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A Novel EP Approach for Multi-area Economic Dispatch with Multiple Fuel Options

P. S. MANOHARAN, P. S. KANNAN, V. RAMANATHAN
Department of Electrical and Electronics Engineering, Thiagarajar College of Engineering, Madurai-625015, Tamilnadu-INDIA
e-mail: psmeee@tce.edu • pskannan@tce.edu • vreee@tce.edu

Abstract

This paper presents a novel approach to multi-area economic dispatch problems with multiple fuel options using a hybrid evolutionary programming method. The objective is to minimize the operation cost of the entire system while satisfying the tie line constraints. In this paper, EP-LMO (Evolutionary Programming with Levenberg-Marquardt Optimization) technique is proposed to solve multi-area economic dispatch problems with multiple fuel options. The EP-LMO is developed in such a way that a simple evolutionary programming (EP) is applied as a base level search to find the direction of the optimal global region. And Levenberg-Marquardt Optimization (LMO) method is used as a fine tuning to determine the optimal solution. The applicability and validity of the proposed approach on multi-area economic dispatch problems are presented in two parts. In Part I, two multi-area bench mark problems without fuel options are considered. In Part II, 10 unit system with both multi-area and multi-fuel options is considered. The proposed approach is compared with the results of Incremental Network Flow Programming, Spatial Dynamic Programming and Evolutionary Programming approaches. The results show that the EP-LMO gives the optimum generation cost than any other methods.

Key Words: *Economic Dispatch, Multi-area, Multiple fuel options, Evolutionary programming, Levenberg-Marquardt Optimization.*

1. Introduction

Power utilities try to achieve high operating efficiency to produce cheap electricity. Competition in the electricity supply industry is allowed in generation and in the marketing of electricity. Therefore, transmission capacity constraints in production cost analysis are very important issues in the operation and planning of electric power systems. The economic dispatch problem is frequently solved without accounting for transmission constraints. However, some researchers have taken transmission capacity constraints into account. In the case of a power pool that involves several generation areas interconnected by tie lines, the objective is to achieve the most economical generation policy that could supply the local demands without violating tie-line capacity constraints. Additionally, the generating units supplied with multi-fuel sources (coal, nature gas, or oil), have the problem of selection of the most economic fuel to burn.

Shoults *et al* [1] considered import and export constraints between areas, and the economic dispatch problem is also carefully addressed. This study provides a complete formulation of multi-area generation scheduling, and is a framework for multi-area studies. Romano *et al* [2] presented the Dantzig-Wolfe decomposition principle to the constrained economic dispatch of multi-area systems. Doty *et al* [3] solved an multi-area economic dispatch problem by using spatial dynamic programming and the result obtained was a global optimum. In this paper, the authors considered transmission constraints with linear losses. Desell *et al* [4] proposed an application of linear programming to transmission constrained production cost analysis. Multi-area economic dispatch with area control error was solved by Helmick [5]. Ouyang [6] solved the heuristic multi-area unit commitment with economic dispatch. This method provides more accurate modeling of large scale, multi-area thermal generation systems. Wang and Shahidehpour [7] proposed a decomposition approach for solving multi-area generation scheduling with tie line constraints using expert systems. The authors showed the efficiency of their proposed approach by testing it on a four area system with each area consisting of 26 units. The same authors reported a decomposition and coordination method for short term generation scheduling of large-scale hydro-thermal power systems in [8]. Network flow models for solving the multi-area economic dispatch problem with transmission constraints have been presented by Streiffert [9]. An algorithm for multi-area economic dispatch and calculation of short range margin cost based prices has been proposed by Wernerus and Soder [10], where the multi-area economic dispatch problem was solved by Newton-Raphson's method.

Recently Jayabarathi *et al* [11] solved multi-area economic dispatch problems with tie line constraints having 2, 4 and 14 areas using Evolutionary Programming. The application of Evolutionary Programming methods to single area economic dispatch problems were discussed in [12-15]. However, none of the studies mentioned above, consider both the multi-area and multi-fuel options.

In this paper, the multi-area economic dispatch problem with multiple fuel options is solved by EP and a novel approach EP-LMO (Evolutionary Programming with Levenberg-Marquardt Optimization). The proposed hybrid method uses the property of EP, which can provide a good direction to the solution even the problem has many local optimum solutions at the beginning. Then, the local searching property of LMO is used to obtain a final solution. Basically, the hybrid method can be divided into two parts. The first part employs EP to obtain a near global solution, while the second part employs LMO to determine the optimal solution.

In this paper, the realistic economic dispatch problems are compared to other methods in two parts. In Part-I of this paper, the proposed approach EP-LMO is applied to two multi-area economic dispatch problems. The first bench mark problem considers 4 areas, each area containing 4 units. The second test problem considers 14 areas and 17 transmission lines. The performance of EP-LMO is compared with Incremental Network Flow Programming, Spatial Dynamic Programming and Evolutionary Programming approaches. Comparative results indicate that the proposed EP-LMO is more effective than the previous methods.

Part-II discusses novel approach EP-LMO and EP-LMO is applied to multi-area economic dispatch problem with multiple fuel options. The bench mark problem considers 10-generators, 3-area system with multiple fuel options.

The rest of the paper is organized as follows: Section II describes the formulation of multi-area economic dispatch problem with multiple fuel options. Section III explains the conventional EP procedure. Section IV explains the proposed EP-LMO approach. In section V, EP-LMO approach is applied to multi-area economic dispatch problems and in section VI, it is applied to multi-area economic dispatch problems with multiple fuel options and their relative performances are compared. Finally, the conclusion is given in section VII.

2. Formulation of Multi-Area Economic Dispatch Problem with Multiple Fuel Options

The main objective of "Economic dispatch with multiple fuel options" is to find which fuel is most economical to burn. Say, for example, a plant consisting of many generating units, which are supplied with numerous (Coal, Nature gas and Oil) of fuel may be faced with the dilemma of determining which fuel is most economical to burn. The piecewise quadratic function is used to represent multiple fuel options and the incremental cost functions are illustrated in Figure 1.

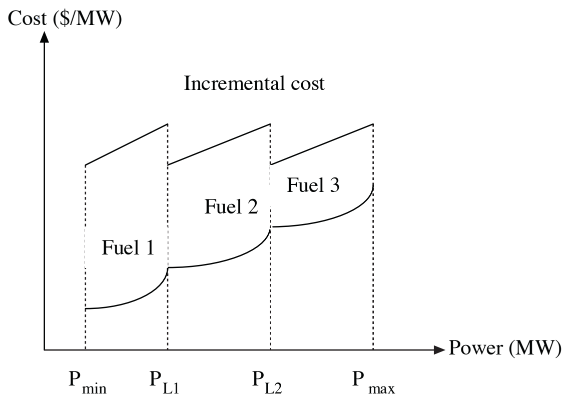

Figure 1. Piecewise quadratic and incremental cost functions of a generator.

The objective of "Multi-area economic dispatch problem with multiple fuel options" is to determine the amount of power can be economically generated in one area and transferred to another area in order to displace generation in second area and to determine economic fuel for each unit.

The achievement of economic dispatch in power system operation consists of minimizing the operating costs depending on demand and subject to certain constraints, i.e., how to allocate the required load demand between the available generation units. The input-output curve represents the conversion of energy from a source into electricity. In this study, the input-output curve is represented as a quadratic. Multiplying the input-output curve equation by the fuel price gives a fuel cost equation $C(P_{mn})$ as a function of the power output. Piecewise quadratic function is used to represent this problem. The hybrid cost function with the inequality constraints is given by,

$$\begin{aligned} C\ (P_{mn}) &= a_{mnk}P_{mn}^2 + b_{mnk}P_{mn} + c_{mnk}\ ;\ k = F_1 if P_{mn(\min)} \leq P_{mn} \leq P_{L1} \\ &= a_{mnk}P_{mn}^2 + b_{mnk}P_{mn} + c_{mnk}\ ;\ k = F_2 if P_{L1} < P_{mn} \leq P_{L2} \\ &= a_{mnk}P_{mn}^2 + b_{mnk}P_{mn} + c_{mnk}\ ;\ k = F_3 if P_{L2} < P_{mn} \leq P_{mn(max\ )} \end{aligned} \tag{1}$$

where

m = 1,2,...... M (areas)

n = 1,2,...... N$_m$ (units)

k = 1,2,...... K$_n$ (fuels)

If the area with excessive power is not adjacent to the area with deficiency or the tie line between the two areas has reached its upper flow limit, it is necessary to find another path between these two areas in order to transmit additional power. Taking into consideration the cost of transmission in each tie-line, the multi-area economic dispatch with multiple fuel options optimization function becomes:

$$\text{Minimize } C = \sum_{m=1}^{M} C_m + \sum_{J=1}^{M-1} \sum_{K=J+1}^{M} f_{JK} T_{JK} \tag{2}$$

where, $C_m = \sum_{n=1}^{N_m} C(P_{mn})$

T_{JK} = Tie line flow from area J to area K

f_{JK} = Cost coefficient associated with the tie line flow T_{JK}

The objective function is minimized subjected to the following constraints:

2.1. Area power balance constraints

The power balance constraints of the system is,

$$\sum_{n=1}^{N_m} P_{mn} = D_m + \sum_{\substack{k=1 \\ k \neq m}}^{M} T_{mk} \qquad \text{for} \qquad m = 1, 2, ...M \tag{3}$$

2.2. Operation Unit Constraint

The MW output of an on-line unit must be allocated within the range bounded by its lower and upper limits of real power generation.

$$P_{mn(\min)} \leq P_{mn} \leq P_{mn(\max)} \qquad \text{for} \qquad n = 1, 2, 3.....N_m \tag{4}$$

2.3. Tie-line limits Constraint

The tie-line power transfer from area J to area K. T_{JK} should be between its minimum and maximum capacity limits.

$$T_{JK(\min)} \leq T_{JK} \leq T_{JK(\max)} \tag{5}$$

3. Application of EP to Multi-Area Economic Dispatch Problem with Multiple Fuel Options

The general scheme of the EP follows the sequence below:

1. Vector representation of solution has to be done before getting into Evolutionary programming.
2. Generation of an initial population i.e. parent population is done at random and each individual of population has assigned a fitness value.
3. Creation of offspring by altering each parent individual with respect to Guassian normal distribution and the entire offspring individual is assigned a fitness value.

4. According to competition rule, the surviving individuals of the next generation are selected.

5. Stopping rule is the given count of total generation.

3.1. Representation of solution

The initial population comprises combination of only the candidate dispatch solutions and the tie line flows, which satisfy all the constraints. It consists of p_i for i= 1,2...I trial parent individuals. The elements of a parent individual are the combinations of

1. Power outputs of the generating units randomly chosen using random number ranging over [$P_{mn(min)}$, $P_{mn(,max)}$] and

2. Tie-line flows randomly selected by the uniform random number ranging over [$T_{JK(min)}$, $T_{JK(max)}$]. This range covers the minimum and maximum flows in either direction i.e., if T_{JK} is positive, it is the flow area J to area K if T_{JK} is negative, it is the flow area K to area J.

The number of elements in a parent is equal to N_m on-line generating units in M areas plus the total tie-lines interconnecting M areas.

In multi-area generation scheduling with multiple fuel options, the solution need to represent both generation scheduling and fuel selection.

3.1.1. Generation Schedule

Each individual of population represents a candidate of the generation scheduling solution. They can be represented as an array of vectors as below:

$$p_i = \begin{pmatrix} P_{11} & P_{12} & \cdots & P_{1N(1)}, \\ P_{21} & P_{22} & \cdots & P_{2N(2)}, \\ \vdots & \vdots & & \vdots \\ P_{M1} & P_{M2} & \cdots & P_{MN(m)}, \\ T_{12} & T_{13} & \cdots & T_{1M}, \\ T_{23} & T_{24} & \cdots & T_{2M}, \\ T_{34} & T_{35} & \cdots & T_{3M}, \cdots T_{M-1,M} \end{pmatrix} \tag{6}$$

where i = 1,2,.......I (number of population)

Fuel selection:

$$f_i = \begin{pmatrix} f_{11} & f_{12} & \cdots & f_{1N(1)} \\ f_{21} & f_{22} & \cdots & f_{2N(2)} \\ \vdots & \vdots & & \vdots \\ f_{M1} & f_{M2} & \cdots & f_{MN(m)} \end{pmatrix} \tag{7}$$

To meet exactly the load demand any one of the generating units in each area is arbitrarily selected as the dependent unit among the committed units. Since the problem considered is a special class of economic dispatch problem, it is assumed that unit commitment problem has already solved. The dependent unit power P_{md} is calculated as,

$$P_{md} = D_m + \sum_{\substack{k=1 \\ k \neq m}}^{M} T_{mk} - \sum_{\substack{n=1 \\ n \neq md}}^{N_m} P_{mn} \qquad \text{for} \qquad m = 1, 2, ...M \tag{8}$$

3.2. Initialization

The initial population of parent individuals p_i for i = 1,2...I is selected randomly from a feasible range for each independent unit n in area m. Typically the distribution of initial trial is uniform.

Only generation scheduling vector (p_i) is found randomly and the fuel selection vector (f_i) is then determined by using the components of generation scheduling vector (P_{mn}) such that,

$$\begin{aligned} f_i &= F_1 \quad \text{if} \;\; P_{mn(\min)} \leq P_{mn} \leq P_{L1} \\ &= F_2 \quad \text{if} \;\; P_{L1} \leq P_{mn} \leq P_{L2} \\ &= F_3 \quad \text{if} \;\; P_{L2} \leq P_{ij} \leq P_{mn(\max)} \end{aligned} \tag{9}$$

3.3. Creation of Off Spring

A new offspring population of the solution is produced from the existing parent population by mutating each individual. The new power generation p'_i is formed from the old generation p_i by adding it with a Gaussian random number N. The offspring individuals are represented as:

$$p'_i = \begin{pmatrix} P'_{11} & P'_{12} & \cdots & P'_{1N(1)}, \\ P'_{21} & P'_{22} & \cdots & P'_{2N(2)}, \\ \vdots & \vdots & & \vdots \\ P'_{M1} & P'_{M2} & \cdots & P'_{MN(m)}, \\ T'_{12} & T'_{13} & \cdots & T'_{1M}, \\ T'_{23} & T'_{24} & \cdots & T'_{2M}, \\ T'_{34} & T'_{35} & \cdots & T'_{3M}, \cdots T'_{M-1,M} \end{pmatrix} \tag{10}$$

$$f'_i = \begin{pmatrix} f'_{11} & f'_{12} & & f'_{1N(1)} \\ f'_{21} & f'_{22} & \cdots f'_{2N(2)} & \\ \vdots & \vdots & & \vdots \\ f'_{M1} & f'_{M2} & \cdots & f'_{MN(m)} \end{pmatrix} \tag{11}$$

$$P'_{mn} = P_{mn} + N(0, \sigma^2_{mn})$$

$$T'_{JK} = T_{JK} + N(0, \sigma^2_{JK}) \tag{12}$$

The Gaussian random numbers have a mean of zero and a standard deviation σ (Mutation Factor). Standard deviations are represented as,

$$\sigma_{mn} = \beta(P_{mn(\max)} - P_{mn(\min)})\; f_i/f_{\max} \qquad ; i = 1, 2, ...I$$

$$\sigma_{JK} = \beta(T_{JK(\max)} - T_{JK(\min)})\ f_i/f_{\max} \qquad ; i = 1, 2, ...I \tag{13}$$

The scaling factor (β) is to be tuned during the process of search for the optimum around the initial points. Both β and $f_i/f_{\max}$ are in the range of [0,1]. Multiplying the terms β and $f_i/f_{\max}$ with feasible range of a variable gives the proper range for the random variable which is to be added to it. And the standard deviation is same for tie-line flows in either direction.

However, after mutation the elements of offspring P'_{mn} and T'_{JK} may violate the constraints. These violations are corrected for the independent units in area m as follows:

$$\begin{aligned} P'_{mn} &= P_{mn(\min)} \quad \text{if } (P'_{mn} < P_{mn(\min)}) \\ &= P_{mn(\max)} \quad \text{if } (P'_{mn} > P_{mn(\max)}) \end{aligned}$$

$$\begin{aligned} T'_{JK} &= T_{JK(\min)} \quad \text{if } (T'_{JK} < T_{JK(\min)}) \\ &= T_{JK(\max)} \quad \text{if } (T'_{JK} > T_{JK(\max)}) \end{aligned} \tag{14}$$

Similarly, the violation of the dependent generator (P_{md}) output in area m is corrected as,

$$\begin{aligned} P_{md(\lim)} &= P_{md(\min)} \quad if \ (P'_{md} < P_{md(\min)}) \\ &= P_{md(\max)} \quad if \ (P'_{md} > P_{md(\max)}) \end{aligned} \tag{15}$$

A penalty term is introduced in the objective function to penalize its fitness value. The selection γ is purely heuristic and it is maintained as constant, through in some cases it can be increased in the optimization procedure. Now the objective function is modified as,

$$Minimize\ C = \sum_{m=1}^{M} C_m + \sum_{J=1}^{M-1} \sum_{K=J+1}^{M} f_{JK} T_{JK} + \sum_{m=1}^{M} \gamma \left(P_{md(\lim)} - P'_{md}\right)^2 \tag{16}$$

The penalty term in the above equation is equal to zero during initialization and non-zero value after mutation only if P'_{md} violates its minimum or maximum generation limits. The violation is squared to ensure that it always remain positive even if the violation is of the lower limit. This guarantees that the objective function always has a higher value when violations occur.

The initial population I individuals and their offspring I individuals created by mutation form a competing pool with 2I individuals.

3.4. Competition and Selection

The parent trial vector P_{mn} and the corresponding off-spring P'_{mn} compete for survival with each other within the competing pool and the selection is done by comparing the objective function of parent vectors with the corresponding objective function of off-spring vectors in the population. The best vectors having minimum cost, whether parent vector P_{mn} or offspring vector P'_{mn} are selected as new parents for the next generation.

3.5. Stopping Rule

During initialization, the maximum number of generations is fixed and it is checked for convergence. If the convergence condition is not met the Mutation and Competition processes will run again.

An adaptive mutation scale is given to change the scaling factor for increasing the rate of convergence.

$$\begin{aligned} \beta(g+1) &= \beta(g) - \beta(\text{step}) && \text{if} \quad C_{\min(g)} \text{unchanged} \\ &= \beta(g) && \text{if} \quad C_{\min(g)} \text{ decreased} \\ &= \beta(\text{final}) && \text{if} \quad \beta(g) - \beta(\text{step}) < \beta(\text{final}) \end{aligned} \tag{17}$$

where,

g = Generation number

β (initial)=1.0;

β (step)=0.001 to 0.01;

β (final)=0.005

The mutation scale will decrease as the process goes on. The decreasing speed of the mutation scale depends on the fitness. Such adaptive mutation scale prevents the premature and produces a smooth convergence as well.

4. Proposed EP-LMO Approach

EP is a near global stochastic optimization method starting from multiple points, which placed emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in nature to find a solution. However, EP takes a long computation time to get the solution and sometime EP suffers from the convergence problem. On the other hand, LMO is a gradient-based optimization method starting from a single point and using gradient information to obtain a solution. The solution obtained from LMO is a local optimum solution. In order to obtain a high quality solution, hybrid method has been proposed in this paper. In the first part, EP is applied to obtain a near global solution. After the specified termination criteria for EP is reached, LMO is applied in the second part by using the solution from EP as an initial starting point and searches by using gradient information to obtain the final optimal solution.

The Levenberg–Marquardt algorithm [16] is an approximation to Newton's method and iteratively optimizes the parameter set by using the following relationship:

$$\begin{aligned} &w(t+1) = w(t) + \Delta w(t) \\ &\Delta w = [J^T(w)J(w) + \mu I]^{-1} J^T(w) E(w) \end{aligned} \tag{18}$$

Where,

w = Parameter vector
J= Jacobian matrix
μ = Constant
I = Identity matrix

$E(w)$ = Error function.

The overall procedure of the proposed approach can be described as follows:

Step 1) Read system data.

Step 2) Initialize by random.

Step 3) Solve the economic dispatch problem using EP.

Step 4) Use the answer from step 3 as a starting point and solve the problem using LMO.

Step 5) Get the final result and quit the program.

The above strategies are clearly illustrated in Figure 2.

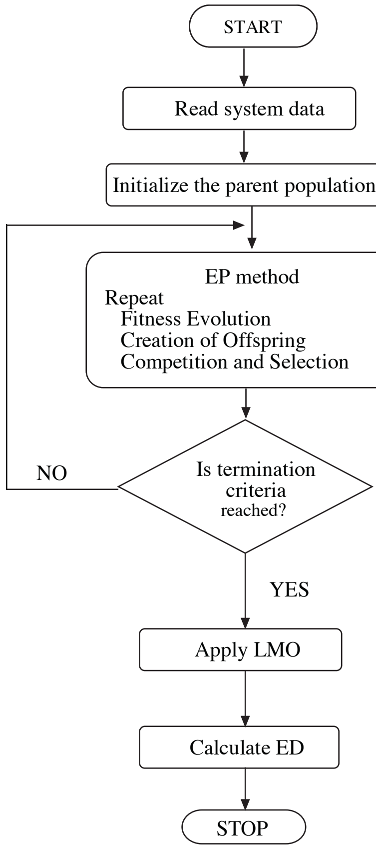

Figure 2. Flow chart for the proposed EP-LMO approach.

5. Part I: EP-LMO Approach to Solve Multi-Area ED Problem

To validate the effectiveness and efficiency of the proposed EP-LMO approach, two bench mark problems are considered. First test problem consists of 16 units, 4 areas and the next problem consists of 14 areas. The results obtained from the EP-LMO are compared with those of other methods: Incremental Network Flow Programming (INFP) [9], Spatial Dynamic Programming (SDP) [3] and Evolutionary Programming method

[11]. The choice of parameters for EP and EP-LMO are given Table 1.

Table 1. Parameter selection.

Algorithm	EP	EP-LMO
Population size	50	25
Maximum generations	2500	**300**
β (initial)	1.0	1.0
β (step)	0.001 to 0.01	0.001 to 0.01
β (final)	0.05	0.005

A. Test Case I

This test case, adapted from [9], comprises 4 areas, each containing 4 units. In this paper, unit costs are defined as a quadratic function of the unit's generation and tie costs are defined as linear functions of the power transfer. The unit's quadratic cost functions and generation limits are as given in [9]. The tie line transfer constraints are all set to 100 MW. This problem consists of three case studies. In Case 1, four areas A_1, A_2, A_3 and A_4 connected by tie lines as shown in Figure 3. Case 2 is identical to case 1 with the addition of a dispatchable purchase available to area A_1 with an upper limit of 50 MW. Case 3 is identical to Case 2 with the addition of a potential sale available in area A_2 with an upper limit of 50 MW.

Table 2 illustrates the power generation, tie line flow and the cost for all cases. The EP-LMO results are compared with INFP [9] and EP [11]. In this paper, the test problem is solved by EP and then EP-LMO. The results of EP are not listed due to limited space. In Case 1, the total cost determined by INFP algorithm as 7337.00 $ and 7338.00 $ by EP method [11]. In this paper, EP method gives the cost as 7336.65 $. The proposed approach EP-LMO gives the total cost as 7334.39 $. Among these methods, the EP-LMO approach provides optimum generation cost. In Case 2, the proposed approach gives the optimum total cost 7333.72 $ compared to other methods. Similarly, EP-LMO have the ability to obtain lower generation cost (7331.07 $) when compared to 7337.00 $ [11] in Case 3.

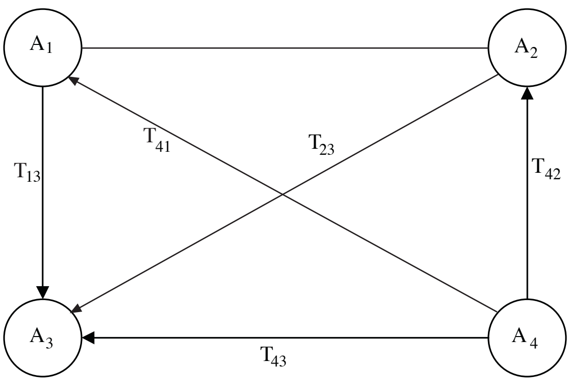

Figure 3. Four Area System with Tie Lines.

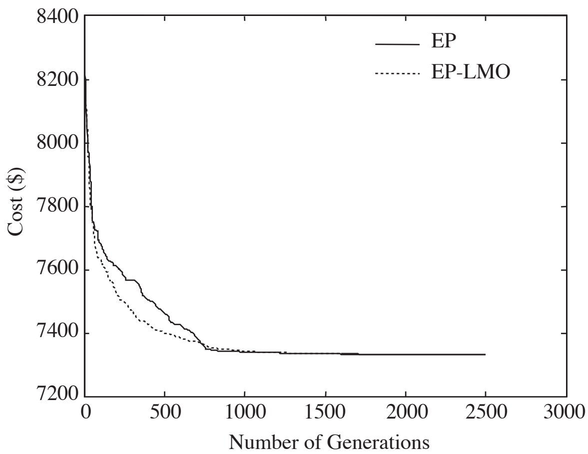

Figure 4. Comparison of EP method with EP-LMO for 4 area system.

Table 3 shows the proposed EP-LMO has a better economic cost than the other methods, even if the proposed algorithm uses a small population. Therefore, Tables 2 and 3 clearly show that the proposed EP-LMO is more robust than the other methods. The Figure 4 shows the comparison of EP method with EP-LMO and Figure 5 shows the zoomed portion of Figure 4. EP-LMO converged faster and attained optimum cost than any other methods. EP-LMO achieves the better economic cost with 350 iterations, as shown in Figure 6. Notice that, in order to achieve the solution, the proposed approach requires a smaller average generation number compared with the other methods.

Table 2. Simulation results for four area system.

Area	Gen/Tie flow	INFP algorithm [9]			EP method			EP-LMO method		
		Case1	Case2	Case3	Case1	Case2	Case3	Case1	Case2	Case3
A_1	P_1	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00
	P_2	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	P_3	66.97	65.04	65.95	65.56	62.69	65.25	65.13	64.64	66.72
	P_4	100.00	100.00	100.00	99.90	98.15	99.70	100.00	100.00	100.00
A_2	P_5	56.97	55.01	56.00	57.88	51.32	52.61	56.56	54.92	53.78
	P_6	96.25	93.74	94.97	93.02	89.86	90.54	96.82	92.78	88.83
	P_7	41.87	40.60	41.20	42.89	38.19	40.28	42.89	38.83	41.22
	P_8	72.52	70.83	71.69	71.48	66.62	69.61	71.64	70.83	70.49
A_3	P_9	50.00	50.00	50.00	50.01	50.00	50.01	50.00	50.00	50.00
	P_{10}	36.27	35.42	35.83	36.98	33.72	34.84	36.98	33.72	34.84
	P_{11}	38.49	37.50	38.02	40.36	35.18	36.32	40.36	35.18	36.32
	P_{12}	37.32	35.55	36.89	38.14	35.34	35.93	38.98	35.55	36.89
A_4	P_{13}	150.00	150.00	150.00	149.98	150.00	150.00	150.00	150.00	150.00
	P_{14}	100.00	100.00	100.00	100.00	100.00	99.98	100.00	100.00	100.00
	P_{15}	57.05	55.56	55.94	56.12	58.26	58.78	57.83	57.87	56.80
	P_{16}	96.27	94.44	94.97	97.68	92.06	91.49	95.36	95.06	91.49
	T_{12}	0.00	0.00	0.00	-0.01	-0.01	0.17	0.00	0.00	0.00
	T_{13}	18.18	30.35	65.95	16.34	49.48	39.54	18.34	39.82	60.47
	T_{14}	-1.21	0.00	0.00	-0.88	0.00	-0.03	-1.28	0.00	-0.02
	T_{23}	69.73	60.18	23.31	68.17	46.30	53.36	69.29	62.64	42.61
	T_{24}	-2.11	0.00	-0.92	-2.90	-0.32	-0.16	-2.11	-0.24	-0.96
	T_{34}	-100.00	-100.0	-100.0	-100.0	-100.0	-100.0	-100.0	-100.0	-100.0
	P_1	0.00	15.31	50.00	0.00	38.62	24.74	0.00	25.56	36.45
	S_2	0.00	0.00	41.47	0.00	0.00	0.00	0.00	0.00	0.00
Total Cost($)		**7337.00**	**7335.00**	**7332.00**	**7338.00**	**7341.00**	**7337.00**	**7334.39**	**7333.72**	**7331.07**

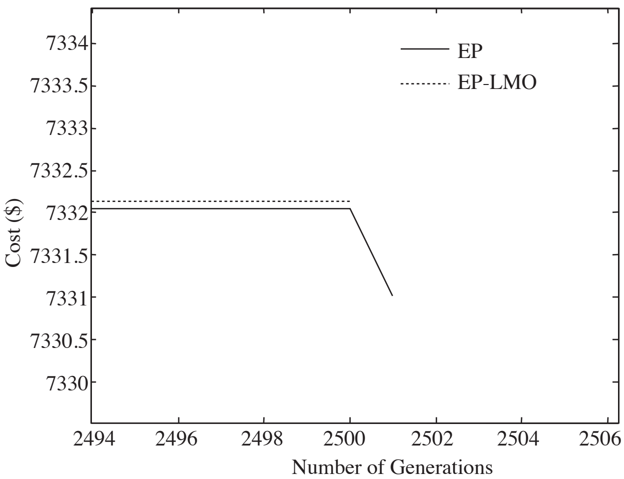

Figure 5. Zoomed portion of Figure 4.

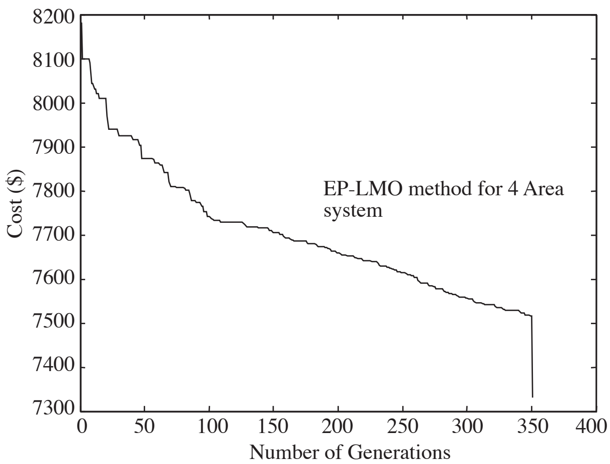

Figure 6. EP-LMO approach for 4 area system (Iterations=350).

Table 3. Comparison of simulation results.

Method	Iterations	Case1 Cost ($)	Case2 Cost ($)	Case3 Cost ($)
INFP [9]	-	7337.00	7335.00	7332.00
EP [11]	14400	7338.00	7341.00	7337.00
EP	2500	7336.65	7334.46	7332.18
EP-LMO	350	7334.39	7333.72	7331.07

B. Test Case II

This test case, adapted from [3], comprises 14 utilities and 17 transmission lines. The generation of each utility is represented by a single cost function. The loads, cost functions, generation upper and lower bounds, transmission constraints and losses are as given in [3]. The EP-LMO results are compared with SDP and EP. The comparative optimal power flow for this system is given in Table 4 and optimal cost is given in Table 5. The optimal cost determined by SDP algorithm is 54613.00 $ and 54619.00 $ by EP method [11]. In this paper, EP method gives the cost as 54421.60 $ and EP-LMO approach gives the total cost as 54410.05 $. Among these methods, the EP-LMO approach provides optimum generation cost.

Table 4. Optimal power flow for 14 utility system.

Branch		Power Flow			
From Node	To Node	SDP[3]	EP[11]	EP	EP-LMO
1	2	186	188.9	186.5	186.5
2	3	1	4.5	4.2	3.9
2	4	165	164.2	164.5	164.8
3	4	0	3.6	2.7	1.2
4	5	0	-0.3	-0.4	-0.4
4	8	-143	-140.0	-140.0	-142.0
5	7	-56	-55.8	-56.6	-55.5
6	7	-50	-50.5	-51.3	-50.7
7	8	194	193.7	193.1	194.0
8	9	-3	-0.2	-1.5	-1.5
9	10	24	21.7	24.7	22.3
9	11	-5	-1.2	-4.5	-6.2
10	11	0	-4.3	-4.6	-3.2
10	12	-2	-0.3	-0.3	-0.3
11	13	0	-0.1	-0.1	-0.1
12	14	-20	-19.0	-20.0	-20.0
13	14	-1	-1.3	-1.5	-1.0

In Table 6, the proposed EP-LMO has a better economic cost than the other methods, even if the proposed algorithm uses a small population. Therefore, Tables 5 and VI clearly show that the performance of EP-LMO is superior to other methods. The Figure 7 shows the comparison of EP method with EP-LMO and Figure 8 shows the zoomed portion of Figure 7. EP-LMO converged faster and attained optimum cost than any other methods. EP-LMO achieves the better economic cost with small number of iterations (300), as shown in Figure 9.

Table 5. Optimal generation for 14 utility system.

Utility	Generation (MW)			
	SDP[3]	EP[11]	EP	EP-LMO
1	3686.0	3688.9	3689.7	3688.5
2	26.7	26.5	27.5	27.2
3	23.0	23.3	25.8	22.7
4	5500.0	5500.0	5500.0	5500.0
5	55.7	56.2	53.7	55.5
6	110.5	110.0	108.4	109.8
7	1900.0	1899.9	1894.9	1898.9
8	550.0	550.0	552.3	550.6
9	2722.0	2720.7	2719.9	2721.2
10	49.5	49.4	50.1	50.1
11	90.0	90.3	91.5	90.3
12	16.4	15.7	16.4	16.4
13	1199.0	1198.9	1199.7	1199.3
14	271.0	270.3	271.6	270.1
Total Cost	**54613.0**	**54619.0**	**54421.6**	**54410.1**

Table 6. Comparison of simulation results.

Method	Iterations	Minimum Cost ($)	Maximum Cost ($)	Average Cost ($)	Computation time (s)
SDP [3]	-	-	-	54613.0	-
EP [11]	16000	-	-	54619.0	-
EP	2500	54700.7	54420.9	54421.6	82.34
EP-LMO	300	54483.6	54410.1	54410.1	13.67

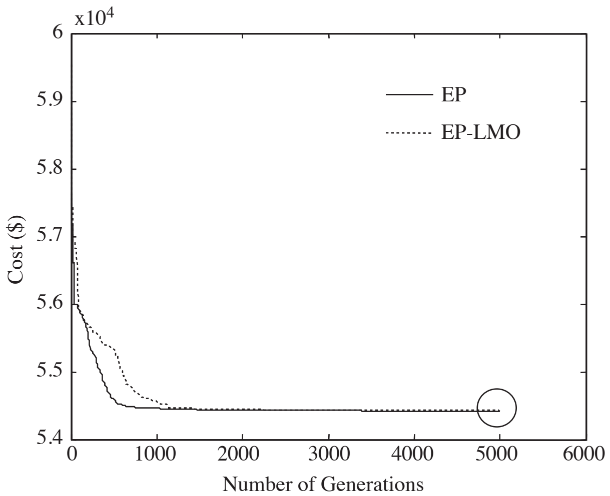

Figure 7. Comparison of EP method with EP-LMO for 14 area system.

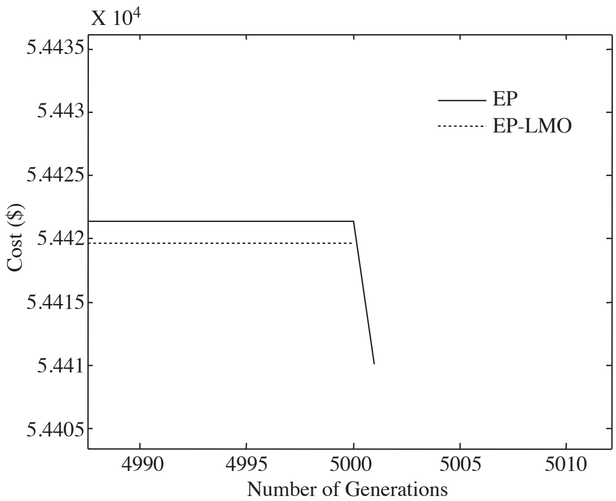

Figure 8. Zoomed portion of Figure 8.

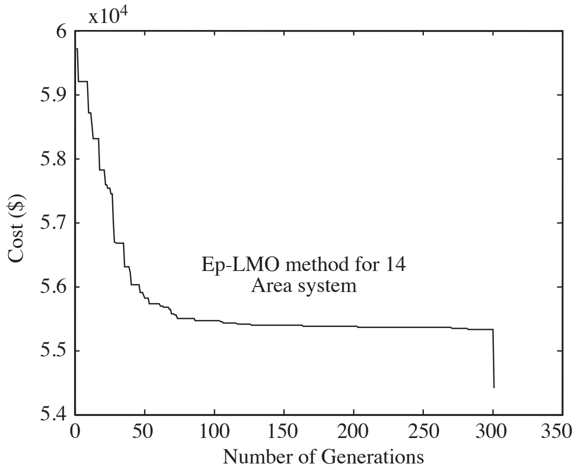

Figure 9. EP-LMO method for 14 area system (Iterations=300).

6. Part II: EP-LMO Approach to Solve Multi-Area ED Problem with Multiple Fuel Options

The input data and constraints of the benchmark problem for economic dispatch with multiple fuel options are taken from the reference [17]. This problem comprises ten generating units with three fuel options. The total system demand is varied from 2400 MW to 2700 MW with 100 MW increments. The ten generating units are divided into three areas as shown if Figure 10. The Area 1 comprises the first four units (P_1, P_2, P_3, P4), the Area 2 includes three units (P5, P_6, P_7) and Area 3 includes remaining three units (P_8, P_9, P_{10}). Each area has both generation and load and each area is represented as having tie line connections to each of the other areas. The load demand in Area 1 is 50% of the total demand. The load demand in Area 2 is 25% and in Area 3 is 25% of the total demand. Table 8 gives the load data for 2400 MW, 2500 MW, 2600 MW and 2700 MW.

The choice of parameters for EP and EP-LMO are given in Table 7.

Table 7. Parameter selection.

Algorithm	EP	EP-LMO
Population size	50	20
Maximum generations	1000	**180**
β (initial)	1.0	1.0
β (step)	0.001 to 0.01	0.001 to 0.01
β (final)	0.005	0.005

As per the algorithm presented in section III, the proposed approach was employed to solve economic dispatch problem represented in equation (16). Table 9 presents the results obtained by EP method for demand levels 2400 MW-2700MW and Table 10 gives the tie line power flow. Table 11 shows the comparisons of the results obtained by the EP and EP-LMO methods. It shows clearly that the proposed approach obtains optimum generation cost for all demand levels.

Owing to the randomness of the heuristic algorithms, their performance cannot be judged by the result of a single run. Many trials with different initializations should be made to acquire a useful conclusion about the performance of the algorithm. An algorithm is robust, if it gives consistent result during all the trials. The comparison of results after 100 trials with the test system is shown in Table 12. It shows the maximum cost, mean cost and minimum cost achieved by EP and EP-LMO methods. Table 12 reveals that the proposed approach has provided the global solution with a high probability to demonstrate its effectiveness and efficiency. Moreover, the proposed EP-LMO has a better economic cost than EP method, even if the proposed algorithm uses a small population.

Table 8. Load Data.

Load Demand	Area	Load	MW
2400 MW	A_1	L_1	1200
	A_2	L_2	600
	A_3	L_3	600
2500 MW	A_1	L_1	1250
	A_2	L_2	625
	A_3	L_3	625
2600 MW	A_1	L_1	1300
	A_2	L_2	650
	A_3	L_3	650
2700 MW	A_1	L_1	1350
	A_2	L_2	675
	A_3	L_3	675

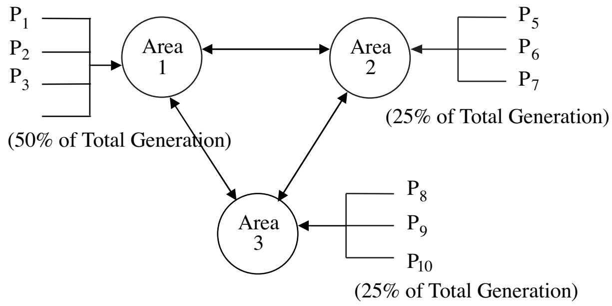

Figure 10. Three area – 10 Unit system.

Table 9. EP method for Multi-area Economic Dispatch with Multiple fuel options.

Area	Unit	2400 MW		2500 MW		2600 MW		2700 MW	
	j	k	P (MW)	k	P (MW)	k	P (MW)	k	P (MW)
Area1	1	2	237.9402	2	248.9708	2	249.7635	2	249.8233
	2	1	218.3068	1	225.8412	1	227.4971	1	229.8882
	3	2	500.0000	2	500.0000	2	500.0000	2	500.0000
	4	3	245.8360	3	249.3470	3	252.3266	3	256.4765
Area2	5	1	190.0882	1	190.3941	1	204.5511	1	227.5199
	6	1	165.1780	1	172.9306	3	225.8334	3	230.7744
	7	1	200.0000	1	203.0832	1	217.8383	1	242.7438
Area3	8	2	165.9977	3	223.2010	3	226.2189	3	229.4518
	9	1	200.0000	1	200.0000	1	202.3776	1	223.1725
	10	1	276.6530	1	286.2321	1	293.5935	1	310.1497
Minimum Cost($/hr)		570.9846		599.0181		660.1843		697.4398	

In order to compare the results in a statistical manner, the frequencies of a cost within the specific ranges are presented in Table 13. Therefore, Tables 12 and 13 clearly show that the proposed EP-LMO is more robust than the other methods. The Figure 11 shows the comparison of EP methods with EP-LMO for $P_D = 2400$ MW and Figure 12 shows the zoomed portion of Figure 11. EP-LMO achieves the better economic cost ($569.1899) with 180 iterations.

Table 10. Tie-line power flow.

Tie-line flow	Tie-line power flow (MW)			
	For demand 2400 MW	For demand 2500 MW	For demand 2600 MW	For demand 2700 MW
T_{21}	55.3019	66.4008	48.2250	101.0393
T_{31}	42.6151	9.4401	122.1878	62.7728
T_{32}	0.0356	-0.0071	0.0022	0.0012
T_{12}	-55.3019	-66.4008	-48.2250	-101.0393
T_{13}	-42.6151	-9.4401	-122.1878	-62.7728
T_{23}	-0.0356	0.0071	-0.0022	-0.0012

Table 11. Comparison of Optimization Methods.

Methods	Minimum Cost ($)			
	P_D= 2400 MW	P_D= 2500 MW	P_D= 2600 MW	P_D= 2700 MW
EP	570.9846	599.0181	660.1843	697.4398
EP-LMO	569.1885	597.3491	658.4466	695.3623

Table 12. Comparison among EP and EP-LMO for 100 Trials for P_D = 2400 MW.

Methods	Total Cost ($)			
	Maximum Cost ($)	Minimum Cost ($)	Average Cost ($)	Computation time (s)
EP method	577.8622	571.2563	570.9846	35.56
EP-LMO method	569.3352	569.1885	569.1899	36.02

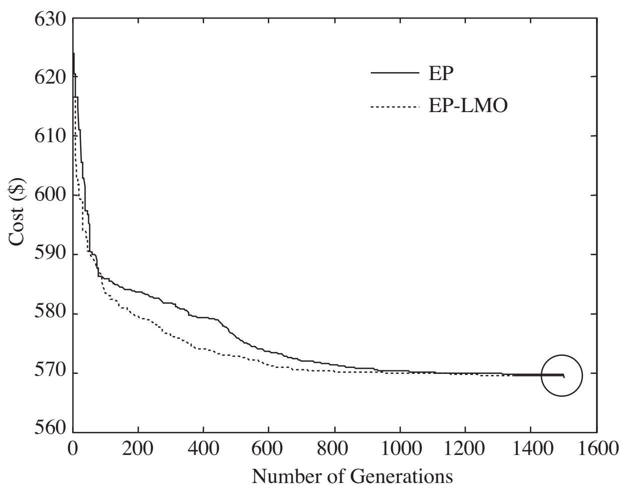

Figure 11. Comparison of EP method with EP-LMO for P_D = 2400 MW.

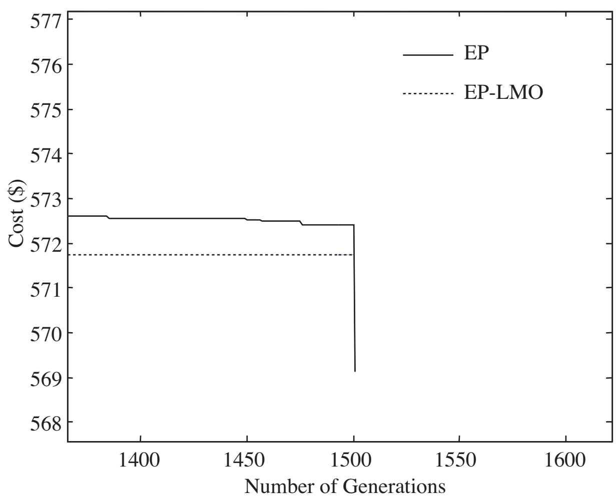

Figure 12. Zoomed portion of Figure 11.

A population size of 20 was used after experimentation with population sizes of 10, 20, 30, 40 and 50. The number of iterations for the proposed approach was used from 100 to 1000. After experimentation EP-LMO achieves the better economic cost with 180 iterations, as shown in Figure 13. Notice that, in order to achieve the solution, the proposed approach requires a small number of iterations compared with EP method.

Table 13. Frequency of convergence for $P_D = 2400$ MW.

Methods	Range of Cost ($)								
	578-577	577-576	576-575	575-574	574-573	573-572	572-571	571-570	570-569
EP	3	5	-	12	4	11	65	-	-
EP-LMO	-	-	-	-	-	-	-	-	100

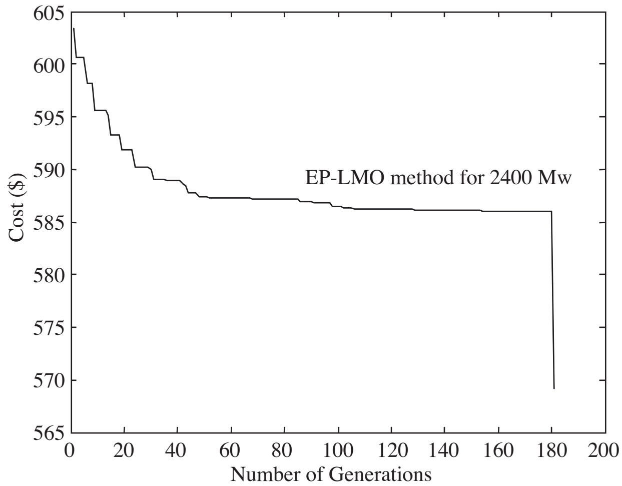

Figure 13. EP-LMO method for $P_D = 2400$ MW (Iterations=180).

7. Conclusion

The proposed EP-LMO approach has achieved efficient and accurate solutions for the considered three area, four area and fourteen area power systems. The performance of EP-LMO approach was compared with other methods such as, Incremental Network Flow Programming, Spatial Dynamic Programming and Evolutionary Programming approaches. It provided good quality solutions. EP is applied as a base level search to find the direction of the optimal global region and LMO is used as a fine tuning to determine the optimal solution. One of the contributions of this paper is the inclusion of multi-area and multi-fuel sources into economic dispatch problem. The other contribution is the combination of the EP and the LMO to solve the multi-area economic dispatch problem with multiple fuel options. However, this paper does not consider the other constraints like ramp rate limit, security constraints. In conclusion, the performance of the EP-LMO approach provides better solution than EP and other methods in terms of convergence rate, solution time, optimum cost and probability.

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List of Symbols

- m - Area
- M - Total number of areas
- n - Generation units
- N_m - Total number of generating units
- k - Fuel
- F_1, F_2 and F_3 - Fuel to be selected for the given P_j
- T_{JK} - Tie-line flow from area J to area K
- f_{JK} - Tie-line cost co-efficient
- C_m - Fuel cost for mth area.
- D_m- Load demand in area m.
- P_{mn} - Power generation generator n in area m.
- $P_{mn(min)}, P_{L1},, P_{L2}, P_{mn(\max)}$ - Limits of generation for selecting the appropriate fuel type.
- P_1,$P_{2,}$....... P_{10} - Power generation of the unit
- S_2-Sale power available in area 2.
- T_{JK} - Tie-line flow from area J to area K.
- $T_{JK(min)}$ - Minimum tie-line flow from area J to area K.
- $T_{JK(max)}$ - Maximum tie-line flow from area J to area K.
- γ - Penalty co-efficient
- f_i - Fitness of the ith individuals
- $f_{\max}$ - Maximum fitness among the I parent individuals.
- β - Scaling factor

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