AN EFFICIENT HYBRID METHOD FOR COMBINED ECONOMIC AND EMISSION DISPATCH PROBLEM USING GENETIC AND WHALE OPTIMIZATION ALGORITHM

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Abstract: *: Economic Dispatch is the process of distributing available power by satisfying equality and inequality constraints, and to meet the load demand at minimum operating cost. The major electrical power has been produced by fossil-fuelled power plants. These 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. Due to increase in public awareness on the environmental pollution and the passage of clean air amendments, all the nations have forced the utilities to modify their operating methods to meet the environmental standards. Economic dispatch minimizes the total fuel cost without considering emission constraints. The emission dispatch minimizes the emission without considering economic aspects. To eliminate the above-mentioned conflicts, and to study the trade-off relationship between fuel cost and emissions, a collective approach called Combined Economic and Emission Dispatch (CEED) is used. This paper proposes a novel hybrid algorithm for solving combined economic and emission dispatch problem which uses both Genetic Algorithm (GA) and Whale Optimization Algorithm (WOA). The effectiveness of the proposed method is tested on the different test system and performance is compared with some other heuristic approaches.*

Keywords: *Economic Dispatch, Emission Dispatch, Combined Economic and Emission Dispatch, Genetic Algorithm, Whale Optimization Algorithm, Hybrid GA-WOA*

1. Introduction

The electrical power system is planned and operated such that it could be reliable, economical, secure and to meet other environmental constraints. Economic Dispatch (ED) is the process of assigning the necessary load between the available power generation units with minimal operational cost [1]. Economic dispatch problem is a large-scale, non-linear, non-convex and multi-dimensional problem that mainly depends on the power system. Fossil-fuel based power stations generate two-thirds of the electric power [2]. The electricity produced from fossil fuel generator releases numerous noxious wastes. These comprise of Carbon oxides (COx), Sulphur Oxides (SOx), and Nitrogen Oxides (NOx),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 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.

The primary objective of CEED is to reduce the emission and fuel cost simultaneously by satisfying the load demand, equality and inequality constraints. During last decay, many researchers have been solved combined economic and emission dispatch using classical methods and metaheuristic algorithms

The CEED problems have been solved by applying the following classical techniques; which includes gradient method [4], lambda iteration method [6], quadratic programming [8], linear programming [10], Lagrangian multiplier method [10], and classical technique based on co-ordination equations [10]. These methods are not efficient due to high computational time and could not produce a satisfactory result because it does not handle nonlinear, and some inequality constraints. To overcome these drawbacks some heuristic algorithms are developed. Genetic Algorithm (GA)[9], Tabu search algorithm[12], Multi-objective backtracking search algorithm[25], Modified Differential Evolution algorithm (MDE), cuckoo optimization algorithm[21], artificial bee colony algorithm[18,19], improved harmony search method are some of the heuristic methods. Even though these heuristic algorithms generate the best optimal solution out of several possible solutions, but none of them would guarantee the best solution.

The following reasons motivate to develop a hybrid method, (i) improving the performance (ii) improving the quality of solution and (iii) handling large-scale problems. This paper uses a hybrid method which combines both genetic algorithm and whale optimization method. Genetic algorithm is limited because of the following reasons, (i) high complexity in choosing genetic parameters, (ii) less convergence speed, and (iii) doesn't guarantee on the optimum solution. To overcome the above drawbacks, this system uses the hybrid algorithm.

Using hybrid algorithm the convergence of solution is higher and it produces a high-quality result with a slight increase in execution time. It has been implemented on two different test systems, which are IEEE -14 with 3 generating unit and IEEE-39 with 10 generating units. The simulation is done via Matlab. Simulation results are compared with other algorithms. The experimental results proved that the hybrid method dominates other heuristic algorithms.

The organization of the paper is as follows. Problem formulation for CEED is given in section 2, Overview of the Genetic algorithm is specified in section 3, Whale optimization algorithm is described in section 4, The next section explains the proposed hybrid GA-WOA algorithm and section 6 provide results and discussion. The last section specifies the conclusion part

2. Formulation of CEED Problem

The Combined Economic and Emission Dispatch (CEED) problem are used to reduce fuel cost and emission simultaneously by satisfying various practical equality and inequality constraints. The formulation of combined economic and emission problem stated as follows [3, 5, 12]

2.1. Objective Function of Fuel Cost

In practice valve point effect is considered as the fuel cost function of the generator. Thus the fuel cost function is expressed by the sum of quadratic and sinusoidal function

$$\sum_{l=1}^{Ng}\left(a_l Pg_l^{\,2} + b_l Pg_l + c_l + \left|d_l * \sin\left(e_l\left(Pg_l^{\min} - Pg_l\right)\right)\right|\right) \quad (1)$$

Where

N_g = No of generator unit

Pg_l = output power of l^{th} generator

$a_{kn,}, b_l, c_l, d_l, e_l =$ fuel cost coefficient of l^{th} generator

2.2. Objective Function of Emission

Fossil fuel-fired power plants emit carbon oxides, nitrogen oxides, and sulfur oxides. The total emission of these pollutants have been expressed as the sum of a quadratic and an exponential function

$$E\left(Pg_l\right) = \sum_{l=1}^{Ng}\left(r_l Pg_l^{\,2} + s_l Pg_l + t_l + u_l \exp\left(v_l * Pg_l\right)\right) \quad (2)$$

$r_l, s_l, t_l, u_l, v_l =$ emission coefficients of l^{th} generator

2.3. Constraints

The following equality and inequality constraints are considered during the optimization process.

2.3.1. Power Balance Constraints

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

$$\sum_{l=1}^{Ng} Pg_l - P_D - P_{Loss} = 0 \quad (3)$$

According to Kron's loss formula

$$P_{Loss} = \sum_{l=1}^{Ng}\sum_{m=1}^{Ng}(Pg_l B_{lm} Pg_m) + \sum_{l=1}^{Ng} B_{0l} Pg_l + B_{00} \quad (4)$$

2.3.2. Generator Capacity Constraints

According to this constraint, each generator should produce power within minimum and maximum limit

k (5)

2.4. Combined Economic and Emission Dispatch

The CEED problem can be solved by combining two independent objectives using the following two methods

(1) Price penalty factor

(2) Weighted sum method

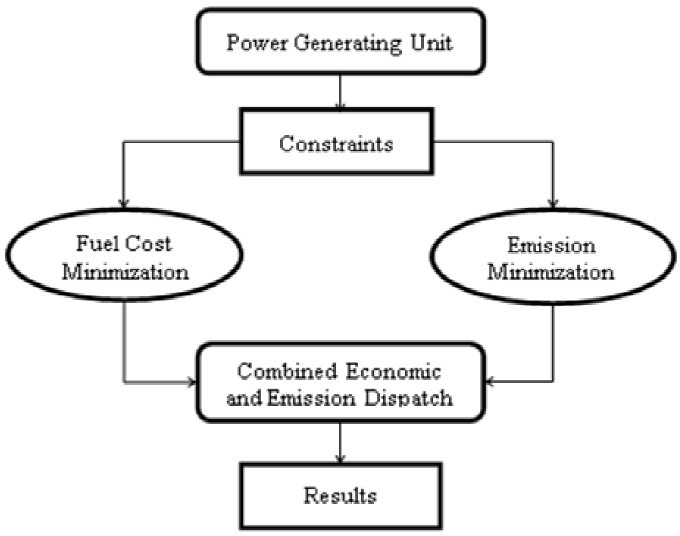

Figure 1.Overview of CEED

2.4.1. Price Penalty Factor

Price penalty factor is the ratio of fuel cost to the emission of the corresponding generator. It is given by

$$Min\left(F_{CEED}\right) = F\left(Pg_l\right) + h_l * E\left(Pg_l\right) \quad (6)$$

Where

$$h_l = F(Pg_{pl}^{\max}) / E(Pg_{pl}^{\max}) \quad (7)$$

2.4.2. Weighted Sum Method

In weighted sum method, the bi-objective function is converted into a single objective function by assigned some weight for every objective function. The weighting factor can be varied from 0 to 1

$$Min\left(F_{CEED}\right) = W * F\left(Pg_l\right) + (1-W) * h_l * E\left(Pg_l\right) \quad (8)$$

3. Overview of Genetic Algorithm

Genetic Algorithm (GA) is an evolutionary technique, which can be used in various searching problems in order to determine optimal or near-optimal solutions. To produce high-quality solutions for any searching and optimization problems genetic algorithm plays a vital role because of its biological mimic operation like mutation, crossover. Genetic algorithm starts by choosing initial sample set randomly and assigns it to an initial population. The fitness of all the individuals in the population is evaluated in each generation. The new population is created by applying the genetic operators such as crossover and mutation in order to select multiple individuals. This newly generated population is considered as the initial population for the next iteration and it terminates when the stopping criteria meet. The stopping criterion is reached either by producing a maximum number of generations or by reaching an acceptable fitness level.

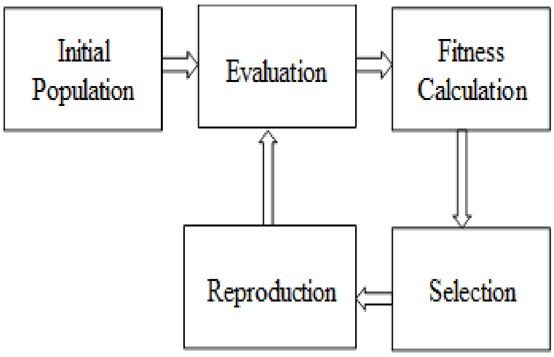

Figure 2. Basic Components of Genetic Algorithm

3.1. Initial Population

Initial population is generated by selecting number of individual solutions. Here the number of individual solution is generated based on random selection of generating power for each generating unit. The population size can be fixed based on the nature of the problem. In general, the population is randomly generated from the entire range of possible solutions. Genetic algorithm operates on a set of strings and this set of strings is known as a population and the process of evolution is to produce new individual strings. Depending on the accuracy requirements of the optimization problem, the string length is selected.

3.2. Evaluation

The fitness of each set of strings in the population is evaluated by means of a function called an evaluation function. Genetic algorithms proceed in the direction of evolving the fittest set of strings and the performance is highly sensitive to the fitness values.

3.3. Fitness Calculation

Once the evaluation process is over, a fitness value is allocated based on the objective function which could be generated from the evaluation process. Minimum fuel cost is set as the fitness value. It is very useful in the execution of the two-stage process of the genetic algorithm. Fitness calculation begins with the individuals in the current population. The intermediate population is generated by selecting best individuals from the current population. Next population is created by applying recombination and mutation on the generated intermediate population.

3.4. Selection

Selection is the process of producing offspring based on the probability, to which the chromosomes satisfy the fitness values. This will be repeated for a number of times until expected number of chromosome is chosen which is relatively proportional to its fitness. This method of selection is called as fitness proportionate selection or *roulette-wheel selection*. Strings with higher fitness values are more likely to be selected as an offspring for the next generation.

3.5. Reproduction

The mating pool is formed by selecting good strings in a population during the reproduction process. Proportionate reproduction operator is the commonly used reproduction operator, where a string is selected for the mating pool with a probability proportional to its fitness. Thus, the i^{th} string in the population is selected with a probability proportional to fitness Fi. Since the population size is usually kept fixed in a simple GA, the sum of the probability of each string being selected from the mating pool must be one. The probability of selecting the ith string is given as:

$$\text{Probability } F_i = F_i \,/ \sum_{i=1}^{n} F_i \qquad (9)$$

Where n=Population Size

The obtained optimum solution is given as an input to the whale optimization algorithm.

4. Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) was developed by Seyedali Mirjalili in 2016 [14]. Humpback whale is one of the biggest baleen whales that use a special hunting method. It uses bubble-net hunting strategy as a food gathering mechanism. In this method food gathering is done by creating unique bubbles along a circular path or '9'-shaped path, around the prey and swim toward the surface. This WOA describes the mathematical model of bubble-net feeding strategy

Figure 3. Behavior of humpback whales in bubble-net feeding

4.1. Encircling Prey

During this phase, humpback whales identify the location of the prey and surround them. Initially, it is considered as an optimal or near optimal solution and other search agents update its position towards the optimum solution by increasing the number of iteration from start to an optimum.

$$\vec{F} = \left|\vec{G}.\vec{Y}^*(i) - \vec{Y}(i)\right| \quad (10)$$

$$\vec{Y}(i+1) = \vec{Y}^*(i) - \vec{E}.\vec{F} \quad (11)$$

Where

$\vec{E}$ & $\vec{G}$ = coefficient vector

$\vec{Y}^*$ = optimum solution for position vector

$\vec{Y}$ = position vector

I = is the current iteration

The coefficient vector $\vec{E}$ & $\vec{G}$ are calculated as follows

$$\vec{E} = 2\vec{v}.\vec{r} - \vec{v} \quad (12)$$

$$\vec{G} = 2.\vec{r} \quad (13)$$

Where

$\vec{v}$ = variable linearly decrease from 2 to 0 over the sequence of iteration

r = random number [0, 1].

4.2. Bubble-Net Attacking (Exploitation Stage)

The bubble-net feeding behavior of humpback whales are modeled by two methods

1. Shrinking encircling mechanism
2. Spiral updating position

4.2.1. Shrinking encircling mechanism

Shrinking encircling mechanism is achieved by decreasing the value of $\vec{v}$ from 2 to 0 over the course of iterations and random variable $\vec{E}$ lies between -1 to 1. The new optimum position is defined in between the position of current optimal best agent and the original position.

4.2.2. Spiral Updating Position

In this method, the distance between the whale position and the prey position is calculated first. The distance gets updated by the movement of both whale and prey and it is represented by a helix-shaped movement. The mathematical model of the spiral equation is given as follows

$$\vec{Y}(i+1) = \vec{F^l}.e^{bl}.\cos(2\Pi l) + \vec{Y}^*(i) \quad (14)$$

Where

$$\vec{F}^l = \left|\vec{Y}^*(i) - \vec{Y}(i)\right| \quad (15)$$

l = random number between -1 to 1,

b = constant for the logarithmic spiral

From the behavior of humpback whales, it is proved that it can swim simultaneously around the prey within the shrinking circle along the spiral-shaped path. From the simultaneous behavior of humpback whales, we assume that there is a 50% chance to choose shrinking encircling mechanism and 50% chance to choose the spiral-shaped path while updating the position of a whale. The mathematical model is represented as follows

$$\begin{cases} \vec{Y}(i+1) = \vec{Y}^*(i) - \vec{E}.\vec{F} & \text{if } p \prec 0.5 \\ \vec{Y}(i+1) = \vec{F^l}.e^{bl}.\cos(2\Pi l) + \vec{Y}^*(i) & \text{if } p \geq 0.5 \end{cases} \quad (16)$$

Where p is the random number between 0 and 1

4.3. Search for prey (Exploration Stage)

In addition to bubble-net hunting method, humpback whales also identify the food prey randomly. In this phase, the position of a search agent is updated based on the randomly chosen search agent instead of the identified best search agent. The variation of $\vec{E}$ is used to search for the prey. $\vec{E}$ can be selected as random values which lies between 1 and -1. The mathematical model of this phase is modeled as follows

$$\vec{F} = \left|\vec{G}.\vec{Y}_{rand} - \vec{Y}\right| \quad (17)$$

$$\vec{Y}(i+1) = \vec{Y}_{rand} - \vec{E}.\vec{F} \quad (18)$$

Where $\vec{Y}_{rand}$ = random position vector for current population

```
Initialize the whale's population
Calculate the fitness of each search agent
Y*=best search agent
while(i< no. of iterations)
for each search agent
    Update v, E, G, l, and p
    if(p<0.5)
        if(|E|< 1)
            Update the position by F = |G.Y*(i) - Y(i)|
        else if(|E| ≥ 1)
            Select a random search agent Y_rand
            Update the position by Y(i+1) = Y_rand - E.F
        end if
    else if(p ≥ 0.5)
        Update the position by Y(i+1) = F^l.e^bl.cos(2Πl) + Y*(i)
    end if
end for
Check if any search agent goes out of search space and modify it
Calculate the fitness of each search agent
Update Y* if v generates better solution
i=i+1
end while
return Y*
```

Figure 4. Pseudo-code of WOA

5. Proposed Algorithm

A hybrid algorithm is formulated by integrating both genetic and whale optimization algorithm for combined economic and emission dispatch problem. The proposed method selects the optimized sample space using a genetic algorithm and it is applied as an input to the whale optimization algorithm. A genetic algorithm is limited because of the following reasons, which includes (i) high complexity in choosing genetic parameters, (ii) less convergence speed, and (iii) doesn't guarantee on the optimum solution. To overcome the above drawbacks, this system uses the hybrid algorithm. Using hybrid algorithm the convergence of solution is higher and it produces a high-quality result with a slight increase in execution time.

Initialize the generator parameters
Initialize the population for genetic algorithm
Generate random population
***for each** individual in currentpopulation*
  individuals are selected based on the fitness function
  selected individuals undergo mutation or crossover to form offspring.
  newpopulation.add(offspring)
end for
return new population

Initialize the whale's population as new population of genetic algorithm

Calculate the fitness of each search agent

Y=best search agent*

***while**(i< no. of iterations)*

***for** each search agent*

  Update v, E, G, l, and p

  ***if**(p<0.5)*

    ***if**(|E|< 1)*

      Update the position by $\vec{F} = \left| \vec{G}.\vec{Y}^{*}(i) - \vec{Y}(i) \right|$

    ***else if**(|E| ≥ 1)*

      Select a random search agent $\vec{Y}_{rand}$

      Update the position by $\vec{Y}(i+1) = \vec{Y}_{rand} - \vec{E}.\vec{F}$

    end if

  ***else if**(p ≥ 0.5)*

    Update the position by $\vec{Y}(i+1) = \vec{F^{l}}.e^{bl}.\cos(2\Pi l) + \vec{Y}^{*}(i)$

  end if

end for

Check if any search agent goes out of search space and modify it

Calculate the fitness of each search agent

Update Y if v generates better solution*

i=i+1

end while

*return Y**

Figure 5. Pseudo-code of Hybrid GA-WOA

6. Results And Discussion

To assess the efficiency of the GA-WOA technique with other optimization methods, two test cases are employed with 3 and 10 generating units. Transmission line losses and valve-point loading are the two inequality constraints which are considered for testing. To simulate these algorithms Matlab is used as a developing platform.

Case (i): In this case, three generators are considered with the power demand of 400MW and the result is presented in table 1. From the obtained results, it is clear that the fuel cost, emission, transmission loss and CEED for the proposed algorithm (GA-WOA) is less than other methods, but there is a slight increase in execution time because of the hybrid nature. The effectiveness of the proposed algorithm is clearly visualized in the following figures from 6-9.

Pd=400 MW				
Output	FPA[3]	GA[5]	WOA	**GA-WOA**
P1(MW)	102.4468	102.617	102.4887	**102.5355**
P2(MW)	153.8341	153.825	153.8043	**153.7200**
P3(MW)	151.1321	151.011	151.1278	**151.1046**
PL(MW)	7.4126	7.41324	7.4208	**7.4182**
Fuel Cost($)	20838.1	20840.1	20838	**20836**
Emission(Kg)	200.2238	200.256	200.2316	**200.1748**
CEED ($)	29559.81	29563.2	29560	**29556**
CPU(s)	0.175	0.282	0.297	**1.783327**

Table1. CEED Result for 3 generating Unit

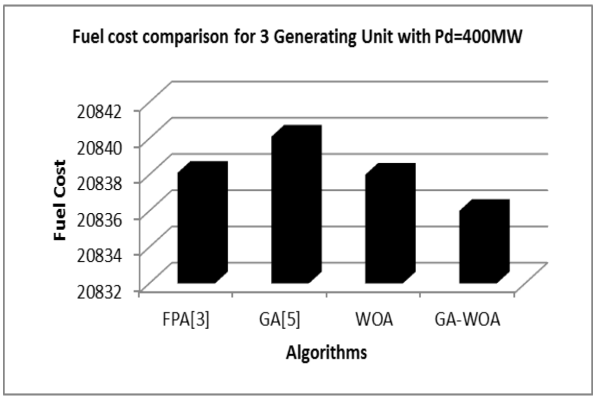

Figure 6. Fuel cost comparison for 3 Generating Unit with Pd=400MW

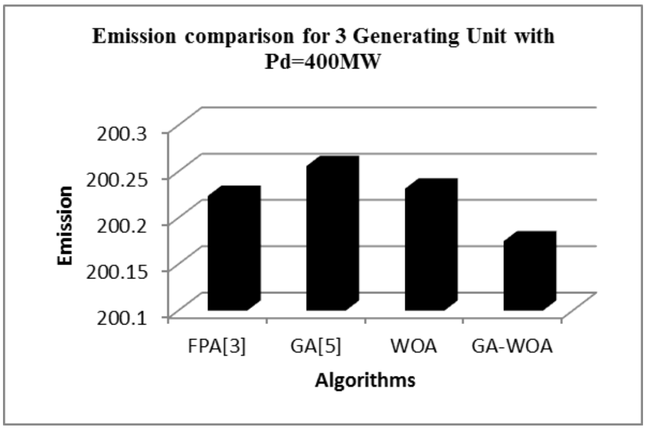

Figure 7. Emission comparison for 3 Generating Unit with Pd=400MW

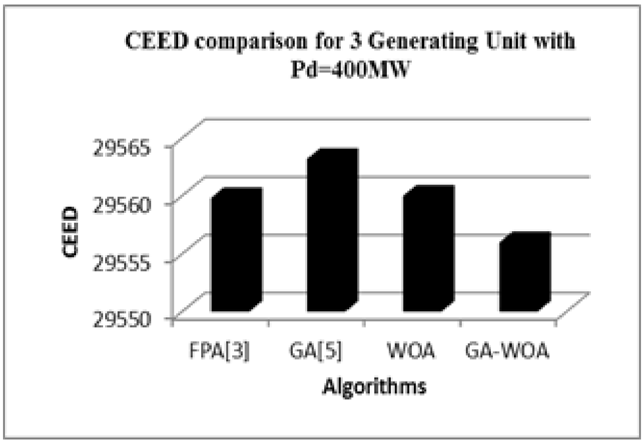

Figure 8. CEED comparison for 3 Generating Unit with Pd=400MW

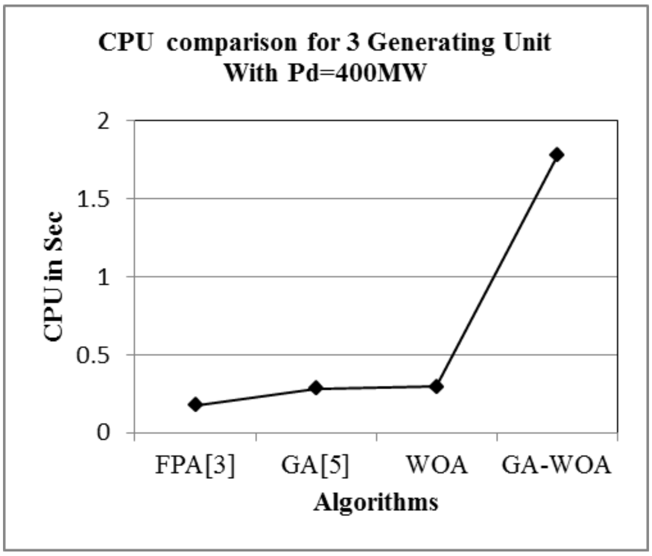

Figure 9. CPU time comparison for 3 Generating Unit with Pd=400MW

Case (ii): In this case, ten generating units are used with the power demand of 2000MW and the comparison of various methods is presented in table 2. Using the simulation results, it shows that the fuel cost, emission, transmission line loss and CEED for the hybrid algorithm (GA-WOA) is less than other methods, but there is a slight increase in execution

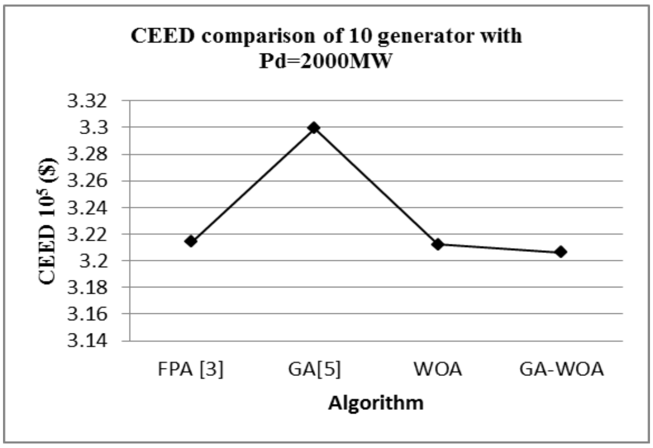

Figure 10. CEED comparison of 10 generating units

PD=2000 MW				
Output	FPA [3]	GA[5]	WOA	GA-WOA
P1(MW)	53.188	54.7663	55.0000	**55.0000**
P2(MW)	79.975	80.0000	78.1490	**78.8626**
P3(MW)	78.105	112.0680	78.2609	**79.1702**
P4(MW)	97.119	92.8733	77.9980	**78.5878**
P5(MW)	152.74	84.5284	160.0000	**160.0000**
P6(MW)	163.08	83.1554	240.0000	**212.4068**
P7(MW)	258.61	300.0000	280.4386	**283.0928**
P8(MW)	302.22	340.0000	283.8195	**288.5064**
P9(MW)	433.21	470.0000	414.6631	**423.6801**
P10(MW)	466.07	470.0000	413.9377	**423.6315**
PL(MW)	84.3	87.4072	82.9669	**82.9392**
Fuel Cost* 10^5 ($)	1.1337	1.1355	1.1361	**1.1388**
Emission(Ib)	3997.7	4158.39	3989.5	**3984.2**
CEED * 10^5 ($)	3.2141	3.2995	3.2122	**3.2062**
CPU(s)	2.23	2.433	2.3032	**6.224**

Table 2. CEED Result for 10 Generating Unit

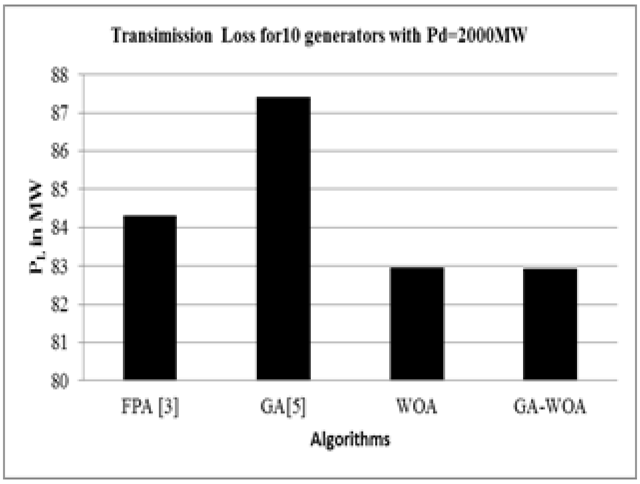

Figure 11. Transmission Loss comparison for 10 generating units

7. CONCLUSION

In this paper, a new hybrid algorithm for combined economic and emission dispatch problem is highlighted. This method integrates two heuristic algorithm namely genetic and whale optimization algorithm. Simulation tests are conducted on two test cases with 3 and 10 generators. Here, inequality constraints like valve-point loading, emission, transmission line loss are addressed. The simulation results provided by GA-WOA algorithm has been compared with other heuristics algorithm in order to assess the performance of the proposed system. Result analysis exposes that the hybrid algorithm is superior to other methods expect there is a small increase in the CPU execution time. It also addresses the limitations caused by genetic algorithm.

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