Hybrid MFGWO Based Optimal Solution for Combined Economic and Emission Dispatch Problem in Power System

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ABSTRACT

In this paper hybrid Moth-flame optimization (MFO) with Grey Wolf Optimization (GWO) algorithm is proposed to obtain the best solution for Combined Economic and Emission Dispatch (CEED) problem in the electrical power system. Combined Economic and Emission problem is used to optimize total fuel cost and emission simultaneously while meeting equality and inequality constraints. The bi-objective optimization problem is converted into the single objective problem by introducing a price penalty factor. The competence of the proposed method is verified by carrying out two test cases with Valve-point effects and multi-fuel along with network loss. The performance and effectiveness of the proposed hybrid optimization algorithm are evaluated on IEEE 30 bus and IEEE 57 bus system and the obtained experimental results are compared with other optimization algorithms. It shows that the proposed hybrid optimization algorithm has more effective, less computation time than other heuristic algorithms.

Key Words —Hybrid Optimization, MFO, GWO, Combined Economic and Emission Dispatch, Valve point loading, Multi-Fuel.

1. INTRODUCTION

The economic dispatch problem is one of the significant tasks in power system operation and control. The main motto of the economic dispatch is to minimize the fuel cost of the generator to meet the load demand by satisfying all the practical constraints in the electrical power system. In global major load demand of the electrical networks is shared by the electrical power produced from thermal power generating stations. The electricity produced from thermal power generating plant releases abundant poisonous wastes such as Sulphur Oxides (SOx), Nitrogen Oxides (NOx) and Carbon oxides (COx), which in turn pollutes the atmosphere. These harmful environmental pollutants emitted from the fossil-fuel power plants can be reduced by means of proper load allocation among the available generators. But this would lead to an increase in the operating cost of the power plant. So, there is a need to identify a solution which balances both emission and fuel cost. This could be achieved by Combined Economic and Emission Dispatch (CEED) problem. In CEED problem two objective functions such as fuel cost and emission are integrated into a single objective function using the price penalty factor. The primary objective of CEED is to optimize the operating cost and emission by meeting various practical system constraints.

There are numerous deterministic and non-deterministic algorithms have been applied to solve the Combined Economic and Emission Dispatch (CEED). Conventional optimization algorithm (deterministic) such as Lambda-iteration method [1], Lagrangian Relaxation Method [2], gradient algorithm, quadratic programming [3], non-linear programming [4, 5], linear programming [4, 5], and Newton's method [4, 5] is deterministic in nature and produces outstanding convergence characteristics. But they have following limitations which include (i) they cannot guarantee for global optimum (ii) they cannot handle binary or integer variables (iii) takes a long time for complex calculations (iv) they cannot handle large scale problem. For the last decay, a large number of meta-heuristic optimization algorithms are developed to overcome the shortcomings of conventional optimization approaches. The meta-heuristic algorithms have been developed based on the inspiration from chemical, physical and biological phenomena of living organisms. The different heuristic algorithms applied for solving CEED problem is PSGWO [8], Gravitational Search Algorithm [9], Spiral Optimization Algorithm [10], Bat Algorithm [12], Flower Pollination Algorithm [13], Particle Swarm Optimization [14], Evolutionary Algorithm [15], Backtracking Search Algorithm [19], and Recursive Approach [23] and these meta-heuristic algorithms have following disadvantages. Some algorithms frequently trapped in local minima, suffer from stagnations, and slower convergence rate.The above disadvantages pay the way for the development of hybrid techniques in power system. Hybridization is the process of combining two or more optimization algorithms which could be done using parallel or pipeline fashion.

The organization of the paper is as follows. Problem formulation for CEED is given in section 2, Overview of the Grey Wolf Optimizer is specified in section 3, Moth Flame optimization algorithm is described in section 4, the proposed hybrid Moth Flame- Grey Wolf Optimizer (MF-GWO) is explained in section 5 and section 6 provides results and discussion. The last section specifies the conclusion part.

2. CEED PROBLEM FORMULATION

The Combined Economic and Emission Dispatch (CEED) problem is used to minimize fuel cost and emission simultaneously by satisfying various practical system constraints. The formulation of CEED is stated as follows.

2.1. Fuel cost Minimization

The fuel cost of the thermal power generating units is estimated by a quadratic function. In practical condition, the thermal power generating units can be supplied with multi-fuel sources and their boilers have valve points for controlling their output power. Many of the thermal generating units are operated with multi-fuel sources such as coal, oil, and natural gas. Therefore, fuel cost functions of thermal power generating unit may be expressed as piecewise quadratic cost functions for different types of fuel [6]. Also, the CEED with valve-point effect is a non-smooth and non-convex problem with multiple ripples in the heat-rate curves of boilers. The valve point effect has been expressed by adding a sinusoidal function to the quadratic fuel cost function. So, the total fuel cost function is given by Eq. (1).

$$F(P_k) = \begin{cases} a_{k1}P_{k1}{}^2 + b_{k1}P_{k1} + c_{k1} + \left| d_{k1} * \sin(e_{k1}(P_{k1}^{\min} - P_{k1})) \right|, \; for\ fuel\ 1, P_k^{\min} \le P_k \le P_{k1} \\ a_{k2}P_{k2}{}^2 + b_{k2}P_{k2} + c_{k2} + \left| d_{k2} * \sin(e_{k2}(P_{k2}^{\min} - P_{k2})) \right|, \; for\ fuel\ 2, P_{k1} \le P_k \le P_{k2} \\ .. \\ a_{kn}P_{kn}{}^2 + b_{kn}P_{kn} + c_{kn} + \left| d_{kn} * \sin(e_{kn}(P_{kn}^{\min} - P_{kn})) \right|, \; for\ fuel\ \mathrm{n}, P_{k(n-1)} \le P_k \le P_k^{\max} \end{cases} \tag{1}$$

Where

P_k = output power of the k^{th} generator

$a_{kn,}, b_{kn,}, c_{kn,}, d_{kn,}, e_{kn,}$ = fuel cost coefficient of k^{th} generator and n^{th} fuel

2.2. Emission Minimization

Fossil fuel power plants emit carbon oxides (COx), sulphur Oxides (SOx) and oxides of nitrogen (NOx). These gases result in global warming which in turn leads to ecological imbalance. In general, the total emission of these pollutants has been expressed as the sum of quadratic and an exponential function. So the total emission of multi-fuel is expressed in eq(2)

$$E(P_k)=\begin{cases}\alpha_{k1}P_{k1}^{\ 2}+\beta_{k1}P_{k1}+\gamma_{k1}+\eta_{k1}\exp\left(\delta_{k1}*P_{k1}\right),\ for\ fuel\ 1, P_k^{\min}\le P_k\le P_{k1}\\ \alpha_{k2}P_{k2}^{\ 2}+\beta_{k2}P_{k2}+\gamma_{k2}+\eta_{k2}\exp\left(\delta_{k2}*P_{k2}\right),\ for\ fuel\ 2, P_{k1}\le P_k\le P_{k2}\\ ..\\ \alpha_{kn}P_{kn}^{\ 2}+\beta_{kn}P_{kn}+\gamma_{kn}+\eta_{kn}\exp\left(\delta_{kn}*P_{kn}\right),\ for\ fuel\ \mathrm{n}, P_{k(n-1)}\le P_k\le P_k^{\max}\end{cases} \tag{2}$$

Where $\alpha_{kn},\beta_{kn},\gamma_{kn},\eta_{kn}$ and δ_{kn} are the emission coefficient of the k^{th} generator and n^{th} fuel

2.3. Combined Economic and Emission Dispatch

. CEED is a multi-objective optimization problem with the minimization fuel cost and emission simultaneously. The solution of CEED problem can be obtained by combining two independent objectives using the Price penalty factor.

$$Min\left(F_{CEED}\right)=F\left(P_k\right)+h_k*E\left(P_k\right) \tag{3}$$

where

$$h_k=F(P_k^{\max})/E(P_k^{\max}) \tag{4}$$

2.4. Constraints

In Combined Economic and Emission Dispatch problem, some equality and inequality constraints should satisfied which are described as follows

2.4.1. Power Balance Constraints

In power balance constraints, the total power generation should meet load demand and total transmission loss

$$\sum_{k=1}^{M}P_k-P_D-P_L=0 \tag{5}$$

According to Kron's loss formula

$$P_L=\sum_{k=1}^{M}\sum_{j=1}^{M}(P_kB_{kj}P_j)+\sum_{k=1}^{M}B_{0k}P_k+B_{00} \tag{6}$$

2.4.2. Generator Capacity Constraints

According to generator capacity constraint, each generator should generate the power within the range of minimum and maximum value

$$P_k^{\min}\le P_k\le P_k^{\max} \tag{7}$$

2.4.3. Ramp Rate Limit

In practical circumstances, the ramp rate limit restricts the operating range of all the units for adjusting the generator operation between two adjacent operating periods. The generation may increase or decrease with corresponding upper and downward ramp rate limits

$$\max(P_k^{\min}, P_{0k} - DR_i) \le P_k \le \min(P_k^{\max}, P_{0k} + UR_i) \quad (8)$$

where P_{0k} indicates the active power output of k^{th} generating unit in the previous hour, UR_i and DR_i represent ramp up and down rate limits of the k^{th} generating unit .

2.4.4. Prohibited Operating Zones

In practical condition, the generator does not work within some operating zone due to vibration in shaft bearing .The possible operating zone of the k^{th} generator is as follows.

$$P_k = \begin{cases} P_k^{\min} \le P_k \le P_{k1}^{l} \\ P_{k,j-1}^{\min} \le P_k \le P_{kj}^{l}\, j = 2,....,z_k \\ P_{k,z_k}^{u} \le P_k \le P_k^{\max} \end{cases} \quad (9)$$

Where $P_{k,j}^{l}, P_{k,j}^{u}$ the lower and upper bound of j^{th} are prohibited operating zone of k^{th} generating unit

2.4.5. Spinning Reserves Constraints

To improve system reliability, the spinning reserve requirement must be supplied by way of regulating the units without prohibited zones.

$$\sum_{k}^{M} S_i \ge S_R \quad (10)$$

Where

$$S_k = \begin{cases} \min((P_k^{\max} - P_k), S_k^{\max}), \text{forunits without prohibited zones} \\ 0, otherwise \end{cases} \quad (11)$$

3. OVERVIEW OF GREY WOLF OPTIMIZER

Mirjalili et. al. [17] proposed a new algorithm called Grey Wolf Optimizer (GWO). GWO is one of the swarms and bio-inspired optimization algorithm which mimics the leadership hierarchy and hunting mechanism of the grey wolves. Grey wolves are the strict social animals and considered as apex hunters. The population grading of grey wolves is divided into four different layers such as alpha (α), beta (β), delta (δ), and omega (ω). The social dominant hierarchy of the grey wolf is shown in figure 1. The first layer in the hierarchy of grey wolves is called alpha (α). Alpha is responsible for deciding about hunting, sleeping place and time to wake, its decisions are dictated to the pack. Beta (β) is in the second level of the hierarchy of the grey wolves that support the decision-making process of alpha and also helpful for other pack activities. The beta wolf could be male or female; it is an advisor to alpha but commands the other lower level wolf in the pack and also gives feedback to the alpha wolf. Delta (δ) lies in the third layer of the hierarchy of grey wolves. Delta wolves are also known as a subordinate wolf, it should submit the feedback to the alphas and betas, but they control the omega.

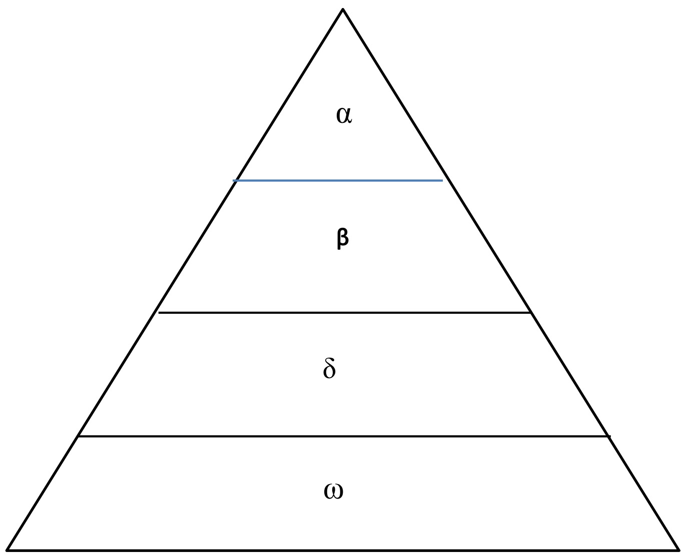

Figure.1 Social Hierarchy of Grey Wolves

The lowest level of the grey wolf hierarchy is omega (ω), it always has to submit the information to all the other dominant wolves and it is the last wolves that are allowed to eat. The group hunting is another one interesting facts about grey wolf along with social behavior. The hunting stages of the grey wolf are (i) Tracking, chasing and approaching the prey (ii) Pursuing, encircling, and harassing the prey until it stops moving (iii) Attack towards the prey.

3.1. Encircling prey

During the process of hunting, grey wolves surround the prey. The mathematical model of encircling behavior of grey wolves is considered in n- dimension search space and updates each location. It is represented as follows

$$\vec{x}(t+1) = \overrightarrow{x_p}(t) - \vec{A} * \vec{d} \tag{12}$$

where t is the iteration count, $\vec{A}$ is the coefficient vector, $\overrightarrow{x_p}$ is the position vector of prey and $\vec{d}$ is the vector that depends on the location of the prey.

Depends on the location of the prey, $\vec{d}$ can be calculated as follows

$$\vec{d} = \left|\vec{c} * \overrightarrow{x_p}(t) - \vec{x}(t)\right| \tag{13}$$

The coefficient vector $\vec{A}$ and $\vec{c}$ can be expressed as

$$\vec{A} = 2\vec{a} * R_1 - \vec{a} \tag{14}$$

$$\vec{c} = 2 * R_2 \tag{15}$$

where $\vec{x}$ is the grey wolf position vector, $\vec{c}$ is the coefficient vector, $\vec{a}$ is the control vector that can be linearly decreases from 2 to 0 and R_1 & R_2 are randomly generated vector in [0, 1]

The control vector $\vec{a}$ can be updated as follows

$$\vec{a} = 2\left(1 - \frac{t}{t_{\max}}\right) \tag{16}$$

where t is the current iteration and $t_{\max}$ is the maximum number of iteration

3.2. Hunting

Grey wolves have the talent to identify the location of prey and surround them. Usually alpha wolves direct the hunting, beta and delta wolves are also sometimes join in hunting process. The hunting behavior of grey wolf can be developed by assuming alpha as the best candidate solution; beta and delta have superior information about the possible location of prey. Therefore, we save the first three best solutions obtained so far and assist the other search agents to update their positions according to the position of the best search agents; mathematically it can be formulated as follows

$$\vec{d}_\alpha = \left|\vec{c}_1 * \vec{x}_\alpha - \vec{x}\right| \tag{17}$$

$$\vec{d}_\beta = \left|\vec{c}_2 * \vec{x}_\beta - \vec{x}\right| \tag{18}$$

$$\vec{d}_\delta = \left|\vec{c}_3 * \vec{x}_\delta - \vec{x}\right| \tag{19}$$

$$\vec{x}_1 = \vec{x}_\alpha - \vec{A}_1 * \vec{d}_\alpha \tag{20}$$

$$\vec{x}_2 = \vec{x}_\beta - \vec{A}_2 * \vec{d}_\beta \tag{21}$$

$$\vec{x}_3 = \vec{x}_\delta - \vec{A}_3 * \vec{d}_\delta \tag{22}$$

$$\vec{x}(t+1) = \frac{\vec{x}_1 + \vec{x}_2 + \vec{x}_3}{3} \tag{23}$$

Estimate the position of the prey can be done by alpha, beta and delta wolves and other wolves update their positions randomly around the prey.

3.3. Attacking prey

The grey wolves complete the searching by attacking the prey and stops moving. While approaching prey, the value of the control vector $\vec{a}$ gets reduced in the mathematical model. When $\vec{a}$ reduces then the variability range of $\vec{A}$ also decreases. The value of the vector $\vec{a}$ is decreasing from 2 to 0 over the course of iterations. $\left|\vec{A}\right| < 1$, forces the grey wolves to attack towards the prey. This attacking behavior represents exploitation or local search of the GWO algorithm.

3.4. Search for prey

Based on the position of alpha (α), beta (β), and delta (δ) the grey wolves searches for the prey. They diverge from each other to search for the prey and converge to attack the prey. It is observed that $\left|\vec{A}\right| > 1$can force the wolves to search for better prey. This divergence behavior refers to exploration or the global search of the GWO algorithm.

4. MOTH FLAME OPTIMIZATION ALGORITHM

Moth Flame Optimization Algorithm (MFO) was developed by Seyedali Mirjalili in 2015[7]. The moth is the decorative insects which are similar to the butterfly family. The moth has a special navigation mechanism in the night is called transverse orientation. In this navigation, a moth flies by retaining a fixed angle with respect to the moon, usually, moths fly spirally around the artificial lights.

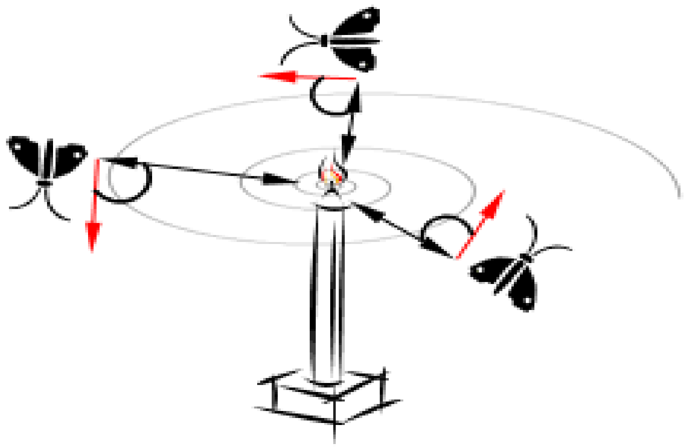

Figure 2 Flying Behavior of Moth around the light source

The Moth Flame Optimization algorithm (MFO) is one of the bio inspired optimization algorithm, in which the set of moths is represented in a matrix as follows

$$R = \begin{bmatrix} R_{1,1} & R_{1,2} & .. & R_{1,d} \\ R_{2,1} & R_{2,2} & .. & R_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ R_{n,1} & R_{n,2} & .. & R_{n,d} \end{bmatrix} \quad (24)$$

Where

n = Number of moth

d = Number of variables

Every moth have an array for storing the resultant fitness values

$$OR = \begin{bmatrix} OR_1 \\ OR_2 \\ \vdots \\ OR_n \end{bmatrix} \quad (25)$$

Where OR_1 is the fitness value of moth R_1

It uses flame as an important component. Flame matrix size is similar to that of moth matrix so, the set flame is represented in a matrix as follows

$$L = \begin{bmatrix} L_{1,1} & L_{1,2} & .. & L_{1,d} \\ L_{2,1} & L_{2,2} & .. & L_{2,d} \\ : & : & : & : \\ L_{n,1} & L_{n,2} & .. & L_{n,d} \end{bmatrix} \tag{26}$$

where

n = Number of moth

d = Number of variables

Each and every flame has an array for storing the resultant fitness values

$$OL = \begin{bmatrix} OL_1 \\ OL_2 \\ : \\ OL_n \end{bmatrix} \tag{27}$$

Here the moths and flames are both solutions. The main difference between moths and flames are update function in every iteration. The mathematical model and behavior is specified in the following equation, where moth in each position is updated with respect to a flame

$$R_i = S(R_i, L_j) \tag{28}$$

Where R_i is the i^{th} moth , L_j is the j^{th} flame and S indicate spiral function.

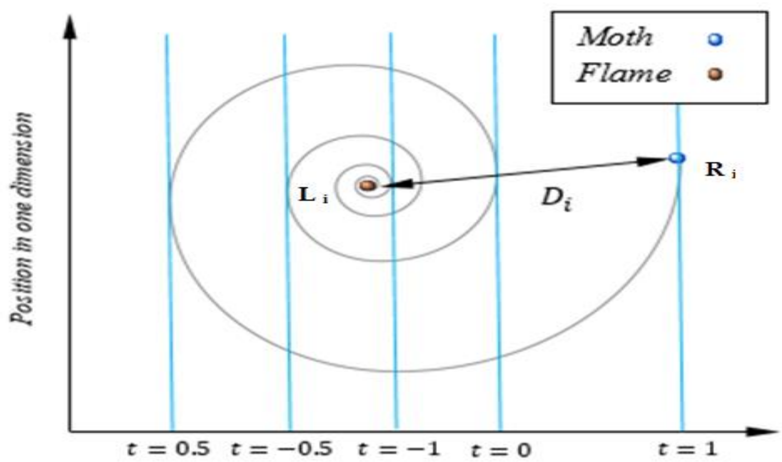

Figure.3 A logarithmic spiral, space around a flame

The logarithmic spiral function is stated as follows

$$S(R_i, L_j) = D_i . e^{bt} . \cos(2\Pi t) + L_j \tag{29}$$

Where D_i is the distance between an i^{th} moth and j^{th} flame, the shape of the logarithmic spiral is represented by a constant b and t is a random number which lies between -1 to 1.

The distance between an i^{th} moth and the j^{th} flame is calculated as follows

$$D_i = \left| L_j - R_i \right| \tag{30}$$

Here the number of flames can be decreased during the iterative process so that, no. of flame can be calculated as

$$\text{flame no} = \text{round}(N - l * \frac{N-1}{T}) \tag{31}$$

where l is represented as the current iteration number, Maximum number of flames is N, and Maximum number of iterations is represented as T.

5. HYBRID MOTH FLAME - GREY WOLF OPTIMIZER (MFGWO)

Hybridization is the process of combining two or more optimization algorithms to solve the same problem. Hybridization is carried out with pipeline run or parallel run fashion. This proposed hybrid optimization algorithm is developed based on Grey Wolf Optimizer with Moth Flame Optimization algorithm. The main motto of the proposed hybrid optimization algorithm is to increase the quality of solution, convergence rate and reduce computational cost.

In this proposed hybrid optimization algorithm the position, speed and convergence accuracy of Grey Wolf Optimizer (GWO) has been improved by applying position update using the logarithmic spiral function of MFO which is used to balance between the exploration and the exploitation process and extending the convergence performance of Grey Wolf Optimizer algorithm.

$$\vec{x}_1 = \vec{x}_\alpha - \vec{A}_1 * (\vec{d}_\alpha . e^{bt} . \cos(2\Pi t) + L_j) \tag{32}$$

$$\vec{x}_2 = \vec{x}_\beta - \vec{A}_2 * (\vec{d}_\beta . e^{bt} . \cos(2\Pi t) + L_j) \tag{33}$$

$$\vec{x}_3 = \vec{x}_\delta - \vec{A}_3 * (\vec{d}_\delta . e^{bt} . \cos(2\Pi t) + L_j) \tag{34}$$

$$\vec{x}(t+1) = \frac{\vec{x}_1 + \vec{x}_2 + \vec{x}_3}{3} \tag{35}$$

6. RESULT AND DISCUSSION

The Hybrid Moth Flame -Grey Wolf Optimizer is used to solve the Combined Economic and Emission Dispatch in an electrical power system. The performance and effectiveness of MFGWO are evaluated with a test system such as IEEE 30 bus and IEEE 57 with six test cases. The maximum number of iterations is set to 500 for all the test system. The value of the initial population is chosen as 50. The value of 'a' is set as 2 at the initial stage (for exploration) and after that, this value is decreased linearly to 0 (for exploitation). The results obtained by MFGWO for the different test case and different objectives function are given and discussed in the following sections.

Table 1. The Best compromise solution for IEEE 30-bus System

OUTPUT	CASE1	CASE2	CASE3	CASE4	CASE5	CASE6
P_1 (MW)	175.5402	150.092	139.466	73.198	133.5084	50.3133
P_2 (MW)	49.8595	48.9423	56.6856	69.0173	58.3457	79.2684
P_5 (MW)	21.5991	40.9814	22.967	48.4704	30.4799	49.9284
P_8 (MW)	20.4744	22.5193	33.8222	34.6642	29.254	34.3833
P_{11} (MW)	12.972	14.1502	19.8995	28.2774	18.5307	29.921
P_{13} (MW)	11.6199	12.2049	16.0521	39.0835	22.2349	39.8573
Fuel cost ($/h)	**800.2932**	**830.223**	**645.594**	**943.531**	**830.4003**	**956.134**
Emission(ton/h)	**0.36516**	**0.43624**	**0.28328**	**0.20403**	**0.2364**	**0.2069**
CEED($/h)	**1292.259**	**1419.14**	**1028.02**	**1218.97**	**1149.540**	**1235.44**
PLoss(MW)	**8.58107**	**10.4903**	**6.49261**	**3.20580**	**9.55363**	**3.03008**
CPU (sec)	**198.94**	**216.68**	**209.98**	**208.659**	**202.483**	**216.635**

Table 2. The best compromise solution for IEEE 57-bus System

OUTPUT	CASE1	CASE .2	CASE.3	CASE. 4	CASE. 5	CASE. 6
P_1 (MW)	142.991	102.9323	161.6254	140.9842	154.8825	226.1865
P_2 (MW)	38376	82.3886	65.0004	63.6252	74.877	80.3558
P_3 (MW)	46.4281	48.4265	65.2173	86.5628	80.4388	69.4647
P_6 (MW)	66.3169	65.4595	66.3844	95.4901	73.1577	78.1169
P_8 (MW)	463.3676	445.2682	465.8816	415.4566	418.2063	415.2076
P_9 (MW)	96.2665	93.3597	68.9325	22.5546	79.8263	61.9312
P_{12} (MW)	356.0338	428.5486	375.4932	444.8012	380.3757	343.9835
Fuel cost ($/h)	**41648.51**	**42089.86**	**40678.78**	**42794.53**	**42011.51**	**42610.84**
Emission (ton/h)	**1.35615**	**1.35201**	**1.35453**	**1.2201**	**1.2208**	**1.25032**
CEED($/h)	**43477.31**	**43915.07**	**42507.39**	**44441.66**	**42438.79**	**44298.77**
PLoss(MW)	**15.27381**	**17.5632**	**15. 4544**	**14.4424**	**14.57549**	**12.35005**
CPU (sec)	**283.295**	**287. 328**	**286.5823**	**269. 996**	**276.4417**	**287.068**

6.1. CEED by Minimizing Fuel Cost without Valve Point Loading

The minimization of the fuel cost is the most familiar objective function in the Combined Economic and Emission Dispatch problem in an electrical power system. This objective function represents the total fuel cost of all generator units without considering valve-point loading and it is expressed in a quadratic function. The optimal solution obtained in this case is given in table 1 & table 2 (see case1). The total fuel cost obtained in IEEE 30 is 800.2932 ($/h) and for IEEE 57 bus system is 41648.51 ($/h).

6.2. CEED by Minimizing Fuel Cost with Valve Point Effect

The main objective of this case is to minimize the operating cost of the generator by considering the valve point loading. The valve-point effect needs to be considered for more realistic and precise modeling of the fuel cost function. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. The valve loading effect of multivalve steam turbines is modeled as a sinusoidal function, the absolute value of which is added to the basic cost function. The real cost curve function of the steam plant becomes non-continuous. The objective of minimization of generating fuel cost with valve-point effect is given by the sum of the fuel cost function and sinusoidal function. In this case, fuel cost obtained for IEEE 30 bus system is 830.223 ($/h) and for IEEE 57 bus test system is 42089.86 ($/h). From the experimental results shows that the fuel cost obtained in case 2 is increased from case 1 due to valve-point loading effect.

6.3. CEED by Minimizing piecewise quadratic fuel cost

In the third case, the solution of CEED is obtained by considering piecewise quadratic cost function as the objective function. In the thermal power generating unit operates a multi-fuel such as coal, oil and natural gas with different real power output. In such a case operating cost, function is subdivided into piecewise quadratic cost function, that will depend on the number and nature of multi-fuel. Due to the piecewise cost function, the total operating cost is reduced. In this case, the generator 1 & 2 is assuming to operate with the help of different fuels and all other generator is operated as the same fuel that is used in case 1. The fuel cost obtained this case in IEEE 30 bus test system is 645.594 ($/h) and 40678.78 ($/h) for IEEE 57 bus system. The solution obtained in CEED problem due to piecewise cost function for the proposed algorithms is given in table 1& 2.

6.4. CEED by Minimizing Emission

The aim of this case is to reduce the environmental pollution due to released emission gases from thermal power plants. The one-third of load demand is meeting by the thermal power plant. These plants emit gaseous pollution, which will affect the environment. If the emission is the objective function then fuel cost increases. The operating cost and emission of the thermal power generation are inversely propositional to each other. The value of emission cost in IEEE 30 bus test system is 0.20403 (ton/h) and for IEEE 57 bus system is 1.2201 (ton/h)

6.5. CEED by Minimizing Fuel Cost and Emission

In this case, two different objective functions such as fuel cost and emission are considered for solving optimal power flow problem. Economic dispatch reduces the total operating cost without considering emission constraints. The emission dispatch reduced the emission without considering economic aspects. To eliminate the conflicts, and to study the trade-off relationship between fuel cost and emissions, a combined method is called Combined Economic and Emission Dispatch (CEED). This case simultaneously minimizes the fuel cost and emission by meeting all the practical constraints. In this case the value of CEED for IEEE 30 bus system is 1149.540 ($/h) and 42438.79 ($/h) for IEEE 57 bus test power system.

6.6. CEED by Minimizing Active Power Loss

The main objective of this case is to minimize the active power loss of the transmission line. In a power system, the electrical power is transmitted and distributed through a transmission line. The transmission line made of high conducting materials, due to resistance in the transmission line active power loss is taking place. So we need to reduce the transmission loss in the power system. The results obtained by the proposed hybrid optimization algorithms for this case are indicated in table 1 & 2 (see case 6). The active power loss of the transmission line for the IEEE 30 bus system is 3.03008 (MW) and 12.35005 (MW) for IEEE 57 bus system.

7. CONCLUSION

This paper proposed and successfully applied Moth Flame Optimization (MFO) based grey wolf optimization (GWO) algorithm to solve Combined Economic and Emission Dispatch (CEED) problem in power system. This approach was examined and validated on IEEE 30-bus and IEEE 57-bus power systems to find global or near-global best settings of the control variables to optimize fuel cost and emission. The performance of the hybrid MFGWO approach has been compared with other heuristic optimization algorithms and the obtained results shows that the proposed hybrid MFGWO optimization algorithm provides better quality of results, faster convergence rate with less execution time.

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