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Improved Grey Wolf Optimization for Economic Load Dispatch Problem Considering Valve Point Loading Effect and Prohibited Operating Zones

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ABSTRACT

Economic load dispatch (ELD) is an important power system operational planning problem. In the past, calculus based techniques have been used for solving convex ELD problem. The practical ELD problem is non convex due to valve point effect. This paper presents a new improved grey wolf optimization (IGWO) for solving ELD problem considering constraints such as valve point effect, transmission losses and prohibited operating zones. Grey wolf optimization (GWO) is a swarm intelligence (SI) technique which suffers from stagnation. To overcome this problem differential mutation and crossover operations are combined with GWO to form IGWO. The proposed IGWO was successfully implemented on 6, 13, 15 and 40 thermal units test systems. For validation, results were compared with recent techniques. This comparison proves the superiority of IGWO.

1. Introduction

Electrical power system is a most essential component of today's world. Optimal operational planning plays a vital role in electrical power system. Thermal power generation mainly depends upon fuel. Fuel is scarce and very costly so it is important to utilize the fuel efficiently. This optimal use of fuel results in saving in fuel cost and also creates a good impact on environment which is an important perspective in today's world. Economic Load dispatch (ELD) is the optimal allocation of generation on thermal units in such a way that total fuel cost for electricity production is minimized subject to the satisfaction of all practical constraints. It is highly non-linear and multi-constrained optimization problem. Confined energy resources, rising energy demand and increasing cost of thermal power generation makes ELD a very important problem in electrical power system [1].

In the past, calculus based techniques were used to solve this problem. Gradient search, Lambda iteration method, Linear programming, Dynamic programming and Lagrange multiplier technique were attempted to solve ELD problem, but these techniques have some limitations. Objective function needs to be differentiable, convex and smooth. These techniques get stuck in local minima so, could not achieve global minima [2].

Artificial intelligence (AI) techniques have been very popular for solving global optimization problems. These techniques offer several advantages over classical techniques. These are simple in nature, robust, flexible and gradient free. These also do not stick in local minima [3]. These include evolutionary algorithms (EA's) and swarm intelligence (SI) algorithms. EA's are inspired from natural evolution process. SI algorithms are inspired from natural colonies, flocking of birds and school of fishes.

Various AI algorithms have been used for solving ELD problem like Multi-Tabu Search (MTS) [1], Differential Evolution (DE) [2], Hybrid Harmony Search (HHS) [3], Real Coded Genetic Algorithm (RCGA) [4], Time Varying Acceleration Coefficients with Particle Swarm Optimization (TVAC-PSO) [5], Civilized Swarm Optimization (CSO) [6], Bacterial Foraging Algorithm (BFA) [7], Improved Particle Swarm Optimization (IPSO) [8], New Fuzzy Adaptive based Particle Swarm Optimization (NAPSO) [9], Ant Colony Optimization (ACO) [10], Distributed Sobol Particle Swarm Optimization and Tabu Search Algorithm (DSPSO-TSA) [11], Fuzzy and Self-Adaptive Particle Swarm Optimization (FAPSO) [12], Gravitational Search Algorithm (GSA) [13], Shuffled DE (SDE) [14], Genetic Algorithm with special class of Ant Colony Optimization (GA-API) [15], Cuckoo Search Algorithm (CSA) [16], Particle Swarm Optimization (PSO) [17], Hybrid Particle Swarm Optimization with Gravitational Search Algorithm (PSO-GSA) [18], Krill Herd Algorithm (KHA) [19], Species-based Quantum Particle Swarm Optimization (SQPSO) [20], Hybrid Harmony Search with Arithmetic Crossover Operation (ACHS) [21], Grey Wolf Optimizer (GWO) [22], Random Drift Particle Swarm Optimization (RDPSO) [23], Backtracking Search Algorithm (BSA) [24], Modified Artificial Bee Colony (MABC) [25], Hybrid Chemical Reaction Optimization with Differential Evolution (HCRO-DE) [26], Chaotic Bat Algorithm (CBA) [27] and Kinetic Gas Molecular Optimization (KGMO) [28], Grey Wolf Optimization (GWO) [29] and Quasi-Oppositional Teaching Learning Based Optimization (QOTLBO) [30].

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There are some limitations associated with these algorithms. Some algorithms have good global searching ability but poor local searching ability. Some techniques are very sensitive to control parameters. Conventional KHA [19] does not find global optimum in high dimensional problems. Both DE [2] and PSO [17] suffer from premature convergence.

Grey Wolf Optimization (GWO) is a SI algorithm developed by Mirjalili et al. [22]. It has been implemented on ELD problem by Prahadan et al. in 2016 [29]. It has been observed that GWO suffers from stagnation problem due to less effective global searching ability. In this paper Differential Mutation and Crossover is combined with GWO to form improved Grey Wolf Optimization (IGWO). This integration improves the global searching ability of the former algorithm.

2. Problem Formulation

ELD is a fuel cost minimization problem subject to satisfaction of various practical constraints [19].

2.1 Objective Function

Mathematically the minimization of total fuel cost for thermal power generation can be expressed as**:**

$$\text{Minimize: } F_T = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

Where F_T represents total fuel cost of generation, $F_i(P_i)$ is the fuel cost of i_{th} generator and Pi is the active power generation of i_{th} generator.

There are two types of ELD problems based on the objective function, convex and non-convex problems. The convex problem has quadratic fuel cost equation. This behavior of thermal units can be modeled as:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

In Eq. (2) a, b and c are the fuel cost coefficients.

In practice, thermal generation units have multiple valves for fuel input. The opening and closing of valves significantly changes the fuel cost equation of the thermal unit. This is known as valve point effect. This results in non-convexity in the behaviour of thermal units. This non convex behavior can be modeled as:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 |e_i sin(f_i(P_{i,min} - P_i))| \tag{3}$$

where *e* and *f* are constants of valve point effect.

2.2 Constraints

ELD is a multi-constrained optimization problem. The constraints are generation limits, power balance, prohibited operating zones, transmission losses and valve point effect.

2.2.1 Power balance constraint

Total generation must be equal to the sum of load demand and transmission losses.

$$\sum_{i=1}^{n} P_i = P_D + P_{Loss} \tag{4}$$

In Eq. (4) P_D is load demand, P_{Loss} is transmission loss and P_i is the generation.

2.2.2 Generation limits constraint

The generation from a thermal unit must be in limits

$$P_{i,min} \le P_i \le P_{i,max} \tag{5}$$

Where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum limits of generation of i_{th} generator.

2.2.3 Prohibited operating zones

There are some regions in the output power of a thermal unit where generation is avoided. These regions are known as prohibited operating zones.

$$\begin{gathered} P_{i,min} \le P_i \le P_{i,1^l} \\ P_{i,j-1^u} \le P_i \le P_{i,j^l} \; j = 2, \dots\dots\dots, \mathrm{m} \\ P_{i,m^u} \le P_i \le P_{i^{max}} \end{gathered} \tag{6}$$

Where m is number of prohibited operating zones,

$P_{i,1^l}$ is lower limit of j_{th} operating zone of i_{th} unit and P_{i,j^u} is upper limit of j_{th} operating zone of i_{th} unit

2.2.4 Transmission losses

Load centre are located at very large distance from power generation plants. So, transmission losses are significant and cannot be neglected. Transmission losses are considered using B coefficient method. Losses can be modeled as:

$$P_{Loss} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{j}=1}^{\mathrm{n}} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{7}$$

Where B_{00} is constant, B_{0i} is vector of same dimension as P_i and B_{ij} is Loss coefficient matrix.

3. Grey Wolf Optimization

GWO is a novel SI technique developed by Mirjalili et al. [22]. The SI algorithm was developed from the observance of social hierarchy and collective hunting behaviour of grey wolves.

Grey wolves live in pack. They have group hunting behaviour. There are four types of wolves in a pack namely alpha, beta, delta and omega wolves. The grey wolves follow a leadership hierarchy. Alpha is the leader of the grey wolves pack. Alpha is responsible for every type of decision making in the pack. They have best knowledge about the prey. Therefore, alpha is considered as best wolf in the pack. All other wolves follow the decisions made by alpha wolves. The second and level leadership in the pack is beta wolves. They help alpha in decision making. When alpha passes away then beta becomes the best candidate for leadership. The third level hierarchy is the delta wolves. The delta wolf obeys alpha beta. Delta wolves provide security to the grey wolves pack. The last level of hierarchy is the omega. Omega wolves are ordinary wolves. These wolves obey all other wolves in the pack. These wolves are not involved in the decision making process. These omega wolves are allowed to eat when all other wolves finish eating.

Grey wolves are popular for their group hunting behaviour. In GWO algorithm the grey wolves move through a bumpy search space in order to hunt a prey. The alpha, beta and delta wolves estimate the prey location and update themselves and omega wolves position around the prey. The distance of a grey wolf from the prey determines its fitness value. The goal is to reach the prey through shortest path. The alpha wolf has better information about the position of prey so these are considered as best wolves in a pack, then comes beta and delta wolves. In this algorithm best solutions are saved throughout the whole iterative process. The group hunting behavior of grey wolves is presented in three different stages; searching, encircling and hunting.

4. Improved Grey Wolf Optimization

GWO has been implemented on ELD problem by Pradhan et al. [29]. It has been observed that GWO technique has lower global searching ability due to the fact that sometimes it goes into stagnation [33]. So if we avoid this problem we can get better results. We have operators like differential mutation which is famous for its global searching ability. In this paper differential mutation and crossover operations are combined with GWO to enhance exploration of this technique in order to get better results. The combination of these operations with GWO results in IGWO.

4.1 IGWO implemented on ELD

Step 1:

In this step initial population containing generation allocation is randomly initialized. Population size which is the no. of grey wolves is chosen in this step. The population contains Nw number of grey wolves each containing Ng number of thermal generators.

$$\begin{bmatrix} P_1^1 & \cdots & P_j^1 & \cdots & P_{Ng}^1 \\ \vdots & \vdots & & \vdots & \\ P_1^i & \cdots & P_j^i & \cdots & P_{Ng}^i \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_1^{Nw} & \cdots & P_j^{Nw} & \cdots & P_{Ng}^{Nw} \end{bmatrix} = \begin{bmatrix} P^1 \\ \vdots \\ P^i \\ \vdots \\ P^{Nw} \end{bmatrix} \tag{8}$$

Step 2:

Evaluate the fitness value of all the wolves (solutions). For this place feasible solutions in the objective function of the problem. Identify $P\alpha$, $P\beta$ and $P\delta$ as first, second and third best wolves according to their fitness values and also identify the global best solution. In the first iteration $P\alpha$ (alpha solution) is the global best solution.

Step 3:

Apply the operation of encircling to find distance between any omega wolf and three best wolves.

$$D\alpha = |\, C1 * P\alpha - P^i(t)\,| \tag{9}$$

$$D\beta = |\, C2 * P\beta - P^i(t)| \tag{10}$$

$$D\delta = \left|C3 * P\delta - P^i(t)\right| \tag{11}$$

Step 4:

Apply the operation of hunting to compute next generation$P^i\ (t+1)$. The positions of omega wolves are updated relative to the positions of alpha, beta and delta wolves.

$$P^1 = P\alpha - (A1 * D\alpha) \tag{12}$$

$$P^2 = P\beta - (A2 * D\beta) \tag{13}$$

$$P^3 = P\delta - (A3 * D\delta) \tag{14}$$

$$P^i\ (t+1) = (\,P^1 + P^2 + P^3\,)/3 \tag{15}$$

Step 5

Apply the mutation operation

$$P^i = P^{gbest} + F\,(P^a - P^b) \tag{16}$$

Where $i = 1,2,3, \dots \dots \dots, Nw$,

$i \neq gbest$,$a \neq b \neq i \neq gbest$

The mutation scaling factor is represented by 'F'. Its value ranges from 0.4 to 1. This factor controls the global searching ability of the optimization process.

Step 6:

Apply the crossover operation. Uniform crossover will be used. After this operation j_{th} component of i_{th} wolf is given by:

$$P_j^i = \begin{cases} P_{ji}^r ifrand < Cr \\ P_j^i\, else \end{cases} \tag{17}$$

Where= $1,2, \dots \dots . D$, $i = 1,2, \dots \dots . Nw$, C_r is the crossover probability. In proposed IGWO, crossover probability is not a constant rather it depends upon the relative fitness of an individual in the population. It is defined in [20] as:

$$C_r = 0.2 * \text{relative fitness} \tag{18}$$

Step 7:

Check generation limits and prohibited operating zones. If these constraints are violated then fix them. Check load balance constraint. If equality constraint violates then apply equality constraint handling mechanism.

Step 8

If stopping criteria is satisfied then stop, get the optimum generation allocation otherwise go to Step 2 and perform next iteration.

5. Simulation Results

In this research proposed IGWO has been applied on 6, 13, 15 and 40 thermal units test systems. The proposed algorithm has been implemented using MATLAB 11 on dual core PC.

Test system 1 is a convex six units test system with load demand of 1263 MW. Prohibited operating zones and transmission losses are considered.

Test system 2 is a non-convex thirteen units test system. Load demands of 1800 MW and 2520 MW are considered. Transmission losses are accounted in both cases

Test system 3 is a convex fifteen units test system. Prohibited operating zones and transmission losses are taken into account.

Test system 4 is a non-convex forty units test system. Transmission losses and prohibited operating zones are considered.

5.1 Test System 1

The system data for this test system is obtained from Mandal et al. [19]. The number of wolves for this case is 30. The maximum iterations are 300. The numbers of trials are 50. Table 1 provides the generation and total fuel cost achieved from IGWO. The total fuel cost is 15442.2 $/hr. Transmission losses calculated are 12.3123 MW. For validation the total fuel cost achieved from IGWO is compared with other algorithms in Table 2. From this comparison it is concluded that fuel cost achieved from IGWO is lowest. Fig. 1 gives the convergence curve for test system 1.

Table 1: Results for test system11

Unit	Pmin (MW)	Pmax (MW)	Generation (MW)	Fuel cost ($/hr)
1	100	500	449.706	4803.6
2	50	200	170.060	2175.3
3	80	300	264.036	3091.7
4	50	150	141.972	1943.1
5	50	200	164.547	2164.3
6	50	120	85.0014	1264.2
Total			1275.30	15442.2
Transmission losses	12.3123 MW			

5.2 Test System 2

This is a thirteen units test system. The system data is obtained from Adarsh et al. [27]. Load demands are 1500 MW and 2520 MW. The numbers of wolves for this case are 30. The maximum iterations are 1000. The numbers of trials are 50. In Table 3 the results of this test system with load demand of 1800 MW are given. A comparison of results achieved from IGWO with other algorithms is provided in Table 4. Similarly for 2520 MW results and comparison with other algorithms are given in Tables 5 and 6. Convergence curve for these two cases are provided in Figs. 2 and 3.

Table 2: Comparison of results for test system 1

Technique	Best cost ($/hr)	Worst cost ($/hr)	Average Cost($/hr)	Standard deviation
MTS [1]	15450.06	15453.64	15451.17	0.9287
DE [2]	15449.77	15449.874	15449.77	NA
NAPSO[9]	15443.76	15443.765	15443.76	NA
GAAPI [15]	15607.47	15449.85	15449.81	NA
CSA [16]	15443.07	-	-	NA
PSO [17]	15450.84	15,492	-	NA
KHA-1 [19]	15450	15455.456	15452.82	NA
KHA-2 [19]	15448.2117	15453.428	15450.83	NA
KHA-3 [19]	15445.3560	15449.607	15447.21	NA
KHA-4 [19]	15443.0752	15443.326	15443.18	NA
SQPSO[20]	15442.9543	15443.021	15442.97	0.0180
MABC [25]	15449.8995	15,449.89	15,449.8	$6.04 * 10^{-8}$
HCRO-DE[26]	15443.075	-	-	-
CBA [27]	15450	15,518.65	15,454.7	2.965
GWO [29]	15443	15445	15444	0.77459
Proposed IGWO	15442.20	15442.76	15442.6	0.123299

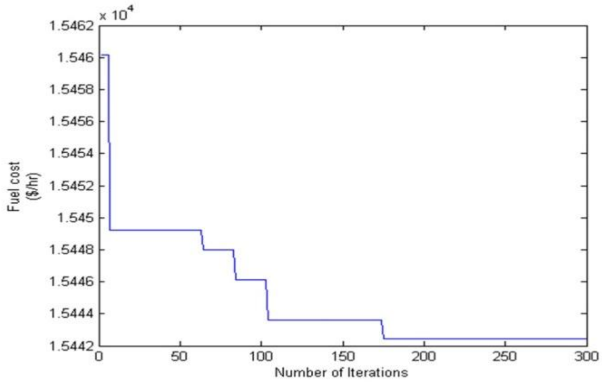

Fig 1: Convergence curve for test system1

5.3 Test System 3

The system data is obtained from Gaing [31]. The numbers of wolves for this case are 30. The maximum iterations are 500. The numbers of trials are 50. Prohibited operating zones are considered. The 2^{nd}, 5^{th} and 6^{th} generators have only one prohibited operating zone. The 12^{th} generator has two prohibited operating zones. The total generation and fuel cost achieved from proposed IGWO is provided in Table 7. The minimum generation achieved from proposed algorithm is 32550.32 $/hr. Transmission losses are 26.9 MW. A comparison of results with other algorithms is provided in Table 8. Convergence curve for this test system is given in Figure 4. After some iteration, there is no significant change in fuel cost because the iterative process converges.

Table 3: Results for test system 2 (load=1800MW)

Unit	Pmin (MW)	Pmax (MW)	Generation (MW)	Fuel cost ($/hr)
1	0	680	627.57	5751.5
2	0	360	299.24	2783.3
3	0	360	299.83	2791.2
4	60	180	160.98	1506.2
5	60	180	160.35	1495.3
6	60	180	159.91	1487.7
7	60	180	160.79	1502.8
8	60	180	159.21	1485.4
9	60	180	159.27	1485.3
10	40	120	118.65	1218.2
11	40	120	77.421	809.0
12	55	120	89.606	942.7
13	55	120	91.784	944.4
Total			2564.6	24202.2

Table 4: Comparison of results for test system 2

Technique	Best cost ($/hr)	Worst cost ($/hr)	Average cost ($/hr)	Standard deviation
SDE [14]	18134.49	-	18138.56	NA
MABC [25]	18127.78	18134.31	18129.70	2.95
GWO [29]	17974.22	18031.00	17994.67	7.00
Proposed IGWO	17945.07	18001.00	17962.00	5.00

Table 5: Results for test system 2 (load=2520MW)

Unit	Pmin (MW)	Pmax (MW)	Generation (MW)	Fuel cost ($/hr)
1	0	680	448.31	4242.7
2	0	360	74.678	918.0
3	0	360	222.71	2152.9
4	60	180	108.35	1096.7
5	60	180	159.25	1485.4
6	60	180	159.39	1485.1
7	60	180	109.26	1095.3
8	60	180	159.04	1485.7
9	60	180	159.41	1485.1
10	40	120	39.987	474.5
11	40	120	74.013	806.1
12	55	120	54.987	607.6
13	55	120	55.114	609.6
Total			1824.41	17945.1
Transmission losses			24.4066 MW	

Table 6: Comparison of results for test system 2 (load = 2520 MW)

Technique	Best cost ($/hr)	Worst cost ($/hr)	Average cost ($/hr)	Standard deviation
SDE [14]	24514.88	-	24516.31	NA
MABC [25]	24514.8756	24514.8756	24514.875	3.50 * 10^{-7}
GWO [29]	24308	24335	24319	8.5
Proposed IGWO	24202.156	24228.351	24210	7.021

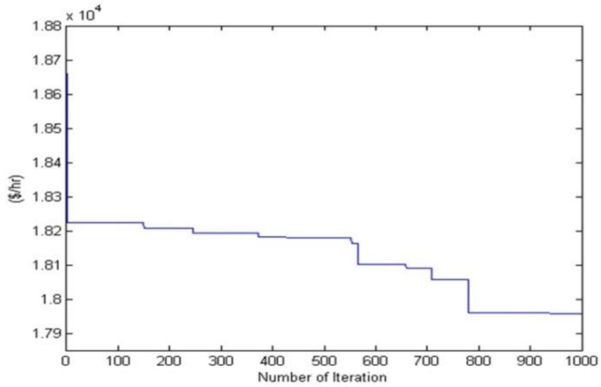

Fig. 2: Convergence curve for test system 2(load=1800 MW)

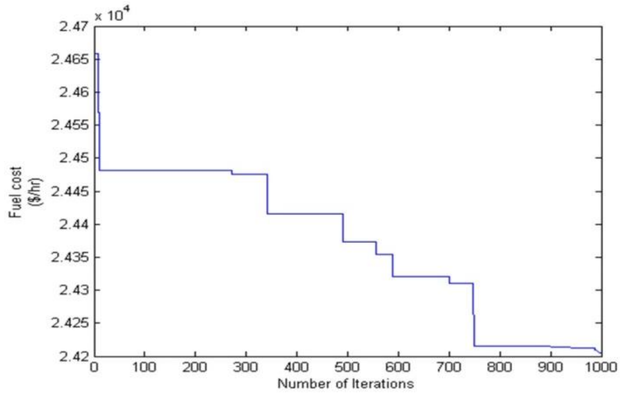

Fig. 3: Convergence curve for test system 2(load=2520MW)

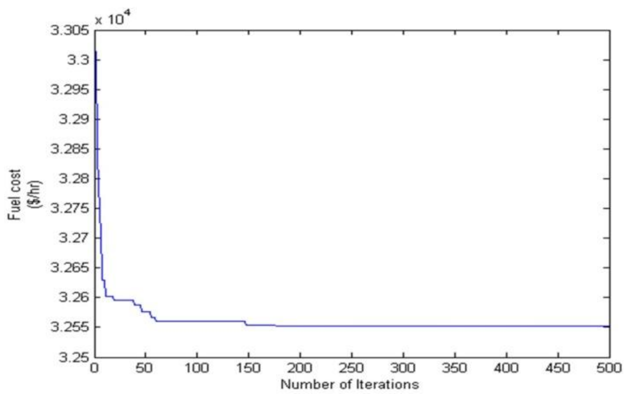

Fig. 4: Convergence curve for test system 3

5.4 Test System 4

This is a large test system containing forty thermal units. The system data is obtained from Coelho and Mariani [32]. The valve point effect prohibited operating zones and transmission losses are considered. The numbers of wolves for this case are 40. The maximum iterations are 1000. The numbers of trials are 50.The generation and total fuel cost achieved from IGWO is presented in Table 9 .The minimum fuel cost achieved from proposed IGWO is 136430$/hr. A comparison of fuel costs is provided in Table 10. It is concluded from this comparison that fuel cost achieved from proposed IGWO is lowest. Convergence curve is provided in Fig. 5. After some iteration the iterative process converges.

6. Conclusion

Both convex and non-convex ELD problems considering transmission losses are solved by IGWO. The minimized fuel cost achieved from proposed algorithm will results in fuel cost saving of thermal units. The results of this research provided the following conclusions:

i. Fuel cost saving for first test system (6 units) is 0.8$/hr.
ii. Fuel cost saving for second test system (13 units with load demand=2520 MW) is 105.844 $/hr.
iii. Fuel cost saving for third test system (15 units) is 4.7 $/hr.
iv. Fuel cost saving for forth test system (40 units) is 16.85 $/hr.

Table 7: Results for test system 3

Unit	Pmin (MW)	Pmax (MW)	Generation (MW)	Fuel cost ($/hr)
1	150	455	455.00	5328.4
2	150	455	455.00	5252.9
3	20	130	130.00	1539.3
4	20	130	130.00	1539.3
5	150	470	241.79	2987.6
6	135	460	460.00	5339.7
7	135	465	465.00	5183.7
8	60	300	60.00	900.2
9	25	162	25.00	453.5
10	25	160	25.00	443.3
11	20	80	75.03	971.5
12	20	80	80.00	1057.3
13	25	85	25.00	552.7
14	15	55	15.00	490.9
15	15	55	15.00	510.0
Total			2656.90	32550.3
Transmission losses (MW)			26.9	

Table 8: Comparison of Results for test system 3

Technique	Best cost ($/hr)	Worst cost ($/hr)	Average Cost($/hr)	Standard deviation
DE [2]	32609.85	32641.42	32609.85	NA
CSO [6]	32588.92	32796.78	32679.88	NA
IPSO [8]	32704.45	32704.45	32704.45	0
DSPSOTSA [11]	32715.06	32730.30	32724.63	8.40
GAAPI [15]	32732.95	-	-	NA
PSO [17]	32858.54	33031.00	32989.00	NA
KHA-1 [19]	32586.37	32598.01	32592.04	NA
KHA-2 [19]	32569.80	32573.63	32571.45	NA
KHA-3 [19]	32564.38	32567.33	32566.59	NA
SQPSO [20]	32704.86	32711.62	32707.08	1.08
ACHS [21]	32706.57	32706.65	32706.65	NA
GWO [29]	32555.00	32558.00	32556.95	1.25
Proposed IGWO	32550.32	32554.80	32552.48	0.99

Table 9: Results for test system 4

Technique	Best cost ($/hr)	Worst cost ($/hr)	Average cost ($/hr)	Standard deviation
SDE [14]	138157.46	-	-	NA
GAAPI [15]	139864.96	-	-	NA
KHA-1 [19]	136702.58	136723.84	136715.09	NA
KHA-2 [19]	136692.65	136713.11	136704.67	NA
KHA-3 [19]	136683.65	136698.50	136690.77	NA
KHA-4 [19]	136670.37	136671.86	136671.23	NA
TLBO [30]	137814.17	-	-	-
QOTLBO [30]	137329.86	-	-	-
GWO [29]	136446.85	136492.07	136463.96	0.098
Proposed IGWO	136430.00	136500.00	136460.00	1.500

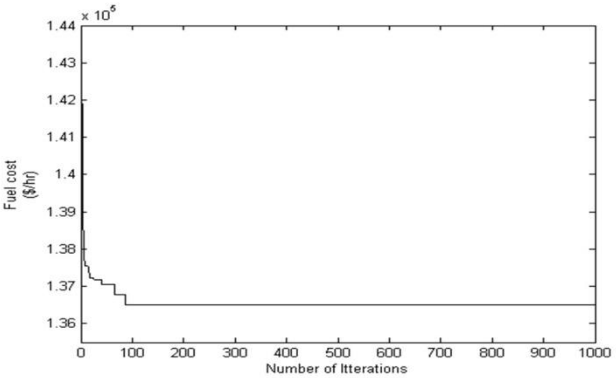

Fig. 5: Convergence curve for test system 4

Table 10: Comparison results for test system 4

Technique	Best cost ($/hr)	Worst cost ($/hr)	Average cost ($/hr)	Standard deviation
SDE [14]	138157.46	-	-	NA
GAAPI [15]	139864.96	-	-	NA
KHA-1 [19]	136702.58	136723.84	136715.09	NA
KHA-2 [19]	136692.65	136713.11	136704.67	NA
KHA-3 [19]	136683.65	136698.50	136690.77	NA
KHA-4 [19]	136670.370	136671.86	136671.23	NA
TLBO [30]	137814.17	-	-	-
QOTLBO [30]	137329.86	-	-	-
GWO [29]	136446.85	136492.07	136463.96	0.098
Proposed IGWO	136430.00	136500.00	136460.00	1.500

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