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Optimizing Environmental-Economic Power via Genetic Algorithms in Bilevel Programming

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Abstract: This article presents a model for addressing the environmental-economic power generation and dispatch (EEPGD) challenge using a multiobjective bilevel programming (MOBLP) approach. The optimization is conducted through a genetic algorithm (GA) based fuzzy goal programming (FGP) applied within the operational system of a thermal power plant. The MOBLP formulation involves segregating the first objectives into two sets and allocating them to distinct hierarchical decision levels (top-level and bottom-level) for optimization. Each level encompasses one or more control variables associated with the power generation decision system. Fuzzy descriptions are employed in the optimization problems of both levels to capture the nuances inherent in the decision-making context.
The FGP model formulation includes the design of membership n functions corresponding to defined fuzzy goals. These functions are then transformed into membership goals by assigning the highest membership value (unity) as the achievement level. Additionally, under- and over-deviational variables are introduced for each membership goal. The goal achievement function aims to minimize under-deviational variables of membership goals based on their weights of importance to attain an optimal solution in the decision environment. In solving the developed FGP model, a GA scheme is applied in two stages.
The first stage involves the direct optimization of individual objectives for their fuzzy representation. In the second stage, the evaluation of the goal achievement function is performed to reach an optimal power generation decision. The efficacy of the proposed method is demonstrated through its application to the IEEE 6-generator 30-bus System.

Keywords: Environmental-economic power generation, Fuzzy goal programming, Genetic algorithm, Membership function

Introduction

The primary means of generating electric power predominantly relies on thermal power plants, with over 75% utilizing coal for power generation to meet societal demands. However, the combustion of fossil-fuel coal in power generation leads to the release of various harmful pollutants, including carbon, nitrogen, and sulfur oxides. These by-products have widespread implications for all living beings on Earth. Hence, there is an imperative need to address the Environmental-Economic Power Generation and Dispatch (EEPGD) problem, where the simultaneous optimization of real-power generation costs and environmental pollution, subject to operational constraints, is essential for the sustainable operation of thermal power plants.
The optimization challenges within thermal power plant operations, initially explored by Dommel and Tinney [2], later extended to emission control by Gent and Lament [3], have evolved into a comprehensive study of EEPGD the

way for subsequent studies in this domain [8-11]. During the 1990s, the focus on controlling power plant emissions intensified, leading to various optimization methods [12-17] in compliance with the Clean Air Amendment Act of the 1990s [18]. Traditional approaches to EEPGD problems involved transforming multiobjective models into single objective problems, leading to decision-making challenges due to conflicting objectives.

The article introduces Genetic Programming (GP) as an efficient tool for multi objective decision analysis [19], applied to EEPGD problems [20] for goal-oriented solutions in a crisp decision environment. However, the imprecise nature of parameter values associated with objectives in real-world scenarios necessitates the incorporation of Fuzzy Programming (FP) [21] and Stochastic Programming (SP) [24-25]. Despite these advancements, extensive literature on solving such problems remains limited.

The article proposes the use of Genetic Algorithms (GAs) to solve Multi-Objective Decision Making (MODM) problems, particularly in the context of EEPGD [26-28]. Recognizing the conflicting nature of EEPGD objectives, the concept of hierarchical optimization using Bilevel Programming (BLP) [29] is introduced, considering the decision maker's priorities in thermal power generation. Although recent studies [30] have explored this area, the application of the MOBLP method to solve EEPGD problems within the framework of Fuzzy Goal Programming (FGP) using GA is a novel contribution.

The article outlines a two-stage methodology involving GA-based fuzzy goal description of objectives and the subsequent evaluation of the goal achievement function. The effectiveness of this approach is demonstrated using the IEEE 6-generator 30-bus System. The paper is structured to provide a detailed description of the problem, MOBLP model formulation, the GA scheme, the proposed FGP model, an illustrative case example, and concluding remarks with suggestions for future research in subsequent sections. Now, objectives and constraints associated with EEPGD problem are discussed in the Sect. 2.

Problem Description

Let P_{gi} be the decision variables defined for generation of power (in p.u) from the *i*th generator of the system, $i = 1,2, ..., n$. Then, let P_D be total demand of power, T_L be total transmission- loss (in p.u) and P_L be the real power-loss in power generation system.

Then, objectives as well as constraints involved with the proposed EEPGD problem are presented in the following section.

Description of Objective Functions

The two types of objectives that are inherent to EEPGD model are presented as follows.

Economic Power Generation Objectives

a) Fuel-cost Function

The total fuel-cost (\$/h) incurred for of power generation can be expressed as:

$$F_C = \sum_{i=1}^{n} (a_i P_{gi}^2 + b_i P_{gi} + c_i) \quad , (1)$$

where a_i, b_i and c_i represent cost-coefficients concerninggeneration of power from *i*th generator.

b) Transmission-loss function

The function associated with power transmission lines involves certain parameters which directly affect the ability to transfer power effectively. Here, the transmission-loss (T_L) (in p.u.) occurs during power dispatch can be modelled as a function of generator output and that can be expressed as:

$$T_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{g_i} B_{ij} P_{g_j} + \sum_{i=1}^{n} B_{0i} P_{g_i} + B_{00} \quad , \qquad (2)$$

where B_{ij}, B_{0i} and B_{00} are *B*-coefficients in [23] associated with *i*-th generator in power transmission network.

Pollution Control Functions

In a thermal power generation system, the most harmful pollutants that are discharged separately to earth's environment are oxides of nitrogen (NO_x), sulphur (SO_x) and carbon (CO_x). Thepollution control functions are quadratic in nature and they are expressed in terms of generators' output P_{gi}, $i = 1,2,\ldots, n$
The functional expression oftotal quantity of NO_xemissions (kg/h))is of the form:

$$E_N = \sum_{i=1}^{n} d_{Ni} P_{gi}^2 + e_{Ni} P_{gi} + f_{Ni}, \quad (3)$$

where d_{Ni}, e_{Ni}, f_{Ni} represent NO_x emission-coefficients concerned with power generation from *i*th generator.
Similarly, the pollution control functions arise for SO_x-and CO_x-emissions appear as:

$$E_S = \sum_{i=1}^{n} d_{Si} P_{gi}^2 + e_{Si} P_{gi} + f_{Si}, \quad (4) \qquad E_C = \sum_{i=1}^{n} d_{Ci} P_{gi}^2 + e_{Ci} P_{gi} + f_{Ci}, \text{ respectively,} \quad (5)$$

where the emission-coefficients associated with respective expressions can be defined in an analogous to the expression in (3).

Description of System Constraints

The constraints that are adhered to EEPGD problem are defined as follows.

Generator Capacity Constraints

In thermal power generation system, the constraints on generators' outputs can be presented as:

$$\begin{aligned} &P_{gi}^{min} \le P_{gi} \le P_{gi}^{max}, \\ &V_{g_i}^{min} \le V_{g_i} \le V_{g_i}^{max}, \quad i = 1, 2, \ldots, n \end{aligned} \quad (6)$$

where P_{gi} and V_{gi} represent active power and generator-bus voltage of *i*th generator, respectively.

Power Balance Constraint

The total power generated from the system must be equal to total demand (P_D) and total transmission-loss in thermal power generation system.
The power balance constraint takes the form:

$$\sum_{i=1}^{n} P_{gi} - (P_D + T_L) = 0 \quad (7)$$

Now, formulation of MOBLP model of the problem is discussed below.

MOBLP Formulation

In MOBLP formulation of the problem, the objectives concerning environmental-emission control are considered leader's optimization problems and that concerned with economic-power generation are considered follower's problems in hierarchical structure of EEPGD problem. The MOBLP model is presented as follows.

MOBLP Model

In the context of designing the proposed model, the vector of decision variables is divided into two distinct vector groups with regard to control them separately by DMs located at two hierarchical levels.

Let $\boldsymbol{X}$ be the vector of decision variables in power generation system. Then, let $\boldsymbol{X_L}$ and $\boldsymbol{X_F}$ be the subsets of $\mathbf{X}$ that are controlled by leader and follower, respectively, where L and F are used to denote leader and follower, respectively.
Then, MOBLP model can be stated as [29]:

Find $\boldsymbol{X(X_L, X_F)}$ so as to:

$$\underset{X_L}{Minimize}\, E_N = \sum_{i=1}^{n} d_{N_i} P_{gi}^2 + e_{N_i} P_{gi} + f_{N_i},$$

$$\underset{X_L}{Minimize}\, E_S = \sum_{i=1}^{n} d_{S_i} P_{gi}^2 + e_{S_i} P_{gi} + f_{S_i},$$

$$\underset{X_L}{Minimize}\, E_C = \sum_{i=1}^{n} d_{C_i} P_{gi}^2 + e_{C_i} P_{gi} + f_{C_i},$$

(leader's problem)

and, for given $\boldsymbol{X_L}$, $\boldsymbol{X_F}$ solves

$$\underset{X_F}{Minimize}\;\; F_C = \sum_{i=1}^{n} (a_i P_{gi}^2 + b_i P_{gi} + c_i),$$

$$\underset{X_F}{Minimize}\, T_L = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{g_i} B_{ij} P_{g_j} + \sum_{i=1}^{n} B_{0i} P_{g_i} + B_{00},$$

(follower's problem)

subject to the constraints in (6) and (7), (8)

where $\boldsymbol{X_L} \cap \boldsymbol{X_F} = \varphi$, $\boldsymbol{X_L} \cup \boldsymbol{X_F} = \boldsymbol{X}$ and $\boldsymbol{X} \in \mathrm{P}(\neq \varphi)$,where P denotes the feasible solution set, $\cap$ and $\cup$ stand for 'intersection' and 'union', respectively.

Now, the GA scheme adopted in the decision-making environment is described below.

GA Scheme

There is a variety of GA schemes in [32-33] for generating new population by employing the 'selection', 'crossover' and 'mutation' operators.
In genetic search process, binary coded solution candidates are considered where initial population is generated randomly. The fitness of each chromosome (individual feasible solution) at each generation is justified with a view to optimizing objectives of the problem.
Now, formulation of FGP model of the problem in (8) is described as follows.

FGP Model Formulation

In the structural framework of a BLP problem, it is conventionally considered that DM at each level is motivated to cooperative with other one concerning achievement of objectives in decision environment. In the sequel of making decision, since leader is with the power of making decision first, relaxation on his/her decision is essentially needed to make decision by follower to certain satisfactory level. Consequently, relaxation on individual objective values and components of $\boldsymbol{X_L}$ need be given to certain tolerance levels for benefit of follower. Therefore, use of the notion of fuzzy set to solve the problem in (8) would be effectiveone to reach overall satisfactory decision.
The fuzzy version of the problem is discussed as follows.

Fuzzy Goal Description

In fuzzy environment, objective functions of the problem are to be expressed as fuzzy goals by means of incorporating an imprecise target value to each of them.

In the decision making context, since minimum value of an objective of a DM is highly acceptable, solutions achieved for minimization of objectives of individual DMs can be considered the best solutions, and they are determined as $(\boldsymbol{X}_L^{lb}, \boldsymbol{X}_F^{lb}; E_N^{lb}, E_S^{lb}, E_C^{lb})$ and $(\boldsymbol{X}_L^{fb}, \boldsymbol{X}_F^{fb}; F_C^{fb}, T_L^{fb})$, respectively, by employing GA scheme, where *lb* and *fb* indicate the best for leader and follower, respectively.

Then, the successive fuzzy goals take the form:

$$E_N \precsim E_N^{lb}, E_S \precsim E_S^{lb} \text{ and } E_C \precsim E_C^{lb}$$

$$F_C \precsim F_C^{fb} \quad \text{and } T_L \precsim T_L^{fb}, \tag{9}$$

where '$\precsim$' indicates softness of $\leq$ restriction and signifies 'essentially less than' in [34].

Again, since most dissatisfactory solutions of DMs correspond to maximum values of objectives, the worst solutions of leader and follower can be obtained by using the same GA scheme as $(\boldsymbol{X}_L^{lw}, \boldsymbol{X}_F^{lw}; E_N^{lw}, E_S^{lw}, E_C^{lw})$ and $(\boldsymbol{X}_L^{fw}, \boldsymbol{X}_F^{fw}; F_C^{fw}, T_L^{fw})$, respectively, where *lw* and, *fw* indicate worst cases for leader and follower, respectively.

As a matter consequence, $E_N^{lw}, E_S^{lw}, E_C^{lw}, F_C^{fw}$ and T_L^{fw} could be taken as upper-tolerance values towards achieving the respective fuzzy target levels E_N, E_S, E_C, F_C and T_L.

Again, fuzzy goal representation of control vector $\boldsymbol{X}_L$ can be reasonably taken as:

$$\boldsymbol{X}_L \precsim \boldsymbol{X}_L^{lb} \tag{10}$$

Now, it may be mentioned that an increase in the valueof a goal defined by goal vector in (10) would never be more than upper-bound of corresponding generator capacity defined in (6).

Let $\boldsymbol{X}_L^t, (\boldsymbol{X}_L^t < \boldsymbol{X}_L^{max}),$ be the vector of upper-tolerance values to achieve the associated vector of fuzzy goal levels defined in (10).

Now, characterization of membership functions of fuzzy goals is described below.

Characterization of Membership Function

The membership function of the fuzzy objective goal E_N can be algebraically presented as:

$$\mu_{E_N}[E_N] = \begin{cases} 1, & \text{if } E_N \leq E_N^{lb} \\ \dfrac{E_N^{lw} - E_N}{E_N^{lw} - E_N^{lb}}, & \text{if } E_N^{lb} < E_N \leq E_N^{lw} \\ 0, & \text{if } E_N > E_N^{lw} \end{cases} \tag{11}$$

where $(E_N^{lw} - E_N^{lb})$ represents tolerance range for fuzzy goal achievement defined in (9).

Again, membership functions associated with other two objectives, E_s and E_c of leader as well as objectives of follower can be obtained.

The membership function associated with $\boldsymbol{X}_L$ can be obtained as:

$$\mu_{\boldsymbol{X}_L}[\boldsymbol{X}_L] = \begin{cases} 1, & \text{if } \boldsymbol{X}_L \leq \boldsymbol{X}_L^{lb} \\ \dfrac{\boldsymbol{X}_L^t - \boldsymbol{X}_L}{\boldsymbol{X}_L^t - \boldsymbol{X}_L^{lb}}, & \text{if } \boldsymbol{X}_L^{lb} < \boldsymbol{X}_L \leq \boldsymbol{X}_L^t \\ 0, & \text{if } \boldsymbol{X}_L > \boldsymbol{X}_L^t \end{cases} \tag{12}$$

where $(\boldsymbol{X}_{\boldsymbol{L}}^{\boldsymbol{t}} - \boldsymbol{X}_{\boldsymbol{L}}^{\boldsymbol{lb}})$ represents vector of tolerance ranges for achievement of vector of decision variables defined in (10). Now, *minsum* FGP model of the problem is presented as follows.

Minsum FGP Model

To formulate FGP model of the problem, membership functions are converted into membership goals by assigning highest membership value (unity) as target level and introducing under- and over-deviational variables to each of them. In achievement function of *minsum* FGP model, minimization of the sum of weighted under-deviational variables associated with membership goals is taken into account.

The model appears as [31]:

Find $\boldsymbol{X}(\boldsymbol{X_L}, \boldsymbol{X_F})$ so as to:

Minimize: $Z = \sum_{k=1}^{5} w_k^- d_k^- + \boldsymbol{w_6^- d_6^-}$

and satisfy

$$\frac{E_N^{lw} - E_N}{E_N^{lw} - E_N^{lb}} + d_1^- - d_1^+ = 1, \qquad \frac{E_S^{lw} - E_S}{E_S^{lw} - E_S^{lb}} + d_2^- - d_2^+ = 1,$$

$$\frac{E_C^{lw} - E_C}{E_C^{lw} - E_C^{lb}} + d_3^- - d_3^+ = 1, \qquad \frac{F_c^{fw} - F_C}{F_C^{fw} - F_C^{fb}} + d_4^- - d_4^+ = 1,$$

$$\frac{T_L^{fw} - T_L}{T_L^{fw} - T_L^{fb}} + d_5^- - d_5^+ = 1, \ \frac{\boldsymbol{X}_{\boldsymbol{L}}^{\boldsymbol{t}} - \boldsymbol{X}_{\boldsymbol{L}}}{\boldsymbol{X}_{\boldsymbol{L}}^{\boldsymbol{t}} - \boldsymbol{P}_{\boldsymbol{GL}}^{\boldsymbol{lb}}} + \boldsymbol{d_6^-} - \boldsymbol{d_6^+} = \mathbf{I}$$

subject to the constraints in (6) and (7), (13)

where $d_k^-, d_k^+ \geq 0$, (k = 1,…,5) represent under- and over-deviational variables, respectively. $\boldsymbol{d_6^-}, \boldsymbol{d_6^+} \geq 0$ indicate vector of under- and over-deviational variables, respectively, and where I is a column vector. Z is goal achievement function, $w_k^- > 0$, k = 1, 2, 3, 4, 5are relative numerical weights of importance of achieving target levels of goals, and $w_6^- > 0$ is the vector of numerical weights associated with d_6^-, and they are actually the inverse of respective tolerance ranges [31]concerning achievement of goal levels.
The effective use of the model in (13) is illustrated below through a case example.

A Case Example

The IEEE 30-bus 6-generator test system in [15] is taken into account to demonstrate the proposed method.
The system is with 41 transmission lines and total power demand for 21 load buses is 2.834 p.u. The generator capacity limits and load data were discussed in [15] previously. The different types of coefficients associated with the model are given in Tables 1-4.

Table 1. Power generation cost-coefficients

Generator ⟶	g_1	g_2	g_3	g_4	g_5	g_6
Cost-Coefficients						
a	100	120	40	60	40	100
b	200	150	180	100	180	150
c	10	12	20	10	20	10

Table 2. NO_x emission-coefficients

Generator →	g_1	g_2	g_3	g_4	g_5	g_6
NO_x Emission-Coefficients						
d_N	0.006323	0.006483	0.003174	0.006732	0.003174	0.006181
e_N	-0.38128	-0.79027	-1.36061	-2.39928	-1.36061	-0.39077
f_N	80.9019	28.8249	324.1775	610.2535	324.1775	50.3808

Table 3. SO_x emission-coefficients

Generator →	g_1	g_2	g_3	g_4	g_5	g_6
SO_x Emission-Coefficients						
d_S	0.001206	0.002320	0.001284	0.000813	0.001284	0.003578
e_S	5.05928	3.84624	4.45647	4.97641	4.4564	4.14938
f_S	51.3778	182.2605	508.5207	165.3433	508.5207	121.2133

Table 4. CO_x emission-coefficients

Generator →	g_1	g_2	g_3	g_4	g_5	g_6
CO_x Emission-Coefficients						
d_S	0.265110	0.140053	0.105929	0.106409	0.105929	0.403144
e_S	-61.01945	-29.95221	-9.552794	-12.73642	-9.552794	-121.9812
f_S	5080.148	3824.770	1342.851	1819.625	13.42.851	11381.070

The *B-coefficients* in [20] are presented as follows:

$$B=\begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix}_{(6\times 6)}$$

$$B_0=\begin{bmatrix} -0.0107 & 0.0060 & -0.0017 & 0.0009 & 0.0002 & 0.0030 \end{bmatrix}_{(1\times 6)}, \quad B_{00}=9.86E-04$$

Now, to formulate MOBLP model, it is considered that $\boldsymbol{X_L}(P_{g3}, P_{g5})$ is under the control of leader, and $\boldsymbol{X_F}(P_{g1}, P_{g2}, P_{g4}, P_{g6})$ is that of follower.

Using the data presented in Tables1- 4, the executable MOBLP model for EEPGD problem is stated as follows.

Find $\boldsymbol{X}(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}\ P_{g6})$ so as to:

$$\begin{aligned} \underset{\boldsymbol{X_L}}{Minimize}\ E_N(\boldsymbol{X}) = (&0.006323P_{g1}^2 - 0.38128P_{g1} + 80.9019 + 0.006483P_{g2}^2 - 0.79027P_{g2} + 28.8249 \\ &+ 0.003174P_{g3}^2 - 1.36061P_{g3} + 324.1775 + 0.006732P_{g4}^2 - 2.39928P_{g4} + 610.2535 \\ &+ 0.003174P_{g5}^2 - 1.36061P_{g5} + 324.1775 + 0.006181P_{g6}^2 - 0.39077P_{g6} + 50.3808) \end{aligned} \tag{14}$$

$$\underset{X_L}{Minimize}\ E_S\ (\boldsymbol{X}) = (0.001206P_{g1}^2 + 5.05928P_{g1} + 51.3778 + 0.002320P_{g2}^2 + 3.84624P_{g2} + 182.2605$$
$$+ 0.001284P_{g3}^2 + 4.45647P_{g3} + 508.5207 + 0.000813P_{g4}^2 + 4.97641P_{g4} + 165.3433$$
$$+ 0.001284P_{g5}^2 + 4.45647P_{g5} + 508.5207 + 0.003578P_{g6}^2 + 4.14938P_{g6} + 121.2133) \quad (15)$$

$$\underset{X_L}{Minimize}\ E_C\ (\boldsymbol{X}) = (0.265110P_{g1}^2 - 61.01945P_{g1} + 5080.148 + 0.140053P_{g2}^2 - 29.95221P_{g2} + 3824.770$$
$$+ 0.105929P_{g3}^2 - 9.552795P_{g3} + 1342.851 + 0.106409P_{g4}^2 - 12.73642P_{g4} + 1819.625$$
$$+ 0.105929P_{g5}^2 - 9.552794P_{g5} + 1342.851 + 0.403144P_{g6}^2 - 121.9812P_{g6} + 11381.070)$$

(leader's objectives) (16)

and, for given $\boldsymbol{X_L}$; $\boldsymbol{X_F}$ solve

$$\underset{X_F}{Minimize}\ F_C\ (\boldsymbol{X}) = (100P_{g1}^2 + 200P_{g1} + 10 + 120P_{g2}^2 + 150P_{g2} + 10 + 40P_{g3}^2$$
$$+ 180P_{g3} + 20 + 60P_{g4}^2 + 100P_{g4} + 10 + 40P_{g5}^2 + 180P_{g5} \quad (17)$$
$$+ 20 + 100P_{g6}^2 + 150P_{g6} + 10)$$

$$\underset{X_F}{Minimize}\ T_L(\boldsymbol{X}) = 0.1382P_{g1}^2 + 0.0487P_{g2}^2 + 0.0182P_{g3}^2 + 0.0137P_{g4}^2 + 0.0109P_{g5}^2 + 0.0244P_{g6}^2$$
$$- 0.0598P_{g1}P_{g2} + 0.0088P_{g1}P_{g3} - 0.0044P_{g1}P_{g4} - 0.0020P_{g1}P_{g5} - 0.0016P_{g1}P_{g6}$$
$$- 0.0050P_{g2}P_{g3} + 0.0008P_{g2}P_{g4} + 0.0032P_{g2}P_{g5} + 0.0082P_{g2}P_{g6} - 0.140P_{g3}P_{g4}$$
$$- 0.0132P_{g3}P_{g5} - 0.0132P_{g3}P_{g6} + 0.010P_{g4}P_{g5} + 0.0066P_{g4}P_{g6} + 0.0010P_{g5}P_{g6}$$
$$- 0.0107P_{g1} + 0.0060P_{g2} - 0.0017P_{g3} + 0.0009P_{g4} + 0.0002P_{g5} + 0.0030P_{g6} + 9.8573X10^{-4}$$

(follower's objectives) (18)

subject to, $0.05 \le P_{g1} \le 0.50$, $0.05 \le P_{g2} \le 0.60$,

$0.05 \le P_{g3} \le 1.00$, $0.05 \le P_{g4} \le 1.20$,

$0.05 \le P_{g5} \le 1.00$, $0.05 \le P_{g6} \le 0.60$,

(generator capacity constraints) (19)

and $P_{g1} + P_{g2} + P_{g3} + P_{g4} + P_{g5} + P_{g6} - (2.834 + L_T) = 0$,

(Power balance constraint) (20)

Now, in the GA scheme, 'Roulette-wheel selection' and 'single point crossover' with populationsize50 are initially introduced. The parameter values adopted to execute the problem are crossover- probably = 0.8 and mutation-probability = 0.07.

The computer program developed in MATLAB and GAOT (Genetic Algorithm Optimization Toolbox) in MATLAB-Ver. R2010a is used to execute the problem. The execution is made in Intel Pentium IV with 2.66 GHz. Clock-pulse and 4 GB RAM.

Following the procedure, individual best solutions of leader and follower are found as:

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_N^{lb})$

$= (0.05, 0.05, 0.5177, 1.20, 1.00, 0.05\ ;\ 1413.708)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_S^{lb})$

$= (0.05, 0.60, 0.8379, 0.05, 0.7320, 0.60\ ;\ 1549.535)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; E_C^{lb})$

$= (0.50, 0.60, 0.05, 1.0985, 0.05, 0.60\ ;\ 24655.09)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; F_C^{fb})$

$= (0.1220, 0.2863, 0.5832, 0.9926, 0.5236, 0.3518\ ;\ 595.9804)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; T_L^{fb})$

$= (0.0861, 0.0978, 0.9764, 0.5001, 0.8533, 0.3373\ ;\ 0.0170)$.

Further, worst solutions of leader and follower are obtained as:

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; E_N^{lw})$

$= (0.50, 0.60, 0.6036, 0.05, 0.5269, 0.60\ ;\ 1416.167)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; E_S^{lw})$

$= (0.50, 0.05, 0.1002, 1.2, 1.00, 0.05\ ;\ 1551.043)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; E_C^{lw})$

$= (0.05, 0.05, 1.00, 0.7040, 1.00, 0.05;\ 24752.86)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; F_C^{fw})$

$= (0.500, 0.600, 0.1397, 0.05, 1.00, 0.600;\ 705.2694)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}\ ; T_L^{fw})$

$= (0.50, 0.05, 0.05, 1.20, 1.00, 0.1036\ ;\ 0.0696)$

Then, the fuzzy objective goals are obtained as:

$E_N \lesssim 1413.708,\ E_S \lesssim 1549.535,\ E_C \lesssim 24655.09,\ F_C \lesssim 595.9804,\ T_L \lesssim 0.0170.$

The fuzzy goals for power generation decisions under the control of leader appear as:

$$P_{g3} \lesssim 0.15 \text{ and } P_{g5} \lesssim 0.15.$$

The upper-tolerance limits of E_N, E_S, E_C, F_C *and* T_L are obtained as $(E_N^{lw}, E_S^{lw}, E_C^{lw}, F_C^{fw}, T_L^{fw}) = ($1416.167, 1551.043, 24752.86, 705.2694, 0.0696 ,). Again, the upper-tolerance limits of the decision variables associated with $\mathbf{X_L}$ are considered $(P_{g3}^t,\ P_{g5}^t) = (0.6, 0.6)$.

Then, the membership functions are constructed as follows:

$$\mu_{E_N} = \frac{1416.167 - E_N}{1416.167 - 1413.708},\ \mu_{E_S} = \frac{1551.043 - E_S}{1551.043 - 1549.535},\ \mu_{E_C} = \frac{24752.86 - E_C}{24752.86 - 24655.09},$$

$$\mu_{F_C} = \frac{705.2694 - Z_1}{705.2694 - 595.9804},\ \mu_{T_L} = \frac{0.0696 - T_L}{0.0696 - 0.0170},$$

$$\mu_{P_{g3}} = \frac{0.60 - P_{g3}}{0.60 - 0.40},\ \mu_{P_{g5}} = \frac{0.60 - P_{g5}}{0.70 - 0.40}$$

Then, the executable *minsum* FGP model is constructed as follows.

Find $\boldsymbol{X}(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6})$ so as to:

Minimize $Z = 0.4067d_1^- + 0.6631d_2^- + 0.0102d_3^- + 0.0092d_4^- + 19.0114d_5^- + 2.5d_6^- + 2.5d_7^-$

and satisfy

$$\frac{1416.167 - \sum_{i=1}^{n} d_{Ni}P_{gi}^2 + e_{Ni}P_{gi} + f_{Ni}}{1416.167 - 1413.708} + d_1^- - d_1^+ = 1$$

$$\frac{1551.043 - \sum_{i=1}^{n} d_{Si}P_{gi}^2 + e_{Si}P_{gi} + f_{Si}}{1551.043 - 1549.535} + d_2^- - d_2^+ = 1$$

$$\frac{24752.86-\sum_{i=1}^{n} d_{Ci}P_{gi}^2+e_{Ci}P_{gi}+f_{Ci}}{24752.86-24655.09}+d_3^- - d_3^+ = 1$$

$$\frac{705.2694-\sum_{i=1}^{n}(a_iP_{gi}^2+b_iP_{gi}+c_i)}{705.2694-595.9804}+d_4^- - d_4^+ = 1$$

$$\frac{0.0696-\sum_{i=1}^{n}\sum_{j=1}^{n}P_{g_i}B_{ij}P_{g_j}+\sum_{i=1}^{n}B_{0i}P_{g_i}+B_{00}}{0.0696-0.0170}+d_5^- - d_5^+ = 1$$

$$\frac{0.60-P_{g3}}{0.60-0.40}+d_6^- - d_6^+ = 1,\quad \frac{0.60-P_{g5}}{0.60-0.40}+d_7^- - d_7^+ = 1$$

subject to the constraints in (19) and (20). (21)

The function Z in (21) acts as evaluation function in solution search process.
The function to evaluate the fitness of a chromosome takes the form:

$$Eval\,(E_v)=(Z)_v=(\sum_{k=1}^{5} w_k^- d_k^- + \sum_{k=6}^{7} w_k^- d_k^-)_v,\; v=1,2,...,PS,$$

where *PS* stands for population-size. (22)
where $(Z)_v$ represents the achievement function (Z) to measure fitness value of *v*th chromosome.

The best objective value (Z^*) at any solution stage is obtained as:

$$Z^* = min\,\{eval(E_v)\,|\,v=1,2,...,PS\} \quad (23)$$

The resultant objective values are found as:

$(E_N, E_S, E_C, F_C, T_L) = (1414.69,\ 1550.38, 24669.95, 629.73, 0.0522)$

with the respective membership values:

$(\mu_{E_N}, \mu_{E_S}, \mu_{E_C}, \mu_{F_C}, \mu_{T_L}) = (0.5978, 0.4357, 0.8479, 0.6912, 0.0255).$

The power generation decision is obtained as:

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}) = (0.1821, 0.4197, 0.40, 0.9885, 0.40, 0.47737).$

The bar-diagram to represent power generation decision is depicted in Figure 1.

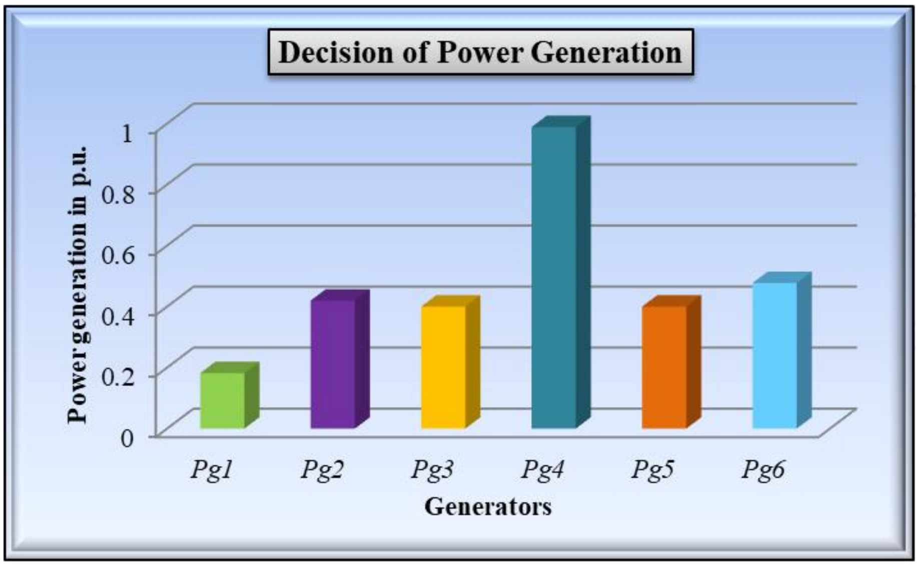

Figure 1. Graphical representation of power generation decision

The result indicates that the solution is quite satisfactory, and sequential executions of decision powers of DMs are preserved there in the hierarchical order of optimizing objectives of the EEPGD problem.

Performance Comparison

To highlight more the effectiveness of the proposed method, a comparison of resultant solution is made with the solution achieved by employing the conventional *minsum* FGP method in [35].

Here, values of the objectives are found as:

$(E_N, E_S, E_C, F_C, T_L) = (1414.847, 1550.01, 24719.38, 631.60, 0.0175).$

The resultant power generation decision is:

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}) = (0.05, 0.1409, 0.9898, 0.4379, 0.8938, 0.3389).$

The above result indicates that reduction of49.43 kg/hr of NO_x emission and reduction of1.87 $/hr fuel cost are made here by using the proposed method without sacrificing total units of power demand.

Conclusions and Future Research Direction

The main advantage of using BLP to EEPGD problem is that optimization of objectives individually in a hierarchical order can be obtained in inexact environment. Again, order of hierarchy of objectives as well as fuzzy descriptions of objectives / constraints can easily be rearranged under the flexible nature of the proposed FGP model in decision making horizon. Furthermore, computational burden arises with linearization of objectives by using conventional technique does not involve here owing to the use of bio-inspired tool to make power generation decision. Here, it may be claimed that the GA based FGP method presented here may open up future research for thermal power generation decision and to make pollution free living environment on earth. However, the proposed method can be extended to formulate multilevel programming (MLP) [36] model with multiplicity of objectives in power plant operation and management system, which is an emerging problem in future research.

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