Optimisation of combined economic emission dispatch problem with the cubic cost function

R. DHANAVIJAYAN

Principal,

Muthiah Polytechnic College,

Annamalai Nagar, India - 608002.

***Abstract*:**

In this work, we introduce the grasshopper optimisation technique for solving the cubic function-based combined economic emission dispatch (CEED) issue while accounting for power flow restrictions. The electrical grid aims to meet customers' load requirements at the lowest possible cost and emission level. The fuel price and its emissions are directly proportional to that of electricity. To get the best outcomes, the cost penalty plays a pivotal part in the CEED issue. We compare and contrast the many price penalty factors proposed in the literature to find the most effective one for our use cases. This CEED issue uses a 3-unit system taking transmission loss into account and a 13-unit system taking valve point effects into account. Total cost, fuel cost, and emission optimisation are prioritised in both test situations. Compared to other algorithms used to solve CEED issues, the numerical and statistical results confirm the excellent quality of the solution created by GIA.

***Keywords*: Combined Economic Emission Dispatch, Emission, Fuel cost, Optimization Algorithm.**

I. INTRODUCTION

Thermal power plants fueled by fossil fuels are the backbone of the world's electrical power-producing systems. It is important to limit the use of fossil fuels in electricity production [1]. Researchers are motivated to reduce fossil fuel consumption in thermal plants since generating electricity from these facilities contributes significantly to environmental degradation via the emission of enormous amounts of polluting gas particulates. Despite developing and implementing alternative methods for generating electricity, such as hydroelectric power generation, nuclear power generation, and the most current renewable energy approach, thermal power production using fossil fuels is still the most common. Thus, the Economic Dispatch (ED) problem and the Emission Dispatch (EmD) problem, which seek to minimise fuel costs and emissions, respectively, are the primary concerns in energy-generating systems. These two goals are inherently at odds with one another and cannot be maximised simultaneously. Combined (CEED) is a multi-objective optimisation problem that arises from these competing goals and seeks to reduce harmful gas emissions and generator fuel consumption simultaneously [2].

Many optimisation strategies have been tried over the years in an effort to solve the CEED issue [3]. Many AI-based techniques have been used to solve the CEED problem with quadratic cost functions, including the Flower Pollination Algorithm (FPA) [4], the Hybrid Bat Algorithm (HBA), the Enhanced Moth-Flame Optimization (EMFO), and the Particle Swarm Optimization (PSO) [5].

Existing methods typically aim to minimise quadratic cost functions in the CEED optimisation issue [6]. High-order polynomial representations of power plants' cost and emission functions are more realistic and accurate than quadratic representations. To solve the CEED problem, several methods are used, including Multi-objective Dynamic Economic Dispatch (MODED), Modified Firefly Algorithm (MFA), Simulated Annealing (SA), Novel Bat Algorithm (NBA), Direct Search Method (DSM), and Bacterial Foraging and Nelder-Mead (BF-NM) Algorithm.

The multi-objective CEED issue is reduced by outlining the financial penalties involved to a single objective function [7]. The two seemingly incompatible goals, cost and emission, may be reconciled with the help of this price penalty factor. Most studies combined the two aims by using the hmax-max price penalty factor [8]. In addition to hmax-min, hmin-max, hmin-min, haverage, and hcommon, various price penalty variables are employed in literature [9], [10]to address the CEED issue. However, it is uncommon to employ any of the penalties above in a single testing function. In this article, the overall cost of the test system is calculated by combining the cost mentioned above and emission penalty components, and the optimal value of the h parameter is selected for optimisation.

Writers have often used the test systems they describe to implement their methodologies and determine which ones work best for both small and big systems while attempting to optimise the CEED issue. Although the hybrid solutions are viewed as computationally challenging but more prospective, the comprehensive study of CEED shows that naturally inspired metaheuristic approaches outperform better than the standard methods to tackle the CEED issue. To find the best answer to the CEED problem when the objective functions are expressed as cubic equations, this work proposes using an algorithm based on the swarming behaviour of grasshoppers called the Grasshopper Inspired Algorithm (GIA) [11], [12].

II. PROBLEM FORMULATIONS

The goal of the CEED problem is to reduce fuel expense and pollution while meeting the equality and inequality restrictions imposed by the system. The following is a statement of the problem:

2.1 Economic Dispatch (ED)

$$F_C = \sum_{i=1}^{N}\left(a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i\right) + \left|e_i \sin(f_i (P_{i,\min} - P_i))\right| \left(\frac{\$}{h}\right)$$

(2.1)

where F_C = fuel cost of the generator, P_i = real power generation of unit i, a_i, b_i, c_i, d_i = cost coefficients of generating unit i, e_i, f_i = valve point effect coefficients of generating unit i, and N = number of generating units.

2.2 Emission Dispatch (EmD)

$$E_T = \sum_{i=1}^{N}\left(\alpha_i P_i^3 + \beta_i P_i^2 + \eta_i P_i + \gamma_i\right)\left(\frac{kg}{h}\right) \quad (2.2)$$

where E_T =emission of the generator, P_i= real power generation of unit i, α_i, β_i, η_i, γ_i = emission coefficients of generating for unit i and N = number of generating units.

2.3 Combined economic emission dispatch (CEED)

The price penalty factor h_i converts multi-objective optimisation into single objective optimisation problem as follows.

$$F_T = \sum_{i=1}^{N}\left(\left(a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i\right) + \left|e_i \sin(f_i(P_{i,\min} - P_i))\right|\right) + \left(\frac{\$}{h}\right) \quad (2.3)$$
$$h_i\left(\alpha_i P_i^3 + \beta_i P_i^2 + \eta_i P_i + \gamma_i\right)$$

where F_T = total cost of generating units

2.4 Various price penalty factors of CEED's as follows

The six price penalty factors viz., $h_{min-max}$, $h_{max-max}$, $h_{max-min}$, $h_{min-min}$, $h_{average}$ and h_{common} are applied to solve the CEED problem and are as follows

2.4.1 min-max price penalty factor

$$h_{\min-\max\ i} = \frac{\left(\left(a_i P_{\min}^3 + b_i P_{\min}^2 + c_i P_{\min} + d_i\right) + \left|e_i \sin(f_i(P_{i,\min} - P_i))\right|\right)}{\left(\alpha_i P_{\max}^3 + \beta_i P_{\max}^2 + \eta_i P_{\max} + \gamma_i\right)}\left(\frac{\$}{kg}\right) \quad (2.4)$$

2.4.2 max-max price penalty factor

$$h_{\max-\max\ i} = \frac{\left(\left(a_i P_{\max}^3 + b_i P_{\max}^2 + c_i P_{\max} + d_i\right) + \left|e_i \sin(f_i(P_{i,\min} - P_i))\right|\right)}{\left(\alpha_i P_{\max}^3 + \beta_i P_{\max}^2 + \eta_i P_{\max} + \gamma_i\right)}\left(\frac{\$}{kg}\right) \quad (2.5)$$

2.4.3 max-min price penalty factor

$$h_{\max-\min\ i} = \frac{\left(\left(a_i P_{\max}^3 + b_i P_{\max}^2 + c_i P_{\max} + d_i\right) + \left|e_i \sin(f_i(P_{i,\min} - P_i))\right|\right)}{\left(\alpha_i P_{\min}^3 + \beta_i P_{\min}^2 + \eta_i P_{\min} + \gamma_i\right)}\left(\frac{\$}{kg}\right) \quad (2.6)$$

2.4.4 min-min price penalty factor

$$h_{\min-\min\ i} = \frac{\left(\left(a_i P_{\min}^3 + b_i P_{\min}^2 + c_i P_{\min} + d_i\right) + \left|e_i \sin(f_i(P_{i,\min} - P_i))\right|\right)}{\left(\alpha_i P_{\min}^3 + \beta_i P_{\min}^2 + \eta_i P_{\min} + \gamma_i\right)}\left(\frac{\$}{kg}\right) \quad (2.7)$$

2.4.5 Average price penalty factor

$$h_{average_i} = \frac{h_{\min-\max\ i} + h_{\max-\max\ i} + h_{\max-\min\ i} + h_{\min-\min\ i}}{4}\left(\frac{\$}{kg}\right) \quad (2.8)$$

2.4.6 Common price penalty factor

$$h_{common\,i} = \frac{\sum_{i=1}^{N} h_{avg_i}}{n}\left(\frac{\$}{kg}\right) \quad (2.9)$$

2.5 Constraints

The CEED problem is subject to the following constraints

2.5.1 Power balance constraint

The total power generated should be the equal to sum of the total power demand (P_D) and the power line loss (P_{LOSS}). Thus, the power balance equation is as follows

$$\sum_{i=1}^{N} P_i = P_D + P_{LOSS} \quad (MW) \quad (2.10)$$

The transmission loss is a function of active power generation of each generating unit for a given load demand. The same may realised as follows

$$P_{LOSS} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo}(MW) \quad (2.11)$$

where B_{ij} = elements of the (i-j)th symmetric loss coefficient matrix(B), B_{oi} = loss coefficient vector of ith element and B_{oo} = coefficient of the system constant loss.

2.5.2 Generator operational constraint

The power output of each unit should be within the minimum and maximum generating limits. The generating capacity constraint is as follows

$$P_i^{\min} \le P_i \le P_i^{\max} \quad (2.12)$$

where P_i^{min} = minimum bound value of ith generator and P_i^{max} = maximum bound value of ith generator.

III. GRASSHOPPER OPTIMISATION ALGORITHM

Knowledge and foresight about the natural world are the foundations of scientific development. Nature is the best problem-solver since it provides us with inspiration for all facets of our lives. Nature is the inspiration for many algorithm designs. GIA is an algorithm inspired by the naturally occurring behaviour of swarming grasshoppers [12]. Finding food (prey) in one's surroundings is the primary activity of all organisms. The grasshopper can now hunt from afar since it has learned to fly. The nymph and the adult are the two major phases of the grasshopper's life cycle. The insect's movement and range are drastically different between its nymph and adult stages. Grasshoppers go through two phases while hunting: investigating and then eating their prey. The GIA algorithm is based on observations of grasshopper swarming behaviour and the way in which it captures prey.

When trying to solve a complex scientific or technological issue, optimisation is a powerful tool. An algorithm is a set of instructions for a computer to follow in order to solve a certain issue. The machine may be used to implement the invention and achieve the desired effects. The greatest results may be found using reputable search agents that use a recognisable algorithm called GIA. Grasshopper seeking strategies are shown, and search agents are picked from the grasshopper population.

Use of a Mathematical Model

$$X_i = S_i + G_i + A_i \quad (3.1)$$

where Xi = position of the ith grasshopper, Si = social interaction, Ai = wind advection and Gi = gravity force of the ith grasshopper.

$$S_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s\left(d_{ij}\right)\hat{d}_{ij} \quad (3.2)$$

where $\hat{d}_{ij}$ = distance between the ith and jth grasshopper,

The social interaction (Si) module is calculated as follows

$$s(r) = f_i e^{\frac{-r}{l}} - e^{-r} \quad (3.3)$$

where f = intensity of attraction, l = attractive length scale

Grasshoppers' ability to attract and repel one another as they move closer together and farther apart in the search area is the next crucial element in swarming performance. The regions of attraction, repulsion, and comfort vary significantly as a function of l and f. When the distance is larger than 10, the function S yields a value closer to zero, dividing the space into an attraction area, a comfort zone, and a repulsion region.

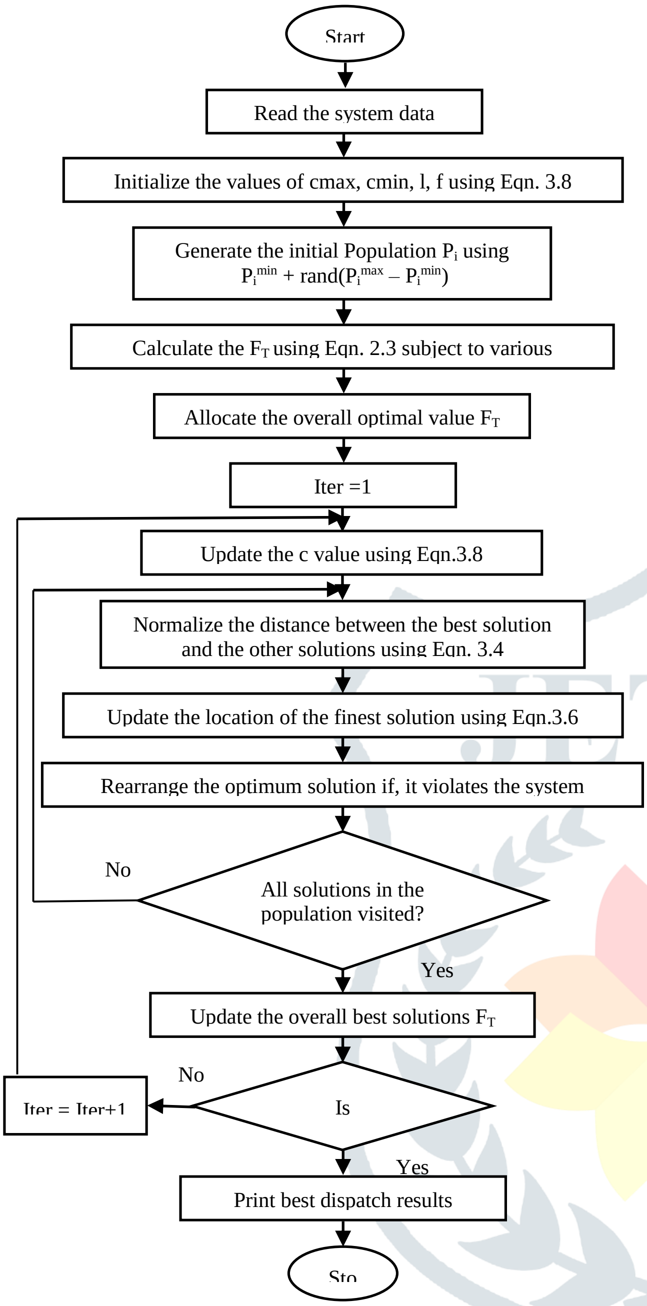

Fig. 1 GIA Implementation for CEED problem

The wind advection (A_i) module is calculated

$$A_i = u\hat{e}_w \tag{3.4}$$

where u = constant drift, $\hat{e}_w$ = unity vector in the wind's direction.

The gravity force (G_i) module is calculated as follows

$$G_i = -g\hat{e}_g \tag{3.5}$$

where g = gravitational constant, $\hat{e}_g$ = unity vector towards the centre of earth.

The S_i, A_i and G_i values substituting the Eqn. (3.1), and to extended as follows:

$$X_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} s\left(\left|x_j - x_i\right|\right)\frac{x_j - x_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \tag{3.6}$$

where s(r) = social force and N = number of grasshoppers.

The procedure is repeated until a cohesive swarm of grasshoppers forms. When people get to their safe zone, their behaviour freezes. Grasshoppers either arrive at their safe zone quickly, rendering the mathematical model useless, or the swarms don't converge on a single location. In addition, the following equation may be used to explicitly resolve the optimisation issue.

$$X_i^d = c\left(\sum_{\substack{j=1 \\ j\neq i}}^{N} c\frac{ub_d - lb_d}{2} s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j - x_i}{di_j}\right) + \hat{T}_d \tag{3.7}$$

The coefficient c minmizes the comfort zone proportional to the iteration count and is computed as,

$$c = c_{\max} - l\frac{c_{\max} - c_{\min}}{L} \tag{3.8}$$

where c_{max} = maximum value, c_{min} = minimum value, l = current iteration, L = maximum number of iterations

The integration of optimisation with GIA is a triumph of careful planning. Both the attraction and repulsion criteria have automatically explored the search space and taken use of the promising area. A reproduction of the implementation flow diagram for the CEED issue is shown in Fig. 1.

IV. Numerical Simulation Results and Discussions

The feasibility and efficiency of the suggested GIA algorithm for the solution of the CEED issue are verified by a simulation research analysing the following test cases.

3 unit system

Scenario 1: ED neglecting transmission loss

Scenario 2: ED with transmission loss

Data come from [9] and [4], respectively, for further information. A Core i5, 2.65GHz computer with 4 GB RAM is doing 100 iterations of the CEED issue analysis. The suggested GIA code is implemented on the Matlab 7.10 platform.

To determine the ideal 'h' parameter for both test cases, we run the CEED issue with six alternative price penalty factors and see how they affect the cost reduction process. Furthermore, many optimisation techniques are compared to GIA in terms of performance.

4.1 3 unit system

In this benchmark, a three-unit system with cubic cost functions is taken into account. All of the input parameters for the generators come from [13], including their limit values, fuel cost coefficients, pollution coefficients, and transmission loss coefficients. This testing framework covers six distinct case studies.

Scenario 1: ED neglecting transmission loss

In this scenario, the suggested GIA is used to minimise fuel costs for 400MW, 500MW, and 600MW of load while ignoring transmission loss. Table 1 displays the outputs, fuel costs, and emission data for each producing unit.

Table 1: ED results of 3 unit system neglecting transmission loss

		600 MW	**500 MW**	**400 MW**
GIA	P_1	101.4800	67.9700	52.9600
	P_2	123.5200	81.5600	75.0000
	P_3	375.0000	350.4700	272.0400
	E_T (kg/h)	796.6500	628.1700	373.7600
	F_C ($/h)	66173.0000	44772.9900	30708.6800

WOA	F_C ($/h)	66189.3800	44786.5800	30721.2900

The minimum fuel cost value for the 400MW, 500 MW and 600MW is 30708.68($/h), 44772.99($/h) and 66173.00($/h) and corresponding emission values are 373.76(kg/h), 628.17(kg/h) and 796.65(kg/h) respectively. The proposed GIA method is compared with the whale optimisation algorithm (WOA) results and it is found comparatively less than WOA. The convergence characteristics of variations of fuel cost against iterations for 600MW load demand in 3 unit system is represented in the Fig.2.

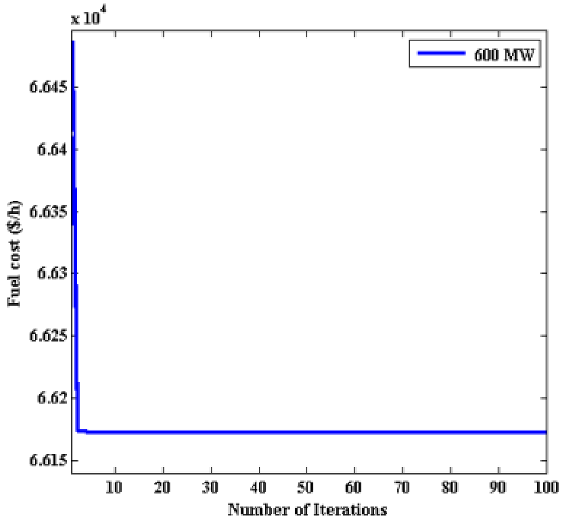

Fig. 2 Convergence characteristics of 3 unit system during ED neglecting transmission loss

Scenario 2: ED with transmission loss

Here, we take the 3unit system with transmission loss into account for various load requirements (400MW, 500MW, and 600MW) and determine which one yields the best outcomes. Table 2 lists the generated power, fuel cost, emissions, and transmission losses for each individual producing unit.

Table 2: ED results of 3 unit system with transmission loss

		600 MW	500 MW	400 MW
GIA	P_1	106.5800	67.2300	50.0000
	P_2	134.4200	84.1700	75.0000
	P_3	375.0000	358.9700	281.4000
	P_L(MW)	16.0000	10.3700	6.4000
	E_T(kg/h)	818.1900	660.0500	395.5100
	F_C($/h)	71296.7900	46499.3200	31496.9300
WOA	F_C($/h)	71318.3700	46512.5800	31507.4700

Emission values of 818.19 kg/h equate to a minimum fuel cost of 71296.79 $/h for the 600MW. 16.00MW of power is lost in transmission during operation. When compared to other algorithms, the GIA approach yields the lowest gasoline cost value.

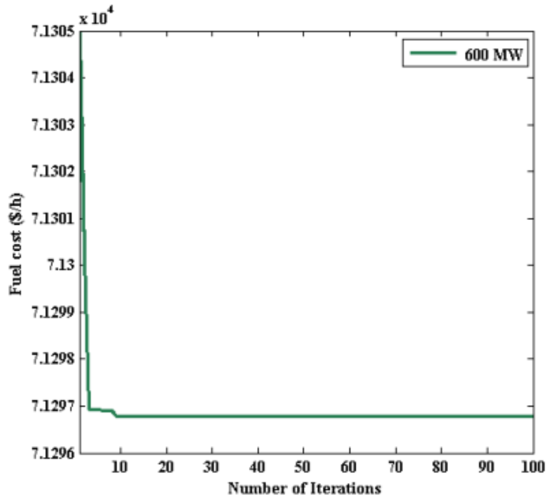

Fig. 3 Convergence characteristics of 3 unit system during ED with transmission loss

Convergence features of fuel cost fluctuations versus 100 iterations for 600MW load demand are shown in Fig. 3.

V. Conclusion

In this paper, the ED, EmD, and CEED are successfully solved using the GIA method on test systems with cubic cost functions. To determine the ideal total cost, the CEED issue applies a variety of price penalty variables to both test scenarios. All the test case situations are run separately, with different penalty factors considered, and the best result-giving factor is identified as the most practical price penalty factor. The findings show that the min-max penalty strategy is superior to other considerations in achieving the lowest possible total cost in both test circumstances. In addition, GIA yields the smallest objective function values compared to WOA in all the situations tested, demonstrating the method's applicability for CEED issues whose objective functions are expressed as cubic equations.

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