International Journal of Engineering, Science and Mathematics
Vol7. Issue2, february 2018,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

GA Based FGP Model for Power Loss Minimization and Voltage Stability Improvement in Electrical Power Systems

Papun Biswas*

Abstract

Power loss minimization and voltage stability improvement is one of the major issues of modern power system operation and planning. This article presents an efficient genetic algorithm (GA) approach to solve these problems with fuzzy representation of objective functions. In the proposed approach, the fuzzy goal programming (FGP) and GA are applied in two stages for formulation and solving the problem for optimal setting of VAR control variables. The proposed approach is tested on the standard IEEE 6-Generator 30-Bus System with the objectives and compared with the solutions obtained in previous study.

Keywords:

Fuzzy Programming;
Genetic Algorithm;
Goal Programming;
Optimal VAR dispatch;
Voltage Stability.

Author correspondence:

Papun Biswas,
Associate Professor, Department of Electrical Engineering
JIS College of Engineering (An Autonomous Institute), Kalyani-741235, West Bengal, India

1. Introduction

The purpose of optimal reactive power planning is to provide the system with sufficient VAR sources so that it can operate in an economically feasible operation condition while all loads and operational constraints are met.

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers.

In the past decade, the problem of reactive power control for improving economy and security of power system operation has received much attention.

Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. Generally, the load bus voltages can be maintained within their permissible limits by reallocating reactive power generations in the system. This can be achieved by adjusting transformer taps, generator voltages, and switchable VAR sources. In addition, the system losses can be minimized via redistribution of reactive power in the system. Therefore, the problem of the reactive power

* Associate Professor, Department of Electrical Engineering, JIS College of Engineering, Kalyani, WB, India

International Journal of Engineering, Science and Mathematics
Vol7. Issue2, february 2018,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

dispatch can be optimized to improve the voltage profile and minimize the system losses as well. It involves a non linear optimization problem.

Several methods to solve the optimal reactive power dispatch problem have been proposed in the literature. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the Newton method [1], gradient method [2-3], nonlinear programming technique [4] and linear programming [5-6]. The Newton and gradient methods suffer from the difficulty in handling inequality constraints and also the methods are susceptible to be trapped in local minima and the solution obtained will not be the optimal one. Nonlinear programming based procedures have many drawbacks, such as insecure convergence properties, long execution time, and algorithmic complexity. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy.

Recently global optimization techniques utilize the heuristic methods to search for the optimal solution in the problem space [7]. These heuristic methods have been applied to solve the optimal VAR dispatch problem with impressive success.

The conventional reactive power dispatch problem is formulated as an optimization problem with crisp constraints.

Recently, fuzzy set methods have been applied to obtain more realistic models. Fuzzy set methods have already been used in many applications such as control, scheduling, robotics, artificial intelligence, etc. In the field of power engineering, they have been applied to some areas including optimal reactive power dispatch problem [8], [9], [10].

Since most of the VAR dispatch problems are multiobjective in nature, the goal programming (GP) methodology in [11] can be used as an efficient tool for solving the problem.

Although, the GP has appeared as a rich field of solving multiobjective decision making (MODM) problems, the main weakness of using the conventional GP to decision problems is that in the real-world MODM situations, the decision maker (DM) is often faced with the problem of assigning the precise aspiration levels to the goals due to inherent inexactness in nature of the decision parameters as well as imprecision in human judgments.

To overcome the above difficulty, FGP [12] in the framework of conventional GP and as an extension of fuzzy programming (FP) [13] have been studied in the past, and implemented to different decision making problems [14], [15].

Now, in practical decision situations, it is found that nonlinearity in general form as well as in fractional form are frequently involved with the defining of various relationships among the parameters and decision variables. In such a case, the use of conventional approximation approaches to FGP problems [14] involve computation load and often lead to local optimal solutions.

To overcome the computational complexity in practical decision problems, GAs [16] appear as a robust tool for searching satisfactory decisions for MODM problems. GAs to real-world multiobjective decision problems have been studied in [15] in the past. However, the study of GA based FGP approaches to real-life problems are at an early stage. Moreover, the use of GA based FGP technique to reactive power dispatch problem is yet to appear in the literature.

In this article, FGP formulation of multiobjective optimal reactive power dispatch problem with various constraint functions is considered. A solution scheme based on GA is introduced to reach a satisfactory decision of achieving the defined objectives in the decision making environment.

The simulation results of IEEE 6-generator 30-bus System expound the potential use of the proposed approach.

2. Problem Description

The optimal VAR dispatch problem is formulated as a multi-objective mathematical programming problem in which all objective functions are simultaneously improved and all constraints (equality and inequality) satisfied. Generally the problem can be formulated as follows.

2.1. Objective Functions

2.1.1 *Real Power Loss (P_L)*: This objective is to minimize the real power loss in transmission lines that can be expressed as:

$$P_L = \sum_{k=1}^{nl} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \tag{1}$$

where nl is the number of transmission lines; g_k is the conductance of the k_{th} line; $V_i \angle\delta$ and $V_j \angle\delta$ are the voltages at end buses i and *j* of the k_{th} line respectively.

2.1.2 *Voltage Deviation (VD)*: This objective is to minimize the deviations in voltage magnitudes at load buses that can be expressed as:

$$VD = \sum_{k=1}^{NL} |V_K - 1.0| \tag{2}$$

2.2. Problem Constraints

2.2.1 *Equality Constraints*: These constraints represent typical load flow equations as follows.

The Real power balance is as follows:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \tag{3}$$

The Reactive power balance is:

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)] = 0 \tag{4}$$

where i = 1,2,…,NB; NB is the number of buses; P_G and Q_G are the generator real and reactive power respectively; P_D and Q_D are the load real and reactive power respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j respectively.

2.2.2 *Inequality Constraints*: These constraints represent the system operating constraints as follows.

Generation constraints: Generator voltages V_G and reactive power outputs Q_G are restricted by their lower and upper limits as follows:

$$\begin{aligned} V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max} \ , i = 1,\dots,NG \\ Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max} \ , i = 1,\dots,NG \end{aligned} \tag{5}$$

where NG is number of generators.

Transformer constraints: Transformer tap T settings are bounded as follows:

$$T_i^{min} \le T_i \le T_i^{max} \ , i = 1,\dots,NT \tag{6}$$

where NT is the number of transformers.

International Journal of Engineering, Science and Mathematics
Vol7. Issue2, february 2018,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

Switchable VAR sources constraints: Switchable VAR compensations *QC* are restricted by their limits as follows:

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max} \quad ,i = 1,...,NC \tag{7}$$

where NC is the number of switchable VAR sources.

Load Bus Voltage: These include the constraints of voltages at load buses *VL* as follows:

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max} \quad ,i = 1,...,NL \tag{8}$$

The generic method of standard FGP problem formulation is presented in the following Section 3.

3. FGP Problem Formulation

In a fuzzy decision making environment, instead of crisp description of the objectives and constraints, fuzzification of them depend on the needs and desires of the DM in the decision situation.

In the present FGP formulation of the problem, a full fuzzy version of goal achievement is considered to make the model a flexible one in the decision making context.

Now, fuzzy goal description is presented in the following Section 3.1.

3.1 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 (**X**) & b_k and F_k(**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 more than' and 'essentially less than', respectively, in the sense of Zimmermann[13].

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

3.2 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 μ_k (**X**), for the fuzzy goal F_k(**X**) can be characterized as follows [14].

For & type of restriction, μ_k (**X**) takes the form:

$$\mu_k(\mathbf{X}) = \begin{cases} 1 & \text{if } F_k(\mathbf{X}) \ge b_k, \\ \dfrac{F_k(\mathbf{X}) - (b_k - t_{\ell k})}{t_{\ell k}} & \text{if } b_k - t_{\ell k} \le F_k(\mathbf{X}) < b_k, \\ 0 & \text{if } F_k(\mathbf{X}) < b_k - t_{\ell k}, \end{cases} \tag{9}$$

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

International Journal of Engineering, Science and Mathematics
Vol7. Issue2, february 2018,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

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

$$\mu_k(\mathbf{X}) = \begin{cases} 1 & \text{if } F_k(\mathbf{X}) \le b_k, \\ \dfrac{(b_k + t_{uk}) - F_k(\mathbf{X})}{t_{uk}} & \text{if } b_k < F_k(\mathbf{X}) \le b_k + t_{uk}, \\ 0 & \text{if } F_k(\mathbf{X}) > b_k + t_{uk}, \end{cases} \tag{10}$$

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 3.3.

3.3 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 problem, and they often conflict each other for achievement of their aspired goal levels, a priority based FGP model for goal achievement is considered in the decision making situation.

The *minsum* FGP formulation of the 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

$$\frac{F_k(\mathbf{X}) - (b_k - t_{\ell k})}{t_{\ell k}} + d_k^- - d_k^+ = 1$$

$$\frac{(b_k + t_{uk}) - F_k(\mathbf{X})}{t_{uk}} + d_k^- - d_k^+ = 1$$

subject to $AX \begin{pmatrix} \le \\ = \\ \ge \end{pmatrix} b$, $X \ge 0$, $d_k^-, d_k^+ \ge 0$ with $d_k^- . d_k^+ = 0$, k = 1, 2, ..., K

(11)

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. $W_k^- (\ge 0)$ represents the relative importance for achieving the k-th fuzzy goal in a decision-making environment and is determined as:

$$W_k^- = \begin{cases} \dfrac{1}{t_{kl}}, & \text{for the defined } \mu_k \text{ in } (9) \\ \dfrac{1}{t_{ku}}, & \text{for the defined } \mu_k \text{ in } (10) \end{cases} \qquad (12)$$

When some of the objectives $F_k(\mathbf{X})$, k=1, 2,…,K, are non-linear in form, then conventionally the traditional linearization approach is used in the solution process of the MODM problems which involve huge computational complexity. But to avoid the computational load involved in linearization of the objectives as well as the inherent decision error involved in the approximation approach, a GA procedure is used in the process of solving the FGP model in (3).
The GA scheme used in the process of solving the problem in (3) is presented in the following Section 4.

4. Design of GA Scheme

For the given FGP structure of the proposed problem, the task of the DM is to search the solution which satisfies fuzzy linear as well as fractional goals to the extent possible by evaluating the defined goal achievement function on the basis of priorities assigned to them. As such, GAs as the global search algorithms can be efficiently used to achieve the most satisfactory decision in the planning environment.

Now, in the literature of GAs, there is large number of schemes [16] for generating new populations with the use of different operators: selection, crossover and mutation. However, the basic steps of the GA procedure with the core functions adopted in the solution process are presented via the following steps.

In the literature of the GAs, there are a number of schemes [16] for generation of new populations with the use of the different operators: selection, crossover and mutation. Here, the binary coded representation of a candidate solution called chromosome is considered to perform genetic operations in the solution search Process. The conventional Roulette wheel selection scheme, single-point crossover and bit-by-bit mutation operations are adopted to generate offspring in new population in search domain defined in the decision making environment.

The fitness score of a chromosome *v* (say) in evaluating a function, say, eval (E_v), based on maximization or minimization of an objective function defined on the basis of DMs' needs and desires in the decision making context.

The fitness value of each chromosome is determined by evaluating an objective function.

The fitness function is defined as:

$$\text{eval}\,(E_v) = (Z)_v = \sum_{k=1}^{K} \{w_k^- d_k^-\}_v, \qquad (13)$$

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:

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

which depends on searching the maximum or minimum value of an objective function.

Now, the FGP model of the proposed multiobjective reactive power planning problem is described in the follows Section 5.

5. FGP Model for the Problem

The membership functions for each of the objectives (1) and (2) must be defined for fuzzy description of them. Since, the real power loss and voltage deviation both are minimization type objectives, the smaller the objective value of them, the better is the results of operation planning.

Here, the fuzzy goal for real power loss objective-function takes the form:

$$P_L = \sum_{k=1}^{nl} g_k [V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j)] .b_1 \quad (14)$$

Similarly, the fuzzy goal for voltage deviation objective function takes the form:

$$VD = \sum_{k=1}^{NL} |V_K - 1.0| .b_2 \quad (15)$$

Here, b_1 and b_2 are the imprecise aspiration levels of the real power loss minimization and voltage deviation minimization objectives respectively.

Therefore, let $P_L \le (b_1 + t_{u1})$ represent an imprecise upper bound on the maximum permissible real power loss and t_{u1} be the "tolerance" parameter, that is, a measure of fuzziness in this constraint. So the mathematical formulation of the membership function is as follows:

$$\mu(P_L) = \begin{cases} 1 & ,\text{if } P_L \le b_1 \\ \dfrac{(b_1 + t_{u1}) - P_L}{t_{u1}} & ,\text{if } b_1 < P_L \le b_1 + t_{u1} \\ 0 & ,\text{if } P_L > b_1 + t_{u1} \end{cases} \quad (16)$$

Similarly, let $VD \le (b_2 + t_{u2})$ represent an imprecise upper bound on the maximum permissible voltage deviation and t_{u2} be the "tolerance" parameter. So, a linear membership function can be defined as follows:

$$\mu(VD) = \begin{cases} 1 & ,\text{if } VD \le b_2 \\ \dfrac{(b_2 + t_{u2}) - VD}{t_{u2}} & ,\text{if } b_2 < VD \le b_2 + t_{u2} \\ 0 & ,\text{if } VD > b_2 + t_{u2} \end{cases} \quad (17)$$

In fuzzy programming approaches, the highest degree of membership function is 1(one). Thus, for the defined membership functions in (16) and (17), the flexible membership goals with the aspired level 1 can be presented as:

$$\frac{(b_1 + t_{u1}) - P_L}{t_{u1}} + d_1^- - d_1^+ = 1$$

$$\frac{(b_2 + t_{u2}) - VD}{t_{u2}} + d_2^- - d_2^+ = 1 \quad (18)$$

$d_k^-(\ge 0)$ and $d_k^+(\ge 0)$ with $d_k^- . d_k^+ = 0 , k = 1,2$ represent the under- and over-deviational variables, respectively, from the aspired levels.

In the model formulation, the under-and / or over-deviational variables are included in the achievement function for minimizing them and that depend upon the type of the objective functions to be optimized.

In the proposed approach, only the under-deviational variables d_k^-, $i=1,2$ are required to be minimized to achieve the aspired levels of the fuzzy goals. It may be noted that any over-deviation from a fuzzy goal indicates the full achievement of the membership value.

The FGP model of the problem under weighted structure for the achieving of the aspired goal levels can be presented as:

Minimize Z= $[w_1^- d_1^- + w_2^- d_2^-]$

and satisfy

$$\frac{(b_1 + t_{u1}) - F_1}{t_{u1}} + d_1^- - d_1^+ = 1$$
$$\frac{(b_2 + t_{u2}) - F_2}{t_{u2}} + d_2^- - d_2^+ = 1 \qquad (19)$$

Subject to equality constraints in (3) and (4) and inequality system constraints in (5) – (8).

Now, since GA is a goal satisficer in [16] rather than optimizer, the proposed GA scheme can be employed here to minimize the achievement function 'Z' in (19) and thereby to reach a satisfactory solution. Here the goal achievement functions 'Z' appears as the fitness function in the evaluation process of using the GA.

The efficient use of the proposed approach is illustrated by a demonstrative case example in the Section 6.

6. Demonstrative Case Example

In this paper, a standard IEEE 30-bus 6-generator test system is used to illustrate the potential use of the approach. The representation of the test system and the detailed data are given in [2]. The model system has 6 generators and 41 lines and 4 transformers. The number of the optimized variables is 10 in this problem with a base MVA of 100. The lower and upper voltage magnitude limits at all buses are 0.95 pu and 1.1 pu respectively for generator buses 1, 2, 5, 8, 11, and 13, and 1.05 pu for the remaining buses.

Now for the stated membership goals of the problem, using the expression in (19), the achievement function of the executable FGP model is obtained as:

Find **X** so as to:

$$\text{Minimize } Z = [1.2878 \;\; d_1^- + 1.0335\, d_2^-] \qquad (20)$$

Then, the GA approach presented in the Section 3 is used to solve the problem in (20) using the data given in [2] subject to the goal constraints in (19) and the system constraints in (3) – (8).

The objective function of the model appears as the fitness function in the solution search process.

International Journal of Engineering, Science and Mathematics
Vol7. Issue2, february 2018,
ISSN: 2320-0294 Impact Factor: 6.765
Journal Homepage: http://www.ijesm.co.in, Email: ijesmj@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories Indexed & Listed at: Ulrich's Periodicals Directory ©, U.S.A., Open J-Gage as well as in Cabell's Directories of Publishing Opportunities, U.S.A

The computer program developed in MATLAB and GAOT (Genetic Algorithm Optimization Toolbox) is used together for the calculation to obtain the results.
The parameter values used in genetic algorithm solution are given in Table 1. These parameter values are found after several trials to give the best results in terms of accuracy and computation time.

TABLE- 1

THE PARAMETER VALUES USED IN GA

Parameter	Value
Number of individuals in the initial population	50
Crossover probability	0.7
Mutation probability	0.03
Maximum generation number	100

The program is run 40 times and the obtained best results are given in Table 2.

TABLE- 2

SOLUTIONS UNDER THE PROPOSED MODEL

Decision Variables and Objectives	Value (Compromise Solution)
V_{G1}	1.0612
V_{G2}	1.0211
V_{G5}	1.0351
V_{G8}	1.0619
V_{G11}	1.0425
V_{G13}	1.0643
T_{6-9}	0.9512
T_{6-10}	0.9645
T_{4-12}	0.9827
T_{27-28}	0.9658
Real Power Loss (MW)	5.1274
Voltage Deviation (pu)	0.3744

The solution obtained using Fast and Elitist Multi-Objective Genetic Algorithm technique in [17] (Single objective optimization):

For Best **Real Power Loss:**

- Real Power Loss (MW) = 4.7791 Voltage Deviation (pu) = 1.1592
- Real Power Loss (MW) = 4.7891 Voltage Deviation (pu) = 1.0822

For Best **Voltage Deviation**:

- Real Power Loss (MW) = 5.5556 Voltage Deviation (pu) = 0.1916
- Real Power Loss (MW) = 5.4665 Voltage Deviation (pu) = 0.2257

A comparison shows that a better compromise solution is obtained here in terms of achieving the goal values of the objectives of the problem.

6. Conclusions

In this paper, an GA based FGP approach is presented to solve the multiobjective optimal reactive power planning problem.

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. Further, the proposed approach is flexible enough to accommodate different other restrictions as and when needed in the decision making context.

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

References

[1] Monticelli, A., Pereira, M .V.F., and Granville, S.: Security constrained optimal power flow with post contingency corrective rescheduling. IEEE Transactions on Power Systems. PWRS-2(1), 175-182., (1987)
[2] Alsac, O., and Scott, B. : Optimal load flow with steady state security. IEEE Transaction. PAS-93, 745-751, (1974)
[3] Mamandur, K. R. C., and Chenoweth, R. D. : Optimal Control of Reactive Power Flow for Improvements in Voltage profiles and for Real Power Loss Minimization. IEEE Trans. on Power Apparatus and Systems, PAS-100(7), 3185-3193, (1981)
[4] Mansour, M. O., and Abdel-Rahman, T. M.: Non-Linear VAR Optimization Using Decomposition and Coordination. IEEE Trans. on Power Apparatus and Systems, PAS-103(2), 246-255, (1984)
[5] Deeb, N., Shahidehpur, S.M.: Linear reactive power optimization in a large power network using the decomposition approach. IEEE Transactions on power system. 5(2), 428-435, (1990)
[6] Mangoli, M.K., and Lee, K.Y. : Optimal real and reactive power control using linear programming. Electr. Power Syst. Res, 26,1-10, (1993)
[7] Iba, K.: Reactive Power Optimization by Genetic Algorithm. IEEE Trans. on Power Systems. 9(2), 685-692, (1994)
[8] Tomsovic, K.: Fuzzy Linear Programming Approach to the ReactivePower/Voltage Control Problem. IEEE Transactions on Power Systems. 7(1), 287-293, (1992)
[9] Miranda, V., and Saraiva, J. T. : Fuzzy Modeling of Power System Optimal Load Flow. IEEE Transactions on Power Systems. 7(2), 843- 849, (1992)
[10] Abdul-Rahman, K. H., and Shahedehpour, S. M. : A Fuzzy-Based Optimal Reactive Power Control. IEEE Transactions on Power Systems. 8(2), 662-670, (1993)
[11] Romero, C.: A Survey of Generalized Goal Programming. European Journal of Operational, 25(2), 183-191,(1986)
[12] Tiwari, R.N., Dharmar, S., and Rao, J.R. : Fuzzy goal programming – an additive model. Fuzzy Sets and Systems. 24, 27-34, (1987)
[13] Zimmermann, H.-J.: Fuzzy Sets, Decision Making and Expert Systems, Kluwer Academic Publisher, Boston, Dordrecht, Lancaster, (1987).
[14] Pal B.B. and Moitra, B.N. : Fuzzy goal programming procedure for solving quadratic bilevel programming problems. International Journal of Intelligent Systems. 18 (5), 529-540, (2003)
[15] Pal, B.B., Chakraborti, D., Biswas, P. and Mukhopadhyay, A.: An application of genetic algorithm method for solving patrol manpower deployment problems through fuzzy goal programming in traffic management system: a case study. *Int. J. Bio-Inspired Computation*. 4 (1), 47–60, (2012)
[16] Goldberg, D.E.: Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, Reading. MA, (1989)
[17] Subramanian, R., Subramanian, K., Subramanian, B.: Application of a Fast and Elitist Multi-Objective Genetic Algorithm to Reactive Power Dispatch. Serbian Journal of Electrical Engineering. 6(1), 119-133, (2009)