Optimal Coordination and Penetration of Distributed Generation with Shunt FACTS Using GA/Fuzzy Rules

Belkacem Mahdad†, Kamel Srairi* and Tarek Bouktir**

Abstract – In recent years, integration of new distributed generation (DG) technology in distribution networks has become one of the major management concerns for professional engineers. This paper presents a dynamic methodology of optimal allocation and sizing of DG units for a given practical distribution network, so that the cost of active power can be minimized. The approach proposed is based on a combined Genetic/Fuzzy Rules. The genetic algorithm generates and optimizes combinations of distributed power generation for integration into the network in order to minimize power losses, and in second step simple fuzzy rules designs based upon practical expertise rules to control the reactive power of a multi dynamic shunt FACTS Compensator (SVC, STATCOM) in order to improve the system loadability. This proposed approach is implemented with the Matlab program and is applied to small case studies, IEEE 25-Bus and IEEE 30-Bus. The results obtained confirm the effectiveness in sizing and integration of an assigned number of DG units.

Keywords: Distribution generation, Economic dispatch (ED), Genetic Algorithm, Fuzzy logic, SVC, FACTS, Reactive sensitivity index

1. Introduction

In an open electricity market, every consumer will be able to buy his own electricity from any source desired with the result that unplanned power exchanges are increasing. In order to cope with such problems and increase usable power distribution capacity, distribution generation technology (DG) and Flexible AC transmission systems (FACTS) have been developed and introduced into the market.

Optimal placement and sizing of distribution generation is a well-researched subject that in recent years has been of interest to many professional engineers. Efficient placement and sizing of distribution generation (DG) in practical networks can result in minimizing operational costs, environmental protection, improved voltage regulation, power factor correction, and power loss reduction [1]. DG is defined as any source of electrical energy of limited size interconnected to the distribution system. DG technologies include photovoltaic systems, wind turbines, fuel cells, small micro-sized turbines, sterling-engine based generators and internal combustion engine-generators [2]. In practical installation and integration of DG in power systems with consideration of FACTS devices, there are five common requirements as follows [3]:

- What Kinds of DG and FACTS devices should be installed?
- Where in the system should it be placed?
- How to estimate economically the number and optimal size of DG and FACTS to be installed in a practical network?
- How to coordinate dynamically the interaction between multiple DGs, FACTS devices and the network to better exploit DG and FACTS devices and to improve the index power quality?
- How to review and adjust the system protection devices to assure service continuity and keep the index power quality at the margin security limits?

The global optimization techniques known as genetic algorithms (GA), simulated annealing (SA), tabu search (TS), and evolutionary programming (EP), which are forms of probabilistic heuristic algorithm, have been used successfully to overcome the non-convexity problems of the constrained ED [4-5]. The GA method usually has better efficiency because the GA has parallel search techniques. Due to its high potential for global optimization, GA has received great attention in solving optimal power flow (OPF) problems. Fig. 1 shows the global strategy of the approach proposed to enhance the optimal power flow (OPF) in the presence of multi shunt FACTS devices and a multi distribution generation.

A number of approaches for placement of DG to minimize losses have been proposed [6]. In [7] the authors propose a method that places DG at the optimal place along the feeder and within networked systems with consideration of losses. The authors in Paper [8] proposed a strategy for voltage control for distribution networks with dispersed generation. In [9] the authors developed a methodology to optimally allocate DG capacity on the distribution network. The constraints

† Corresponding Author: Dept. of Electrical Engineering, Biskra University, Algeria (bemahdad@yahoo.fr)
* Dept. of Electrical Engineering, Biskra University, Algeria
** Dept. of Electrical Engineering, Oum Elbouaghi University, Algeria (tbouktir@ yahoo.fr)
Received 23 February, 2008 ; Accepted 7 October, 2008

taken into consideration were the voltage deviation, thermal limit, and short circuit capacity. The methodology guarantees that the network capacity is maximized. The authors in [11] proposed a methodology based GA to place generators of discrete capacities in order to minimize losses and costs. Authors in [12] suggest a heuristic approach where an investment based objective function determines optimal DG site and size.

It is clear from the approaches cited in the literature that they offer optimal solutions to the penetration of DG in a practical network, but few approaches treat the problem of optimal coordination of multi DG with multi shunt FACTS devices to minimize fuel cost and improve the system loadability.

This paper presents a dynamic methodology based GA/Fuzzy practical rules for optimal allocation and sizing of DG units in coordination with multi shunt dynamic Compensators for a given practical distribution network, so that the cost of active power can be minimized and the system loadability enhanced.

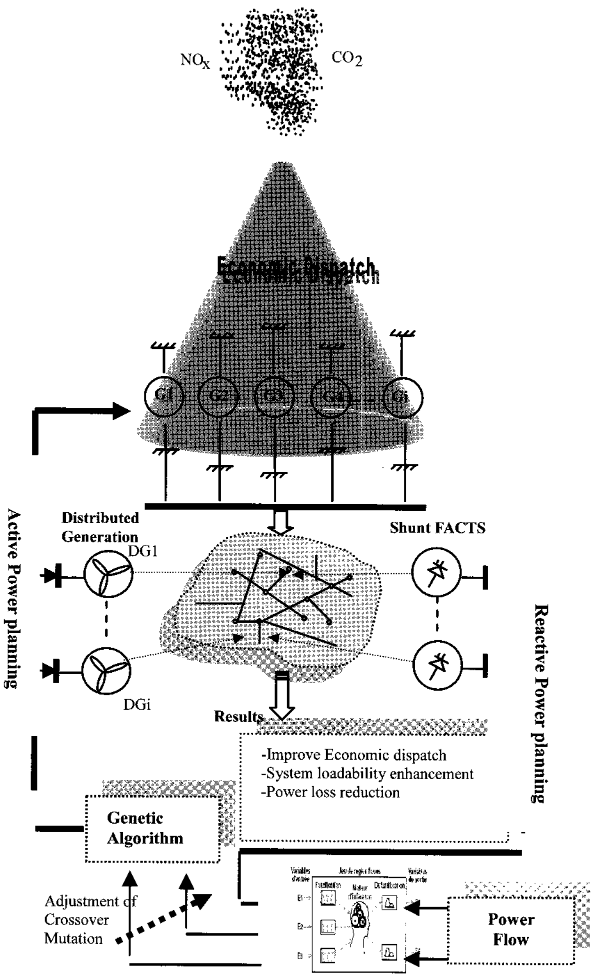

Fig. 1. Global strategy of OPF proposed with consideration of shunt FACTS and DG

2. Active Power Planning

The active power planning problem is considered a general minimization problem with constraints, and can be written in the following form:

Minimize $f(x)$ (1)

Subject to: $g(x) = 0$ (2)

$h(x) \le 0$ (3)

$f(x)$ is the objective function, $g(x)$ and $h(x)$ are respectively the set of equality and inequality constraints. x is the vector of control and state variables. The control variables are generator active and reactive power outputs, bus voltages, shunt capacitors/reactors and transformers tap-setting. The state variables are the voltage and angle of load buses. For optimal active power dispatch, the objective function f is the total generation cost expressed as follows:

$$\text{Min } f = \sum_{i=1}^{N_g} \left(a_i + b_i P_{gi} + c_i P_{gi}^2\right) \quad (4)$$

where N_g is the number of thermal units, P_{gi} is the active power generation at unit i and a_i, b_i and c_i are the cost coefficients of the i^{th} generator.

The equality constraints $g(x)$ are the power flow equations, expressed as follows:

$$P_{gi} - P_{di} - \sum_{j=1}^{N} |V_i||V_j||Y_{ij}|\cos\left(\delta_i - \delta_j - \delta_{ij}\right) = 0 \quad (5)$$

and $$Q_{gi} - Q_{di} - \sum_{j=1}^{N} |V_i||V_j||Y_{ij}|\sin\left(\delta_i - \delta_j - \delta_{ij}\right) = 0 \quad (6)$$

The inequality constraints $h(x)$ reflect the limits on physical devices in the power system as well as the limits created to ensure system security:

- Upper and lower limits on the active power generations:

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \quad (7)$$

- Upper and lower limits on the reactive power generations:

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \quad (8)$$

- Upper and lower bounds on the tap ratio (t):

$$t_{ij}^{\min} \le t_{ij} \le t_{ij}^{\max} \quad (9)$$

- Upper and lower bounds on the shifting (α) of variable transformers:

$$\alpha_{ij}^{\min} \le \alpha_{ij} \le \alpha_{ij}^{\max} \quad (10)$$

- Upper limit on the active power flow (P_{ij}) of line i-j:

$$|\mathrm{P}_{ij}| \le \mathrm{P}_{ij}^{\max} \quad (11)$$

- Upper and lower bounds in the bus voltage magnitude:

$$V_i^{\min} \le V_i \le V_i^{\max} \quad (12)$$

• Upper and lower bounds in the Shunt FACTS parameters:

$$X^{\min} < X_{FACTS} < X^{\max} \tag{13}$$

3. Strategy of the GA-Coordination Fuzzy Rules for DG-Shunt Facts

3.1 Principle of the Approach Proposed

A flexible methodology based on two-subproblem algorithms solving the new formulation of an optimal power flow (OPF) problem incorporating a DG and shunt flexible AC transmission system (FACTS) is presented in Fig 2. The controllable FACTS devices considered include shunt compensators (SVC) and Static Compensators (STATCOM).

The proposed algorithm breaks down the solution of such a modified OPF problem into three linked subproblems. The first subproblem is an active power generation by efficient Genetic Algorithm, the second subproblem is an active power planning of multi distributed generation to be integrated into the network in order to minimize power losses, and the third subproblem is a reactive power planning coordinated with an efficient power flow problem to make fine adjustments on the optimum values obtained from the Genetic Algorithm. This will provide updated voltages, angles and point out generators which have exceeded reactive limits.

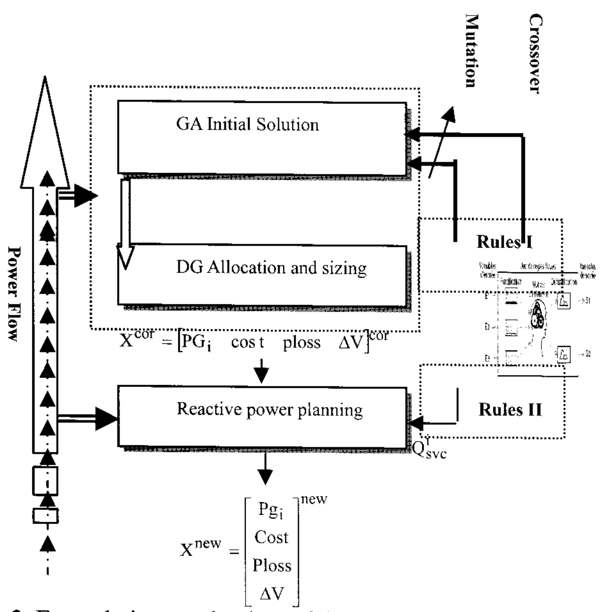

Fig. 2. Formulation mechanism of the approach proposed

Where:

X : Initial vector solution generated by GA.

X^{cor} : The corrected vector solution introduced by DG.

X^{new} : The final vector solution after reactive power planning.

ΔV : Voltage deviation.

3.2 Objective Functions

3.2.1. Fuel Cost Minimization

The objective function of the first subproblem is to minimize the total fuel cost without consideration of DG units.

$$\text{Min}\, J_1 = \sum_{i=1}^{NG} f_i \tag{14}$$

while f_i is the fuel cost ($/h).

NG is the number of generators.

3.2.2. Power Loss Minimization

The objective function is modified to minimize the power losses while at the same time minimizing fuel costs, and the active power of the slack bus is adjusted in coordination with the active power delivered by the DG units. The objective function can be formulated as:

$$\text{Min}\, J_2 = Ploss \tag{15}$$

while Ploss is the power loss (MW).

3.2.3. Reactive Power Dispatch for Voltage Support

The goal here is to assure the minimum reactive exchange between the dynamic shunt compensator and the network. Based on experience [13] there is a maximum load increase on load margin with respect to the compensation level, the minimum reactive power is defined as the least amount needed from the network system to maintain the same degree of system security. The problem can be formulated as a reactive power dispatch problem as follows:

$$\text{Max}\;\; RIS = \frac{LoadFactor(KLd)}{\sum_{i=1}^{NSVC} Q_{svc}^{i}} \tag{16}$$

Subject to:

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{17}$$

$$Q_{SVC}^{\min} \le Q_{SVC}^{j} \le Q_{SVC}^{\max} \tag{18}$$

where

RIS: reactive index sensitivity.

$NSVC$: the number of shunt compensators.

KLd : loading factor.

Q_{SVC} : Reactive power exchanged.

To solve the above optimization problem, we adopted coordination rules based on heuristic strategy. A global database was generated during the successive action.

Fig. 3 shows the principle of the reactive index sensitivity proposed to improve the economical size of shunt compensators installed in a practical network.

In this Figure, the curve represents the evolution of minimum reactive power exchange based on system loadability;

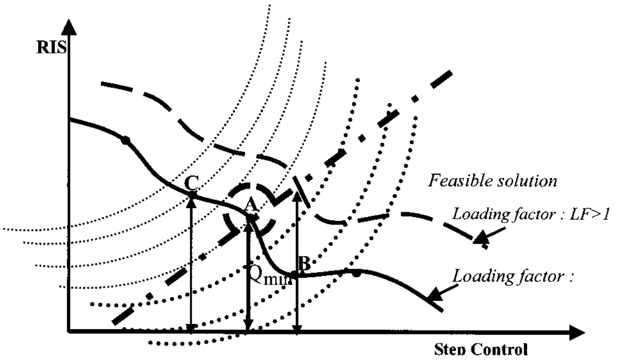

Fig. 3. Schematic diagram of minimum reactive power sensitivity

the curve has two regions, the feasible region which contains the feasible solution of reactive power. At point 'A', if the SVC outputs less reactive power than the optimal value such as at point 'B', it has a negative impact on system security since the voltage margin is less than the desired margin, but the performances of the SVC Compensator are not violated. On the other hand, if the SVC produces more reactive power than the minimum value (Q_{min}), such as point 'C', it contributes to improving the security system with a reduced margin of system loadability. This reactive power delivered accelerates the saturation of the SVC Compensator.

3.3 GA Solution for the Economic Dispatch

GAs are general purpose optimization algorithms based on the mechanics of natural selection and genetics [14]. They operate on string structure (chromosomes), typically a concatenated list of binary digits representing a coding of the control parameters (phenotype) of a given problem. Chromosomes themselves are composed of genes. The real value of a control parameter encoded in a gene is called an allele.

A genetic algorithm is governed by three factors: the mutation rate, the crossover rate and the population size. GAs are search processes, which can be applied to unconstraint problems. Constraints may be included into the fitness function as added penalty terms [15].

3.3.1. Chromosome Type

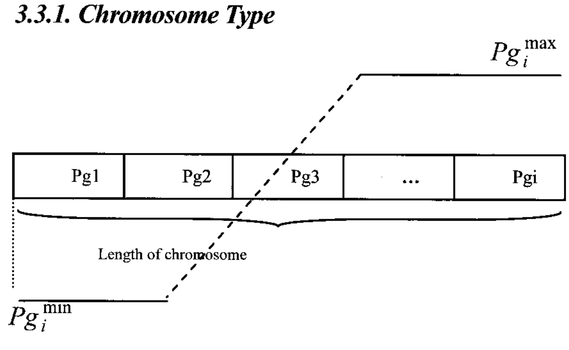

Fig. 4. Chromosome structure

Implementation of a problem in a GA starts from the parameter encoding. The encoding must be carefully designed to utilize the GA's ability to efficiently transfer information between chromosome strings and the objective function of the problem. The encoded parameter is the power generation. Fig. 4 shows the structure of the chromosome proposed.

3.3.2. Fitness of Candidate Solution

Evaluation of a chromosome is accomplished by decoding the encoded chromosome string and computing the chromosome's fitness value using the decoded parameters. The fitness function adopted is given as:

$$\text{Fitness} = \frac{\text{M}}{\text{f}_\text{i} + \text{Penality}_\text{Q}^\text{V}} \qquad (19)$$

where M is the maximum possible cost of generation, Objective function is the generation cost and $Penality\ _Q^V$ denotes a penalty for violating voltage limits V_j^{min}, V_j^{max}, and the penalty on the slack node for violating the reactive power limit.

3.4 Fuzzy Logic Method

The use of fuzzy logic has received increased attention in recent years because of it's usefulness in reducing the need for complex mathematical models in problem solving [16-17]. Fuzzy logic employs linguistic terms, which deal with the causal relationship between input and output variables. For this reason, the approach makes it easier to manipulate and solve problems.

3.4.1. Fuzzy Rules for Crossover and Mutation Adjustment

For better results and to get faster convergence, conventional GA modes have been modified. In recent years various techniques have been studied to achieve this objective, including [18]:

-Using advanced string coding.

-Generating initial population with some prior knowledge.

-Establishing some better evaluation function.

-Including new operators such as elitism, multi- point or uniform crossover and creep mutation. A refined GA was used to solve the economic dispatch in [19] and a pyramid Genetic Algorithm (PGA) has been used in [20-21] for voltage profile optimization.

This approach proposes a flexible Genetic Algorithm based on fuzzy logic rules with the ability to continuously adjust the crossover and mutation parameters. Fig. 5 presents the proposed block diagram of a fuzzy controlled genetic algorithm.

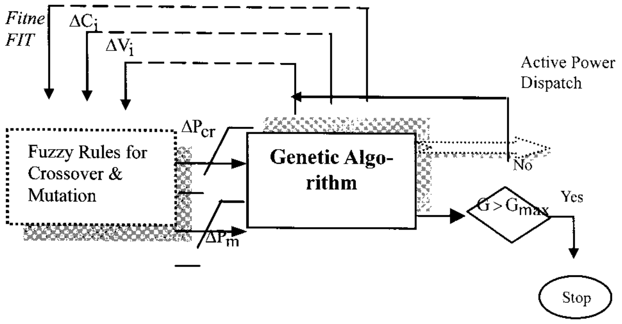

Fig. 5. Block diagram of the genetic parameters adjustment

Crossover and mutation are considered critical for GA convergence. A suitable value for mutation provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate a good near solution. Experimental results based upon the application of GA to many practical networks in normal and abnormal conditions with load incrementation indicated that it is better to adjust dynamically the value of the crossover and mutation of the two parameters.

It is intuitive that for a small variation in the chromosomes in a particular population the effect of crossover during this critical stage becomes insignificant. Therefore, creating diversity in the population is required by increasing the mutation (High value) probability of the chromosome and reducing (Low value) the value of crossover. (Note that the terms, small and high are linguistic.)

The proposed approach employs practical rules interpreted in fuzzy logic rules to adjust dynamically the two parameters (crossover and mutation) during execution of the GA standard algorithm.

a) Membership Function Design

The membership function is adopted by engineer differences from person to person and depends upon problem difficulty. Therefore they are rarely optimal in terms of reproduced desired output.

b) Inputs and Outputs of Crossover and Mutation Fuzzy Controller

The inputs of the crossover fuzzy controller are changes of chromosomes fitness, the diversity in the cost generation, and voltage deviation, and the output is the rate variation in crossover. The inputs and outputs of mutation are the same as the crossover fuzzy controller. Sample rules for crossover and mutation changes are presented in Fig. 6.

In this study, the upper and lower value for crossover probability and mutation probability respectively are changed based upon the membership function for each variable from 0.9 to 0.4 and from 0.01 to 0.1. The consequent effects on the final value of crossover probability and mutation probability are calculated using the following equations:

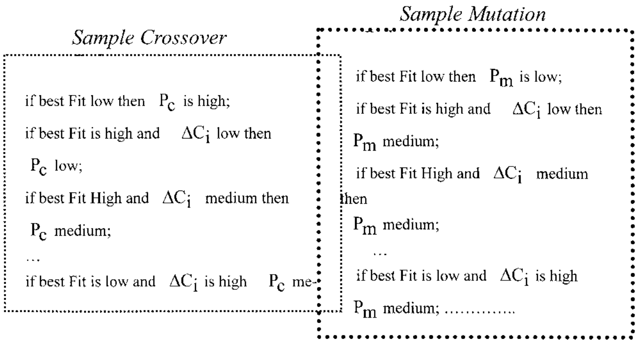

Fig. 6. Sample rules for crossover and mutation tuning

$$P_c^{(t)} = P_c^{(t-1)} + \Delta P_c \tag{20}$$

$$P_m^{(t)} = P_m^{(t-1)} + \Delta P_m \tag{21}$$

where, $P_c^{(t)}, P_m^{(t)}$ are respectively the crossover and mutation probability at the iteration 't'.

3.4.2. Fuzzy Rules for Reactive Power Planning

The fuzzy variables associated with the Reactive Power Planning Problem 'RPP' of a multiple dynamic shunt compensator are stated below.

1. *Fuzzy Input Variables*
   - Bus voltage
   - Active Power loss
   - Reactive Power loss

2. *Fuzzy Output Variables*
   - Voltage regulation for the shunt compensator.

3. *Membership Function*

A membership function uses a continuous function in the range [0-1]. It is usually chosen based upon human expertise and observations made, and it can be either linear or nonlinear. This choice is critical for the performance of the fuzzy logic system since it determines all the information contained in a fuzzy set. Engineer experience is an efficient tool to achieve a design of an optimal membership function, if the experienced operator is not satisfied with the conception of the fuzzy logic model, he can adjust the parameters used to design the membership functions to adapt them to the new database introduced to the practical power system. Fig. 7 shows the general block diagram of the proposed coordinated fuzzy approach applied to enhance the system loadability with minimum reactive power exchanged. Fig. 8 shows the combination of the voltage, active power and reactive power as input to the shunt compensator controller.

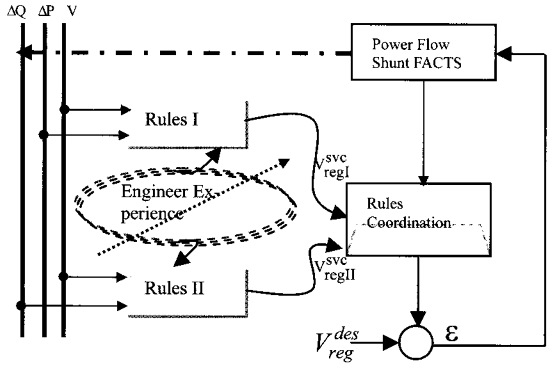

Fig. 7. Diagram of the proposed coordinated fuzzy approach

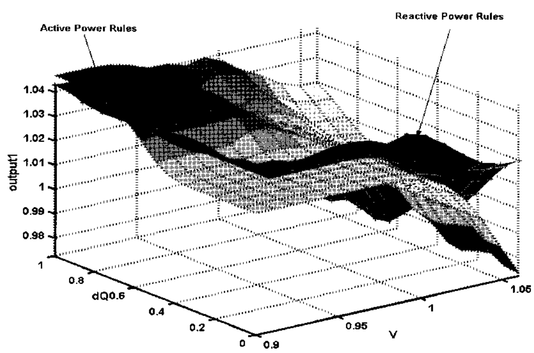

Fig. 8. Combination voltage, active and reactive power rules

The solution algorithm steps for the fuzzy control methodology are as follows:

1) Initial database:
   - Introduce the initial vector solution for power generation $X^{cor} = [PG_i \quad \cos t \quad ploss \quad \Delta V]^{cor}$
   - Introduce the initial vector solution for distribution generation units DG_i.
2) Perform the initial operational power flow to generate the initial database $(V_i, \Delta P, \Delta Q)$.
3) Identify the candidate bus using continuation load flow.
4) Install the specified dynamic shunt compensator to the best bus chosen, and generate the reactive power using power flow based in the fuzzy expert approach.

4. Shunt Facts and DG Modeling

4.1 Steady State Model of DG

The approach proposed requires that the user define the number of DG units to be installed based upon the voltage stability index (loading factor). The genetic algorithm generates and optimizes the combination of DG sizes for each combination of solution. Power losses and minimal cost are used as a fitness function for the GA.

DG unit modelling depends on constructive technology and their combined active and reactive power control schemes [22].

In this study DG has been considered as not having the capability to control voltages, and therefore has been modelled in the power flow study as a negative load, as a PQ node. Dynamic shunt compensators (SVC and STATCOM) were modelled as PV nodes used in coordination with DG to control the voltage by a flexible adjustment of reactive power exchanged with the network [22]. Fig. 9 shows the proposed combined model of DG and SVC.

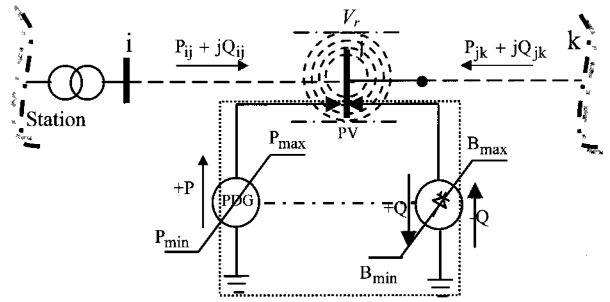

Fig. 9. The proposed combined model of DG/SVC Compensators integrated in power flow algorithm

4.2 Static VAR Compensator (SVC)

The steady-state model proposed in [23] is used here to incorporate the SVC on power flow problems. This model is based on representing the controller as a variable impedance, assuming an SVC configuration with a fixed capacitor (FC) and Thyristor Controlled Reactor (TCR) as depicted in Fig. 10. Simultaneously applying a gate pulse to all thyristors of a thyristor valve brings the valve into conduction. The valve will block approximately at the zero crossing of the ac current in the absence of firing signals. Thus, the controlling element is the Thyristor valve. The thyristors are fired symmetrically, in an angle control range of 90 to 180 with respect to the capacitor (inductor) voltage.

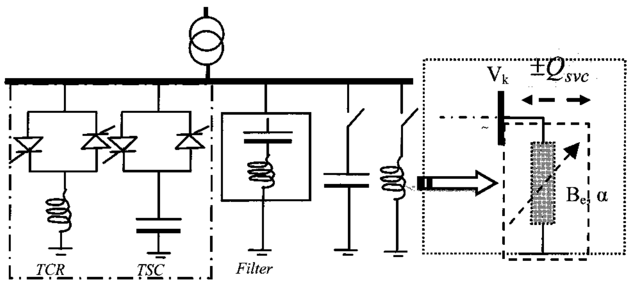

Fig. 10. Basic circuit representation of SVC Compensator

$$V = V_{ref} + X_{sl} I \tag{22}$$

X_{sl} is in the range of 0.02 to 0.05 p.u. with respect to the SVC base. The slope is needed to avoid hitting limits. At the voltage limits the SVC is transformed into a fixed reactance. The total equivalent impedance Xe of SVC may be represented by:

$$X_e = X_C \frac{\pi / k_X}{\sin 2\alpha - 2\alpha + \pi(2 - 1/k_X)} \tag{23}$$

where $k_X = x_C / x_L$ and $B_e = 1/X_e$.

The SVC is usually connected to the transmission system through a step-down transformer, which is treated in a similar manner as other transformers in the system.

Steady-state limits of the firing angle are $90^0 < \alpha < 180^0$ where partial conduction is obtained. Firing angles less than 90^0 are not allowed, as they produce unsymmetrical current with a high dc component.

4.3 Multi Function Control

The objective function of the multi control functional operation of a coordinated multi DG with shunt FACTS devices is the combination of the prescribed control targets:

$$F_{DG/SVC} = \alpha_1 \left| P - P^{des} \right| + \alpha_2 \left| Q - Q^{des} \right| + \alpha_3 \left| V - V^{des} \right| \tag{24}$$

Where P^{des}, Q^{des}, and V^{des} are the control targets of active and reactive power flow along the line, and the voltage of bus K, respectively. Fig. 11 illustrates the three combined voltage active and reactive power control.

Coefficients α_1, α_2, and α_3 can take 1 or 0 based on the control strategy adopted.

For a power system with N_{DG} and N_{SVC} devices integrated in a practical network to enhance the power flow control, the optimization objective is:

$$Min \quad F \tag{25}$$

The mathematical descriptions of the three control modes of coordinated multi DG with shunt Compensators are presented as follows:

Target 1: Bus Voltage Control

The bus Voltage control constraint is given by

$$V_m - V_m^{des} = 0 \tag{26}$$

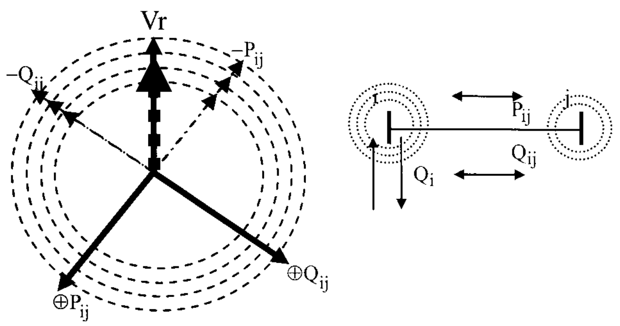

Fig. 11. Three control mode: voltage, active and reactive power control

where V_m^{des} is the desired bus voltage control

Target 2: The active Power Flow Control

$$P_{mk} - P_{mk}^{des} = 0 \tag{27}$$

where P_{mk}^{des} is the desired active power control

Target 3: The Reactive Power Flow Control

$$Q_{mk} - Q_{mk}^{des} = 0 \tag{28}$$

where Q_{mk}^{des} is the desired reactive power control.

5. Case Studies

The combined GA/Fuzzy rules were coded in the Matlab program, and two test cases were used to demonstrate the performance of the proposed algorithm. Consistently acceptable results were observed.

5.1 Case Studies on the IEEE 30-Bus System

The first test is the IEEE 30-bus, 41-branch system, and for voltage constraint the lower and upper limits are 0.9 p.u and 1.1 p.u., respectively (except for PV buses where (V_{max} =1.1 p.u.). For the purpose of verifying the efficiency of the proposed approach, we made a comparison of our algorithm with other competing OPF algorithms. In [24], a standard GA was presented, in [14] the authors presented an enhanced GA, and then in [25] they proposed an Ant Colony Optimization (ACO). The authors of [26] proposed a Fuzzy GA for OPF. The operating cost proposed in our approach is 801.3445 $/h and the power loss is 9.12 MW, which are better than the others methods reported in the literature. Results depicted in Table 1 show clearly that the approach proposed provides better results. Table 2 shows the results of the reactive power generation and phase angle for the PV bus. Table 3 shows the best solution for shunt compensation obtained at the standard load demand (Pd=283.4 MW) using reactive power planning.

Table 1. Results of the Minimum Cost and Power Generation Compared to SGA, EGA, ACO and FGA for IEEE 30-Bus

Variables	GA/FRules	SGA[24]	EGA[14]	ACO[25]	FGA[26]
P1(MW)	180.12	179.367	176.20	181.945	175.137
P2(MW)	44.18	44.24	48.75	47.0010	50.353
P5(MW)	19.64	24.61	21.44	20.5530	21.451
P8(MW)	20.96	19.90	21.95	21.1460	21.176
P11(MW)	14.90	10.71	12.42	10.4330	12.667
P13(MW)	12.72	14.09	12.02	12.1730	12.11
Cost ($/hr)	**801.3445**	803.699	802.06	802.578	802.0003
Ploss (MW)	**9.120**	9.5177	9.3900	9.8520	9.494

Table 2. Results of the Reactive Power Generation and Phase Angle of GA/Fuzzy Rules Compared to SGA, FGA for IEEE 30-Bus

Variables	GA/FRules	SGA[24]	FGA[26]
Q1(Mvar)	-4.50	-3.156	-6.562
Q2(Mvar)	30.71	42.543	22.356
Q5(Mvar)	22.59	26.292	30.372
Q8(Mvar)	37.85	22.768	18.89
Q11(Mvar)	-2.52	29.923	21.737
Q13(Mvar)	-13.08	32.346	22.635
θ1(deg)	0.00	0.000	0.00
θ2(deg)	-3.448	-3.674	-3.608
θ5(deg)	-9.858	-10.14	-10.509
θ8(deg)	-7.638	-10.00	-8.154
θ11(deg)	-7.507	-8.851	-8.783
θ13(deg)	-9.102	-10.13	-10.228

Table 3. Comparative Results of the Shunt Reactive Power Compensation for IEEE 30-Bus

Shunt N°	1	2	3	4	6	7	8	9
Bus N°	10	12	15	17	21	23	24	29
Best Qsvc [pu]	0.155	0.0798	0.03012	0.0495	0.0615	0.0384	0.0458	0.025
bsh [pu] [14]	0.05	0.05	0.03	0.05	0.05	0.04	0.05	0.03

5.2 Case Studies on the IEEE 25-Bus test System without SVC and DG Installation

The approach proposed has been tested on an IEEE 25-bus electrical network. It consists of 25 buses, 35 branches (lines and transformers), 5 generators and 24 loads.

5.2.1. Initial OPF with Genetic Algorithm

In this first step, DG and dynamic shunt compensation are not taken into consideration, and for the voltage constraint the lower and upper limits are 0.94 p.u and 1.06 p.u., respectively.

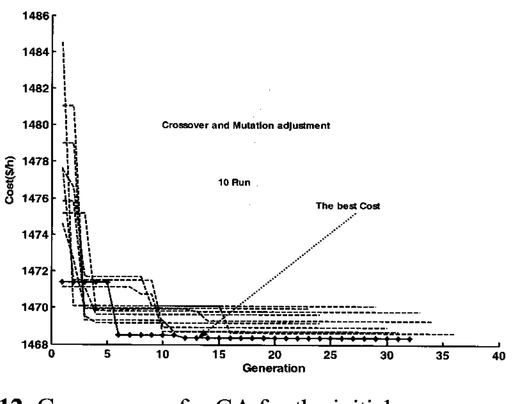

Fig. 12. Convergence for GA for the initial power generation subproblem with crossover and mutation adjustment (IEEE 25-bus)

Table 4. Results of the Generators Voltage, Active and Reactive Power without DG and Shunt Compensation

Bus	|V| (p.u)	Pg (MW)	Qg (Mvar)
1	1.051	164.95	23.357
2	1.052	89.00	7.3780
3	1.043	81.82	34.748
4	1.012	20.98	24.699
5	1.042	184.58	15.600
PD (MW)		530.00	
Ploss (MW)		11.332	
Cost ($/hr)		1467.9	

The GA population size is taken as equal to 30, the maximum number of generation is 100, and crossover and mutation are applied with an initial probability 0.95 and 0.01 respectively. 10 test runs were performed; the convergence of this initial OPF is shown in Fig. 12.

Table 4 shows the results of the generators voltage, active and reactive power generation without DG and shunt FACTS devices.

5.2.2. Optimal Placement of Shunt FACTS and DG

Before the insertion of SVC and DG devices, the system was pushed to its collapsing point by increasing both active and reactive loads discretely using continuation load flow. In this test system, according to results obtained from the continuation load flow, we can see that based on Fig. 13 buses 15, 22, 24, 25 are the best location points for the initial installation of DG and reactive power planning for multi SVC Compensators.

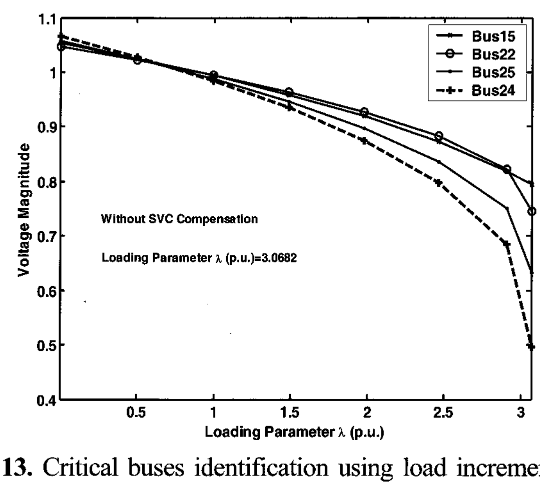

Fig. 13. Critical buses identification using load incrementation without DG and SVC installation (λ=3.0682)

5.2.3. Optimal Active Power Plannning for DG for Power Loss Reduction

In this step the fuzzy controlled genetic algorithm with the same initial crossover and mutation parameter is used to generate and optimize the active power of multi distributed generation in order to minimize power losses. Fig. 14 shows the best solution obtained at different load incrementation.

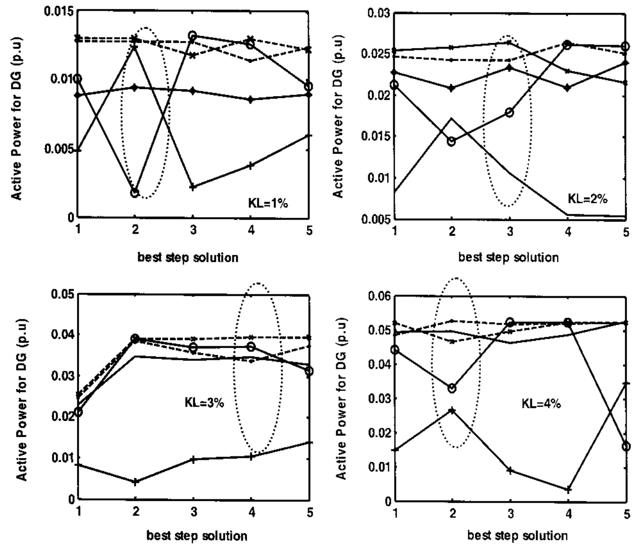

Fig. 14. The best solution (5 run) with load incrementation: (KL=1-4%)

Table 5. Results of Active Power Planning with Load Incrementation

Loading λ	0%	1%	2%	3%	4%	5%
Dg15	0	0.0130	0.0242	0.0338	0.0482	0.0586
Dg21	0	0.0128	0.0258	0.0396	0.0520	0.0650
Dg22	0	0.0124	0.0172	0.0104	0.0148	0.0450
Dg24	0	0.0018	0.0144	0.0372	0.0442	0.0306
Dg25	0	0.0094	0.0208	0.0348	0.0492	0.0622
Ploss	0.11332	0.11568	0.11076	0.10715	0.10502	0.1036
Cost	1467.9	1469.3	1468.1	1467.2	1466.8	1466.5
PD	5.3000	5.353	5.406	5.459	5.512	5.565
Pg1	1.6495	1.6555	1.6506	1.6466	1.6448	1.6434

5.2.4. System loadability Enhancement with Efficient Reactive Power Planning for Multi SVC Installation

In this second step, the initial SVC data used to control the reactive power are presented in Table 4. To demonstrate the efficiency of the reasoning why fuzzy rules were designed as a second subproblem to control the reactive power exchanged with the network, the algorithm was applied again on the IEEE 25-bus.

From Table 5, it is observed that there is a decrease in power losses due to the integration of DG. Table 7 shows the results of the reactive power planning for the shunt FACTS devices installed at the critical buses. Fig.15 shows that the system loadability is enhanced (3.4453 p.u) compared to the case (3.0682 p.u) without DG and shunt FACTS devices installation. Fig. 16 shows clearly that the voltage profile is

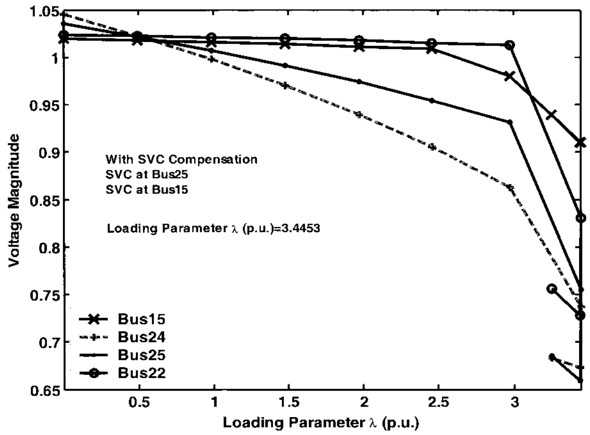

Fig. 15. Voltage profile improvement for the critical buses with SVC installation with load incrementation (λ=3.4453)

Table 6. SVCs data

		B_{min} (p.u)	B_{max} (p.u)	B_{init} (p.u)
Susceptance	SVC Model	-0.35	0.35	0.035

Table 7. Results of Reactive Power Planning with Load Incrementation

Reactive Power (p.u)	0%	1%	2%	3%	4%	5%
Q_{svc} **15**	0	-0.06545	0.00091	0.06924	0.13723	0.19889
Q_{svc} **21**	0	-0.03883	0.03221	0.10459	0.17904	0.24125
Q_{svc} **22**	0	-0.05308	-0.04193	-0.02599	-0.01366	-0.01093
Q_{svc} **24**	0	0.06026	0.05544	0.04669	0.04390	0.04726
Q_{svc} **25**	0	-0.07026	-0.04735	-0.02466	-0.00158	0.02157
Q_{G1}	0.23357	0.32462	0.23159	0.13585	0.03958	-0.04922
Q_{G2}	0.07378	0.07638	0.07898	0.08161	0.08427	0.08682
Q_{G3}	0.34748	0.37618	0.35897	0.34182	0.32468	0.30747
Q_{G4}	0.24699	0.28302	0.25136	0.22124	0.19151	0.15712
Q_{G5}	0.15600	0.19297	0.16237	0.13209	0.10183	0.07083
PD (p.u)	5.3000	5.353	5.406	5.459	5.512	5.565

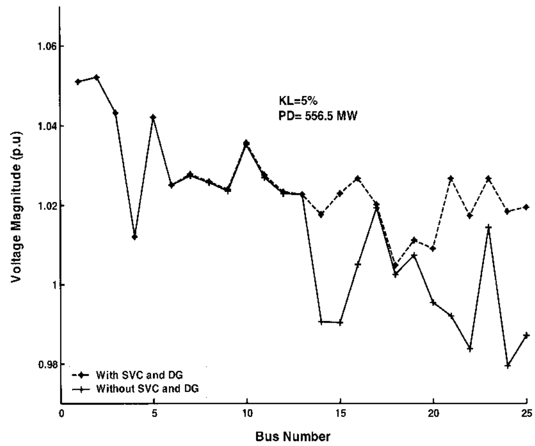

Fig. 16. Voltage profile in two cases: without SVC/DG, and with SVC/DG

enhanced at the base case (530 MW). Fig. 17 illustrates the reactive power exchanged between the shunt compensators and the network at different loading factors. Fig. 18 shows the active power exchanged between the distributed generation and the network at different loading factors.

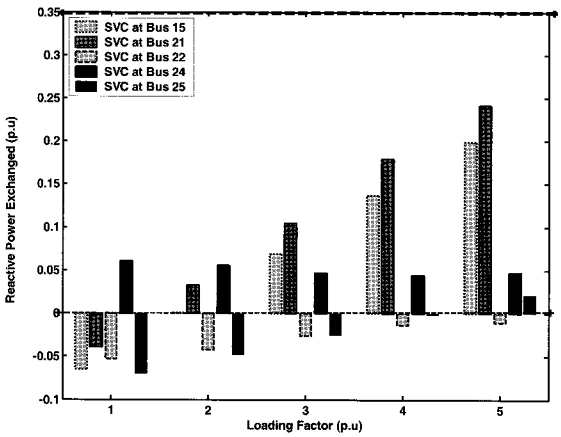

Fig. 17. Reactive power exchanged with the network at different loading factor

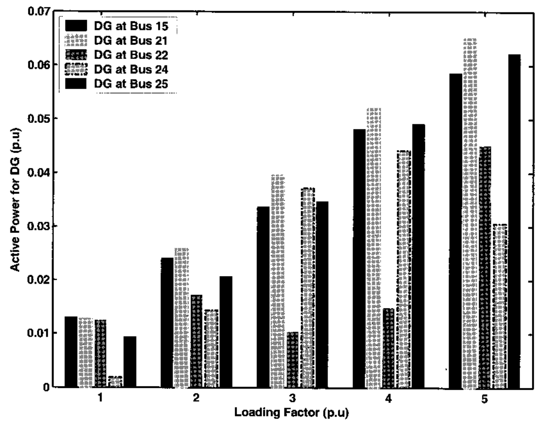

Fig. 18. Active power of DG exchanged with the network at different loading factor

6. Discussions

- It is clear from the results depicted in Table 7 that the dynamic voltage control using shunt FACTS Compensators has a significant impact on the potential integration of DG.
- The power losses and, correspondingly, the optimal cost for standard generation are enhanced at an acceptable technical value considering the load incrementation; for example, at loading factor KL=5% the power losses were reduced to 10.36 MW and the cost maintained at 1466.5 $/hr compared to the base case.
- It was found that based on the dynamic reactive index sensitivity introduced, the professional engineer can choose economically the size of the shunt Compensators to be installed in a practical network. The proposed new size of shunt dynamic Compensators are depicted in Table 8. The size of the SVC installed at bus 22, 24, and 25 was reduced from the initial value 0.35 p.u to 0.1 p.u.
- Further research is required to include the real cost of DG units into the objective function.

Table 8. SVC Size

Bus	Initial SVC Size	New SVC Size	Marge Security utilization in %
15	$-0.35 < Q_{SVC} < 0.35$	$-0.35 < Q_{SVC} < 0.35$	56.83
21	//	$-0.35 < Q_{SVC} < 0.35$	68.93
22	//	$-0.10 < Q_{SVC} < 0.10$	10.93
24	//	$-0.10 < Q_{SVC} < 0.10$	47.26
25	//	$-0.10 < Q_{SVC} < 0.10$	21.57

7. Conclusion

An approach combining Genetic Algorithm and fuzzy logic expert rules aims to demonstrate the importance of finding the best locations and sizes of a distribution generation to be integrated dynamically in a practical network.

One might think that the larger the size of DG or shunt dynamic Compensators, the greater the increase in the maximum load. However, based on experience and the results given in this paper it is clear that this is not always true. There is a maximum increase on load margin with respect to the compensation level for shunt FACTS devices and the active power injected by DG. The objective of the approach proposed is to coordinate and adjust the active power for DG and the reactive power exchanged with dynamic Compensators and the network to minimize fuel cost and to improve the index power quality (voltage deviation, power losses).

As for future work along this line, the author will strive to develop an adaptive and flexible algorithm to optimize the allocation and coordinate the control parameters of multiple DG with Multi FACTS devices installed in a large practical network in order to enhance the power quality in a critical situation.

References

[1] V. H. Méndez, J. Rivier, and T. Gomez, "Assesment of energy distribution losses for increasing penetration of distribution generation," *IEEE Trans. Power Systems*, vol. 21, n. 21, pp. 533-5400, May 2006.

[2] P. N. Vovos, A. E. Kiprakis, A. R. Wallace, and G. P. Harrison, "Centralized and distribution voltage control: impact on distribution generation penetration," *IEEE Trans. Power Systems*, vol. 22, n. 1, pp. 476-683, February 2007.

[3] B. Mahdad, T. Bouktir, K. Srairi, "Flexible methodology based in fuzzy logic rules for reactive power planning of multiple shunt FACTS devices to enhance system loadability," *Power Engineering Society General Meeting,* 2007. IEEE, 24-28 June 2007 Page(s):1-6, Digital Object Identifier 10.1109/PES.2007.385750.

[4] R. C. Bansal, "Optimization methods for electric power systems: an overview," *International Journal of Emerging Electric Power Systems*, vol. 2, no. 1, pp. 1-23, 2005.

[5] M. Huneault, and F. D. Galiana, "A survey of the optimal power flow literature," *IEEE Trans. Power Systems*, vol. 6, no. 2, pp. 762-770, May 1991.

[6] A. Keane, M. O'Malley, "Impact of distribution generation capacity on losses," *in Proc. IEEE*, pp. 1-7, 2006.

[7] C. Wang, and M. H. Nehrir, "Analytical approaches for optimal placment of distribution generation sources in power systems," *IEEE Trans. Power Systems*, vol. 19, no. 4, pp. 2068-2076, May 2004.

[8] A. Hanif, M. A. Choudhry, "Inversigation smooth power flow control for dispersed generator working parallel to the grid system on the level load," *in Proc.PSCE*, pp. 2241-2248, 2006.

[9] A. Keane, M. O'Malley, "Impact of distribution network constraints on distribution generation capacity," *in Proc. of 40th Inter national Universities power engineering conference*, Cork, 2005.

[10] B. Kuri, M. Redfern, and F. Li, "Optimization of rating and positionning of dispersed generation with minimum network disruption," *In Proc. IEEE Power Eng. Soc. Gen. Meeting, Denver,CO*, Juin 2004, pp. 2074-2078.

[11] W. El-Khaltam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama, "Optimal investment planning of distributed generation in a competetive electricity market," *IEEE Trans. Power Syst.* , vol. 19, no. 3, pp. 1674-1684, Aug. 2004.

[12] G. P. Harrison, A. Piccolo, P. Siano, A. R. Wallace, "Distributed generation capacity evaluation using combined genetic algorithm and OPF," *Intenational Journal of Emerging Electric Power Systems*, vol. 8, Issue. 2, 2007.

[13] B. Mahdad, T. Bouktir, K. Srairi, "Methodology based in practical fuzzy rules coordinated with asymetric dynamic compensation applied to the unbalanced distribution network," *International Review of Electrical Engineering (IREE)*, vol. 3, no. 2, pp. 145-153 (2007), ISSN 1827-6660, Praise Worthy Prize, Italy.

[14] A. G. Bakistzis, P. N. Biskas, C. E. Zoumas, and V. Petridis, "Optimal power flow by enhanced genetic algorithm," *IEEE Trans. Power Systems*, vol. 17, no. 2, pp. 229-236, May 2002.

[15] L. Davis, "Adapting operator probabilities in genetic algorithms," *in Proc. 3rd Int. Conf. Genetic Algorithms Applications,* J. Schaffer, Ed., SanMateo, CA, June 1989, pp. 61-69.

[16] H. N. Ng, M. M. A. Salama, and A.Y. Chikhani, "Capacitor allocation by approximate reasoning: fuzzy capacitor placament," *IEEE Trans. Power Delivery*, vol. 15, no. 1, pp. 393-398, January 2000.

[17] H. N. Ng, M. M. A. Salama and A.Y. Chikhani, "Classification of capacitor allocation techniques," *IEEE Trans. Power Delivery*, vol. 15, no. 1, pp. 387-392, January 2000.

[18] T. Yalcinoz, H. Altun, and M. Uzam, "Economic dispatch solution using genetic algorithm based on arithmetic crossover," *in Proc. IEEE Porto Power Tech. Conf.*, Porto, Portugal, Sep. 2001.

[19] M. Todorovski, and D. Rajičič, "An initialization procedure in solving optimal power flow by genetic algorithm," *IEEE Trans. Power Systems*, vol. 21, no. 2, pp. 480-487, May 2006.

[20] K. Iba, "Reactive power optimization by genetic algorithm," *IEEE Trans. Power Systems*, vol. 9, no. 2, pp. 685-692, May1994.

[21] L. L. Lai, J. T. Ma, R. Yokoyama, and M. Zhao, "Improved genetic algorithm for optimal power flow under both normal and contingent operation states," *Elec. Power Energy Syst.*, vol. 19, no. 5, pp. 287-292, 1997.

[22] M. E. H. Golshan, and S. A. Arefifar, "Distribution genartion, reactive sources and network-configuration planning for power and energy-loss reduction, " *IEE Proc.-Gener. Transm. Distrib.*, vol. 153, no. 2, pp. 127-136, March 2006.

[23] C. R. Feurt-Esquivel, E. Acha, Tan SG, JJ. Rico, "Efficient object oriented power systems software for the analysis of large-scale networks containing FACTS controlled branches," *IEEE Trans. Power Systems*, vol. 13, no. 2, pp. 464-472, May 1998.

[24] T. Bouktir, L. Slimani, B. Mahdad, "Optimal power dispatch for large scale power system using stochastic search algorithms, "*International Journal of Power and Energy Systems,* vol. 28, no. 1, pp. 1-10 2008.

[25] L. Slimani, T. Bouktir, "Economic power dispatch of power system with pollution control using multiobjective ant colony optimization," International Journal of Power and Computational Intelligence Research, vol. 03, no. 2, pp. 145-153, 2007.

[26] A. Saini, D. K. Chaturvedi, A. K. Saxena, "Optimal power flow solution: a GA-Fuzzy system approach," *International journal of emerging electric power systems*, vol. 5, Issue. 2, pp. 1-21, 2006.

[27] C. A. Canizares, "Power flow and transient stability models of FACTS controllers for voltage and angle stability studies, " *IEEE Proceeding* , 2000.

[28] B. Sttot and J. L. Marinho, "Linear programming for power system network security applications," *IEEE Trans. Power Apparat. Syst.*, vol. PAS-98, pp. 837-848, May/ June 1979.

[29] O. Alsac and B. stott. "Optimal load flow with steady state security," *IEEE Trans. Power Appara. Syst.*, pp. 745-751, May-June 1974.

[30] L. L. Lai, J. T. Ma, R. Yokoyama, and M. Zhao, "Improved genetic algorithm for optimal power flow under both normal and contingent operation states," *Elec. Power Energy Syst.*, vol. 19, no. 5, pp. 287-292, 1997.

[31] G. Dhaoyun, and T. S. Chung, "Optimal active power flow incorporating FACTS devices with power flow constraints," *Electrical Power & Energy Systems*, vol.

20, no. 5, pp. 321-326, 1998.
[32] M. Chis, M. M. A. Salama, and S. Jayaram, "Capacitor placement in distribution systems using heuristic search strategies," *IEE Proceedings Generation, Transmission and Distribution,* vo. 144, n. 2, pp. 225-230, May 1997.

Belkacem MAHDAD (S'07) was born in Biskra, Algeria. He received a B.Sc degree in Electrical Engineering (Power system) from Biskra University Algeria in 1990, and his MSc degree from Annaba University in 2000. He is currently working towards his Ph.D degree in Electrical Engineering at Biskra University, Algeria. His areas of interest are optimal power flow, FACTS modelization, application of Artificial Intelligence (AI) techniques to FACTS control and improvement in electric power systems.
Email: bemahdad@yahoo.fr

Kamel Srairi was born in Batna, Algeria, in 1967. He received a B.Sc. degree in Electrical Engineering in 1991 from the University of Batna, Algeria; an M.Sc. degree in Electrical and Computer Engineering from the National Polytechnic Institute of Grenoble, France, in 1992; and a Ph.D. degree also in Electrical and Computer Engineering from the University of Nantes, France, in 1996. After graduation, he joined the University of Biskra, Algeria, in 1998 where he is a Professor in the Electrical Engineering Department. His main research interests include analysis, design, and magnetic modeling.
Email: ksrairi@yahoo.fr

Tarek Bouktir was born in Ras El-Oued, Algeria. He received a B.S degree in Electrical Engineering Power System from Setif University (Algeria) in 1994, his MSc degree from Annaba University in 1998, and his PhD degree in power system from Batna University (Algeria) in 2003. His areas of interest are the application of meta-heuristic methods in optimal power flow, FACTS control and improvement in electric power systems, Multi-Objective Optimization for power systems, and Voltage Stability and Security Analysis.