced a time varying acceleration co-efficient (TVAC), which reduces the cognitive component, c1 and increases the social component, c2 of acceleration co-efficient with time. With a large value of c1 and a small value of c2 at the beginning, particles are allowed to move around the search space, instead of moving toward pbest. A small value of c1 and a large value of c2 allow the particles converge to the global optima in the latter part of the optimization. The PSO-TVAC strategy finds a proper balance between the local and the global component and hence, the problem of premature convergence has been overcome to a much greater extent. So, the proposed approach considered PSO-TVAC algorithm to manage congestion with optimal location of TCSC. From the survey it is observed that, economic constraints are not taken into the account of congestion management problem. So, the proposed approach is solved congestion management problem under Combined Economic Emission Dispatch (CEED) environment. Venkatesh et al.[28] proposed price penalty factor method to solve the CEED problem.

The proposed objective Congestion Management with optimal placement of TCSC under CEED environment is solved using PSO-TVAC and the obtained results are compared with PSO and PSO-TVIW. The proposed approach utilizes price penalty factor method to solve CEED problem. The test systems IEEE-30 bus system is used to serve as test systems for showing the capability of the proposed method. The simulation results show that the proposed method is efficient for lowering the congestion cost in a deregulated electricity market.

The main contributions of this paper are as follows:

i. The proposed approach optimal congestion management with optimal location of TCSC under CEED environment comprises of two steps. First step, Sensitivity Analysis is carried out for finding the optimal location of TCSC, i.e., real power flow performance index sensitivity. Second step Cost benefit analysis is carried out to minimize the investment cost of TCSC and GENCOs' cost.

ii. Novel technique Particle Swarm Optimization with Time Varying Acceleration Factors (PSO-TVAC) is used to implement the proposed approach for Congestion Management with optimal placement under CEED environment.

2. STATIC MODELING OF TCSC

Fig. 1 shows a model of transmission line with TCSC connected between buses i and j. The transmission line is represented by its lumped π—equivalent parameters connected between the two buses. During steady state, the TCSC can be considered as a static reactance −jxc. The controllable reactance xc is directly used as the control variable in the power flow equations [6].

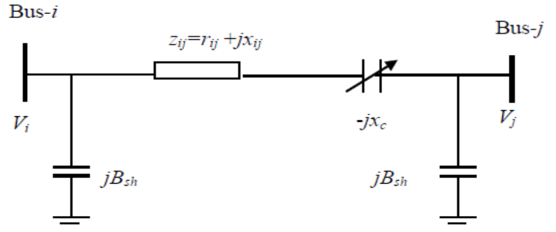

Fig.1.Modeling of TCSC

The real and reactive power injections at bus *i* and bus *j* are given by [3],

$$P_i^F = V_i^2 \Delta G_{ij} - V_i V_j \left[\Delta G_{ij} \cos\left(\delta_i - \delta_j\right) + \Delta B_{ij} \sin\left(\delta_i - \delta_j\right) \right]$$
$$P_j^F = V_j^2 \Delta G_{ij} - V_i V_j \left[\Delta G_{ij} \cos\left(\delta_i - \delta_j\right) - \Delta B_{ij} \sin\left(\delta_i - \delta_j\right) \right] \quad (1)$$
$$Q_i^F = -V_i^2 \Delta B_{ij} - V_i V_j \left[\Delta G_{ij} \sin\left(\delta_i - \delta_j\right) - \Delta B_{ij} \sin\left(\delta_i - \delta_j\right) \right]$$
$$Q_j^F = -V_j^2 \Delta B_{ij} + V_i V_j \left[\Delta G_{ij} \cos\left(\delta_i - \delta_j\right) + \Delta B_{ij} \sin\left(\delta_i - \delta_j\right) \right]$$

Where,

$$\Delta G_{ij} = \frac{x_c r_{ij}\left(x_c - x_{ij}\right)}{\left(r_{ij}^2 + x_{ij}^2\right)\left\{r_{ij}^2 + \left(x_{ij} - x_c\right)^2\right\}} \quad (2)$$
$$\Delta G_{ij} = \frac{x_c\left(r_{ij}^2 - x_{ij}^2 + x_c x_{ij}\right)}{\left(r_{ij}^2 + x_{ij}^2\right)\left\{r_{ij}^2 + \left(x_{ij} - x_c\right)^2\right\}}$$

In the present study, the above model is incorporated in the OPF. The maximum compensation by TCSC is limited to 70% of the reactance of the un-compensated line where TCSC is located.

3. PROBLEM FORMULATION

Congestion management (CM) problem is formulated in two steps. The criteria for optimal placement of TCSC have been done through Sensitivity Analysis and device cost is minimized using Bacterial Foraging Particle Swarm Optimization.

3.1 Sensitivity Analysis

The Sensitivity Analysis is carried out for finding the optimal location of TCSC. Real power flow performance index[6] is used to find the optimal location of TCSC. The severity of the system loading under normal and contingency cases can be described by a real power line flow performance index, as given below

$$PI = \sum_{m=1}^{N_l} \frac{w_m}{2n}\left(\frac{P_{Lm}}{P_{Lm}^{\max}}\right)^{2n} \quad (3)$$

Where P_{LM} the real power is flow and $P_{LM}^{\max}$ is the rated capacity of the line- *m*, *n* is the exponent and w_m is a real non-negative weighting coefficient which may be used to reflect the importance of the lines. *PI* will be small when all the lines are within their limits and reach a high value when there are overloads. Thus, it provides a good measure of severity of the line overloads for given state of the power system. The real power flow *PI* sensitivity factors with respect to the parameters of TCSC can be defined as,

$$b_k = \frac{\partial PI}{\partial X_{ck}} \text{ at } X_{ck} = 0 \quad (4)$$

TCSC should be placed in a line having most negative sensitivity index.

3.2 Objective function

Due to high cost of FACTs devices, it is necessary to use cost-benefit analysis to analyze whether new FACTs device is cost effective among several candidate locations where they are actually installed. The objective function for placement of TCSC will be,

$$\textit{Minimize} \quad \sum_{\substack{i=1 \\ \neq s}}^{N_G} C_{pi}(P_i) + \sum_{\substack{i=1 \\ \neq s}}^{N_G} C_{qi}(Q_i) + IC \quad (5)$$

Subject to:

Power balance equation

$$\begin{aligned} P_{Gi}^{\min} &\le P_{Gi} \le P_{Gi}^{\max} \\ Q_{Gi}^{\min} &\le Q_{Gi} \le Q_{Gi}^{\max} \end{aligned} \quad (6)$$

If TCSC is located in line between buses *i* and *j*, the power balance equations in nodes *i* and *j* are given by

$$\begin{aligned} &P_i\left(\theta, V\right) - P_{Gi} + P_{Di} + P_i^F = 0, \text{ for node } i \\ &P_j\left(\theta, V\right) - P_{Gj} + P_{Dj} + P_j^F = 0, \text{ for node } j \\ &Q_i\left(\theta, V\right) - Q_{Gi} + Q_{Di} + Q_i^F = 0, \text{ for node } i \\ &Q_j\left(\theta, V\right) - Q_{Gj} + Q_{Dj} + Q_j^F = 0, \text{ for node } j \end{aligned} \quad (7)$$

Power generation limit

$$\begin{aligned} P_{Gi}^{\min} &\le P_{Gi} \le P_{Gi}^{\max} \\ Q_{Gi}^{\min} &\le Q_{Gi} \le Q_{Gi}^{\max} \end{aligned} \quad (8)$$

Bus voltage limit

$$\begin{aligned} V_i^{\min} &\le V_i \le V_i^{\max} \\ \theta_i^{\min} &\le \theta_i \le \theta_i^{\max} \end{aligned} \quad (9)$$

TCSC reactance limit

$$x_c^{\min} \le x_c \le x_c^{\max} \quad (10)$$

Where, IC is the installment cost of TCSC. The cost of installation of TCSC devices has been mathematically formulated and is given by,

$$\begin{aligned} &IC = C_{TCSC} \times S \times 1000\left(\$\right) \\ &C_{TCSC} = 0.0015S^2 - 0.7130S + 153.75(\$/KVAR) \\ &S = \left|Q_1 - Q_2\right| \end{aligned} \quad (11)$$

C_{TCSC} is the cost of TCSC devices in $/KVAR, S is the operating range of TCSC in MVAR, Q_1 is the reactive power flow through the branch before TCSC installation and Q_2 is the reactive power flow through the branch after TCSC installation.

Generator Reactive Power support:

$$C_{qi}(\Delta Q_i) = \left[C_{pi}\left(S_{Gi\max}\right) - C_{pi}\left(\sqrt{S_{Gi\max}^2 - \Delta Q_i^2}\right)\right] k_i \quad (12)$$

where, C_{qi} is the cost of the Reactive power rescheduling, C_{pi} is the active power generation cost, S_{Gimax} is the nominal apparent power of the generator and k_i is an assumed profit rate of the active power generation at bus *i*. Here k_i is taken as 5%. Here $S_{Gimax}=P_{Gimax}$

GENCOs' cost considering Combined Economic Emission Dispatch (CEED):

Here minimization of generator cost is considering both Fuel cost coefficients and emission coefficients.

$$C_{pi}(P_i) = F(P_i) + h \times E\left(P_i\right) \quad (13)$$

Where $F(P_i)$, $E(P_i)$ and $C(P_i)$ are fuel cost, emission cost and GENCOs' cost of i^{th} GENCO. Venkatesh et al. [28] proposed the bi-objective combined economic emission dispatch problem is converted into single optimization problem by introducing price penalty factor *h* as follows. Similar procedure followed here for finding the penalty factor.

$$h_i = \frac{F_i\left(P_{gi}^{\max}\right)}{E_i\left(P_{gi}^{\max}\right)}, \qquad i = 1, 2......., N_g \tag{14}$$

The Fuel cost coefficients and emission coefficients are represented as,

$$F(P_i) = a_i(P_i)^2 + b_i(P_i) + C_i$$
$$E(P_i) = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i(P_i) + \gamma_i(P_i^2)) + \varsigma_i \exp(\lambda_i(P_i)) \tag{15}$$

where a_i, b_i, c_i are the cost coefficients of i^{th} GENCO. The total emission $E(P_i)$in (ton/hr) of atmospheric pollutants such as sulpher oxides (SO_X) and nitrogen Oxides (NO_X) caused by the operation of fossil fuelled thermal generation. $\alpha_i, \beta_i, \varsigma_i$ and λ_i are coefficients of the i^{th} generator emission characteristics.

The proposed optimization problem is solved using PSO, PSO TVIW and PSO TVAC. So, next section is dealing with the formulation of PSO-TVAC.

4. PARTICLE SWARM OPTIMIZATION WITH TIME VARYING ACCELERATION COEFFICIENTS (PSO-TVAC)

Particle Swarm Optimization (PSO) is based on the collective motion of a flock of particles: the particle swarm. In the simplest and original version of PSO, each member of the particle swarm is moved through a problem space by two elastic forces. One attracts it with random magnitude to the best location so far encountered by the particle. The other attracts it with random magnitude to the best location encountered by any member of the swarm [21, 22]. PSO consists of a swarm of particles and each particle flies through the multi-dimensional search space with a velocity, which is constantly updated by the particle's previous best performance and by the previous best performance of the particle's neighbors. The position and velocity of each particle are updated at each time step (possibly with the maximum velocity being bounded to maintain stability) until the swarm as a whole converges to an optimum. Particles update their velocity and position through tracing two kinds of 'best' value. One is its personal best (pbest), which is the location of its highest fitness value. In global version, another is the global best (gbest), which is the location of overall best value, obtained by any particles in the population. Particles update their positions and velocities according to equation below equations.

$$V_{id}(t+1) = \omega V_{id}(t) + \varphi_1 rand_1(p_{id}(t) - x_{id}(t)) + \varphi_2 rand_2(p_{gd}(t) - x_{id}(t))$$
$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{16}$$

Here, $V_d(t)$ is the velocity of d^{th} dimension of the i^{th} particle in the i^{th} iteration, $x_{id}(t)$ is the corresponding position and $p_{id}(t)$ and $p_{gd}(t)$ is personal best and global best respectively. The variables ϖ is the inertia weight, the parameters ϕ_1 and ϕ_2 are the accelerate parameters, which respectively adjust the maximal steps particles flying to the personal best and the global best, *rand1* and *rand2*are two random numbers in [0,1]. Here w is the inertia weight parameter which controls the global and local exploration capabilities of the particle. A large inertia weight helps in good global search while a smaller value facilitates local exploration. In order to improve the performance of the PSO, the time-varying inertia weight (PSO-TVIW) was proposed in [24]. A large inertia weight factor enhances global exploration while a low inertia weight factor helps in local search. Hence, a suitable selection of inertia weight provides a balance between global and local explorations, thus requiring lesser iterations on average to find a sufficiently optimal solution. However, in PSO-TVIW the velocity update equation is modified by the construction factor C and the inertia weight w is linearly decreasing as iteration grows.

$$v_{pd}^{k+1} = C\left\{w.v_{pd}^{k} + C_1.rand_1.\left(pbest_{pd} - X_{pd}\right) + C_2.rand_2.\left(gbest_{gd} - X_{pd}\right)\right\}$$
$$w = \left(w_{\max} - w_{\min}\right).\frac{\left(K_{\max} - K\right)}{K_{\max}} + w_{\min} \tag{17}$$
$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|},$$

Where $4.1 \le \varphi \le 4.2$

As φ increases, the Construction factor decreases and convergence becomes slower because population diversity is reduced. Kennedy and Eberhart [22] described that a relatively high value of the cognitive component, compared with the social component, will result in excessive wandering of individuals through the search space. To overcome this, Ratnaweera et al. [] introduced a time varying acceleration co-efficient (TVAC), which reduces the cognitive component, c1 and increases the social component, c2 of acceleration co-efficient with time. With a large value of c1 and a small value of c2 at the beginning, particles are allowed to move around the search space, instead of moving toward pbest. A small value of c1 and a large value of c2 allow the particles converge to the global optima in the latter part of the optimization. The PSO-TVAC strategy finds a proper balance between the local and the global component and hence, the problem of premature convergence has been overcome to a much greater extent. PSO-TVAC is extended from TVIW. All coefficients including inertia weight and acceleration coefficients are varied with iterations. The velocity updating equation of PSO-TVAC can be expressed as,

$$v_{pd}^{k+1} = c\left\{w.v_{pd}^{k} + \left(\left(C_{1f} - C_{1i}\right)\frac{K}{K_{\max}} + C_{1i}\right).rand_1.\left(pbest_{pd} - X_{pd}\right) + \left(\left(C_{2f} - C_{2i}\right)\frac{K}{K_{\max}} + C_{2i}\right).rand_2.\left(gbest_{pd} - X_{pd}\right)\right\} \tag{18}$$

The parameters used for PSO, PSO- TVIW and PSO-TVAC to solve the proposed problem Congestion Management with optimal placement of TCSC are given in Table I.

Table I: Parameters variation for all techniques

Parameters	PSO	PSO-TVIW	PSO-TVAC
C1	2	2	C_{1i}=2.5
			C_{1F}=0.2
C2	2	2	C_{2i}=2.5
			C_{2F}=0.2
W	0.5	W_{min}=0.4	W_{min}=0.4
		W_{max}=0.9	W_{MAX}=0.9
C	--	$\varphi = 4.1$	$\varphi = 4.1$
No. of iterations	50	50	40

5. RESULTS AND DISCUSSION

To illustrate the efficiency of the proposed idea for congestion Management is applied on IEEE- 30 bus system. The numerical data for IEEE-30 bus system is taken from [25]. It consists of six generators and twenty four loads. To analyze the proposed approach different combinations of market structures comprising pool model and mix of pool plus bilateral and multilateral contracts taken for study are:

P: Pool model without bilateral and multilateral contracts.

C1: Pool model with one bilateral contract between buses 3-25.

C2: Pool model with two bilateral contracts between buses 3-25 and 8-21.

C3: Pool model with one multilateral contract between buses 3-25, 26.

C4: Pool model with one bilateral contract between bus 8-21and multilateral contract between 3-25, 26.

Because of these contracts congestion occurred between 1-2 & 2-6 lines as shown in Table I.

Table I: Congested line details for 30-bus system

Congested Line	Power flow (MW)	Line Limit (MW)
1-2	1.3748	1.00
2-6	1.546	1.00

As mentioned in section III, sensitivity analysis is carried out to find the optimal location of TCSC. The sensitivities based on real power flow performance index with respect to TCSC control parameter has been computed and shown in Table II. TCSC should be placed in a line having most negative sensitivity index. From the Table, the placement of TCSC in line 6-8 is optimal for reducing the *PI* and congestion relief.

Table II: Sensitivity indices for IEEE- 30 bus system

FROM	TO	P	C1	C2	C3	C4
5	7	-0.4521	-0.5983	-0.3981	-0.2904	-0.5621
6	**8**	**-0.8696**	**-0.7432**	**-0.8662**	**-0.7093**	**-0.8213**
12	15	-0.2378	-0.3143	-0.5894	-0.4729	-0.5598
14	15	-0.6529	-0.0018	-0.7142	-0.5109	-0.6731
21	22	-0.7721	-0.7021	-0.5583	-0.4670	-0.4390
28	27	0.7821	-0.4468	-0.7421	-0.4355	-0.3028

After selecting the optimum placement of TCSC for CM, then the criteria is minimization of TCSC cost using PSO, PSO-TVIW and PSO-TVAC. After placing TCSC, minimization of TCSC cost GENCOs' cost is solved under CEED environment and compared with Economic Load dispatch (ELD) and Economic Emission dispatch (EED) environment. The TCSC control parameters for Pool with bilateral/multilateral transactions under all environments using PSO, PSO-TVIW, and PSO-TVAC are listed in Table III. Here the Economic Load Dispatch (ELD) is computed based on minimum cost and Economic Emission Dispatch (EED) is computed based on minimum emission and Combined Economic Emission Dispatch (CEED) is computed based on penalty factor (*h*) approach. As explained in section III, similar procedure is followed and penalty factor is founded as 2.1346. The obtained results are compared with different dispatch environments as mentioned above i.e., ELD, EED & CEED.

Table III: TCSC control parameters for 30-bus system

		P	C1	C2	C3	C4
X_{TCSC} (P.U) (ELD)	PSO	0.3482	0.2841	0.3106	0.3287	0.339
	PSO-TVIW	0.2890	0.2367	0.2481	0.2523	0.2723
	PSO-TVAC	0.2583	0.2142	0.2207	0.2388	0.2491
X_{TCSC} (P.U) (EED)	PSO	0.3257	0.2658	0.2906	0.3075	0.3171
	PSO-TVIW	0.2703	0.2214	0.2321	0.2360	0.2547
	PSO-TVAC	0.2416	0.2004	0.2065	0.2234	0.2330
X_{TCSC} (P.U) (CEED)	PSO	0.3188	0.2601	0.2843	0.3009	0.3103
	PSO-TVIW	0.2646	0.2167	0.2271	0.2310	0.2493
	PSO-TVAC	**0.2365**	**0.1961**	**0.2020**	**0.2186**	**0.2280**

From the Table III, it is cleared that the TCSC control parameter is less under CEED environment than ELD and EED for all transactions. With this control parameter associated cost of TCSC is computed for all transactions under all dispatching environments is computed and listed in Table IV. GENCOs' cost during and after CM under all dispatching environments are listed in Table IV. From the Table IV, it is observed that GENCOs' cost is increased after CM under all dispatching environments. The GENCOs' cost after CM under ELD environment using PSO-TVAC is 2252.4 ($/hr) it is reduced to 2055.0 ($/hr). Similarly under all transactions GENCOs' cost is less in CEED environment than the ELD and EED. Under pool transaction with CEED environment the GENCOs' cost using PSO 2268.9 ($/hr) it is reduced to 2055.0 ($/hr) using PSO-TVAC. Similarly under all transactions GENCOs' cost is less using PSO-TVAC under all dispatching environments. After CM, under CEED environment the GENCOs' cost using PSO, PSO-TVIW and PSO-TVAC is depicted in Fig.2.

Table IV: Cost details for IEEE- 30 bus system during and after placing TCSC

($/hr)	Technique	P	C1	C2	C3	C4
	ELD					
During CM GENCOs' cost	PSO	2340.98	2331.82	2333.81	2336.00	2338.93
	PSO-TVIW	2259.9	2167.90	2186.4	2203.8	2215.5
	PSO-TVAC	2120.25	2106.54	2113.87	2115.66	2117.85
After CM GENCOs' cost	PSO	2486.9	2477.2	2479.3	2481.6	2484.8
	PSO-TVIW	2400.8	2303.1	2322.7	2341.2	2353.6
	PSO-TVAC	2252.4	2237.9	2245.7	2247.6	2249.9
TCSC Cost	PSO	782.21	746.06	759.52	763.64	771.17
	PSO-TVIW	772.03	736.36	749.65	753.71	761.14
	PSO-TVAC	741.87	715.93	721.10	731.63	736.80
	EED					
During CM GENCOs' cost	PSO	2452.5	2442.9	2445.0	2447.3	2450.4
	PSO-TVIW	2367.6	2.2712	2.2906	2.3088	2.3210
	PSO-TVAC	2221.3	2206.9	2214.6	2216.5	2218.7
After CM GENCOs' cost	PSO	2605.4	2595.2	2597.4	2599.8	2603.2
	PSO-TVIW	2515.2	2412.8	2433.4	2452.7	2465.7
	PSO-TVAC	2359.7	23445	2352.7	2354.7	2357.1
TCSC Cost	PSO	820.56	782.65	796.77	801.09	808.99
	PSO-TVIW	809.89	772.47	786.41	790.67	798.47
	PSO-TVAC	778.25	751.04	756.46	767.51	772.93
	CEED					
During CM GENCOs' cost	PSO	2135.8	2127.4	2129.2	2131.2	2133.9
	PSO-TVIW	2061.8	1977.9	1994.7	2010.6	2021.3
	PSO-TVAC	1954.4	1921.9	1928.6	1930.2	1942.2
After CM GENCOs' cost	PSO	2268.9	2260.0	2262.0	2264.1	2267.0
	PSO-TVIW	2190.3	2101.2	2119.1	2136.0	2147.3
	PSO-TVAC	2055.0	2041.7	2048.8	2050.6	2052.7
TCSC Cost	PSO	739.52	705.35	718.08	721.97	729.09
	PSO-TVIW	729.90	696.17	708.74	712.58	719.60
	PSO-TVAC	**691.6**	**636.86**	**651.75**	**661.71**	**676.59**
Computation Time (Secs)	PSO	111.49	103.61	105.56	107.41	109.17
	PSO-TVIW	100.20	93.92	96.99	97.21	98.07
	PSO-TVAC	**97.19**	**95.20**	**95.33**	**95.96**	**96.42**

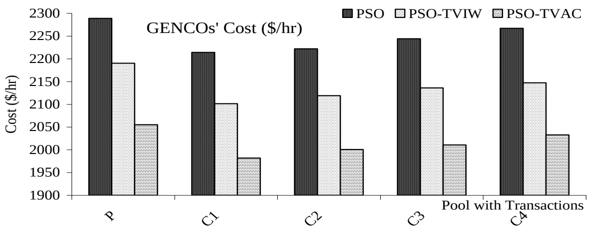

Fig.2.GENCOs' cost for all transactions after CM

The TCSC cost is also reduced using PSO-TVAC under all dispatching environment is listed in Table IV. Under CEED environment the TCSC cost using PSO, PSO-TVIW and PSO-TVAC is depicted in Fig. 3. The TCSC cost convergence criterion under CEED environment after CM using all techniques are depicted in Fig.4.

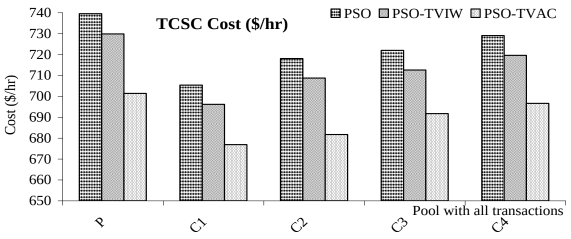

Fig.3.Cost of TCSC for all transactions

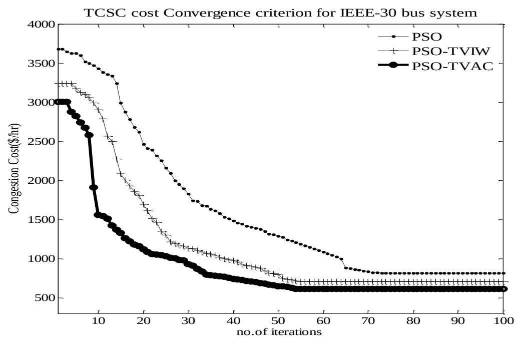

Fig.4.IEEE-30 bus system TCSC Cost convergence criterion

From the Fig.4, it is cleared that PSO-TVAC, PSO-TVIW and PSO finds better solution after 42, 54 and 69 iterations. So, for the proposed optimization problem PSO-TVAC converges faster than the PSO-TVIW and PSO. After placing TCSC the voltage profile under CEED environment using PSO-TVAC is depicted in Fig.5 and compared with during CM. From the Fig.5, it is cleared that after placing TCSC Voltage profile is improved. Similar results are observed under all dispatching environments. After placing TCSC in the line 6-8, the power flow in congested lines are shown in Table V.

Table V: Congested lines power flow after placing TCSC

Congested Line	Power flow (MW)			Line Limit (MW)
	ELD	EED	CEED	
1-2	0.9481	0.9932	0.8984	1.00
2-6	0.9527	0.9980	0.9028	

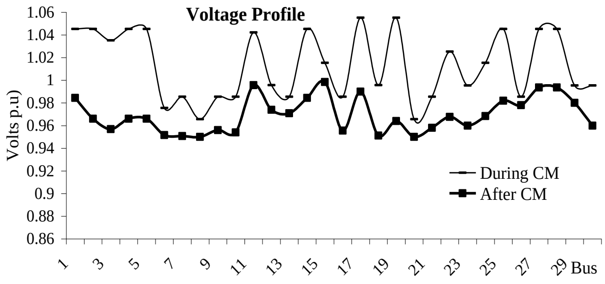

Fig.5.Voltage profile for IEEE-30 bus system during and after placing TCSC

6. CONCLUSION

This paper focuses on congestion management with optimal placement of TCSC using particle swarm optimization with time varying particle swarm optimization (PSO-TVAC) under CEED environment. Real power flow performance index is used to find the optimal placement of TCSC. The proposed algorithm has proper control on local optimum and global optimum, so that it can performs consistently and efficiently improves optimum solutions in the search space. Feasibility and robustness of the proposed method is tested on IEEE 30 bus system. From the results, TCSC cost and GENCOs' cost is less under CEED environment compared to ELD and EED environment using PSO-TVAC. The results of case study is shown that, PSO-TVAC would be an effective tool in handling transmission congestion in deregulated environment in term of solution quality and convergence characteristic and results in secure operating condition.

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