Multi-objective Bi-level Programming for Environmental Constrained Electric Power Generation and Dispatch via Genetic Algorithm

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Abstract- *This article presents how multiobjective bilevel programming (MOBLP) in a hierarchical structure can be efficiently used for modeling and solving environmental-economic power generation and dispatch (EEPGDD) problems through Fuzzy Goal Programming (FGP) based on genetic algorithm (GA) in a thermal power system operation and planning horizon. In MOBLP formulation, first the objectives associated with environmental and economic power generation are considered two optimization problems at two individual hierarchical levels (top level and bottom level) with the control of more than one objective, that are inherent to the problem each level. Then, the optimization problems of both the levels are described fuzzily to accommodate the impression arises for optimizing them simultaneously in the decision situation. In the model formulation, the concept of membership functions in fuzzy sets for measuring the achievement of highest membership value (unity) of the defined fuzzy goals in FGP formulation to the extent possible by minimising under-deviational variables associated with membership goals defined for them on the basis of their weights of importance is considered. Actually, the modeling aspects of FGP are used here to incorporate various uncertainties arises in generation of power and dispatch to various locations. In the solution process, a GA scheme is used in the framework of FGP model in an iterative manner to reach a satisfactory decision on the basis of needs in society in uncertain environment. The GA scheme is employed at two different stages. At the first stage, individual optimal decisions of objectives are determined for fuzzy goal description of them. At the second stage, evaluation of goal achievement function to arrive at the highest membership value of the fuzzy goals in the order of hierarchical of optimizing them in the decision situation. The effective use of the approach is tested on the standard IEEE 6-Generator 30-Bus System.*

Keywords- M Bi-level programming, Environmental-economic power dispatch, Fuzzy goal programming, Goal programming, Genetic algorithm, Membership function, Transmission-losses.

I. INTRODUCTION

The major electric power generation sources are thermal plants, where more than 75% of the power plants across the countries use fossil fuel coal for generation of power. But, generation of electric power by burning coal leads to produce various harmful pollutants like oxides of carbon, oxides of nitrogen and oxides of sulphur. These by-products not only affect the human but also the entire living beings in this world. So, economic-dispatch problem of electric power plant is actually a combined optimization problem where real-power generation cost and environmental emission from a plant during generating of power has to be optimized simultaneously, where several operational constraints need be satisfied for smooth running of power generation system.

Actually, the thermal power operation and management problems in [1] are optimization problems with multiplicity of objectives and various system constraints. The general mathematical programming model for optimal power generation was introduced by Dommel and Tinney in [2]. The constructive optimization model for minimization of thermal power plant emissions was first introduced by Gent and Lament in [3]. Thereafter, the field was explored by Sullivan and Hackett in [4] among other active researchers in the area of study.

Now, consideration of both the aspects of economic power generation and reduction of emissions in a framework of mathematical programming was initially studied by Zahavi and Eisenberg in [5], and thereafter optimization models for EEPGD problems were investigated in [6, 7] in the past.

The study on environmental power dispatch models developed from 1960s to 1970s was surveyed by Happ in [8]. Thereafter, different classical optimization models developed in the past century EEPGD problems have been surveyed in [9, 10, 11] in the past.

During 1990s, emissions control problems were seriously considered and different strategic optimization approaches were developed with the consideration of 1990's

Clean Air Amendment [12] by the active researchers in the field and well documented in [13, 14, 15] in the literature. Here, it is to be mentioned that in most of the previous approaches the inherent multiobjective decision making problems are solved by transforming them into single objective optimization problems. As a result, decision deadlock often arises there concerning simultaneous optimization of both the objectives.

To cope with the above situations and to overcome the shortcomings of the classical approaches, the concept of membership functions in fuzzy sets theory (FST) in [16] has appeared as a robust tool for solving the optimization problems.

Now, since an EEPGD problem is multiobjective in nature, the GP approach can be used as a robust and flexible tool for multiobjecive decision analysis and which is based on the satisficing (coined by the noble laureate H. A. Simon in [17]) philosophy has been studied in [18] to obtain the goal oriented solution of economic-emission power dispatch problems.

However, in most of the practical decision situations, it is to be observed that decision parameters of problems with multiplicity of multiplicity of objectives are inexact in nature owing to inherent impressions in parameter themselves as well as imprecise in nature of human judgments of setting parameter values. To cope with the situation, fuzzy programming (FP) approach to EEPGD problems has been discussed in [19, 20]. The traditional stochastic programming (SP) approaches to EEPGD problems was studied in [21, 22] in the past. But, the extensive study in this area is at an early stage.

During the last decade, different multiobjective optimization methods for EEPGD problems have been studied in [23, 24, 25] by considering the Clean Air Act Amendment.

In the context of solving MODM problems by employing conventional approaches in crisp/ fuzzy environment, it is worthy to note that uses of such an approach often leads to local optimal solution to owing to competing in nature of objectives in optimizing them in actual practice. Again, when nonlinearity occurs in objectives / constraints, computational difficulties arises in most of the decision situations. To overcome the difficulty, GAs based on natural selection and natural genetics in biological system and as a goal satisficer rather than objective optimizer can be used to solve MODM problems. The GA based several soft computing approaches to EEPGD problems have been studied by the active researchers in [26, 27, 28] in the past.

Now, it is to be observed that the objectives of power system operation and control are highly conflict each other. As an essence, optimization of objectives in a hierarchical structure on the basis of needs of decision makers (DMs) can be considered. As such, bilevel programming (BLP) in [29] in hierarchical decision system might be an effective one for solving the problems. Although, the problem of balancing thermal power supply and market demand have been studied in [30] in the recent past, but the study in this area is yet to be explore in the literature. Moreover, the MOBLP approach to EEPGD problem by employing GA based FGP method is yet to appear in the literature.

In this article, the GA base FGP approach is used to formulate and solve MOBLP for EEPGD problem. In the model formulation, the minsum FGP in [31] the most widely used and simplest version of FGP is used to achieve a rank based power generation decision in an inexact decision environment. In the decision making process, a GA scheme is employed at two different stages. At the first stage, individual optimal decisions of the objectives are determined for fuzzy goal description of them. At the second stage, evaluation of goal achievement function for minimization of the weighted under-deviational variables of the membership goals associated with the defined fuzzy goals is considered for achieving the highest membership value (unity) of the defined fuzzy goals on the basis of hierarchical order of optimizing them in the decision situation. A case example of IEEE 6-Generator 30-Bus System is considered to illustrate the potential use of the approach.

The paper is organizing as follows. Section 2 contains the description of proposed problem by defining the objectives and constraints in power generation system. Section 3 provides the MOBLP model formulation by defining the leaders and followers objectives and decision vector. In Section 4, computational steps of the proposed GA scheme for modeling and solving the problem is presented. In Section 5 the FGP Model formulation of the proposed problem is presented. Section 6 gives an illustrative case example in order to demonstrate the feasibility and efficiency of the proposed approach. Finally, Section 7 provides some general conclusions and future research.

Now, the general mathematical structures of various objectives and system constraints of an EEPGD problem are discussed in the following section.

II. PROBLEM DESCRIPTION

P_{gi} , i = 1,2, ..., N, be the decision variables associated with power generation (in p.u) from the *i-th* generator. Then, let P_D

be the total demand of power (in p.u.), T_L be the total transmission- loss (in p.u), P_L be the real power losses associated with the system.

Then, the objectives and constraints that are associated with the proposed EEPGD problem are discussed as follows.

A. Description of Objective Functions

1. Economic Power Generation Objectives

a) Fuel-cost Function:

The total fuel-cost ($/h) function associated with generation of power from all generators of the system 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 are the estimated cost-coefficients associated with generation 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 modeled as a function of generator output and that can be expressed as:

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

where B_{ij}, B_{0i} and B_{00} are called Kron's loss-coefficients or B-coefficients in [20] associated with the power transmission network.

2. Environmental Objectives

In a thermal power plant operational system, various types of pollutions are discharged to the earth's Environment due to burning of coal for power generation.

The amount of NO_x emission (kg/h)) is given as a quadratic function of generator output P_{gi} as:

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

where d_{Ni}, e_{Ni}, f_{Ni} are NO_x emission-coefficients associated with generation of power from i-th generator.

Similarly, the amount of SO_x emission (kg/h) is given as a quadratic function of generator output P_{gi} as:

$$E_S = \sum_{i=1}^{N} d_{Si} P_{gi}^2 + e_{Si} P_{gi} + f_{Si} \ , \quad (4)$$

where d_{Si}, e_{Si}, f_{Si} are SO_x emission-coefficients associated with generation of power from i-th generator.

The amount of CO_x emission (kg/h) is also represented as a quadratic function of generator output P_{gi} as: $E_C = \sum_{i=1}^{N} d_{Ci} P_{gi}^2 + e_{Ci} P_{gi} + f_{Ci}$, (5)

where d_{Si}, e_{Si}, f_{Si} are CO_x emission-coefficients associated with generation of power from i-th generator.

B. Description of System Constraints

The system constraints which are commonly involved with the problem are defined as follows.

1. Power Balance Constraint

The generation of total power must cover the total demand (P_D) and total transmission-loss inherent to a thermal power generation system.

The total power balance constraint can be obtained as:

$$\sum_{i=1}^{N} P_{gi} - (P_D + T_L) = 0 \ , \quad (6)$$

2. Generator Constraints

In an electric power generation and dispatch system, the constraints on the generators can be considered as:

$$\begin{aligned} & P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \ , \\ & V_{g_i}^{min} \le V_{g_i} \le V_{g_i}^{max} \ , \quad i = 1, 2, ..., N \end{aligned} \quad (7)$$

where P_{gi} , and V_{gi} are the active power, and generator bus voltage, respectively. 'N' is the number of generators in the system.

Now, MOBLP formulation of the proposed problem for minimizing the objective functions is presented in the following section III.

III. MOBL FORMULATION OF THE PROBLEM

In MOBLP formulation of the proposed problem, environmental objectives are considered as leader's problem and economic objectives are considered as follower's problem in the hierarchical decision system.

Now, the MOBLP model formulation of the proposed problem is presented in the following section A.

A. MOBLP Model Formulation

In a BLP model formulation, the vector of decision variables are divided into two distinct vectors and assigned them separately to the DMs for controlling individually.

Let $\mathbf{D}$ be the vector of decision variables in a thermal power supply system. Then, let $\mathbf{D_L}$ and $\mathbf{D_F}$ be the vectors of decision variables controlled independently by the leader and follower, respectively, in the decision situation, where L and F stand for leader and follower, respectively.

Then, BLP model of the problem appears as in [29]:
Find $\mathbf{D(D_L, D_F)}$ so as to:

$$\underset{D_L}{\text{Minimize}}\ E_N = \sum_{i=1}^{N} d_{Ni}P_{gi}^2 + e_{Ni}P_{gi} + f_{Ni}\,,$$

$$\underset{D_L}{\text{Minimize}}\ E_S = \sum_{i=1}^{N} d_{Si}P_{gi}^2 + e_{Si}P_{gi} + f_{Si}\,,$$

$$\underset{D_L}{\text{Minimize}}\ E_C = \sum_{i=1}^{N} d_{Ci}P_{gi}^2 + e_{Ci}P_{gi} + f_{Ci}\,,$$

(Leader's problem)

and, for given $\mathbf{D_L}$, $\mathbf{D_F}$ solves

$$\underset{D_F}{\text{Minimize}}\ F_C = \sum_{i=1}^{N}(a_iP_{gi}^2 + b_iP_{gi} + c_i)\ ,$$

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

(Follower's problem)

subject to the system constraints in (6) **-** (7), (8)

where $\mathbf{D_L} \cap \mathbf{D_F} = \varphi, \mathbf{D_L} \cup \mathbf{D_F} = \mathbf{D}$ and $\mathbf{D} = \{\mathbf{P_g}; \mathbf{V_g}\ \text{and}\ \mathbf{T}\} \in S(\neq \varphi)$, and where S denotes the feasible solution set, $\cap$ and $\cup$ stand for the mathematical operations 'intersection' and 'union', respectively.

Now, the GA scheme employed for modeling and solving the problem in (8) in the framework of an FGP approach is presented in the following section IV.

IV. GA SCHEME FOR THE PROBLEM

In the literature of GAs, there is a variety of schemes in [32, 33] for generating new population with the use of different operators: selection, crossover and mutation.

In the present GA scheme, binary representation of each candidate solution is considered in the genetic search process. The initial population (the initial feasible solution individuals) is generated randomly. The fitness of each feasible solution individual is then evaluated with the view to optimize an objective function in the decision making context.

Now, FGP formulation of the problem in (8) by defining the fuzzy goals is presented in the next section V.

V. FGP MODEL FORMULATION OF THE PROBLEM

In a power generation decision context, it is assumed that the environmental and economic objectives in both the levels are motivated to cooperative to each other and each optimizes its benefit by paying an attention to the benefit of other one. Here, since leader is in the leading position to make own decision, relaxation on the decision of leader is essentially needed to make a reasonable decision by follower to optimize the objective function to a certain level of satisfaction. Therefore, relaxation of individual optimal values of both the objectives as well as the decision vector controlled by leader up to certain tolerance levels need be considered to make a reasonable balance of execution of decision powers of the DMs.

To cope with the above situation, a fuzzy version of the problem in (8) would be an effective one in the decision environment.

The fuzzy description of the problem is presented as follows Section.

A. Description of Fuzzy Goals

In a fuzzy decision situation, the objective functions are transformed into fuzzy goals by means of assigning an imprecise aspiration level to each of them.

In the sequel of making decision, since individual minimum values of the objectives are always acceptable by each DM, the independent best solutions of leader and follower are determined first as $(\mathbf{D_L^{lb}}, \mathbf{D_F^{lb}}; E_N^{lb}, E_S^{lb}, E_C^{lb})$ and $(\mathbf{D_L^{fb}}, \mathbf{D_F^{fb}}; F_C^{fb}, T_L^{fb})$, respectively, by using the GA scheme, where *lb* and, *fb* stand for leader's best and follower's best, respectively.

Then, the fuzzy goals of the leader and follower can be successively defined as:

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

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

where ‘$\lesssim$’ Refers to the fuzziness of an aspiration level and it is to be understood as ‘essentially less than’ in [34].

Again, since maximum values of the objectives when calculated in isolation by the DMs would be the most dissatisfactory ones, the worst solutions of leader and follower can be obtained by using the same GA scheme as $(\mathbf{D}_{\mathbf{L}}^{\boldsymbol{lw}}, \mathbf{D}_{\mathbf{F}}^{\boldsymbol{lw}}; E_N^{lw}, E_S^{lw}, E_C^{lw})$ and $(\mathbf{D}_{\mathbf{L}}^{\boldsymbol{fw}}, \mathbf{D}_{\mathbf{F}}^{\boldsymbol{fw}}; F_C^{fw}, T_L^{fw})$, respectively, where *lw* and, *fw* stand for leader's worst and follower's worst, respectively.

Then, $E_N^{lw}, E_S^{lw}, E_C^{lw}, F_C^{fw}$ and T_L^{fw} would be the upper-tolerance limits of achieving the aspired levels of E_N, E_S, E_C, F_C and T_L, respectively.

The vector of fuzzy goals associated with the control vector $\mathbf{D_L}$ can be defined as:

$$\mathbf{D_L} \lesssim \mathbf{D}_{\mathbf{L}}^{\boldsymbol{lb}} \tag{10}$$

In the fuzzy decision situation, it may be noted that the increase in the values of fuzzily described goals defined by the goal vector in (10) would never be more than the corresponding upper-bounds of the power generation capacity ranges defined in (7).

Let $\mathbf{D}_{\mathbf{L}}^{\mathbf{t}}, (\mathbf{D}_{\mathbf{L}}^{\mathbf{t}} < \mathbf{D}_{\mathbf{L}}^{\mathbf{max}})$, be the vector of upper-tolerance limits of achieving the goal levels of the vector of fuzzy goals defined in (10).

Now, the fuzzy goals are to be characterized by the respective membership functions for measuring their degree of achievements in a fuzzy decision environment.

B. Characterization of Membership Function

The membership function representation of the fuzzy objective goal of NO_x function under the control of leader appears as:

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

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

Similarly, the membership functions of the other two leader's objectives and follower's objectives can be calculated.

The membership function of the fuzzy decision vector $\mathbf{D_L}$ of the leader appears as:

$$\mu_{\mathbf{D_L}}[\mathbf{D_L}] = \begin{cases} 1, & \text{if } \mathbf{D_L} \le \mathbf{D}_{\mathbf{L}}^{\boldsymbol{lb}} \\ \dfrac{\mathbf{D}_{\mathbf{L}}^{\mathbf{t}} - \mathbf{D_L}}{\mathbf{D}_{\mathbf{L}}^{\mathbf{t}} - \mathbf{D}_{\mathbf{L}}^{\boldsymbol{lb}}}, & \text{if } \mathbf{D}_{\mathbf{L}}^{\boldsymbol{lb}} < \mathbf{D_L} \le \mathbf{D}_{\mathbf{L}}^{\mathbf{t}} \\ 0, & \text{if } \mathbf{D_L} > \mathbf{D}_{\mathbf{L}}^{\mathbf{t}} \end{cases} \tag{12}$$

where $(\mathbf{D}_{\mathbf{L}}^{\mathbf{t}} - \mathbf{D}_{\mathbf{L}}^{\boldsymbol{lb}})$ is the vector of tolerance ranges for achievement of the fuzzy decision variables associated with $\mathbf{D_L}$ defined in (9).

Note 1: $\mu\,[.]$ represents membership function.

Now, *minsum* FGP formulation of the proposed problem is presented in the following section.

C. Minsum FGP Model Formulation

In the process of formulating FGP model of a problem, the membership functions are transformed into membership goals by assigning the highest membership value (unity) as the aspiration level and introducing under- and over-deviational variables to each of them. In *minsum* FGP, minimization of the sum of weighted under-deviational variables of the membership goals in the goal achievement function on the basis of relative weights of importance of achieving the aspired goal levels is considered.

The *minsum* FGP model can be presented as in [31]:

Find $\mathbf{D}(\mathbf{D_L}, \mathbf{D_F})$ so as to:

Minimize: $Z = \sum_{k=1}^{5} w_k^- d_k^- + \mathbf{w}_{\mathbf{6}}^- \mathbf{d}_{\mathbf{6}}^-$

and satisfy

$$\mu_{E_N} : \frac{E_N^{lw} - E_N}{E_N^{lw} - E_N^{lb}} + d_1^- - d_1^+ = 1,$$

$$\mu_{E_S} : \frac{E_S^{lw} - E_S}{E_S^{lw} - E_S^{lb}} + d_2^- - d_2^+ = 1,$$

$$\mu_{E_C} : \frac{E_C^{lw} - E_C}{E_C^{lw} - E_C^{lb}} + d_3^- - d_3^+ = 1,$$

$$\mu_{F_C} : \frac{F_c^{fw} - F_C}{F_C^{fw} - F_C^{fb}} + d_4^- - d_4^+ = 1,$$

$$\mu_{T_L} : \frac{T_L^{fw} - T_L}{T_L^{fw} - T_L^{fb}} + d_5^- - d_5^+ = 1,$$

$$\mu_{D_L} : \frac{\mathbf{D}_L^t - \mathbf{D}_L}{\mathbf{D}_L^t - \mathbf{P}_{GL}^{lb}} + \mathbf{d}_6^- - \mathbf{d}_6^+ = \mathbf{I}$$

subject to the set of constraints defined in (6) - (7),

(13)

where $d_k^-, d_k^+ \geq 0$, (k = 1,…,5) represent the under- and over-deviational variables, respectively, associated with the respective membership goals. $\mathbf{d}_6^-, \mathbf{d}_6^+ \geq 0$ represent the vector of under- and over-deviational variables, respectively, associated with the membership goals defined for the vector of decision variables in $\mathbf{D}_L$, and where I is a column vector with all elements equal to 1 and the dimension of it depends on the dimension of $\mathbf{D}_L$. Z represents goal achievement function, $w_k^- > 0$, k = 1, 2, 3, 4, 5 denote the relative numerical weights of importance of achieving the aspired goal levels, and $w_5^- > 0$ is the vector of numerical weights associated with d_5^-, and they are determined by the inverse of the tolerance ranges [31] for achievement of the goal levels in the decision making situation.

Now, the effective use of the *minsum* FGP model in (13) is demonstrated via a case example presented in the next section.

VI. A DEMONSTRATIVE CASE EXAMPLE

The standard IEEE 30-bus 6-generator test system in [23] is considered to illustrate the potential use of the approach.

The system has 6 generators and 41 lines and the total system demand for the 21 load buses is 2.834 p.u. The data description of generators limit and load data is given in [23]. The detailed data of generation cost-coefficients and emission-coefficients are given in Table 1 - 4.

Table 1. Data description of power generation costs – 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. Data description of NOx 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. Data description of SOx 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. Data description of COx 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:

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

$$B_0 = \begin{bmatrix} -0.0107 & 0.0060 & -0.0017 & 0.0009 & 0.0002 & 0.0030 \end{bmatrix},$$

$$B_{00} = 9.8573\mathrm{E}-4$$

Now, in the proposed MOBLP formulation of the problem, without loss of generality it is assumed that, $\mathbf{D_L}(P_{g3} \text{ and } P_{g5})$ is under the control of the leader, and $\mathbf{D_F}(P_{g1}, P_{g2}, P_{g4}, P_{g6})$ is assigned to the follower.

The data presented in Table 1- 6 is used here to solve the problem in the present decision situation.

Here, the executable MOBLP model for EEPGDD problem appears as follows.

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

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

$$\begin{aligned} \underset{\mathbf{D_L}}{\text{Minimize}}\ E_S(\mathbf{D}) = (&0.001206 P_{g1}^2 + 5.05928 P_{g1} + 51.3778 + 0.002320 P_{g2}^2 + 3.84624 P_{g2} + 182.2605 \\ &+ 0.001284 P_{g3}^2 + 4.45647 P_{g3} + 508.5207 + 0.000813 P_{g4}^2 + 4.97641 P_{g4} + 165.3433 \\ &+ 0.001284 P_{g5}^2 + 4.45647 P_{g5} + 508.5207 + 0.003578 P_{g6}^2 + 4.14938 P_{g6} + 121.2133) \end{aligned} \tag{15}$$

$$\begin{aligned} \underset{\mathbf{D_L}}{\text{Minimize}}\ E_C(\mathbf{D}) = (&0.265110 P_{g1}^2 - 61.01945 P_{g1} + 5080.148 + 0.140053 P_{g2}^2 - 29.95221 P_{g2} + 3824.770 \\ &+ 0.105929 P_{g3}^2 - 9.552795 P_{g3} + 1342.851 + 0.106409 P_{g4}^2 - 12.73642 P_{g4} + 1819.625 \\ &+ 0.105929 P_{g5}^2 - 9.552794 P_{g5} + 1342.851 + 0.403144 P_{g6}^2 - 121.9812 P_{g6} + 11381.070) \end{aligned}$$

(leader's objectives) (16)

and, for given $\mathbf{D}_L$; $\mathbf{D_F}$ solve

$$\begin{aligned} \underset{\mathbf{D_F}}{\text{Minimize}}\ F_C(\mathbf{D}) = (&100 P_{g1}^2 + 200 P_{g1} + 10 + 120 P_{g2}^2 + 150 P_{g2} + 10 + 40 P_{g3}^2 + 180 P_{g3} + 20 + 60 P_{g4}^2 + 100 P_{g4} + 10 + 40 P_{g5}^2 + 180 P_{g5} \\ &+ 20 + 100 P_{g6}^2 + 150 P_{g6} + 10) \end{aligned} \tag{17}$$

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

(18)
(follower's objectives)

subject to

$$P_{g1} + P_{g2} + P_{g3} + P_{g4} + P_{g5} + P_{g6} - (2.834 + L_T) = 0, \quad (19)$$

(Power balance constraint)

and $0.05 \le P_{g1} \le 0.50$, $0.05 \le P_{g2} \le 0.60$,
$0.05 \le P_{g3} \le 1.00$, $0.05 \le P_{g4} \le 1.20$,
$0.05 \le P_{g5} \le 1.00$, $0.05 \le P_{g6} \le 0.60$,

(20)

(Power generator capacity constraints)

Now, employing the proposed GA scheme the individual best and least solutions of the leader's objectives are determined.

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

Now, the following GA parameter values are introduced during the execution of the problem in different stages.

The parameter values used in genetic algorithm solution are given in Table 5.

Table 5. The parameter values used in GA

Parameter	Value
Number of Individual in the initial population	50
Selection	Roulette-wheel
Crossover function	Single Point
Crossover probability	0.8
Mutation Probabiliy	0.06
Maximum Generation Number	100

Following the procedure, the individual best solutions of leaders and followers are obtained as:

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_N^{lb})$
$= (0.05, 0.05, 0.5177, 1.20, 1.00, 0.05\ ; 1413.708)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_S^{lb})$
$= (0.05, 0.60, 0.8379, 0.05, 0.7320, 0.60\ ; 1549.535)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_C^{lb})$
$= (0.50, 0.60, 0.05, 1.0985, 0.05, 0.60\ ; 24655.09)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; F_C^{fb})$
$= (0.1220, 0.2863, 0.5832, 0.9926, 0.5236, 0.3518\ ; 595.9804)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; T_L^{fb})$
$= (0.0861, 0.0978, 0.9764, 0.5001, 0.8533, 0.3373\ ; 0.0170)$

Again, the worst solutions of leader and follower are found as:

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_N^{lw})$
$= (0.50, 0.60, 0.6036, 0.05, 0.5269, 0.60\ ; 1416.167)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_S^{lw})$
$= (0.50, 0.05, 0.1002, 1.2, 1.00, 0.05\ ; 1551.043)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; E_C^{lw})$
$= (0.05, 0.05, 1.00, 0.7040, 1.00, 0.05; 24752.86)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; F_C^{lw})$
$= (0.500, 0.600, 0.1397, 0.05, 1.00, 0.600; 705.2694)$

$(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6}; T_L^{fw})$
$= (0.50, 0.05, 0.05, 1.20, 1.00, 0.1036\ ; 0.0696)$

Then, the fuzzy objective goals appear as:

$E_N \lesssim 1413.708$, $E_S \lesssim 1549.535$,

$E_C \lesssim 24655.09$, $F_C \lesssim 595.9804$ and $T_L \lesssim 0.0170$

The fuzzy goals for power generation decisions under the control of leader are obtained 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 $\mathbf{D_L}$ are considered as $(P_{g3}^t, \text{ and } P_{g5}^t) = (0.6, 0.6)$.

Then, the membership functions are constructed as follows:

$$\mu_{E_N} = \frac{1416.167 - E_N}{1416.167 - 1413.708}, \quad \mu_{E_S} = \frac{1551.043 - E_S}{1551.043 - 1549.535},$$

$$\mu_{E_C} = \frac{24752.86 - E_C}{24752.86 - 24655.09},$$

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

$$\mu_{T_L} = \frac{0.0696 - T_L}{0.0696 - 0.0170},$$

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

Following the procedure, the executable *minsum* FGP model of the problem is obtained as follows.

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

Minimize Z =

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

and satisfy

$$\mu_{E_N} : \frac{1416.167 - \sum_{i=1}^{N} d_{N_i} P_{gi}^2 + e_{N_i} P_{gi} + f_{N_i}}{1416.167 - 1413.708} + d_1^- - d_1^+ = 1$$

$$\mu_{E_S} : \frac{1551.043 - \sum_{i=1}^{N} d_{S_i} P_{gi}^2 + e_{S_i} P_{gi} + f_{S_i}}{1551.043 - 1549.535} + d_2^- - d_2^+ = 1$$

$$\mu_{E_C} : \frac{24752.86 - \sum_{i=1}^{N} d_{C_i} P_{gi}^2 + e_{C_i} P_{gi} + f_{C_i}}{24752.86 - 24655.09} + d_3^- - d_3^+ = 1$$

$$\mu_{F_C} : \frac{705.2694 - \sum_{i=1}^{N} (a_i P_{gi}^2 + b_i P_{gi} + c_i)}{705.2694 - 595.9804} + d_4^- - d_4^+ = 1$$

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

$$\mu_{P_{g3}} : \frac{0.60 - P_{g3}}{0.60 - 0.40} + d_6^- - d_6^+ = 1$$

$$\mu_{P_{g5}} : \frac{0.60 - P_{g5}}{0.60 - 0.40} + d_7^- - d_7^+ = 1$$

subject to the given system constraints in (19) and (20).

(21)

The goal achievement function Z in (21) appears as the evaluation function in the GA search process of solving the problem.

The evaluation function to determine the fitness of a chromosome appears as:

$$\text{Eval } (E_v) = (Z)_v = (\sum_{k=1}^{5} w_k^- d_k^- + \sum_{k=6}^{7} w_k^- d_k^-)_v, \; v = 1, 2, ..., \text{pop\_size} \quad (22)$$

where $(Z)_v$ is used to represent the achievement function (Z) in (21) for measuring the fitness value of v-th chromosome in the decision process.

The best objective value (Z^*) for the fittest chromosome at a generation in the solution search process is determined as:

$$Z^* = \min \{\text{eval}(E_v) \mid v = 1, 2, ..., \text{pop\_size}\} \quad (23)$$

The achieved values of the objectives are:

$$(E_N, E_S, E_C, F_C, T_L)$$
$$= (1414.69, \; 1550.38, 24\,669.95, 629\,.73, \; 0.0522) \; ,$$

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 resultant power generation decision is: $(P_{g1}, P_{g2}, P_{g3}, P_{g4}, P_{g5}, P_{g6})$
$= (0.1821, \; 0.4197, \; 0.40, \; 0.9885, \; 0.40, \; 0.47737)$.

The graphical representation of decision of power generation is displayed in Figure 1.

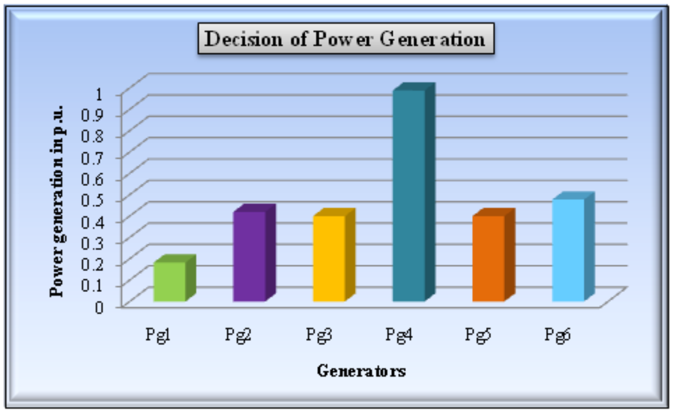

Fig. 1. Graphical representation of power generation decision.

The result reflects that the solution is quite satisfactory from the view point of executing the decision powers of DMs on the basis of hierarchical order in the decision situation.

VII. PERFORMANCE COMPARISON

To expound the effectiveness of the proposed method, the model solution is compared with the solutions obtained by conventional *minsum* FGP approach in [35].

The achieved 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 comparison of the result with the proposed approach shows that, 49.43 kg/hr carbon emission reduction and 1.87 $/hr fuel cost reduction is achieved here without sacrificing the total demand.

VIII. CONCLUSIONS AND SCOPE FOR FUTURE RESEARCH

The main advantage of BLP formulation of EEPGD problem is that individual decisions regarding optimization of objectives on the basis of hierarchy assigned to them can be taken in the decision environment. Again, under the flexible nature of the model, hierarchical ordering of objectives as well as fuzzy descriptions of objectives / constraints can easily be rearranged and that depend on decision environment. Further, computational load occur for traditional use of linearization approaches to nonlinear functions does not arise here owing to the use of bio-inspired approach for power generation decision. Finally, it is hoped that the solution approach presented here may lead to future research for optimal thermal power generation decision by making pollution free living environment on earth.

The GA based FGP approach to EEPGD problems presented here can be extended to formulate multilevel programming (MLP) model with multiplicity of objectives in power plant operation and management system to meet power demand in society as well as to protect health of environment on Earth, which is a problem in future study.

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