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Economic Power Dispatch of Independent Power Producer Using Gray Wolf Optimization

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Abstract

Economic Power Dispatch (EPD) is a useful tool for optimal operation and planning of a modern power system. Optimal generation is made to cost effective. Conventional methods have the assumption on fuel cost characteristics of a generating unit which is a continuous and convex function that results fairly satisfied. This proposed work is to design and apply efficient Gray Wolf Optimization (GWO) technique for the solution of optimal generation. Here the non-convex characteristics of the generator along with the ramping limits of the practical generator operation are considered for the computation. By using optimal generation of the conventional method is carried out for 26 bus system with six generating units having ramp rate limits are taken for computation in Matlab environment. The performance of the GWO algorithm is estimated by multi-line contingency and combined bilateral and multilateral wheeling transactions conditions. The results are compared with Autonomous Group of Particle Swarm Optimization (AGPSO) and found GWO method performs better in solving Economic power dispatch problem.

Keywords: Power Flow, Ramp Rate limits, Autonomous Group of Particle Swarm Optimization, Gray Wolf Optimization, Piecewise Linear Ramp Rate

1. Introduction

The power industries have the conventional EPD problem involves a location of different thermal generating units to minimize the operating cost subjected to equality and inequality constraints. The EPD problem is a large scale highly non-linear constrained optimization problem such as linear programming, quadratic programming, non-linear programming, interior point and Newton-based method. All these methods are made in an assumption that the generation of fuel cost characteristics of a power producer is a smooth and convex function. For example, this situation originates when ramp rate limit and valve-point loading are present in these condition to represent the unit's operating fuel cost characteristics are as convex. So far, the accurate global optimum of the problem could not be reached simply. A novel method is needed to survive with these technique complication and those with high pace search to the optimal and not being fascinated in local minima. In order to optimize the operational cost of power system subjected to the system operating constraints such non- linear problem had explored by Computational Artificial Intelligence (CAI) by many researchers to get optimal solution.

Optimization techniques [1] are meta-heuristics and these are quite simple and inspired by simple concepts typically related with the corporeal phenomena of evolutionary concept and behaviour of animal such meta-heuristics have the flexibility at local optima avoidance. Meta-heuristics are two classes they are single solution based and another is population based. Simulated Annealing (SA) [2] is a search process that starts with the single candidate and improves over the iteration process, Genetic Algorithm (GA) [3] is population based, where the optimization is carried out by set of solutions. Search process start with random initial solution and improved over the iteration process. Artificial Bee Colony (ABC) [4] is the concept of Swarm Intelligence (SI) [5] is coming under the population based meta-heuristics. This Swarm Intelligence (SI) was proposed by Bonabeau, et al [6]. It explains the collective intelligence of group of simple agents. Some of the most popular SI technique are Ant Colony Optimization (ACO) [7], Particle Swarm Optimization (PSO)[8], ABC[4], (AGPSO)[9]. The search process of the meta-heuristics is having the two phases which are exploration and exploitation [10-14] balancing these two phases are challenging task because of stochastic nature. Modified PSO are named as Autonomous Groups of Particles Swarm Optimization (AGPSO) [9]. It is inspired by the individual diversity in swarm flocking (Intersect swarming) which is used for solving high-dimensional problem such as slow convergence rate and trapping in local minima. Every individual in a natural colonies are not similar in ability and intellectual they do their duty as associate member of a colony. In some critical situation each individual's ability is very helpful.

This autonomous group proposed by mathematical model of diverse particles: curvatures, diverse slopes and interception point are called as functions which are employed to tune the social and cognitive parameter of the particle swarm optimization algorithm. These AGPSO are recently modified in terms of convergence speed and escaping local minima. In this proposed work the Gray wolf optimization (GWO) [15] is used to solve the EPD, non-convex, non-continuous, non-linear cost function. An application was performed on the 26 bus test system with six generating units having the ramping limits [16]. The result obtained through the GWO, AGPSO [9] includes AGPSO1, AGPSO2, AGPSO3, SPSO, MPSO, IPSO, TACPSO which were compared and it confirms the efficacy of likely GWO in terms of upshot excellence, reliability.

2. Problem Formation

Mathematically optimization of fuel cost of each power producers in the system has been formulated based on power flow problem with line flow constraints and the overall generation cost of power system is expressed as following form:

$$\text{Minimize } F(G) = \sum_{j=1}^{ng} (f_j \ (p_j\,)) \tag{1}$$

Where F(G) is the operating fuel cost of j^{th} power producer and n_g is the number of power producers in the given power system network.

The fuel cost function of a j^{th} power producer is written as:

$$f_j(p_j) = a_j + b_j P_j + c_j \ P_j^2 \quad \$/h \tag{2}$$

Where p_j is active power output of an j^{th} power producer, $f_j(p_j)$ is the fuel cost of j^{th} power producer and a_j, b_j, $c_j$are the fuel cost co-efficient of the j^{th} power producer.

Power balance constraint is net power generated by the power producers which includes system load demand as well as losses in transmission network.

$$\sum_{j=1}^{ng} p_j - p_l - p_d = 0 \tag{3}$$

Equation (3), is denotes the constraint of power balance equation for EPD, Where $p_d$is the total load of the system and $p_l$is transmission losses in the system.

The output level of the power producer which expressed as

$$p_{L=}\sum_{j=1}^{ng}\sum_{k=1}^{ng}B_{jk}p_kp_k+\sum_{j=1}^{ng}p_jB_{j0}B_{00} \tag{4}$$

Equation (5) denotes the Kron's loss formula which approximated the losses as a function of the system output level.

$Where 1 \leq j$ and $k \leq ngare$ power producers indexes and B_{jk}, B_{j0}, B_{00} are co-efficient of losses (or) B loss co-efficient. $B_{jk}$is (ng x ng) matrix.

The inequality constraint on real power generation $P_j$of each power producer j is given by:

$$p_{jmin} \leq p_j \leq p_{jmax} \tag{5}$$

Ramp Rate limits is an inequality constraint of the power producer and it can be either increases (or) decreases the power generation.

In 24 hours, horizon all the on-line units have operating ranges which are restricted by their elastic limits or Ramp Rate limits. Whenthepowerproducersoperatewithinthe elastic limits [17-20]. Ifpower producersarepermittedtowidentheirlimits,thelifeoftherotorwillbegetting fatigue. These inequality constraints of Ramp Rate limits are expressed as:

$$p_j - p_{j0} \leq U_{rj} \tag{6}$$

$$p_{j0} - p_j \leq D_{rj} \tag{7}$$

Equation (6 & 7) denote the increase in power generation and decrease in power generation due to Ramp Rate limit U_{rj} and D_{rj} are Ramp up Rate and Ramp down Rate.

Combining (5,6&7) which gives the following equation:

$Where$ is the maximum rating of transmission line connecting p and q.

$$max\ (p_{jmin}, p_{j0} - D_{rj}) \leq p_j \leq min\ (p_{jmax}, p_{j0} + U_{rj}) \tag{8}$$

$$MVAf_{p,q} \leq MVAf_{p,q}^{max} \tag{9}$$

3. Overview of Particle Swarm Optimization

PSO is a robusts to chastic optimization technique based on the movement and cleverness of swarms. Concept of social interaction is applied by PSO for solving a real time problem. InPSOa swarm movesaroundinthesearch spaceandlooksfor theparamountsolution. Eachandeveryparticletracksandcoordinates inthesolution spaces that areassociatedwiththebest fitnessvalueachievedsofarbyaparticularparticle. This value is called personal best (p_{id}).Another best value tracked by the PSO is the best value attained so far by any neighboring particle called global best(p_{gid}).The basic concept of PSO lies in accelerating each particle toward it's (p_{id}) and the (p_{gid}) locations, with a random weighted acceleration at each time step. Eachparticlecorrespondstoacandidatesolutionofthe problem. The particle reaches the optimal solution based on its own experience and the experience of its companions. The velocity of each particle is updated by the following equation:

$$v_{id}^{n+1} = w * v_{id}^{n} + c_1 * rand1 * (p_{id} - x_{id}) + c_2 * rand2 * \left(p_{gid} - x_{id}\right) \tag{10}$$

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \tag{11}$$

Where

v_{id}^{n}	: velocityofagent (i)at iteration
w	:weightingfunction
c_1, c_2	:weightingfactor
rand1, rand2	: uniformlydistributedrandom number (0&1)
x_{id}^{n}	:currentpositionofagent (i)atiteration (n)
p_{id}	:pbestofagent (i),
p_{gid}	:gbestofthe group

ThestepbystepprocedureforPSOalgorithmisgiven asfollows:

- Initializethepositionandvelocityofthe particles.
- Checkstoppingcriteria,if yes stopelsego to step3,

- Checkwhetheralltheparticlesarechecked,if no go tostep4 elsego tostep6,
- Computefitnessvalue,
- Update(p_{id})andgo tostep3,
- Computeinertia weight,
- Update(p_{gid}),and Updatevelocity,
- Checkvelocitylimits,
- Updateparticleposition,
- Checkfeasibilitylimitandgotostep2.

3.1 Autonomous group of particle swarm optimization

Particle swarm optimization deals with the fine tuning of the weighing factor c_1 and c_2, by balancing these weighting factor the global minima is found along with the fast convergence speed is also achieved. Here the researchers propose the Autonomous Group Particle Swarm Optimization [9] concept as per modification of the existing PSO technique. In this search space of AGPSO, according to its own strategy is related to the tuning of c_1 and c_2, these autonomous groups contains linear, constant, and exponential of time varying parameters of c_1 and c_2. AGPSO concept is inspired by individual in its group of particle. Individual in a group of particle is not quite same as in their ability and intelligence. Each individual do their duties as a member of workgroup. In some particular situation the ability of individual is very useful to perform their objective. Consider a termite colony that consist of four various termites such as worker, queen, babysitter and solider having various ability to battle with enemies. The diverse ability of an individual in a workgroup is very important for survival from their enemies.

These four termites are considered as four autonomous groups, all termites work together with common objective of their colonys' survival. By using their divergence ability of an individual in an autonomous group with common objective in any population based optimization algorithm hypothetically provides result in additional randomized and direct search concurrently. The mathematical model of Autonomous group PSO are using the various strategies of updating c_1 and c_2, strategies updated by implementing with continuous function with the interval. Those functions may be either ascending or descending linear and polynomial, as well as logarithmic nature and which are used to update the social factor and cognitive. The modified Autonomous group includes AGPSO1, AGPSO2 and AGPSO3. The dynamic co-efficient of these modified autonomous group are given in Table 1. Here the maximum number of iteration is represented as 'T' and the current iteration is represented as't '.

Table 1. Updating strategies of Autonomous group particle swarm optimization.

Group	Updating strategies of various AGPSO					
	AGPSO1		AGPSO2		AGPSO3	
	c_1	c_2	c_1	c_2	c_1	c_2
G1	$(-2.05/T)^t + 2.55$	$(1/T)^t + 1.25$	$2.5-(2log(t)/log(T))$	$(2log(t)/log(T)) + 0.5$	$1.95-2t^{1/3}/T^{1/3}$	$2t^{1/3}/T^{1/3} + 0.05$
G2	$(-2.05/T)^t + 2.55$	$(2t^3/T) + 0.5$	$(-2t^3/T^3) + 2.5$	$(2t^3/T^3) + 0.5$	$(-2t^3/T^3) +2.5$	$(2t^3/T^3) +0.5$
G3	$(-2t^3/T^3) + 2.5$	$(1/T)^t + 1.25$	$0.5+ 2exp[-(4t/T)^2]$	$2.2-2exp[4t/T)^2]$	$1.95-2t^{1/3}/T^{1/3}$	$(2t^3/T^3) +0.5$
G4	$(-2t^3/T^3) + 2.5$	$(2t^3/T^3) + 0.5$	$2.5+ 2(t/T)^2-2(2t/T)$	$0.5-2(t/T)^2+ 2(2t/T)$	$(-2t^3/T^3) +2.5$	$2t^{1/3}/T^{1/3} +0.05$

AGPSO updating strategies contains the logarithmic and exponential functions for c_1 and c_2 which are made effective on the performance of the PSO. These divergent functions are chosen with various curvatures, slopes and intersecting point to examine the effectiveness of these characteristics and to improve the performance of particle swarm optimization. AGPSO could be more efficient and better adaptable than the general PSO in solving a wide range of complex optimization problem.

AGPSO is compared with some modified PSO, the Time varying accelerator are recent modified particle swarm optimization such as SPSO [6], MPSO [21], IPSO [22], TACPSO [23] and their c_1 and c_2 co-efficient are given in Table 2.

Table2. Updating strategies of Modified Particle swarm optimization

Algorithms	Updating strategies of Modified PSO	
	c_1	c_2
SPSO	2	2
MPSO	$(-2.05/T)^t + 2.55$	$(1/T\,)t +1.25$
IPSO	$2.5 + 2(t/T)^2 - 2(2t/T)$	$0.5- 2(t/T\,)^2 +2(2t/T)$
TACPSO	$0.5+ 2exp[-(4t/T)^2]$	$2.2-2exp[-(4t/T)^2]$

4. Gray wolf optimization

The Gray wolf optimizer deals with the nature of social behavior of gray wolves towards group hunting with headship hierarchy [15]. To design and execute the optimization, four types of gray wolves are involved they are alpha (α), Beta (β), delta (δ) and omega (ω). The mathematical model of GWO is working for simulating the headship hierarchy besides three main phases of GWO hunting are searching for quarry (chasing, tracking and approaching the quarry),encircling quarry(pursuing and harassing the quarry until it stop moving) and attacking quarry(attack towards the quarry)[15].

The mathematical models of hunting optimization of gray wolves are designed as follows: The first fittest solution as alpha (α), second best solution as Beta (β), third best solution as delta (δ) and the remaining gray wolves are omega (ω) and this is the lowest among the other respectively.

Encircling quarry (pursuing and harassing the quarry until it stops moving) is modelled as follows:

$$\vec{S} = \left|\vec{R} * \vec{x_i}(k) - \vec{x}(k)\right| \tag{12}$$

$$\vec{x}(k+1) = \vec{x_i}(k) - \vec{P} * \vec{S} \tag{13}$$

Where

k : Indicates the present iteration
$\vec{P}$ and $\vec{R}$: Coefficient vector
$\vec{x_i}$: Position vector of the quarry
$\vec{x}$: Position vector of a gray wolf

$\vec{P}$ and $\vec{R}$are calculated as follows:

$$\vec{P} = 2 * \vec{w} * \vec{c_1} - \vec{w} \tag{14}$$

$$\vec{R} = 2 * \vec{c_2} \tag{15}$$

Here $\vec{w}$ decrease linearly from 2 to 0 during the iteration process, $\vec{c_1}$ and $\vec{c_2}$ are random vector in [0, 1].

If the gray wolf in some position and it can update its position according to the position of the quarry. From the various positions of the agents the best agent adjusts its current position and reached the quarry by adjusting the co-efficient vectors. Random vectors permit the wolves to reach any position inside the search space around the quarry in any random position by the equation (12) and (13). The hunting is guided by alpha along with beta and delta which hunt together (participating). The alpha, beta and delta have the better knowledge towards location point of the quarry and omegas are updating its position according to the alpha, beta and delta it is mathematically expressed as follows:

$$\overrightarrow{S_\alpha} = \left|\overrightarrow{R_1} * \overrightarrow{x_\alpha} - \vec{x}\right| \tag{16}$$

$$\overrightarrow{S_\beta} = \left|\overrightarrow{R_2} * \overrightarrow{x_\beta} - \vec{x}\right| \tag{17}$$

$$\overrightarrow{S_\delta} = \left|\overrightarrow{R_3} * \overrightarrow{x_\delta} - \vec{x}\right| \tag{18}$$

$$\overrightarrow{x_1} = \overrightarrow{x_\alpha} - \overrightarrow{P_1} * \overrightarrow{S_\alpha} \tag{19}$$

$$\overrightarrow{x_2} = \overrightarrow{x_\beta} - \overrightarrow{P_2} * \overrightarrow{S_\beta} \tag{20}$$

$$\overrightarrow{x_3} = \overrightarrow{x_\delta} - \overrightarrow{P_3} * \overrightarrow{S_\delta} \tag{21}$$

$$\vec{x}(k+1) = \frac{\overrightarrow{x_1} + \overrightarrow{x_2} + \overrightarrow{x_3}}{3} \tag{22}$$

Attacking quarry or exploitation by the gray wolves finishes the quarry when it stops moving. In mathematically this can be expressed as by decreasing the value of the $\vec{w}$ likewise the $\vec{P}$ also decrease from 2 to 0 in the overall iteration. When $\vec{P}$ are in [-1, 1], the next location point of the search agent can be in any location between its current location point and the location point of the quarry if $|\vec{P}| < 1$ the strength of the wolves assault in the direction of the quarry. Therefore Gray wolf optimizer algorithm allows its wolves to update the location point based on the alpha, beta and delta wolves and hunting towards the quarry which is the local best solution. The vector $\vec{P}$ is utilized with an unsystematic value higher than 1 or lesser than -1 to fondness the wolves to diverge from the quarry and it emphasizes the look for quarry and let the gray wolf optimizer to search globally. Another component $\vec{R}$ to exploration it contains unsystematic values[0, 2] and it provides the unsystematic weight of the quarry to $\vec{R} > 1$ or $\vec{R} < 1$ the effect of quarry in defining the distance and it help to GWO as more unsystematic behaviour during the optimization, which favour the searching and the avoidance of local optimum solution. $\vec{R}$is not linearly reduce in contrast of $\vec{P}$ and this component is very useful in final iteration. Finally the GWO algorithm stops by fulfilment of the end criterion.

5. Simulation Result and Discussions

The operation of the generating unit is narrow with their power limits (real and reactive). But in real situation load commitments beyond their power limits for a given time duration contingencies, multiple contingencies combined bilateral and multilateral wheeling transactions. This type of functioning will cause rotor fatigue. Even though reliability of power system operation must need to take care and this operation is foreseeable. Therefore, generating units are realistically compensated by the system operators. The change in state of their operation is also narrow by their RR limits. If any violation regarding the elastic RR limits for maintaining the system protection. The RR limits and fuel cost are taken from [16].The power producer has operating power limits and operating power along with the RR limit to get new operating power limits shown below in Table 3.

Table 3. Power generation limits after adding Ramp Rate limits

Gen no.	P_{jmin}	P_{jmax}	P_{i0}	Drj	Urj	$P_j{}'_{min}$	$P_j{}'_{max}$	a_j	b_j	C_j
G1	100	500	440	80	120	321	500	240	7	0.0070
G2	50	200	170	50	90	80	200	200	10	0.0095
G3	80	300	200	65	100	101	266	220	8.5	0.0090
G4	50	150	150	50	90	60	150	200	11	0.0090
G5	50	220	190	50	90	100	220	220	10.5	0.0085
G6	50	120	111	50	90	50	120	190	12	0.0075

5.1 Sixgenerating units of 26bus test system

The optimal generating cost of the power producers were obtained using AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO,TACPSO and GWO algorithm, when subjected with base load condition, multiple contingency and combined bilateral and multilateral wheeling transactions.

5.1.1 Case 1: Base Load Condition

The power flow is carried out for the test system with the 100 base MVA, and the load demand 1263. B loss co-efficient (Boo) of test bus system is taken from [16] is shown below in Table 4.

Table 4. B loss co-efficient for 26 bus test system (base load)

B	0.0017 0.0012 0.0007 -0.0001 -0.0005 -0.0002 0.0012 0.0014 0.0009 0.0001 -0.0006 -0.0001 0.0007 0.0009 0.0031 0.0000 -0.0010 -0.0006 -0.0001 0.0001 0.0000 0.0024 -0.0006 -0.0008 -0.0005 -0.0006 -0.0010 -0.0006 0.0129 -0.0002 -0.0002 -0.0001 -0.0006 -0.0008 -0.0002 0.0150
B0	1.0e-003 * (-0.3908 -0.1297 0.7047 0.0591 0.2161 -0.6635)
B00	0.0056

With this base load the optimal generation cost is obtained through the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO,TACPSO and GWO algorithm and the obtained minimal fuel cost values are compared which are shown below in Table 5.

Table 5. Comparison among different method (base load)

	Conventional method	Optimization method							
Gen no.	**NR method ($/h)**	**AGPSO1 ($/h)**	**AGPSO2 ($/h)**	**AGPSO3 ($/h)**	**MPSO ($/h)**	**SPSO ($/h)**	**IPSO ($/h)**	**TACPSO ($/h)**	**GWO ($/h)**
Gen1	447.6919	500	424.872	490.0655	424.872	490.0895	500	500	437.9554
Gen2	173.1938	200	158.687	126.2701	158.687	182.9178	128.9369	200	180.8478
Gen3	263.4859	249.6076	255.2737	238.8003	255.2737	213.0125	266	248.3405	262.8706
Gen4	138.8142	93.398	146.1874	92.4557	146.1874	103.2731	97.1421	60	127.6967
Gen5	165.5884	100	196.0959	195.4141	196.0959	219.9512	218.8271	134.6651	174.1308
Gen6	87.0260	120	81.8896	120	81.8896	53.7615	52.0995	120	79.4987
Min F(G)	15447.72	15366.286	15290.124	15338.096	15288.263	15343.276	15344.918	15365.412	**15278.120**
Pd	1263								
B loss	0.0056								

From Table 5, it is obvious that, GWO gives the best optimal cost of generation for the test system under Base load condition. The converged characteristic of the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO, TACPSO and GWO algorithm for the base load condition are shown in the Fig 1.

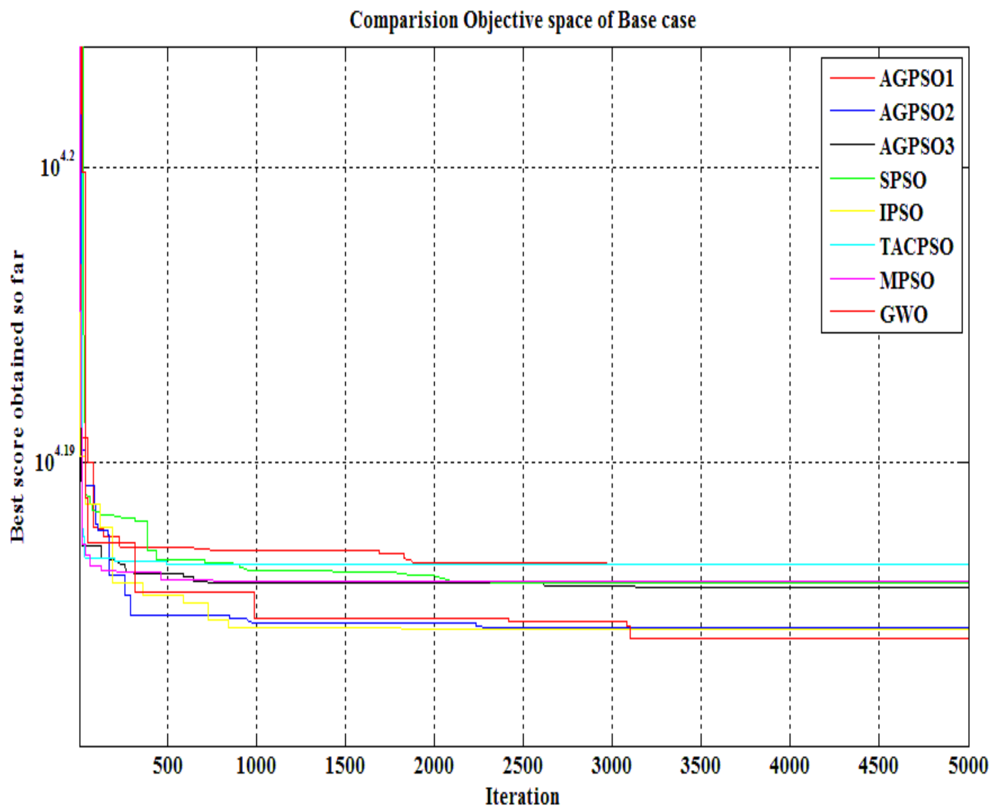

Fig 1. Converged characteristic of AGPSO and GWO in base load condition

5.1.2 Case 2: Optimal Production Cost with multiple Line Contingency

In this case, the optimal generation cost of the test system obtained through the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO,TACPSO and GWO, when subjected to multiple line contingency is illustrated by making the transmission line between the buses are shown in the Table 6.

Table 6. Multiple contingency (transmission line outage)

Transmission line(outage)	From bus	To bus
Line1	2	8
Line2	4	8
Line3	7	8

The B loss co-efficient (Boo) were calculated from [24] for multiline contingency conditions are given in the Table 7.

Table 7. B loss co-efficient for multiple contingency

B	0.0021 0.0014 0.0009 -0.0012 -0.0004 0.0000 0.0014 0.0015 0.0012 -0.0008 -0.0004 0.0001 0.0009 0.0012 0.0033 -0.0003 -0.0010 -0.0005 -0.0012 -0.0008 -0.0003 0.0068 -0.0016 -0.0017 -0.0004 -0.0004 -0.0010 -0.0016 0.0143 0.0000 0.0000 0.0001 -0.0005 -0.0017 0.0000 0.0155
B0	-0.0007 -0.0001 0.0006 0.0015 -0.0002 -0.0009
B00	0.0054

With this multiline contingency condition the optimal generation cost is obtained through the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO,TACPSO and GWO algorithm.

The obtained minimal fuel cost values are compared which are shown below in the Table 8.
From Table 8, it is obvious that, GWO gives the best optimal cost of generation for multiple line contingency condition.

Table 8. Comparison among different method (Multiple contingency)

Gen no.	Conventional method	Optimization method							
	NR method ($/h)	**AGPSO1 ($/h)**	**AGPSO2 ($/h)**	**AGPSO3 ($/h)**	**MPSO ($/h)**	**SPSO ($/h)**	**IPSO ($/h)**	**TACPSO ($/h)**	**GWO ($/h)**
Gen1	446.1992	500	425.7235	499.9416	425.7235	474.9777	470.4662	483.7859	455.7907
Gen2	173.1159	169.6639	194.069	171.1887	194.069	130.012	200	163.787	172.5812
Gen3	262.3577	248.2813	254.2706	254.5442	254.2706	216.7298	262.1636	235.0527	265.6533
Gen4	143.8471	103.1171	111.946	85.841	111.946	132.8012	106.2751	110.3797	122.4546
Gen5	164.5505	191.9431	156.9963	162.559	156.9963	198.4116	141.8093	220	162.0017
Gen6	86.9847	50	120	88.9332	120	110.073	82.2912	50	84.5217
Min F(G)	15465.95	15314.16	15298.25	15311.81	15283.47	15329.26	15298.42	15322.53	**15277.69**
Pd	1263								
B loss	0.0054								

The converged characteristics of the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO,TACPSO and GWO algorithm for the multiple line contingency condition of the test bus system shown in Fig 2.

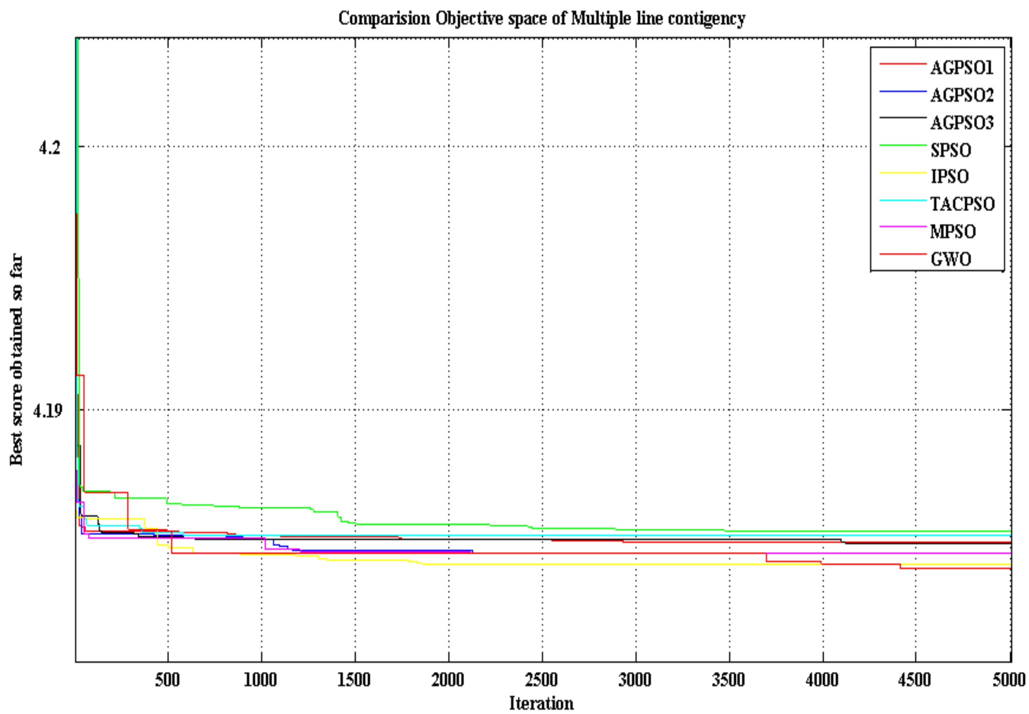

Fig 2. Converged characteristic of PSO and GWO in multiple contingency conditions

5.1.3 Case 3: Optimal Production Cost with Wheeling Transactions (Combined Bilateral and Multilateral)

In this case, the optimal generation cost of the test system obtained through the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO, TACPSO and GWO, when subjected tocombined Bilateral and multilateral wheeling transaction is illustrated by making the transmission line between the buses are shown in Table 9 and the B loss co-efficient (Boo) were calculated from [24] for the test bus system under combined bilateral and multilateral transaction condition are shown below in the Table 10.

With this combined bilateral and multilateral wheeling transaction condition the optimal generation cost is obtained through the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO, TACPSO and GWO algorithm

Table 9. Combined wheeling transaction (Bilateral and Multilateral)

Transmission Transaction	Bus no			Transaction in (MW)
	From bus	**Real power (MW)**	**To bus**	
Bilateral	22	10	25	10
Multilateral	12	30	11	15
			16	15

Table 10. B loss co-efficient for combined wheeling transaction (Bilateral and Multilateral)

B	0.0017 0.0012 0.0007 -0.0000 -0.0005 -0.0003 0.0012 0.0014 0.0010 0.0001 -0.0006 -0.0002 0.0007 0.0010 0.0031 0.0001 -0.0010 -0.0007 -0.0000 0.0001 0.0001 0.0025 -0.0005 -0.0008 -0.0005 -0.0006 -0.0010 -0.0005 0.0129 -0.0003 -0.0003 -0.0002 -0.0007 -0.0008 -0.0003 0.0150
B0	1.0e-003 *(-0.3681 -0.1101 0.7157 0.1357 0.2197 -0.8027)
B00	0.0056

The obtained minimal fuel cost values are compared which are shown below in Table 11.

Table 11. Comparison among different method (Combined wheeling transaction)

Gen no.	Conventional method	Optimization method							
	NR method ($/h)	**AGPSO1 ($/h)**	**AGPSO2 ($/h)**	**AGPSO3 ($/h)**	**MPSO ($/h)**	**SPSO ($/h)**	**IPSO ($/h)**	**TACPSO ($/h)**	**GWO ($/h)**
Gen1	447.5274	444.4629	426.1049	497.9179	426.1049	467.1361	442.4508	463.0382	444.5812
Gen2	173.1008	137.9018	200	200	200	121.8754	165.6139	163.6915	169.0726
Gen3	263.5652	266	251.7548	237.6882	251.7548	267.3993	252.2818	217.7978	263.8072
Gen4	137.8124	131.834	133.5718	92.3326	133.5718	126.6185	135.0405	137.7616	127.0212
Gen5	165.5949	176.7804	131.5739	162.1056	131.5739	207.683	162.1821	199.3394	171.2
Gen6	88.5448	106.0263	120	72.9611	120	72.2932	105.4363	81.3769	87.3273
Min F(G)	15452.15	15290.98	15311.91	15319.87	15295.86	15313.29	15282.92	15305.09	**15276.68**
Pd	1263								
B loss	0.0056								

From Table 11, it is obvious that, GWO gives the best optimal cost of generation for the test system under combined bilateral and multilateral wheeling transaction condition.

The converged characteristic of the AGPSO1, AGPSO2, AGPSO3, MPSO, SPSO, IPSO, TCPSO and GWO algorithms for combined bilateral and multilateral wheeling transaction condition of the test bus system is shown in Fig 3.

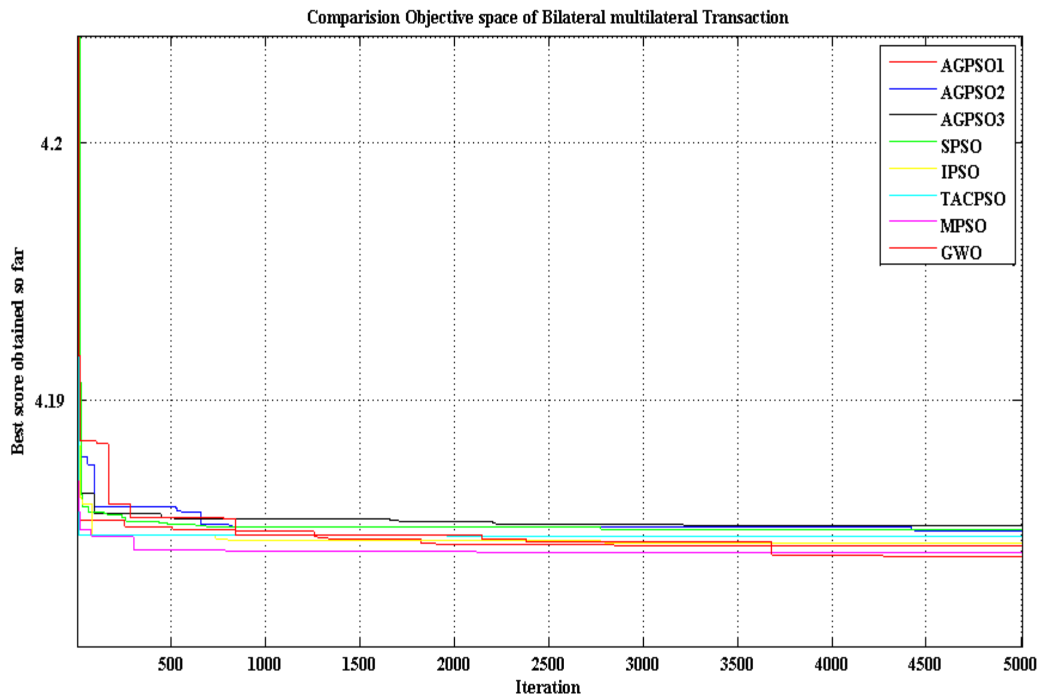

Fig 3. Converged characteristic of PSO and GWO in (Combined wheeling transaction)

The optimal generating cost of the power producers were obtained using Autonomous Group PSO and GWO algorithms along with transmission line constraints. The power flows carried out through the conventional method (Newton-Raphson) and bus loss co-efficient (Boo) were calculated. The result obtained here for base case was near around results from [16].The usefulness of the proposed technique has been performed on the 26bus test system with 6 generating units having ramp rate limits under different cases such as combined bilateral and multilateral Transaction and multiple transmission line contingency condition. The simulation studies were carried out on Intel Pentium Dual Core, 2 GHz system in MATLAB environment.

6. Conclusion

This proposed work explained the social behaviour, headship hierarchy and hunting optimization mechanism of the gray wolves, for solving the EPD problem. This GWO algorithm has the better optimum performance than the Autonomous group particle swarm optimization which includes AGPSO1, AGPSO2, AGPSO3, MPSO, IPSO, TACPSO, SPSO and other heuristic algorithms. The proposed algorithm demonstrated for the 26 bus test system with Ramp rate limit considering multiple contingency as well as combined bilateral and multilateral wheeling transactions. The compared results give the feasible economic dispatch to the producer to meet the load demand when subjected at any cause of risk condition to the power system. More over this GWO algorithm has betterperformance in both constraints as well as unconstraint problem.

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