Soft Computing Approach for Optimal Electric Power Generation and Dispatch

[1]Papun Biswas, [2]Tuhin Subhra das
[1]Associate Professor, [2]M.Tech Student
[1]Department of Electrical Engineering,
[1]JIS College of Engineering, Kalyani,, India

Abstract : This article describes how genetic algorithm (GA) can be efficiently used to fuzzy goal programming (FGP) formulation for optimal power flow in operational and planning phases of power system. In the proposed approach, the objectives of the problem for optimal power flow computation are fuzzily described. In the model formulation of the problem, the membership functions of the defined fuzzy goals are characterized first to measuring the degree of achievement of the specified aspiration levels of the objective goals in the decision making context. Then, the goal achievement function under the *minsum* FGP to minimize the regret arises due to under-deviations from the highest membership value (unity) of the defined membership goals to the extent possible is constructed for making optimal power flow decision in the decision making environment. In the solution process, the proposed GA method is used in an iterative manner to reach a satisfactory decision on the basis of needs and desires of the decision maker (DM). To illustrate the potential use of the approach, the problem tested on IEEE 6-Generator 30-Bus System is considered and the model solution is compared with the solutions obtained in the previous study.

IndexTerms - Fuzzy goal programming, Goal programming, Genetic algorithm, Membership function, Optimal power flow.

I. INTRODUCTION

The Optimal Load Flow problem in power system was first studied by Carpentier [1] in the early 1960s. Thereafter, the developed model has been widely used as a powerful tool for power system operation and planning, and has appeared as a special field of study named 'Optimal Power Flow (OPF)' [2]. Now-a-days, most of the problems which involve the determination of the instantaneous optimal steady state of an electric power system are considered the OPF problems [3], [4], [5]. The study on the uses of nonlinear optimization techniques to OPF problems has been well documented in [6].

Now, it may be noted that the conventional mathematical programming techniques are useful only to computation of specific aspects of OPF problems for power system operations in crisp decision environment. But, computational errors frequently arise there to solving many practical OPF problems involving uncertain values of model parameters. Here, in most of the cased of modeling the real-world decision problems, it may be mentioned that the necessary information to specify the exact model coefficients is imprecise in nature, because data sources are not always exact in nature as well as vagueness in human judgments are frequently created to provide exact data. As a matter of fact, power system models are subject to changes with the changes of decision environment to ensure the steady power flow. Again, in the conventional approaches to OPF problems, the limits of system constraints, physical limits and operating limits, are given fixed values that would have to be controlled exactly in all times. But, relaxations on such limits are frequently needed to enhance the security of power systems. Now, in a practical decision situation, two types of inequality constraints, hard constraints and soft constraints can be taken into account. Here, it is to be followed that the limits on generating unit outputs are in the nature of hard constraints because there are physical limitations on the capacity of the generating units to produce active power. On the other hand, the limits of transmission line flow can be taken as soft, because small violations of these limits are acceptable if consideration of such a situation arises there, particularly during stressed situations (e.g., emergency or peak loaded situations) of the systems. Further, in the decision situation, operators normally desire to operate the system economically within the normal limits of power flow through a transmission line, and a small violation of it is acceptable if physically possible there. However, the emergency limits are always considered hard to take safety measures.

In the above circumstances, to take the necessary measures to ensure the steady operation of power system, the fuzzy set theory, introduced by Zadeh [7] in 1965,in the area soft computing might be considered an efficient tool to resolve the OPF problems. The use of fuzzy set-theoretic approaches to various practical decision systems, viz., traffic controlling, scheduling and robot manufacturing , have already been well documented in the literature. In the field of power engineering, although fuzzy programming (FP) [8] methods have been applied to some areas of OPF problems [9], [10], [11], [12], the extensive study in this field is yet to be widely documented in the literature.

In this article, the FGP [13], [14], [15] approach as an extension of conventional goal programming (GP) [16], [17] for multiobjective decision making (MODM) in the field of FP is considered for modeling and solving OPF problems having the characteristics of nonlinear programming in an uncertain decision environment. Now, it may be noted that the conventional approximation method is generally used to nonlinear FGP problems [14], but computational load is inherently involved there and local optimal solutions are often achieved there in actual practice.

To overcome the computational complexity due to nonlinearity in practical decision problems, GAs [18] appear as a robust tool to searching satisfactory decisions for MODM problems. GAs to real-world multiobjective decision problems have been studied in [15] in the past. But,, the study on the use of using GAs to FGP problems are at an early stage. Again, the GA based FGP technique to Load Flow problems is yet to appear in the literature. In the process of solving the present FGP formulation of the problem of optimal planning of electric power generation and dispatch with the various objectives and constraint functions, an GA scheme is introduced to reach a satisfactory decision in the decision making environment.

The simulation result of IEEE 6-generator 30-bus System is considered to expound the potential use of the proposed approach.

II. FGP PROBLEM FORMULATION

In a fuzzy decision making environment, instead of crisp description of the objectives and constraints, the fuzzy version of them is taken into consideration and that depends on the needs and desires of the DM in the decision making situation.

In the present FGP formulation of the problem, fuzzy version of achieving the aspired levels of the objective goals is considered in the decision making horizon.

Now, the fuzzy goal description is presented in the following Section A.

A. Definition of Fuzzy Goal

Let b_k be the imprecise aspiration level of the k-th objective F_k (**X**), (k = 1,2,...., K). Then the fuzzy goals may appear in one of the forms:

$F_k(\mathbf{X})$ & b_k and $F_k(\mathbf{X})$. b_k ,

where **X** is the vector of decision variables, and where & and . indicate the fuzziness of the aspiration levels, and is to be understood as 'essentially greater than' and 'essentially less than', respectively, in the sense of Zimmermann[8].

Now, in the field of FP, the fuzzy goals are characterized by their respective membership functions.

B. Characterization of Membership Function

Let $t_{\ell k}$ and t_{uk} be the lower- and upper-tolerance ranges, respectively, for achievement of the aspired level b_k of the k-th fuzzy goal. Then, the membership function, say $\mu_k(\mathbf{X})$, for the fuzzy goal $F_k(\mathbf{X})$ can be characterized as [8].

For & type of restriction, $\mu_k(\mathbf{X})$ takes the form:

$$\mu_k(\mathbf{X}) = \begin{cases} 1 & \text{if } F_k(\mathbf{X}) \ge b_k, \\ \dfrac{F_k(\mathbf{X}) - (b_k - t_{\ell k})}{t_{\ell k}} & \text{if } b_k - t_{\ell k} \le F_k(\mathbf{X}) < b_k, \\ 0 & \text{if } F_k(\mathbf{X}) < b_k - t_{\ell k}, \end{cases} \qquad (1)$$

where (b_k - $t_{\ell k}$) represents the lower-tolerance limit for achievement of the stated fuzzy goal.

Again, for . type of restriction, $\mu_k(\mathbf{X})$ becomes:

$$\mu_k(\mathbf{X}) = \begin{cases} 1 & \text{if } F_k(\mathbf{X}) \le b_k, \\ \dfrac{(b_k + t_{uk}) - F_k(\mathbf{X})}{t_{uk}} & \text{if } b_k < F_k(\mathbf{X}) \le b_k + t_{uk}, \\ 0 & \text{if } F_k(\mathbf{X}) > b_k + t_{uk}, \end{cases} \qquad (2)$$

where (b_k + t_{uk}) represents the upper-tolerance limit for achievement of the stated fuzzy goal.

Then, the FGP model formulation for the defined membership functions is presented in Section C.

C. FGP Model Formulation

In FGP model formulation, the membership functions are transformed into membership goals by assigning the highest degree (unity) as the aspiration level and introducing under- and over-deviational variables to each of them. Then, in the goal achievement function, the under-deviational variables are minimized on the basis of importance of achieving the aspired goal levels in the decision making context.

Now, since multiple goals are involved with the proposed problem, and they often conflict each other for achievement of their aspired goal levels, a *minsum* FGP [19] model for goal achievement is considered in the decision making situation.

The generic form of the *minsum* FGP formulation of a problem appears as:

Find **X** ($x_1, x_2, \ldots, x_i$) so as to:

Minimize $Z = W_1^- d_1^- + W_2^- d_2^- + \ldots + W_k^- d_k^- + \ldots + W_K^- d_K^-$

and satisfy $\dfrac{F_k(\mathbf{X}) - (b_k - t_{\ell k})}{t_{\ell k}} + d_k^- - d_k^+ = 1$ and $\dfrac{(b_k + t_{uk}) - F_k(\mathbf{X})}{t_{uk}} + d_k^- - d_k^+ = 1$

$$d_k^-, d_k^+ \ge 0 \ \text{ with } \ d_k^- . d_k^+ = 0, \qquad k = 1, 2, \ldots\ldots, K \qquad (3)$$

where Z represents the fuzzy achievement function consisting of the weighted under- deviational variables d_k^-, and where d_k^-, d_k^+ represent the under- and over-deviational variables associated with the k-th membership goal. $W_k^- (> 0)$ represents the relative weight of importance [19] of achieving the objectives goal to their aspired levels

Now, the GA scheme used in the process of solving the FGP model in (3) is presented in the following Section III.

III. DESIGN OF GA SCHEME

In the literature of GAs, there is a variety of schemes [18] for generating new populations with the use of different operators: selection, crossover and mutation. Here, the basic steps of the GA procedure with the core functions adopted in the solution search process are presented in the following steps.

Step 1. Representation and Initialization

Let E denote the binary coded representation of a chromosome in a population as $E = \{x_1, x_2, \ldots, x_n\}$. The population size is defined by pop_size, and pop_size chromosomes are randomly initialized in its search domain.

Step 2. Fitness function

The fitness value of each chromosome is judged by the value of an objective function. The fitness function is defined as

$$\text{eval}\,(E_v) = (Z)_v = \sum_{k=1}^{K} \{w_{ik}^{-} d_{ik}^{-}\}_v, \qquad (4)$$

where the subscript 'v' refers to the fitness value of the selected v-th chromosome, v=1,2,…,pop_size. The best chromosome with largest fitness value at each generation is determined as

$$E^* = \min\{\text{eval}\,(E_v) \mid v = 1, 2, ..., \text{pop\_size}\} \qquad (5)$$

in searching out the best value of the objective.

Step 3. Selection

The simple roulette-wheel scheme [18] is used for selecting two parents for mating purposes in the genetic search process.

Step 4. Crossover

The parameter P_c is defined as the probability of crossover. The arithmetic crossover operator (single-point crossover) of a genetic system is applied here in the sense that the resulting offspring always satisfy the given linear constraints set, say $S\ (\neq\phi)$. Here a chromosome is selected as a parent, if for a defined random number $r \in [0, 1]$, $r < P_c$ is satisfied.

Here single-point crossover for two parents E_1 and $E_2 \in S$ is defined as:

$$X_1 = \alpha_1 E_1 + \alpha_2 E_2, \quad X_2 = \alpha_2 E_1 + \alpha_1 E_2,$$

for producing two offspring X_1 and X_2, where, $\alpha_1,$□ $\alpha_2 \geq 0$ with $\alpha_1 + \alpha_2 = 1$ always belong to S, and where S is a convex set.

Step 5. Mutation

As in the conventional GA scheme, a parameter P_m of the genetic system is defined as the probability of mutation. The mutation operation is performed on a bit-by-bit basis, where for a random number $r \in [0, 1]$, a chromosome is selected for mutation provided that $r < P_m$.

Step 6. Termination

The execution of the whole process terminates when the fittest chromosome is reported at a certain generation number in the solution search process.

Now, the proposed optimal planning of electric power generation and dispatch problem is described in Section IV.

IV. PROBLEM DESCRIPTION

In the environment of optimal power flow operational planning with transmission constraints and load characteristics in an economic way, two competing objective functions, pool purchase cost and environment emission, for minimizing them subject to certain equality and inequality constraints are generally raised.

The variables and parameters and notations involved with the problem are defined in the Table 4.1.

Table 4.1: List of Variables, Parameters and notations

P_{Gi}	: Active output of generator i
Q_{Gi}	: Reactive output of generator i
P_i	: Active power at the bus i
Q_i	: Reactive power at the bus i
P_i^s	: Active power specified value at the bus i
Q_i^s	: Reactive power specified value at the bus i
$\lvert V_i \rvert$	: Voltage magnitude of bus i
$\lvert V_i \rvert^s$	: Voltage specified value of bus i
N	: Number of generators
P_D	: Total load capacity

hr	: Hour
p.u	: per unit

Now, the objectives and system constraints are described as follows:

A. Definitions of Objective Functions

1) Fuel Cost Function:

The fuel cost of a generator usually takes the quadratic functional form for real power output.
The cost function for the i-th generator appears as:

$$C_i = \alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i \,, \tag{6}$$

where
C_i: fuel cost (in $/hr) of generator i,
α_i, β_i, γ_i : fuel cost coefficients of generator i,
P_{Gi}: power generated (in p.u.) by generator i.

Then the objective function of fuel cost minimization can be presented as:

$$C = \sum_{i=1}^{N} (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i) \,, \tag{7}$$

where C indicates total fuel cost of all the generators, N is the total number of generators in the power system.

2) Emission-discharge function:

The atmospheric pollutants such as sulphur Oxides (*Sox*) and nitrogen oxides (*NOx*) caused by fossil-fueled thermal units are considered separately. Here, emission-discharge function associated with i-th generator can be expressed as:

$$E_i = (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) + d_i \exp(e_i P_{Gi}) \,, \tag{8}$$

where
E_i : Emission (in ton/ hr) of generator *i*.
a_i, b_i, c_i, d_i, e_i: emission characteristic Coefficients of generator i.
Then, the objective function for emission-discharge quantity can be presented as:

$$E = \sum_{i=1}^{N} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) + d_i \exp(e_i P_{Gi}) \,, \tag{9}$$

where E is the total emission of all the generators, N represents the total number of generators in the power system.

B. Definitions of System Constraints

In the context of optimizing a power system in a static state with given objectives, certain equality constraints inherently involved there are defined as follows:

i) For a load bus, the constraints appear as:

$$P_i - P_i^s = 0 \,, \tag{10}$$
$$Q_i - Q_i^s = 0, \tag{11}$$
$$i = 1,2, \ldots, B_L$$

where B_L=Total Number of load buses.

ii) For the case of a generator bus,

$$|V_i| - |V_i|^s = 0 \,, \qquad i = 1,2, \ldots, B_G \tag{12}$$

where B_G= Total number of Generator buses.

iii) Power balance constraint: the total power generation must cover the total demand P_D, if transmission losses are neglected. So, to make a balance of the active power, the constraint takes the form:

$$\sum_{i=1}^{N} P_{Gi} - P_D = 0 \,, \tag{13}$$

where N is the total number of generators in the power system and P_D is total load demand (in p.u.).

Following the conventional power generation and dispatch, the constraints on the generator outputs and bus voltage magnitudes can be considered as:

$$P_{Gi\,min} \le P_{Gi} \le P_{Gi\,max} \,, \tag{14}$$
$$Q_{Gi\,min} \le Q_{Gi} \le Q_{Gi\,max} \,, \tag{15}$$
$$V_{i\,min} \le V_i \le V_{i\,max} \,, \tag{16}$$

where min and max stand for minimum and maximum .

Now, the FGP model formulation of the problem is presented in the following Section V.

V. FGP Model of the Problem

In the decision situation, the fuzzy goals of the objectives (7) and (9) can be defined by assigning the imprecise aspiration levels to each of them.

Here, the fuzzy goal for cost-minimization objective-function takes the form:

$$C = \sum_{i=1}^{N} (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i)\ .C_g \tag{17}$$

The fuzzy goal for emission-discharge minimization objective function takes the form:

$$E = \sum_{i=1}^{N} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) + d_i \exp(e_i P_{Gi})\ .E_g \tag{18}$$

In the above two expressions, C_g and E_g are the fuel-cost and emission-discharge limits, respectively.

Considering T_{Cg} and T_{Eg} as the upper-tolerance limits of achieving the respective fuzzy goals, the associated membership goals can easily be constructed by following the expression in (2).

The efficient use of the proposed approach is illustrated by a demonstrative case example in the Section VI.

VI. Demonstrative Case Example

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

The pictorial representation of a single-line diagram of IEEE 30-bus test system is displayed in the Fig. 1.

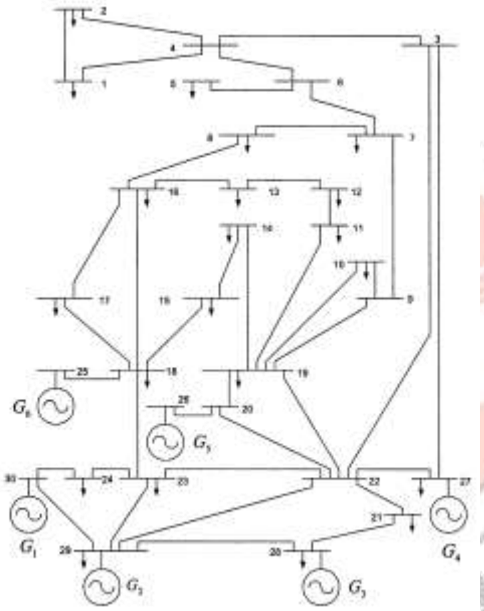

FIG. 1. IEEE 6-generator and 30-bus system

The system shown in Fig. 1 has 6 generators and 41 lines and the total system demand for the 21 load buses is 2.834 p.u. The data for the aspiration levels and tolerance limits of the fuzzy goals and also the parameter values associated with the problem are presented in Table 6.1 – Table 6.5.

Table 6.1: Data Description of Fuzzy Goals and Their Tolerance Limit

Goal	**Aspiration Level**	**Tolerance Limit**
		Upper
Fuel-cost Goal ($/h)	600	620
Emission-discharge Goal (ton/h)	0.21	0.24

Table 6.2: Generators Cost Coefficients Data

Generator No. (i)	$\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i$		
	α	β	γ
1	100	200	10
2	120	150	10
3	40	180	20
4	60	100	10
5	40	180	20
6	100	150	10

Table 6.3: Generators Emission Coefficients Data

GENERATOR NO. (i)	$a_i P_{Gi}^2 + b_i P_{Gi} + c_i) + d_i \exp(e_i P_{Gi})$				
	a	b	c	d	e
1	4.091 $\times 10^{-2}$	-5.554 $\times 10^{-2}$	6.490 $\times 10^{-2}$	2.0×10^{-4}	2.857
2	2.543 $\times 10^{-2}$	-6.047 $\times 10^{-2}$	5.638 $\times 10^{-2}$	5.0×10^{-4}	3.333
3	4.258 $\times 10^{-2}$	-5.094 $\times 10^{-2}$	4.586 $\times 10^{-2}$	1.0×10^{-6}	8.000
4	5.326 $\times 10^{-2}$	-3.550 $\times 10^{-2}$	3.380 $\times 10^{-2}$	2.0×10^{-3}	2.000
5	4.258 $\times 10^{-2}$	-5.094 $\times 10^{-2}$	4.586 $\times 10^{-2}$	1.0×10^{-6}	8,000
6	6.131 $\times 10^{-2}$	-5.555 $\times 10^{-2}$	5.151 $\times 10^{-2}$	1.0×10^{-5}	6.667

Table 6.4: Data Description of Generator Limit (in p.u)

GENERATOR NO. (i)	$P_{Gi\ min}$	$P_{Gi\ max}$	$Q_{Gi\ min}$	$Q_{Gi\ max}$	$V_{i\ min}$	$V_{i\ max}$
1	0.05	0.50	-0.15	0.45	1.000	1.071
2	0.05	0.60	-0.10	0.40	1.000	1.082
3	0.05	1.00	-0.15	0.50	1.000	1.010
4	0.05	1.20	-0.15	0.625	1.000	1.010
5	0.05	1.00	-0.2	0.6	1.000	1.045
6	0.05	0.60	-	-	1.000	1.060

Table 6.5: Specified Bus Data Description

Bus	Type	Active Power(P_i^S)	Reactive Power (Q_i^S)	Bus Voltage ($\|V_i\|^S$)
1	P-Q	-0.106	-0.019	-
2	P-Q	-0.024	-0.009	-
3	P-Q	0.0	0.0	-
4	P-Q	0.0	0.0	-
5	P-Q	-0.035	-0.023	-
6	P-Q	0.0	0.0	-
7	P-Q	-0.087	-0.067	-
8	P-Q	-0.032	-0.016	-
9	P-Q	0.0	0.0	-
10	P-Q	-0.175	-0.112	-
11	P-Q	-0.022	-0.007	-
12	P-Q	-0.095	-0.034	-
13	P-Q	-0.032	-0.009	-
14	P-Q	-0.090	-0.058	-
15	P-Q	-0.035	-0.018	-
16	P-Q	-0.082	-0.025	-
17	P-Q	-0.062	-0.016	-
18	P-Q	-0.112	-0.075	-
19	P-Q	-0.058	-0.020	-
20	P-Q	0.0	0.0	-
21	P-Q	-0.228	-0.109	-
22	P-Q	0.0	0.0	-
23	P-Q	-0.076	-0.016	-
24	P-Q	-0.024	-0.012	-
25	P-V	0.0	0.0	1.071
26	P-V	0.0	0.0	1.082
27	P-V	-0.300	-	1.010
28	P-V	-0.942	-	1.010
29	P-V	-0.217	-	1.045
30	S	0.0	0.0	1.060

Now, incorporating the data in Tables II – IV, the membership goals of the defined fuzzy objectives are obtained as follows:

i) Fuel-cost Goal

The fuel-cost goal appears as:

$$\frac{620 - F_1}{20} + d_1^- - d_1^+ = 1 \ ,$$

where

$F_1 = 100P_{G1}^2+200P_{G1}+10+120P_{G2}^2+150P_{G2}+10+40P_{G3}^2 + 180P_{G3}+20+60P_{G4}^2+ 100P_{G4}+10+40P_{G5}^2 +180P_{G5}+10+100P_{G6}^2 + 150P_{G6}+10$

(19)

ii) Emission-discharge Goal

The emission-discharge goal takes the form:

$$\frac{0.24 - F_2}{0.03} + d_2^- - d_2^+ = 1,$$

where

$F_2 = 10^{-2}$ [$4.091P_{G1}^2$-$5.554P_{G1}$+6.490+2.4×10^{-4} exp($2.857P_{G1}$)+$2.243P_{G2}^2$-$6.047P_{G2}$+5.638+5.0×10^{-4} exp($3.333P_{G2}$)+$4.258P_{G3}^2$-$5.094P_{G3}$+4.586+1.0×10^{-6} exp($8.000P_{G3}$)+$5.326P_{G4}^2$-$3.55P_{G4}$+3.380+2.0×10^{-3} exp($2.000P_{G4}$)+$4.258P_{G5}^2$-$5.094P_{G5}$+4.586+1.0×10^{-6} exp($8.000P_{G5}$)+$6.131P_{G6}^2$-$5.555P_{G6}$+5.515+1.0×10^{-5} exp($6.667P_{G6}$)

(20)

Again, using the data in Tables V and VI, the system constraints corresponding to (10) – (16) can be found as follows:

a) For the case of load bus,

$P_i - P_i^s = 0$

and $Q_i - Q_i^s = 0$

are defined for i= 1,2,3,5,7,8,10,11,…,19,21, 23,24, 27, 29.

Then, the constraints appear are obtained as

$P_3 = 0$, $P_5 + 0.035 = 0$,

$P_7 + 0.087 = 0$, $P_8 + 0.032 = 0$

$P_{10} + 0.175 = 0$, $P_{11} + 0.022 = 0$,

$P_{12} + 0.095 = 0$, $P_{13} + 0.032 = 0$,

$P_{14} + 0.090 = 0$, $P_{15} + 0.035 = 0$,

$P_{16} + 0.082 = 0$, $P_{17} + 0.062 = 0$,

$P_{18} + 0.112 = 0$, $P_{19} + 0.058 = 0$,

$P_{21} + 0.228 = 0$, $P_{23} + 0.076 = 0$,

$P_{24} + 0.024 = 0$, $P_{27} + 0.300 = 0$,

$P_{29} + 0.217 = 0$.

(21)

and

$Q_1 + 0.019 = 0$, $Q_2 + 0.009 = 0$,

$Q_3 = 0$, $Q_5 + 0.023 = 0$,

$Q_7 + 0.067 = 0$, $Q_8 + 0.016 = 0$

$Q_{10} + 0.112 = 0$, $Q_{11} + 0.007 = 0$,

$Q_{12} + 0.034 = 0$, $Q_{13} + 0.009 = 0$,

$Q_{14} + 0.058 = 0$, $Q_{15} + 0.018 = 0$,

$Q_{16} + 0.025 = 0$, $Q_{17} + 0.016 = 0$,

$Q_{18} + 0.075 = 0$, $Q_{19} + 0.020 = 0$,

$Q_{21} + 0.109 = 0$, $Q_{23} + 0.016 = 0$,

$Q_{24} + 0.012 = 0$, $Q_{27} = 0$,

$Q_{29} = 0$.

(22)

b) In case of a generator bus,

$|V_i| - |V_i|^s = 0$ is defined for i= 25,26, …,30.

The expressions are obtained as:

$|V_{25}| - 1.071 = 0$, $|V_{26}| - 1.082 = 0$,

$$|V_{27}| - 1.010 = 0, \quad |V_{28}| - 1.010 = 0,$$
$$|V_{29}| - 1.045 = 0, \quad |V_{30}| - 1.060 = 0. \tag{23}$$

c) The power balance constraint is obtained as:

$$(P_{G1}+P_{G2}+P_{G3}+P_{G4}+P_{G5}+P_{G6}) - 2.834=0$$

d) The generator output constraints are defined as:

$$0.05 \le P_{G1} \le 0.50, \quad 0.05 \le P_{G2} \le 0.60, \quad 0.05 \le P_{G3} \le 1.00,$$
$$0.05 \le P_{G4} \le 1.20, \quad 0.05 \le P_{G5} \le 1.00, \quad 0.05 \le P_{G6} \le 0.60 \tag{24}$$

Similarly,

$$-0.15 \le Q_{G1} \le 0.45, \quad -0.10 \le Q_{G2} \le 0.40, \quad -0.15 \le Q_{G3} \le 0.50,$$
$$-0.15 \le Q_{G4} \le 0.625, \quad -0.2 \le Q_{G5} \le 0.6 \tag{25}$$

And

$$1.000 \le V_1 \le 1.071, \quad 1.000 \le V_2 \le 1.082, \quad 1.000 \le V_3 \le 1.010,$$
$$1.000 \le V_4 \le 1.010, \quad 1.000 \le V_5 \le 1.045, \quad 1.000 \le V_6 \le 1.060 \tag{26}$$

Now, following the expression in (3) and for the stated membership goals of the problem, the executable *mimnsum* FGP model is obtained as:

Find $\{P_{G1}, P_{G2}, P_{G3}, P_{G4}, P_{G5}, P_{G6}\}$ so as to:
Minimize $Z = [0.5\, d_1^- + 0.5\, d_2^-]$

and satisfy the given membership goal expressions in (19)
and (20), subject to the constraints given in (21) – (26). (27)

Now, since GA is a goal satisficer in [18] rather than objective optimizer, the GA scheme described in Section III can be employed here to minimize the achievement function 'Z' in (27), and thereby to reach a satisfactory solution. Here the goal achievement functions 'Z' appears as the fitness function in the GA solution search process.
In the genetic search process, the following parameter values are introduced.

- probability of crossover $P_c = 0.7$
- probability of mutation $P_m = 0.08$
- population size = 50
- chromosome length = 50

The GA based program is designed in Programming Language C^{++}. The execution is done in an Intel Pentium IV with 2.66 GHz. Clock-pulse and 1GB RAM. The optimal solution is reached after 200 generations.

The model solution is presented in the Table 6.6.

Table 6.6: Solutions under the proposed model

Generator Output (in p.u)	P_{G1}	0.2478040
	P_{G2}	0.4275178
	P_{G3}	0.5381419
	P_{G4}	0.7009985
	P_{G5}	0.5381419
	P_{G6}	0.3813958
Total Generation Cost ($/hr)		601.20
Total Emission (ton/hr)		0.232

The achieved membership values are: $\mu_C = 1$ and $\mu_E = 0.67$.

The solutions obtained in [20] by using the €-constrained technique with the consideration of individual optimization of the defined objectives are presented in Table 6.7.

Table 6.7: Solutions under the €-constrained technique

Individual Optimization Scheme	Total generation cost ($/hr)	Total emission (ton/hr)
For Generation Cost Minimization	606.04	0.2215
For Emission Minimization	645.88	0.1952

A comparison of the model solution with the results in the Table VIII reflects that a better compromise solution is achieved here under the proposed approach in terms of achieving the aspired goal levels of the objectives of the problem.

The comparison between two different solution approaches is presented in the following Fig 2 and Fig 3.

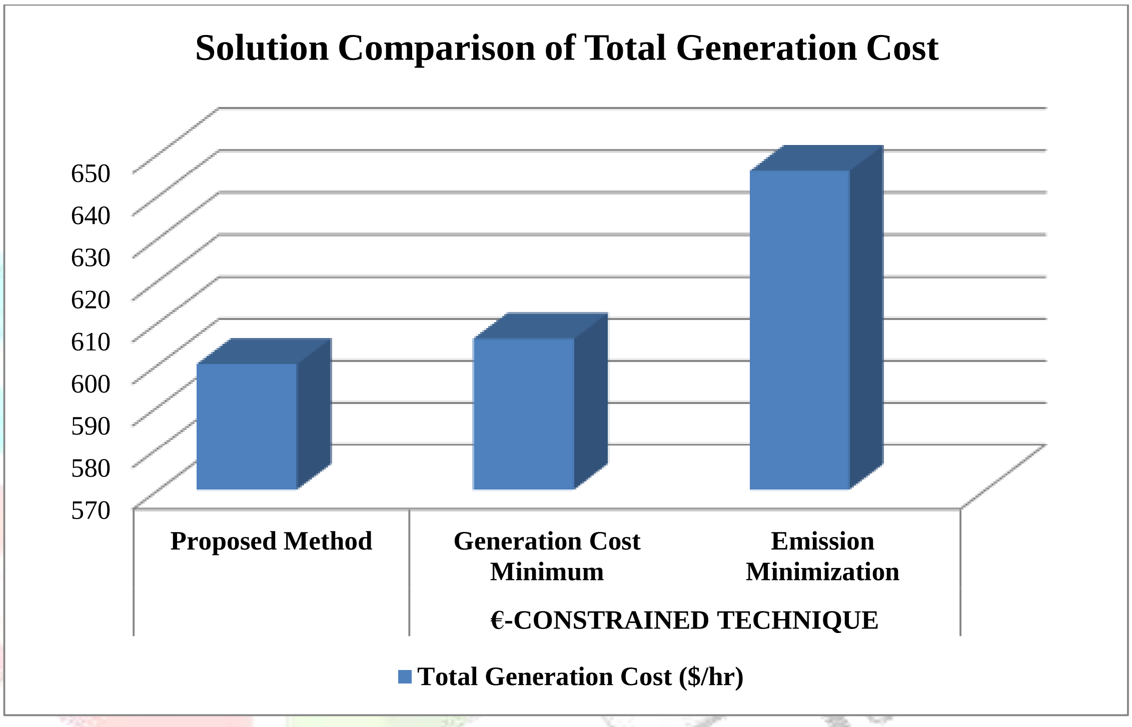

Fig. 2. Graphical representation of solution comparison of Total Generation Cost.

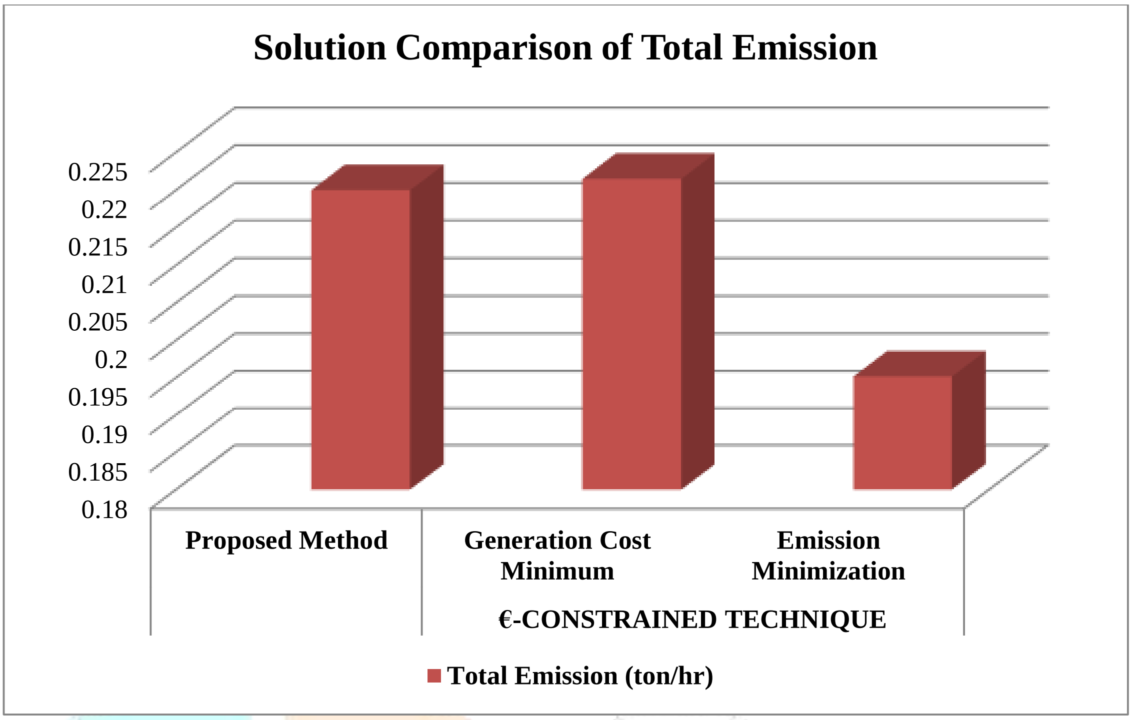

Fig. 3. Graphical representation of solution comparison of Total Emission.

It is apparent from the Fig 2 and Fig 3 that a better power generation planning is achieved here under the proposed GA approach over the €-constrained technique from the view point of minimizing both the power generation cost and emission hazard in the decision making environment.

VII. Conclusions

In this paper, an GA based FGP approach to solve the multi-objective optimal planning of electric power generation and dispatch is presented.

The main advantage of the proposed approach is that the computational load and approximation error inherent to conventional linearization approaches can be avoided here with the use of the GA based solution method.

Again, since the various objectives involved with the optimal power generation and dispatch problem often conflict each other in achieving the aspired goal levels, the use of the GA search method as a global one and goal satisficer offers the most satisfactory decision in the decision making environment.

In the proposed problem, the multiobjective optimization problem with competing fuel cost and environmental impact are only considered. In the framework of the model, an extension of considering other objectives and environmental constraints may be take place in power generation and dispatch planning situation, which is the problem in future study.

Finally, it is hoped that the solution approach presented here may lead to future research for proper planning in the context of solving optimal power flow and dispatch problems on the basis of needs in society.

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