

Congestion Management under Hybrid Electricity Market using Self-organizing Hierarchical Particle Swarm Optimization

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ABSTRACT

This paper proposes an optimal congestion management approach under hybrid electricity market using Self organizing hierarchical particle swarm optimization with Time Varying Acceleration Coefficients (SPSO-TVAC). The aim of the proposed work is to minimize deviations from preferred transaction schedules and hence the congestion cost under hybrid electricity market. The values of Transmission Congestion Distribution factors (TCDFs) are used to select redispatch of generators. Generator reactive power support is considered to lower the congestion cost. Numerical results on IEEE 57 bus system is 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 SPSO-TVAC is one among the challenging optimization methods which is indeed capable of obtaining higher quality solutions for the proposed problem.

Keywords

Congestion Management; Congestion cost; Transmission Congestion Distribution Factors (TCDFs); Particle Swarm optimization (PSO); Self organizing hierarchical Particle swarm optimization with Time Varying Acceleration Coefficients (SPSO-TVAC)

1. INTRODUCTION

The issue of transmission congestion is more pronounced in the competitive environment. Electricity markets will not be able to operate at its competitive equilibrium with congestion in the system. The main objective of congestion management is to take the actions or control measures in relieving congestion of transmission networks and increasing the power transfer capabilities. Hence transmission congestion management (TCM) plays a significant role in power system operation in deregulated environment. Several techniques of congestion management have been reported in literature [1]. In general ISO will manage the congestion management using rescheduling of generators or load curtailment. Congestion occurrence can be experienced in various forms as reported by Besharat et. al [2] which describes that the congestion can be caused by transmission line outages, generator outages, changes in demand and uncoordinated transactions. Hazra and Sinha [3] has formulated congestion management problem a bi-objective optimization problem considering alleviation of overloads and minimization of cost of congestion management as two conflicting objective functions. Talukdar et al [4], a computationally simple method is proposed for congestion management using generation rescheduling and load shed. Kumar et al. [5] have developed real and reactive power flow sensitivity factors to determine real and reactive rescheduling for congestion management using Zonal

approach. Dutta and Singh [6] have used sensitivities of real power injection for rescheduling of real power generation for congestion management. Granelli et al. [7] introduced network reconfiguration is used to manage congestion to avoid costly generation or load curtailments.

Tao and Gross [8] worked on congestion relief in multilateral transaction framework, by making use of power flow over the lines to determine the contribution of individual contracts towards the congestion. Lo et al. [5] presented congestion management techniques applied to various kinds of electricity markets. Singh et al. [9], examines two approaches to dealing with management of costs. The first approach is based on pool model and the second approach is based on bilateral model. Shahidehpour et al. [10], OPF for coordination between generation companies and the ISOs for congestion management using the Benders cuts is discussed. Cutsem et al. [11], OPF is used to adjust the power injection in the least cost manner and optimal curtail transactions due to voltage instability and thermal overload. Yesuratnam and Tukkaram [12], relative electrical distance (RED) concept is introduced to mitigate the transmission overload by real power generation rescheduling. In this minimization of congestion cost is not considered. Amjady et al. [13] proposed a new congestion management framework considering dynamic voltage stability boundary of power system. Wang et al. [14], A Primal– dual Interior Point Linear Programming method is applied to solve congestion model. But these approaches have not been considered reactive power procurement. The reactive power procurement can supplement the real power to reduce the congestion cost, when the system is affected by congestion. Hence there is an urgent need for special attention to be given to reactive power procurement in congestion management of competitive electricity market. In order to operate the system in a secure manner ISO has to procure adequate amount of reactive power from various reactive resources in the system, e.g. generators, synchronous condensers and shunt capacitors. Singh et al.[16] proposed congestion management with reactive power support. Zhao et al.[15] considered the reactive power dispatch problem is a sub problem of the optimal power flow (OPF).

With the complexity of congestion management problem, an efficient heuristic approach is needed to provide the optimal solution. Different techniques have been employed to develop congestion management such as Genetic Algorithm (GA) [7], Modified benders decomposition [18], Interior Point Non-Linear programming [17], Artificial Bee Colony [18], Bacterial Foraging Algorithm [19], Particle Swarm Optimization [3], Fuzzy Evolutionary programming [21]. 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 [22] and further modifications in PSO algorithm were carried out [23-27]. PSO is a population of random solutions, which each individual is referred as a particle and presents a candidate solution to the optimization problem. A particle in PSO like any living objects has a memory in which remain its best experience and the best experience of other particles. In this technique, each candidate solution is associated with a velocity vector, which is adjusted according to the particle's memory. This procedure is repeated until almost all particles converge to the best solution. So in each particle's point of view, its own experience and the best experience of other particles are considered and the experience of others is not regarded. Therefore the probability of becoming trapped in local minima or maxima is increased so as to be premature convergence. 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. In contrast, a relatively high value of the social component may lead particles to rush prematurely towards a local optimum. To avoid this, Wu et al. [25] proposed Particle Swarm Optimization with Time Varying Acceleration Coefficients (PSO-TVAC) would enhance convergence toward the global optima. Later, Ratnaweera et al. [26-27] proposed self organizing hierarchical particle swarm optimization with time varying particle swarm optimization (SPSO-TVAC) algorithm to enhance proper control on local optimum and global optimum. So that it can performs consistently and efficiently improves optimum solutions in the search space. So, the proposed approach considered SPSO-TVAC algorithm to manage congestion under hybrid electricity market.

Therefore the main intent of the present work is to propose a new technique Self hierarchical organizing Particle Swarm Optimization (SPSO-TVAC) for Congestion Management (CM) under hybrid electricity market. Real and reactive power Rescheduling of GENCOs' has been considered to manage congestion in the system. Real and reactive power Transmission Congestion Distribution Factors (PTCDFs & QTCDFs) [5] are used for identifying sensitive GENCOs' for rescheduling. GENCOs' reactive power support is considered to reduce the congestion cost. The proposed algorithm SPSO-TVAC has proper control on local optimum and global optimum. This algorithm performs consistently and efficiently improves optimum solutions in the search space. The proposed objective congestion cost minimization is solved using SPSO-TVAC and the obtained results are compared with PSO and PSO-TVAC.

The main contributions of this paper are as follows:

- i. The proposed approach optimal congestion management under hybrid electricity market comprises of two steps. First step, step, real and reactive power Transmission Congestion Distribution Factors (PTCDFs & QTCDFs) are used to find sensitive GENCOs'. Second step rescheduling is performed on sensitive GENCOs' based on the minimization of congestion cost under hybrid electricity market.
- ii. Novel technique Self hierarchical organizing Particle Swarm Optimization (SPSO-TVAC) is used to

implement the proposed approach for Congestion Management under hybrid electricity market.

2. ADAPTIVE PARTICLE SWARM OPTIMIZATION

2.1 Overview of Particle Swarm Optimization (PSO)

All PSO is a simple and efficient population-based optimization method proposed by Kennedy and Eberhart [12]. 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 (7).

$$V_{id}^{K+1} = \omega V_{id}^K + c_1 rand_1(p_{id}^K - x_{id}^K) + c_2 rand_2(p_{gd}^K - x_{id}^K) \quad (1)$$

$$x_{id}^{K+1} = x_{id}^K + v_{id}^{K+1} \quad (2)$$

Here, V_{id}^K is the velocity of d^{th} dimension of the i^{th} particle in the K^{th} iteration, x_{id}^K is the corresponding position and p_{id}^K and p_{gd}^K is personal best and global best respectively. Finally, the position of the i^{th} particle for d^{th} dimension is updated by (2). 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].

$$v_{id}^{k+1} = C \{ w \cdot v_{id}^k + C_1 \cdot rand_1(p_{best_{id}} - X_{id}) + C_2 \cdot rand_2(g_{best_{gd}} - X_{id}) \} \quad (3)$$

$$w = (w_{max} - w_{min}) \cdot \frac{(K_{max} - K)}{K_{max}} + w_{min}$$

$$C = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}, \quad 4.1 \leq \varphi \leq 4.2$$

Generally for initial stages of the search process, large inertia weight to enhance the global exploration searching new area is recommended while, for last stages, the inertia weight is reduced for local exploration fine tuning the current search area. The velocity update equation is modified by the construction factor C and the inertia weight w is linearly decreasing as iteration grows. In The first component is the previous velocity which provides the necessary momentum for particles to roam across the problem space. The second is the cognitive component that represents the individual experience of each particle. The second component encourages the particles to move toward their own best positions reached. The last component is the social collaboration of the particles in finding the global optimal solution. The particles are pulled toward the global best particle reached. As φ increases, the 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. In contrast, a relatively high value of the social component may lead particles to rush prematurely towards a local optimum. Generally, in population-based optimization methods, it is desirable to encourage the individuals to wander through the entire search space, without clustering around local optima, during the early stages of the optimization. On the other hand, during the latter stages, it is important to enhance convergence toward the global optima, to find the optimal solution efficiently. Considering those concerns, Particle Swarm Optimization with Time Varying Acceleration Coefficients (PSO-TVAC) [25] is introduced. In PSO-TVAC method, the cognitive component is reduced and the social component is increased by changing the acceleration coefficients c_1 and c_2 . With a large cognitive component and small social component at the beginning, particles are allowed to move around the search space, instead of moving toward the population best. On the other hand small cognitive component and large social component allows the particles to converge to the global optima in the latter part of the optimization [25]. The acceleration coefficients are expressed as,

$$\left. \begin{aligned} C_1 &= (C_{1f} - C_{1i}) \frac{K}{K_{\max}} + C_{1i} \\ C_2 &= (C_{2f} - C_{2i}) \frac{K}{K_{\max}} + C_{2i} \end{aligned} \right\} \quad (4)$$

where C_{1i} , C_{1f} , C_{2i} and C_{2f} are initial and final values of cognitive and social acceleration factors, respectively.

2.2 Self-organizing hierarchical Particle Swarm Optimization with Time Varying Acceleration Coefficients (SPSO-TVAC)

In this novel PSO strategy the previous velocity term in (1) is made zero. With this modification the particles rapidly rush towards a local optimum solution and then stagnate because of the absence of momentum. To make this strategy effective, the velocity vector of a particle is reinitialized with a random velocity whenever it stagnates in the search space. When a particle stagnates, its associated p_{best} remains unchanged for a number of iterations. When more particles stagnate, the g_{best} also undergoes the same fate and the PSO algorithm converges prematurely to a local optima and v_{id} becomes zero. A necessary push to the PSO algorithm is imparted by reinitializing v_{id} by a random velocity term. The method works as follows [26]:

Main procedure

Velocity update equation in (1)

if $v_{\text{id}}=0$

if $\text{rand}3 < 0.5$

$v_{\text{id}} = \text{rand}4 * v_{\text{dmax}}$

else $v_{\text{id}} = -\text{rand}5 * v_{\text{dmax}}$

end if

$v_{\text{id}} = \text{sign}(v_{\text{id}}) * \min(\text{abs}(v_{\text{id}}, v_{\text{dmax}}))$

Position update equation in (2)

where $v_{\text{dmax}} = \frac{(x_{\text{dmax}} - x_{\text{dmin}})}{R}$,

Here v_{dmax} is the maximum velocity limit on the d^{th} dimension where x_{dmax} and x_{dmin} are the maximum and minimum position of particles on the d^{th} dimension, respectively, and R is a chosen number between 1 and 10 that reflects the percentage of dynamic range of the solution on each dimension. For example, R could be selected as 5 for the 20% maximum velocity limit. Thus a series of particle swarm optimizers are generated inside the main PSO until the convergence criteria is reached. The variables $\text{rand}_3, \text{rand}_4$ and rand_5 are randomly generated numbers between 0 and 1.

3. RESCHEDULING OF GENCO'S

In real time generally congestion is managed using re-scheduling of GENCOs and load curtailment. In corrective action congestion management schemes, it is crucial for ISO to select the most sensitive generators to re-schedule their real and reactive powers. In the proposed approach selection of most sensitive GENCO's for CM through sensitivity based approach using two sets of sensitivity indices, viz. Real and Reactive Power Transmission Congestion Distribution Factors (*PTCDFs* & *QTCDFs*) for congestion management [5]. After finding sensitive GENCO's, ISO will perform rescheduling of GENCO's based on minimization of cost using PSO, PSO-TVAC and SPSO-TVAC. So, the objective is to minimize the total costs for rescheduling power. To reduce the congestion cost GENCO's reactive power support is used. So, the proposed objective is,

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

The solution of above equation i.e., re-scheduling amount of each GENCO is obtained so that the following constraints are satisfied.

TCDFs:

$$\sum_{\substack{i=1 \\ \neq s}}^{N_G} ((PTCDF_i^k) \Delta P_i) + ((QTCDF_i^k) \Delta Q_i) + F_k^0 \leq F_k^{\max} \quad k=1,2,\dots,N_l \quad (6)$$

$$\text{where } \left. \begin{aligned} PTCDF_j^k &= \Delta P_{ij} / \Delta P_i \\ QTCDF_j^k &= \Delta Q_{ij} / \Delta Q_i; \quad i=1,\dots,n_b, i \neq s \end{aligned} \right\} \quad (7)$$

Power flow equations: The power flow equations as determined by Kirchhoff's laws are given by,

$$\left. \begin{aligned} P_{gi} - P_{di} - \sum_{j=1}^N V_i Y_{ij} V_j \cos(\delta_i - \delta_j - \theta_{ij}) &= 0 \quad i=1,2,\dots,n_b \\ Q_{gi} - Q_{di} - \sum_{j=1}^N V_i Y_{ij} V_j \sin(\delta_i - \delta_j - \theta_{ij}) &= 0 \quad i=1,2,\dots,n_b \end{aligned} \right\} \quad (8)$$

Ramp limit:

$$\left. \begin{aligned} \Delta P_i^{\min} \leq \Delta P_i \leq \Delta P_i^{\max} \quad i=1,2,\dots,N_g, i \neq s \\ \Delta Q_i^{\min} \leq \Delta Q_i \leq \Delta Q_i^{\max} \quad i=1,2,\dots,N_g, i \neq s \end{aligned} \right\} \quad (9)$$

Power limit of generation:

$$\left. \begin{aligned} P_i^{\min} \leq P_i + \Delta P_i \leq P_i^{\max} \quad i=1,2,\dots,N_G, i \neq s \\ Q_i^{\min} \leq P_i + \Delta P_i \leq Q_i^{\max} \quad i=1,2,\dots,N_G, i \neq s \\ V_i^0 - V_i^{\min} \leq \Delta V_i \leq V_i^{\max} - V_i^0 \quad i=1,\dots,N \end{aligned} \right\} \quad (10)$$

Power balance constraint:

$$\left. \begin{aligned} P_{Gm} - P_{Dn} = 0, Q_{Gm} - Q_{Dn} = 0 \\ \sum_m P'_{Gm} - \sum_n P'_{Dn} = 0, \sum_m Q'_{Gm} - \sum_n Q'_{Dn} = 0, \quad t=1,2,\dots,N_t \end{aligned} \right\} \quad (11)$$

Transmission line limits: Transmission line flows are bounded by thermal limits for short lines and stability limits for long lines.

$$S_l \leq S_l^{\max} \quad l = 1, 2, \dots, N_L$$

where, PGm and QGm stand for the real and reactive power transactions into the seller bus-m, respectively and PDn and QDn are the real and reactive powers taken out at the buyer bus-n, respectively and t represents the total number of such transactions. 't' represents bilateral/multilateral transaction.

Rescheduling Cost:

Here Rescheduling cost is considering both Fuel cost coefficients and emission coefficients.

$$C_{pi}(\Delta P_i) = F(\Delta P_i) + E(\Delta P_i) \quad (5)$$

Minimization of Fuel Cost:

$$F(\Delta P_i) = a_i(\Delta P_i)^2 + b_i(\Delta P_i) + C_i$$

C_{pi} is the cost of the active power rescheduling according to the bid functions submitted by the generators participating in congestion management.

Minimization of Emission:

The total emission $E(\Delta P_i)$ in (ton/hr) of atmospheric pollutants such as sulphur oxides (SO_x) and nitrogen Oxides (NO_x) caused by the operation of fossil fuelled thermal generation can be expressed as,

$$E(\Delta P_i) = \sum_{i=1}^N 10^{-2} (\alpha_i + \beta_i(\Delta P_i) + \gamma_i(\Delta P_i^2)) + \zeta_i \exp(\lambda_i(\Delta P_i))$$

Where $\alpha_i, \beta_i, \zeta_i$ and λ_i are coefficients of the i^{th} generator emission characteristics.

Generator Reactive Power support:

$$C_{qi}(\Delta Q_i) = \left[C_{pi}(S_{Gi\max}) - C_{pi}(\sqrt{S_{Gi\max}^2 - \Delta Q_i^2}) \right] k_i \quad (6)$$

Where, C_{qi} is the cost of the Reactive power rescheduling, C_{pi} is the active power generation cost, $S_{G\max}$ 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 $S_{Gi\max} = P_{Gi\max}$

As mentioned in section II, the proposed objective is solved using PSO, PSO-TVAC and SPSO-TVAC. To now the efficiency of proposed approach is applied on IEEE- 30 bus and IEEE- 57 bus system. So, next section is dealing with results and discussion.

4. RESULTS AND DISCUSSION

As mentioned in section I, the proposed problem comprising of two steps. First step, sensitive GENCOs' are selected for CM through sensitivity based approach using two sets of sensitivity indices, viz. *PTCDFs* & *QTCDFs*. Second step, based on the available bids ISO will perform rescheduling of GENCOs' based on minimization of cost using PSO, PSO-TVAC and SPSO-TVAC. To illustrate the efficiency of the proposed idea for congestion Management is applied on IEEE- 57 bus system. The parameters used for PSO, PSO-

TVAC and SPSO-TVAC to solve the proposed problem are given in Table I.

Table I: Parameters variation for all techniques

Parameters	CPSO	PSO-TVIW	PSO-TVAC	SPSO-TVAC
C1	2	2	$C_{1i}=2.5$	$C_{1i}=2.5$
			$C_{1F}=0.2$	$C_{1F}=0.2$
C2	2	2	$C_{2i}=2.5$	$C_{2i}=2.5$
			$C_{2F}=0.2$	$C_{2F}=0.2$
W	0.5	$W_{\min}=0.4$ $W_{\max}=0.9$	$W_{\min}=0.4$ $W_{\max}=0.9$	0
C	--	$\phi = 4.1$	$\phi = 4.1$	--
Computation time (Secs)	121.43	119.66	103.45	89.76
No. of iterations	60	60	50	50

IEEE-57 bus system:

The proposed approach congestion management under hybrid electricity market using SPSO-TVAC is tested on IEEE-57 bus system. The numerical data for IEEE-57 bus system are taken from [27]. It consists of seven GENCOs' and eighty transmission lines. To analyze the proposed approach different combinations of market structures comprising pool model and mix of pool plus bilateral and multilateral contracts are considered and listed in Table II.

Table II: Bilateral/ Multilateral transactions in IEEE-57 bus system

Transactions	From	To	Power (MW)
T1 (Bilateral)	7	33	12
	11	24	12
T2 (Bilateral)	7	33	10
	7	33	16
T3 (Multilateral)	7	26	16
	11	24	
T4 (bilateral & Multilateral)	7	33	14
	7	26	
	11	24	

Because of these contracts congestion occurred between 3-4 & 6-9 lines. The congested line details are given in Table III.

Table III: Congested line details for IEEE-57bus system

Congested lines	Power flow in lines			Line limit (MW)
	PSO	PSO-TVAC	SPSO-TVAC	
6-7	114.97	113.53	112.33	100
14-15	163.77	162.45	160.03	150

To perform CM firstly sensitive GENCOs' are selected based on *PTCDFs* and *QTCDFs*. In this system, *PTCDFs* and *QTCDFs* are computed for the congested lines 6-7 and 14-15 and depicted in Fig. 1 (a) & (b).

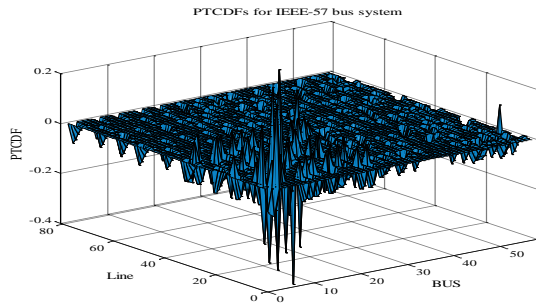


Fig.1 (a). PTCDFs for IEEE- 57 bus system

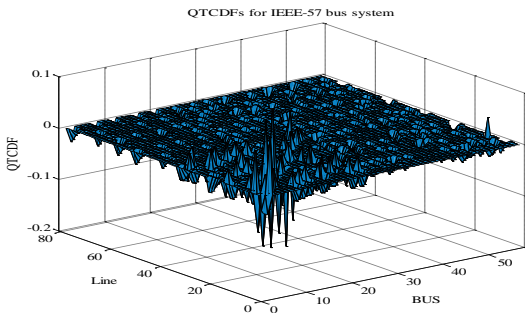


Fig.1 (b) QTCDFs for IEEE- 57 bus system

Table IV: Rescheduling results for IEEE-57 bus system

Active Power Re-scheduling						
Genco	Technique	P	T1	T2	T3	T4
G2	PSO	+4.44	+2.21	+2.45	+2.97	+3.31
	PSO-TVAC	+3.59	+2.03	+2.25	+2.73	+3.03
	SPSO-TVAC	+3.03	+1.80	+1.99	+2.43	+2.70
G12	PSO	+11.33	+7.96	+8.60	+9.11	+10.28
	PSO-TVAC	+10.15	+6.55	+8.04	+8.34	+9.48
	SPSO-TVAC	+9.36	+6.03	+6.53	+7.63	+8.72
G9	PSO	-8.49	-5.81	-6.67	-6.99	-7.34
	PSO-TVAC	-7.32	-5.24	-5.96	-6.34	-6.93
	SPSO-TVAC	-5.95	-3.62	-4.08	-4.54	-5.16
G3	PSO	-6.68	-3.93	-4.59	-5.38	-5.83
	PSO-TVAC	-5.91	-3.66	-4.26	-4.56	-5.07
	SPSO-TVAC	-4.17	-2.37	-2.93	-3.29	-3.67
Reactive power Re-scheduling						
Genco	Technique	P	C1	C2	C3	C4
G3	PSO	+3.70	+1.80	+2.14	+2.66	+3.06
	PSO-TVAC	+3.13	+1.30	+1.83	+2.23	+2.60
	SPSO-TVAC	+2.88	+1.73	+1.94	+2.31	+2.67
G9	PSO	+4.16	+2.07	+2.76	+2.97	+3.48
	PSO-TVAC	+3.36	+1.90	+2.11	+2.55	+2.84
	SPSO-TVAC	+2.84	+1.68	+1.86	+2.28	+2.52
G2	PSO	-1.75	-0.99	-1.19	-1.35	-1.56
	PSO-TVAC	-1.68	-0.94	-1.14	-1.29	-1.48
	SPSO-TVAC	-1.58	-0.90	-1.07	-1.22	-1.39
G12	PSO	-6.48	-4.95	-5.33	-5.54	-5.91
	PSO-TVAC	-5.58	-4.55	-4.30	-4.81	-5.07
	SPSO-TVAC	-4.64	-3.00	-3.57	-3.86	-4.29

From the Fig. 1(a) it is observed that GENCOs' G2, G12, G9 & G3 are having large PTCDFs and are selected for real power rescheduling. Similarly, From the Fig. 1(b) it is observed that GENCOs' G3, G9, G2 & G12 are having large QTCDFs and are selected for reactive power rescheduling. After selecting sensitive GENCOs' ISO will perform GENCOs' rescheduling based on minimization of cost using PSO, PSO-TVAC and SPSO-TVAC and the amount of rescheduling is listed in Table IV. From the Table IV, it is observed that GENCOs' G2 and G12 are increased real power and G8 and G3 are decreased real power to manage congestion. Similarly, GENCOs' G3 and G9 are increased

reactive power and G2 and G12 are decreased reactive power to manage congestion in the system. Under pool transaction, GENCO G2 increased real power 4.44 MW using PSO and it is reduced to 3.59 MW using PSO-TVAC and 3.03 MW using SPSO-TVAC. Similarly under all transactions real and reactive power rescheduling amount is reduced using SPSO-TVAC than PSO and PSO-TVAC. So, SPSO-TVAC is performed better than PSO and PSO-TVAC for the objective minimization of GENCOs' rescheduling amount, hence congestion cost. Based on the real and reactive power rescheduling congestion cost is computed and listed in Table V.

Table V: Cost details for IEEE-57 bus system

(\$/hr)	Techniques	Pool	T1	T2	T3	T4
Congestion cost	PSO	875.61	683.42	721.65	769.11	810.24
	PSO-TVAC	788.68	610.53	650.16	691.15	719.79
	SPSO-TVAC	692.53	529.98	570.76	617.13	650.82
During CM GENCOs' cost	PSO	3044.0	2506.6	2655.4	2741.5	2896.7
	PSO-TVAC	2826.1	2448.5	2586.8	2659.5	2796.4
	SPSO-TVAC	2730.8	2379.5	2413.1	2579.9	2608.9
After CM GENCOs' cost	PSO	3221.8	2335.4	2493.0	2689.9	2960.0
	PSO-TVAC	3121.9	2263.0	2415.7	2606.6	2868.2
	SPSO-TVAC	3024.8	2192.7	2340.6	2525.5	2779.1

From the Table V, it is observed that congestion cost under pool transaction is 875.61(\$/hr) using PSO and it is reduced to 788.68 (\$/hr) using PSO-TVAC and 692.53(\$/hr) using SPSO-TVAC. Similarly for all transactions congestion cost is reduced using SPSO-TVAC than PSO and PSO-TVAC. For the comparison of congestion under all transactions using PSO, PSO-TVAC and SPSO-TVAC is depicted in Fig. 2. From the Fig.2 it is cleared that congestion cost is reduced using SPSO-TVAC under all transactions. So, SPSO-TVAC is performed better than PSO and PSO-TVAC to solve the objective of congestion cost minimization.

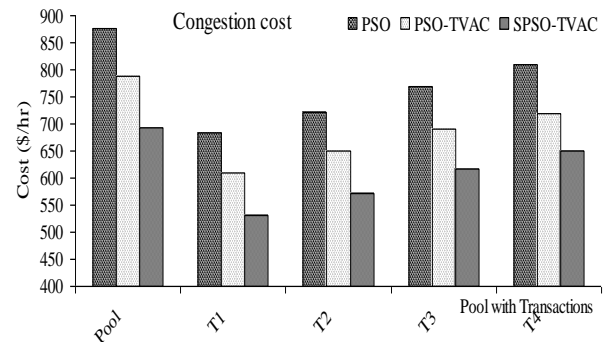


Fig.2. Congestion cost details for IEEE- 57 bus system

The congestion cost convergence criterion under pool transaction using PSO, PSO-TVAC and SPSO-TVAC is depicted in Fig.6. From the Fig.6, it is observed that PSO finds better solution after 76 iterations, PSO-TVAC finds better solution after 57 iterations and SPSO-TVAC finds better solution after 51 iterations. So, SPSO-TVAC is performed better than PSO-PSO-TVAC and SPSO-TVAC, hence convergence time.

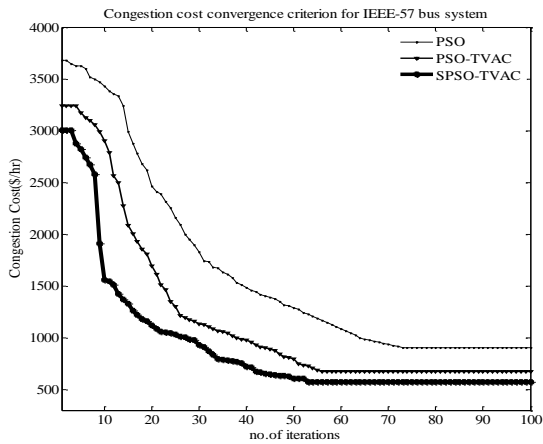


Fig.3. Congestion cost convergence criterion for IEEE- 57 bus system

After performing CM, the power flow in the congested line is listed in Table VI.

Table VI: Congested line details after CM for IEEE-57 bus system

Congested lines	Power flow in lines			Line limit (MW)
	PSO	PSO-TVAC	SPSO-TVAC	
6-7	99.44	98.66	98.02	100
14-15	149.47	148.85	148.21	150

After performing CM, based on the available bids and power dispatch GENCOs' cost is computed and compared with GENCOs' cost during CM is listed in Table V. From the Table V, it is observed that under pool transaction during CM using PSO is 3044.0 (\$/hr) and it is increased to 3221.8(\$/hr). Similarly, for all transaction GENCOs' cost is increased after CM. under pool transaction GENCOs' cost after CM using PSO is 3221.8(\$/hr) it is reduced to 3121.9(\$/hr) using PSO-TVAC and 3024.8(\$/hr) using SPSO-TVAC. Similarly for all transaction during and after CM using SPSO-TVAC GENCOs' cost is lesser than PSO and PSO-TVAC. From the obtained results, SPSO-TVAC is performed better for congestion management using rescheduling of GENCOs' under hybrid electricity market.

5. CONCLUSION

This paper focuses on congestion management under hybrid electricity market using self organizing hierarchical particle swarm optimization with time varying particle swarm optimization (SPSO-TVAC). 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. The proposed approach is considered to manage congestion in the system by GENCOs' real and reactive rescheduling. GENCOs' reactive power support is helping to reduce the congestion cost. After Congestion Management total GENCOs' cost is increased for all transactions. From the results obtained demonstrate the performance of the proposed approach transmission congestion under hybrid electricity market based SPSO-TVAC in term of solution quality and convergence characteristic.

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