Chapter 6

Power Quality Management Based Security OPF Considering FACTS Using Metaheuristic Optimization Methods

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Additional information is available at the end of the chapter

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1. Introduction

Power quality management based environmental optimal power flow (OPF) is a vital research area for power system operation and control, this type of problem is complex with non-linear constraints where many conflicting objectives are considered like fuel cost, gaz emission, real power loss, voltage deviation, and voltage stability[1-2]. The solution of this multi objective problem becomes more complex and important when flexible ac transmission systems (FACTS) devices and renewable energy are considered. In the literature a wide variety of optimization techniques have been applied, a number of approaches have been developed for solving the standard optimal power flow problem using mathematical programming, lambda iteration method, gradient method, linear programming, quadratic programming and interior point method [3-4-5]. However all these developed techniques rely on the form of the objective function and fail to find the near global optimal solution, authors in [6-7] provide a valuable introduction and surveys the first optimization category based conventional optimization methods.

To overcome the major problem related specially to restriction on the nature of the objective function, researchers have proposed a second optimization category based evolutionary algorithms for searching near-optimum solutions considering non linear objective function characteristic and practical generating units constraints such as: Genetic algorithms (GA), simulated annealing (SA), tabu search (TS), and evolutionary programming (EP) [8-9-10], which are the forms of probabilistic heuristic algorithm, author in [11] gives a recent and significant review of many global optimization methods applied for solving many problems related to power system operation, planning and control.

In order to enhance the performance of these standard global optimization methods for solving complex and practical problem, many hybrid variants based evolutionary algorithm have been proposed and applied with success for solving many problems related to power system operation and control like: hybrid EP–SQP[12], Quantum genetic Algorithm (QGA) [13], artificial immune system (AIS) [14], Adaptive particle swarm optimization (APSO) [15], improved PSO (IPSO) [16], improved chaotic particle swarm optimization (ICPSO) [17], adaptive hybrid differential evolution (AHDE) [18], and a hybrid multi agent based particle swarm optimization (HMPSO) [19]. These methods have a better searching ability in finding near global optimal solution compared to mathematical methods and to the standard evolutionary algorithms. Very recently a significant review of recent non-deterministic and hybrid methods applied for solving the optimal power flow problem is proposed in [7].

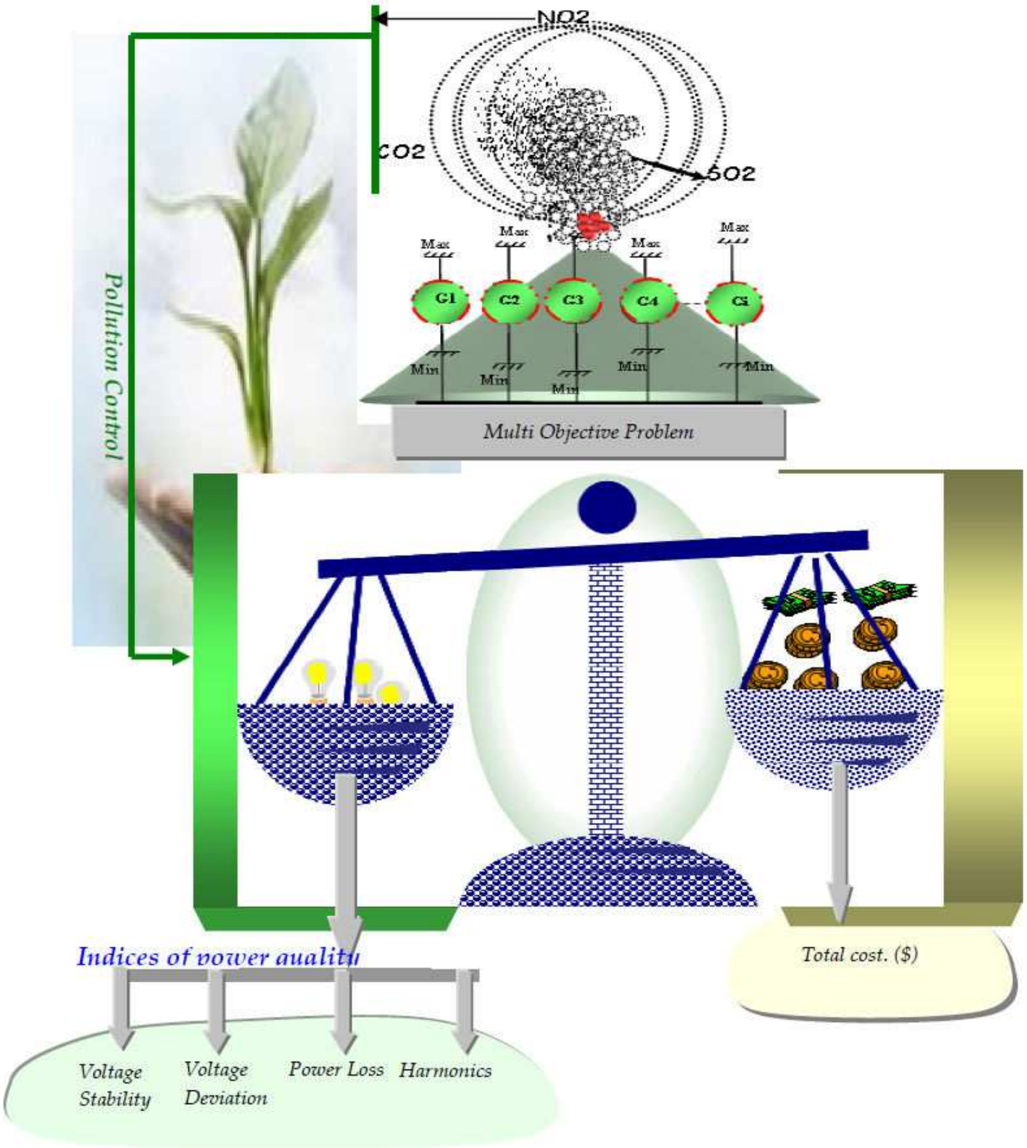

Figure 1. Strategy of the power quality management based SOPF.

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Recently a new metaheuristic optimization method called Firefly research method introduced and attracted many researchers due to its capacity and efficiency to find the global optimal solution, this method applied with success to solving many real optimization problems [20-21]. In this chapter firefly algorithm is proposed to solve the combined economic dispatch problem, and a decomposed genetic algorithm considering multi shunt FACTS proposed for solving the multi objective optimal power flow [22-23]. The remainder of this chapter is organized as follows; section 2 provides a formulation of the multi objective optimization problem, Section 3 introduces the mechanism search of the firefly algorithm. Brief description and modelling of shunt FACTS devices is developed in section 4. Simulation results based Matlab program are demonstrated in section 5, finally, the chapter is concluded in section 6.

2. Energy planning strategy: Economic issue and power quality

It is important to underline the importance of energy efficiency planning in power systems, the combined term energy planning is usually associated with power quality; how energy is produced (economic aspect), how energy is consumed at the point of end use (technical aspect), and what is the impact of the total energy produced on the environment (gaz emissions). Figure 1 shows the structure of energy planning strategy considering FACTS technology; the following points should be taken by expert engineers and researchers to assure energy efficiency.

1. *Environmental Issue*: The environment (gaz emissions) can be considered as the first step towards the improvement of energy efficiency by forcing the utilities and expert engineers to introduce the environmental constraints to the standard optimal power flow problem.
2. *Technology Issue:* Energy planning strategy becomes a complex problem and difficult to solving efficiently with the wide integration of two new technologies, flexible ac transmission systems (FACTS) and renewable energy.
3. *Economic Issue*: How to estimate economically the number, the size of FACTS Controllers coordinated with renewable sources to be installed in a practical and large electrical network?

3. Multi objective optimal power flow formulation

The real life problems involve several objectives and the decision maker would like to find solution, which gives compromise between the selected objectives. The multi objective OPF is to optimize the settings of control variables in terms of one or more objective functions while satisfying several equality and inequality constraints.

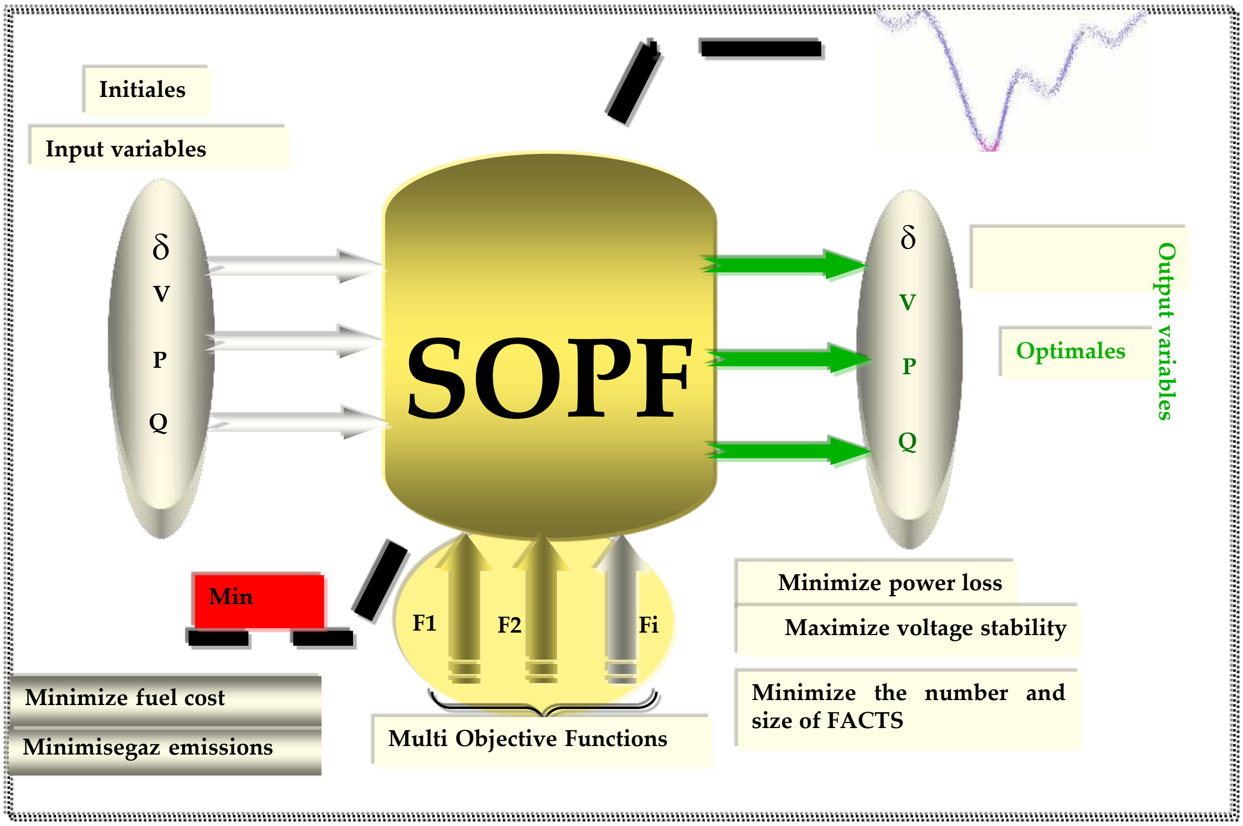

Figure 2. Schematic presentation of security multi objective OPF problem

In multi objective OPF we have to optimize two or more objective functions. Figure 2 shows a general presentation of the multi objective OPF problem. The mathematical problem can be formulated as follows:

Minimize

$$J_i(x,u) \quad i=1,\ldots,\ N_{obj} \tag{1}$$

Subject to:

$$g(x,u)=0 \tag{2}$$

$$h(x,u)\le 0 \tag{3}$$

Where J_i is the *ith* objective function, and N_{obj} is the number of objectives,$g(x,\ u)$ and $h(x,\ u)$ are respectively the set of equality and inequality constraints, x is the state variables and u is the vector of control variables. The control variables are generator active and reactive power outputs, bus voltages, shunt capacitors/reactors and transformers tap-setting. The state variables are voltage and angle of load buses.

3.1. Active power planning with smooth cost function

For optimal active power dispatch, the objective function f is the total generation cost expressed in a simple form as follows:

Min

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

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 *ith* generator.

The equality constraints $g(x)$ are the power flow equations.

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.

3.2. Emission objective function

An alternative dispatch strategy to satisfy the environmental requirement is to minimize operation cost under environmental requirement. Emission control can be included in conventional economic dispatch by adding the environmental cost to the normal dispatch. The objective function that minimizes the total emissions can be expressed as the sum of all the three pollutants (NO_x,CO_2, SO_2) resulting from generator real power [22].

In this study,NO_x emission is taken as the index from the viewpoint of environment conservation. The amount of NO_x emission is given as a function of generator output (in Ton/hr), that is the sum of quadratic and exponential functions [9].

$$f_e = \sum_{i=1}^{Ng} 10^{-2} \times \left(\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \omega_i \exp\left(\mu_i P_{gi} \right) \right) \text{Ton / h} \tag{5}$$

where α_i, β_i, γ_i, ω_i and μ_i are the parameters estimated on the basis of unit emissions test results.

The pollution control can be obtained by assigning a cost factor to the pollution level expressed as:

$$f_{ce} = \omega . f_e \$ / \text{h} \tag{6}$$

where $\omega$is the emission control cost factor in \$/Ton.

Fuel cost and emission are conflicting objective and can not be minimized simultaneously. However, the solutions may be obtained in which fuel cost an emission are combined in a single function with different weighting factor. This objective function is described by:

Minimize

$$F_T = \alpha f + (1-\alpha) f_{ce} \tag{7}$$

where α is a weighting factor that satisfies$0 \le \alpha \le 1$.

In this model, when weighting factor α=1, the objective function becomes a classical economic dispatch, when weighting factor α=0, the problem becomes a pure minimization of the pollution control level.

3.3. Active power planning with valve-point loading effect

The valve-point loading is taken in consideration by adding a sine component to the cost of the generating units [9]. Typically, the fuel cost function of the generating units with valve-point loadings is represented as follows:

$$f_T = \sum_{i=1}^{NG} \left(a_i + b_i P_{gi} + c_i P_{gi}^2 \right) + \left| d_i \sin\left(e_i \left(P_{gi}^{\min} - P_{gi} \right) \right) \right| \tag{8}$$

$d_i$and $e_i$are the cost coefficients of the unit with valve-point effects.

3.4. Reactive power planning

The main role of reactive power planning (RPP) is to adjust dynamically the control variables individually or simultaneously to reduce the total power loss, transit power flow, voltages deviation, and to improve voltage stability, but still satisfying specified constraints (generators constraints and security constraints). The basic vector control structure is well presented in Fig 3.

3.4.1. Power loss objective function

The objective function here is to minimize the active power loss (P_{loss}) in the transmission system. It is given as:

$$P_{loss} = \sum_{k=1}^{N_l} g_k \left[\left(t_k V_i \right)^2 + V_j^2 - 2 t_k V_i V_j \cos \delta_{ij} \right] \tag{9}$$

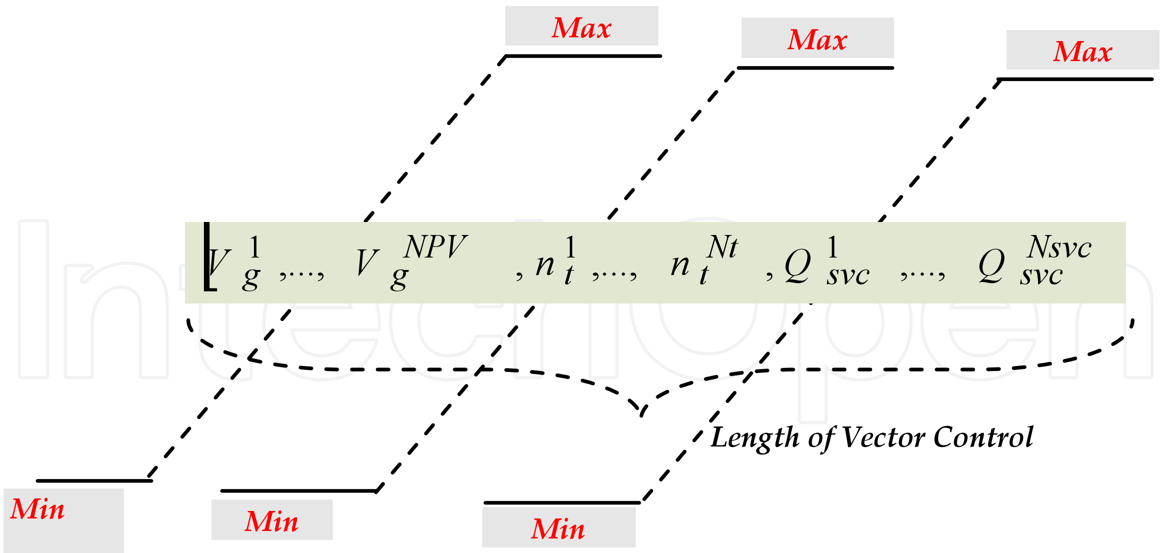

Figure 3. Basic vector control structure for reactive power planning.

Where, N_l is the number of transmission lines; g_k is the conductance of branch k between buses i and j; t_k the tap ration of transformer k; V_i is the voltage magnitude at bus i; δ_{ij} the voltage angle difference between buses *i* and *j*.

3.4.2. Voltage deviation objective function

One of the important indices of power system security is the bus voltage magnitude. The voltage magnitude deviation from the desired value at each load bus must be as small as possible. The deviation of voltage is given as follows:

$$\Delta V = \sum_{k=1}^{N_{PQ}} \left| V_k - V_k^{des} \right| \tag{10}$$

where, $N_{PQ}$is the number of load buses and V_k^{des} is the desired or target value of the voltage magnitude at load bus k.

3.5. Constraints

3.5.1. Equality constraints

The equality constraints $g(x)$ are the real and reactive power balance equations.

$$P_{gi} - P_{di} = V_i \sum_{j=1}^{N} V_j \left(g_{ij} \cos \delta_{ij} + b_{ij} \sin \delta_{ij} \right) \tag{11}$$

$$Q_{gi} - Q_{di} = V_i \sum_{j=1}^{N} V_j \left(g_{ij} \sin\delta_{ij} - b_{ij} \cos\delta_{ij} \right) \tag{12}$$

Where N is the number of buses, P_{gi}, Q_{gi} are the active and the reactive power generation at bus i;P_{di}, $Q_{di}$are the real and the reactive power demand at bus i, V_i, V_j, the voltage magnitude at bus i, j , respectively; δ_{ij} is the phase angle difference between buses i and j respectively, g_{ij} and b_{ij} are the real and imaginary part of the admittance (Y_{ij}).

3.5.2. Inequality constraints

The inequality constraints h reflect the generators constraints and power system security limits,

a. Generator Constraints

- Upper and lower limits on the generator bus voltage magnitude:

$$V_{gi}^{\min} \le V_{gi} \le V_{gi}^{\max},\ i = 1,2,\ldots,NPV \tag{13}$$

b. Security Limits

The inequality constraints on security limits are given by:

- Constraints on transmission lines loading

$$S_{li} \le S_{li}^{\max},\ i = 1,2,\ldots,NPQ \tag{14}$$

- Constraints on voltage at loading buses (PQ buses)

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max},\ i = 1,2,\ldots,NPQ \tag{15}$$

- Upper and lower limits on the tap ratio (t) of transformer.

$$t_i^{\min} \le t_i \le t_i^{\max}, i = 1,2,...,NT \tag{16}$$

- Parameters of shunt FACTS Controllers must be restricted within their upper and lower limits.

$$X^{\min} \le X_{FACTS} \le X^{\max} \tag{17}$$

4. Metaheuristic optimization methods

The difficulties associated with using mathematical optimization on large-scale engineering problems have contributed to the development of alternative solutions, during the last two decades; the interest in applying new metaheuristic optimization methods in power system field has grown rapidly.

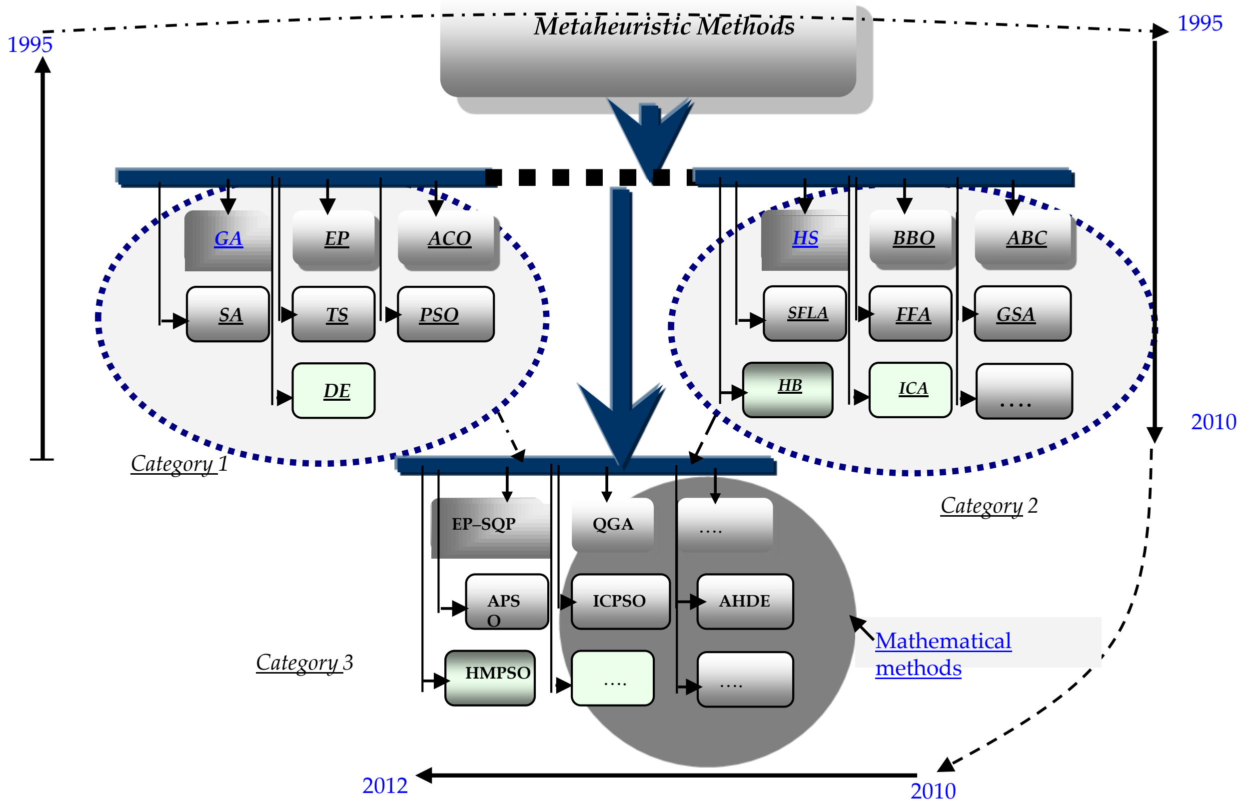

Figure 4. Presentation of metaheuristic optimization methods

In general, metaheuristic optimization methods can be classified into three large categories.

1. The first category such as: GA, TS, SA, ACO, PSO, DE and theirs successive developed variants.

2. The second category includes: Harmony search (HS), Biogeography based optimization (BBO), Artificial bee colony (ABC), Honey bee (HB), Shuffled frog leaping algorithm (SFLA), Firefly algorithm (FFA), Gravitational search algorithm (GSA), Imperialist competition algorithm (ICA) and many other variants.

3. The third category called hybrid optimization methods includes a combination between metaheuristics and conventional methods.

Details about their performances and the application of metaheuristic optimization techniques for solving many practical problem related to power system field particularly multi objective OPF can be found in a recent state of the art of non-deterministic optimization and hybrid methods presented in [11]. Figure 4 shows a simplified presentation about the most popular metaheuristic methods applied by researchers for solving many complex problems.

4.1. Firefly search algorithm

This section introduces and describes a solution to the combined economic dispatch problem using a new metaheuristic nature inspired algorithm. Firefly research algorithm is one of the new Biology inspired metaheuristic algorithms which have recently introduced by Dr. Xin-She Yang at Cambridge University in 2007, as an efficient way to deal with many hard combinatorial optimization problems and non-linear optimization constrained problems [20-21]. In general, the firefly algorithm has three particular idealized rules which are based on some of the major flashing characteristics of real fireflies these are presented on the following schematic diagram (Figure 5), and described in brief as follows:

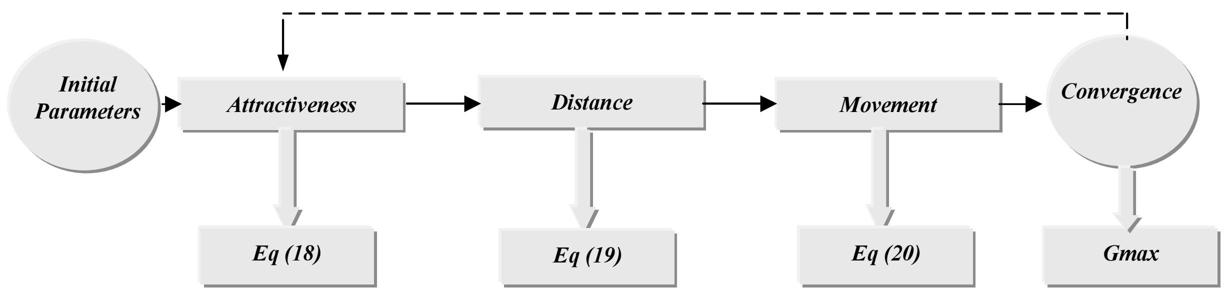

Figure 5. Basic mechanism search of firefly algorithm.

1. All fireflies are unisex, and they will move towards more attractive and brighter ones regardless their sex.
2. The degree of attractiveness of a firefly is proportional to its brightness which decreases as the distance from the other firefly increases due to the fact that the air absorbs light. If there is not a brighter or more attractive firefly than a particular one, it will then move randomly.
3. The brightness or light intensity of a firefly is determined by the value of the objective function of a given problem.
4. Attractiveness

The basic form of attractiveness function of a firefly is the following monotonically decreasing function:

$$\beta(r) = \beta_0 \exp\left(-\gamma r^m\right), \; with \; m \geq 1, \tag{18}$$

Where r is the distance between any two fireflies, β0 is the initial attractiveness at r=0, and γ is an absorption coefficient which controls the decrease of the light intensity.

- Distance

The distance between two fireflies I and j at positions xi and xj can be defined by the following relation:

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k} \right)^2} \tag{19}$$

Where, $x_{i,k}$ is the kth component of the spatial coordinate x_i and x_j and d is the number of dimension.

- Movement

The movement of a firefly i which is attracted by a more attractive firefly j is given by the following equation.

$$x_i = x_i + \beta_0 . \exp\left(-\gamma r_{ij}^2\right) . \left(x_j - x_i\right) + \alpha . (rand - 0.5), \tag{20}$$

Where the first term is the current position of a firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies, and the third term is for the random movement of a firefly in case there are not any brighter ones.

- Parameters settings

Like many metaheuristic optimization methods, choosing the initial values of parameters is an important task which affects greatly the convergence behaviors of the algorithm. These parameters depend on the nature of the problem to be solved.

$\alpha \in [0, \ 1]$ is a randomization parameter determined based on the complexity of the problem to be solved.

$$\beta_0 = 1 \tag{21}$$

The attractiveness or absorption coefficient $\gamma = 1$.

4.1.1. Solving combined economic emission problem based FFA

The pseudo code depicted in Figure 6 gives a brief description about the adaptation of the firefly algorithm for solving the combined economic emission problem.

At the first stage an initial solution is generated based on the following equation:

$$x_i = rand.\left(x_i^{\max} - x_i^{\min}\right) + x_i^{\min} \tag{22}$$

Where $x_i^{\max}$ and $x_i^{\min}$ are the upper range and lower range of the *ith* firefly (variable), respectively.

Begin of algorithm

Generate initial population of fireflies nf

Light Intensity of firefly n is determined by objective function

Specify algorithm's parameters value a, β0 and γ

While t ≤ Max Gen

For i=1: nf %for all fireflies (solutions)

    For j=1: nf %for all fireflies (solutions)

        If (Ii <Ij)

        Then move firefly i towards firefly j (move towards brighter one)

        Attractiveness varies with distance rij via eq (18)

        Generate and evaluate new solutions and update Light Intensity

    End for j loop

End for i loop

Check the ranges of the given solutions and update them as appropriate

Rank the fireflies, find and display the current best % max solution for each iteration.

End of while loop

End of algorithm

Figure 6. Pseudo code: Basic firefly algorithm.

After evaluation of this initial solution, the initial solution will be updated based on the mechanism search, final solution will be achieved after a specified number of generations.

Test1: Benchmark function

In this case, the proposed algorithm is tested with many benchmark functions. All these problems are minimization problems. Due to the limited chapter length, only one function are considered for minimization problem, details can be retrieved from [21]. Fig 7 shows the shape of the objective function, Fig 8 shows the path of fireflies during optimization's process, Fig 9 shows the Final stage corresponding to global solution.

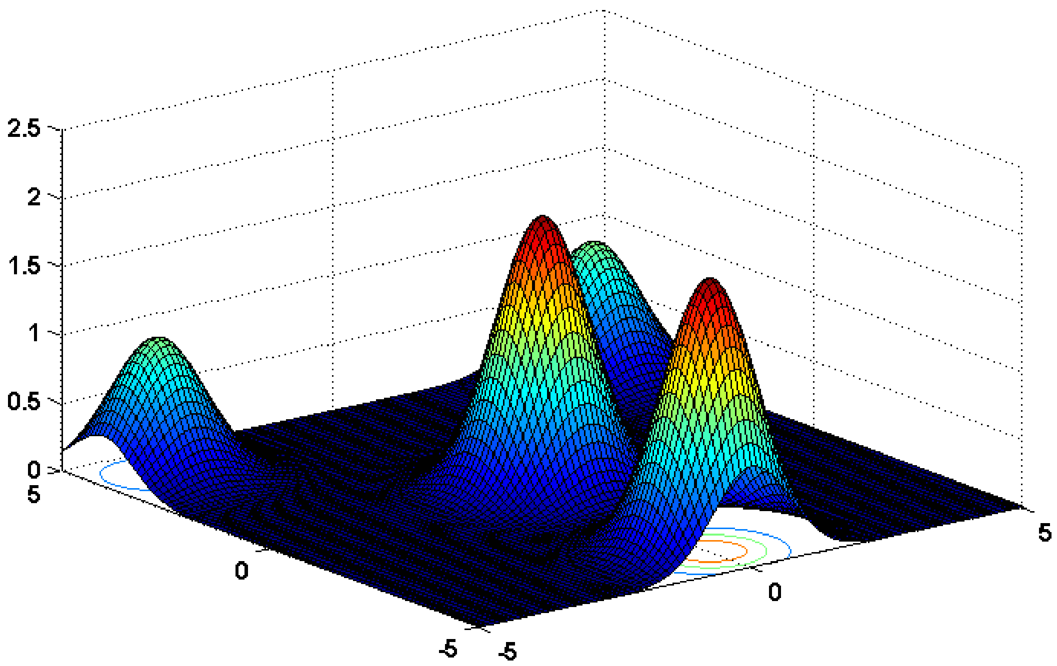

Figure 7. The shape of the objective function

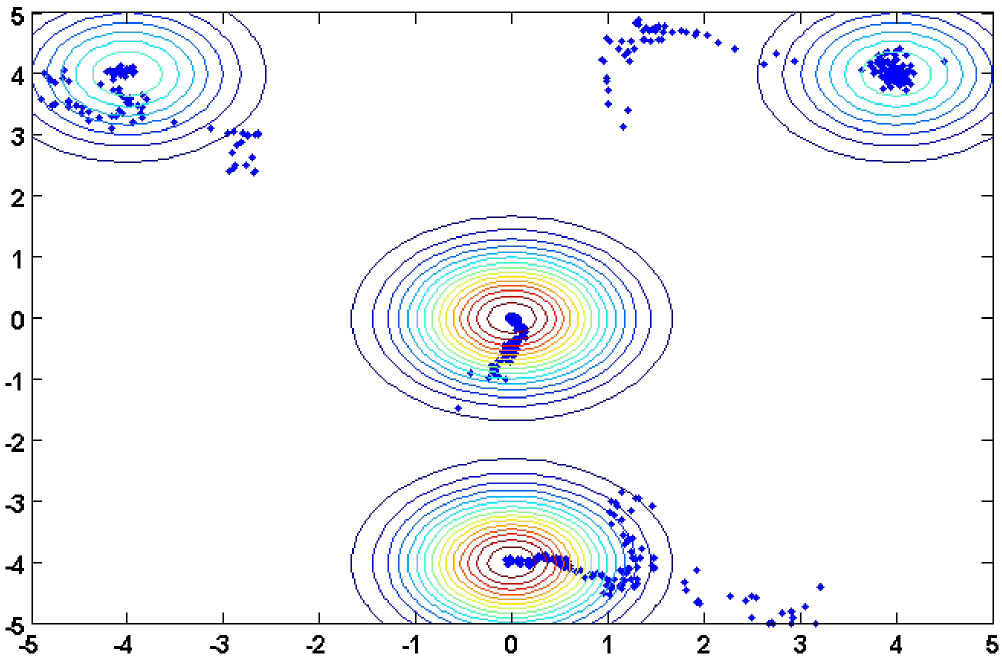

Figure 8. Path of fireflies during optimization's process.

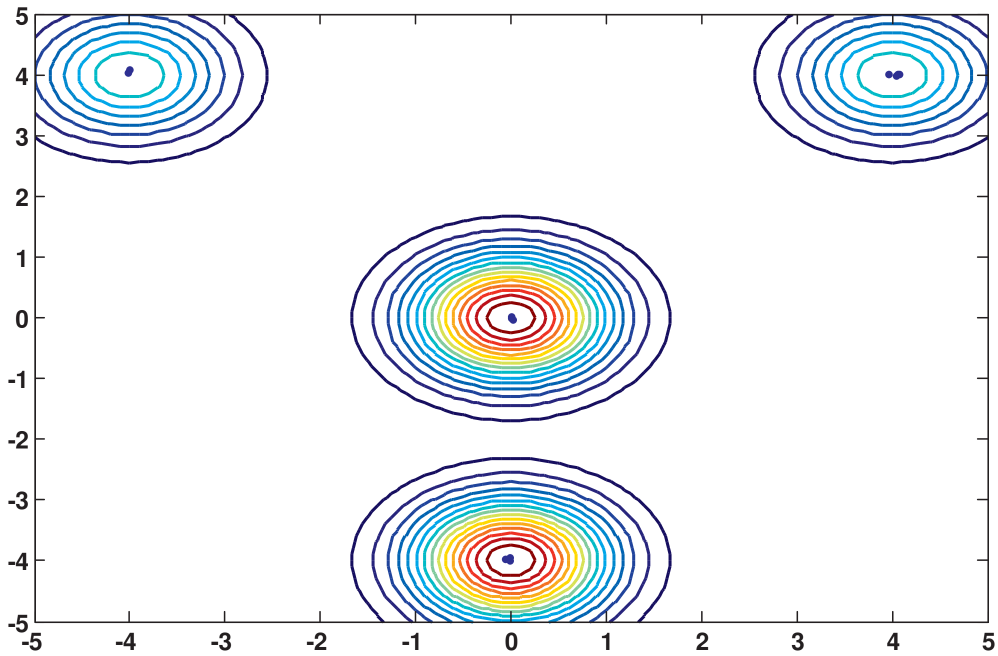

Figure 9. Final stage: global solution

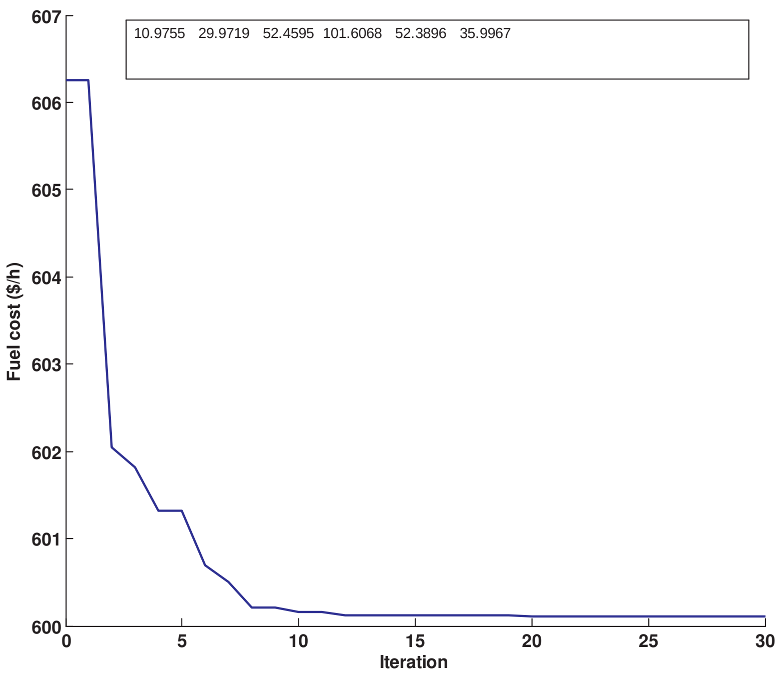

Figure 10. Convergence characteristic for optimal fuel cost.

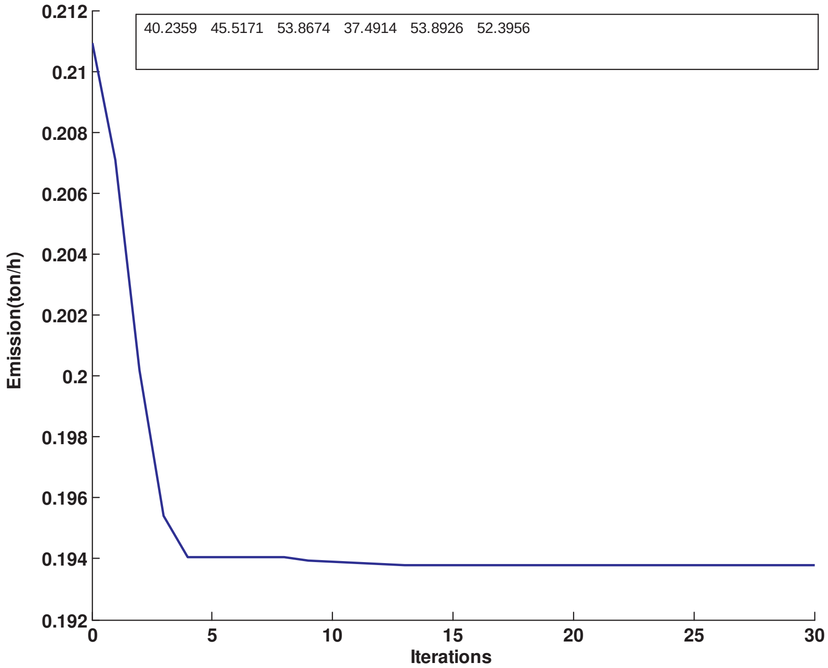

Figure 11. Convergence characteristic for optimal emission.

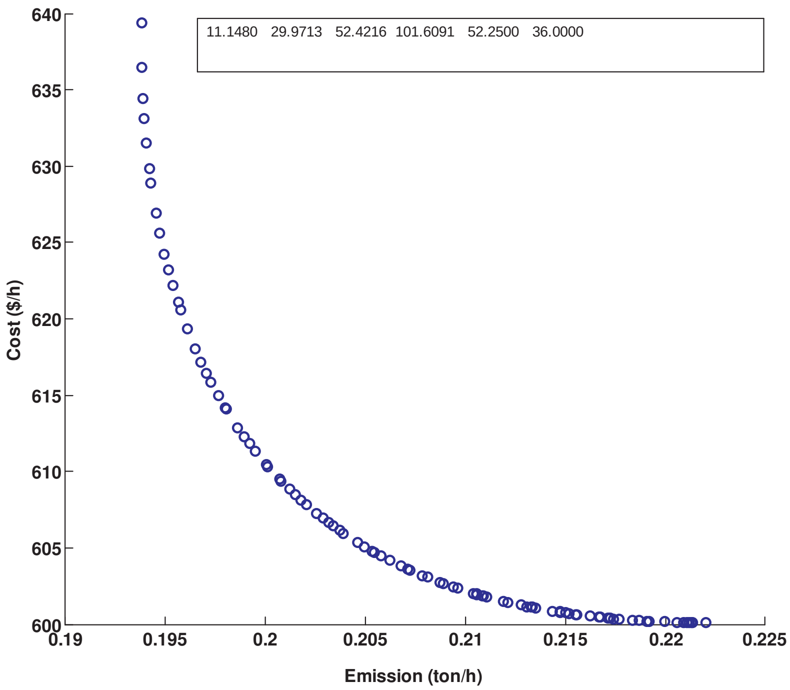

Figure 12. Convergence characteristic for combined fuel cost and emission.

Test 2: Combined economic-emission dispatch with smooth cost function

To demonstrate the performance of the proposed FFA, the algorithm is applied and tested to the six generating units without considering power transmission loss. The problem is solved as single and multi objective optimization. Detail data of this test system is given in [22-23]. For 20 runs, the best cost is 600.1114 ($/h), the algorithm converges at low number of iteration.

Figs 10-11 show the convergence characteristics of the proposed FFA when objective function optimized separately. Fig 12 shows the convergence characteristic for combined fuel cost and emission. Table 1 summarizes the best solutions obtained for three cases.

Control Variables (MW)	Case 1 Fuel cost	Case 2 Emissions	Case3 Combined: Cost-Emissions
P_{G1}	10.9755	40.2359	10.9485
P_{G2}	29.9719	45.5171	29.8834
P_{G5}	52.4595	53.8674	52.1869
P_{G8}	101.6068	37.4914	101.7170
P_{G11}	52.3896	53.8926	52.7216
P_{G13}	35.9967	52.3956	35.9426
FC ($/h)	**600.1114**	638.7807	**612.0227**
Emission (ton/h)	0.2219	**0.1938**	**0.1991**
Loss (MW)	0	**0**	0

Table 1. Control variables optimized using FFA

4.2. Solving security OPF based parallel GA considering SVC controllers

4.2.1. Strategy of the parallel GA

Parallel Genetic Algorithms (PGAs) have been developed to reduce the large execution times that are associated with simple genetic algorithms for finding near-optimal solutions in large search spaces. They have also been used to solve larger problems and to find better solutions. PGAs can easily be implemented on networks of heterogeneous computers or on parallel mainframes. The way in which GAs can be parallelized depends upon the following elements [22-23]:

- How fitness is evaluated.
- How selection is applied locally or globally.
- How genetic operators (crossover and mutation are used and applied)
- If single or multiple subpopulations are used.
- If multiple populations are used how individuals are exchanged.

- How to coordinate between different subpopulations to save the proprieties of the original chromosome.

In the proposed approach the subpopulations created are dependent, efficient load flow used to test the performance of the new subpopulations generated.

The proposed algorithm decomposes the solution of such a modified OPF problem into two coordinated sub problems. The first sub problem is an active power generation planning solved by the proposed algorithm, and the second sub problem is a reactive power planning [14-15] to make fine adjustments on the optimum values obtained from the first stage. This will provide updated voltages, angles and point out generators having exceeded reactive power limits.

4.2.2. Decomposition mechanism

Problem decomposition is an important task for large-scale OPF problem, which needs answers to the following two technical questions.

1. How many efficient partitions needed?

2. Where to practice and generate the efficient inter-independent sub-systems?

The decomposition procedure decomposes a problem into several interacting sub-problems that can be solved with reduced sub-populations, and coordinate the solution processes of these sub-problems to achieve the solution of the whole problem.

4.2.3. Algorithm of the Proposed Approach

1. Initialization based in decomposition mechanism

In the first stage the original network was decomposed in multi sub-systems and the problem transformed to optimize the active power demand associated to each partitioned network. The main idea of the proposed approach is to optimize the active power demand for each partitioned network to minimize the total fuel cost. An initial candidate solution generated for the global N population size.

Suppose the original network under study decomposed into S sub-systems 1,2…..S with Pg1, Pg2,…..PgN, the active power control variables, for this decomposed sub-systems related to S sub-populations, 1,2……S, with population sizes, N1……..NS, and (N1+N2+…… NS=N).

- Each sub-population contains NP1 control variables to be optimized.
- Each sub-population updated based on the GA operators.

1-For each decomposition level estimate the initial active power demand:

For NP=2 Do

$$Pd1 = \sum_{i=1}^{M1} P_{Gi} \tag{23}$$

$$Pd2 = \sum_{i=1}^{M2} P_{Gi} = PD - Pd1 \tag{24}$$

Where NP the number of partition

$Pd1$: the active power demand for the first initial partition.

$Pd2$: the active power demand for the second initial partition.

PD: the total active power demand for the original network.

The following equilibrium equation should be verified for each decomposed level:

For level 1:

$$Pd1 + Pd2 = PD + Ploss \tag{25}$$

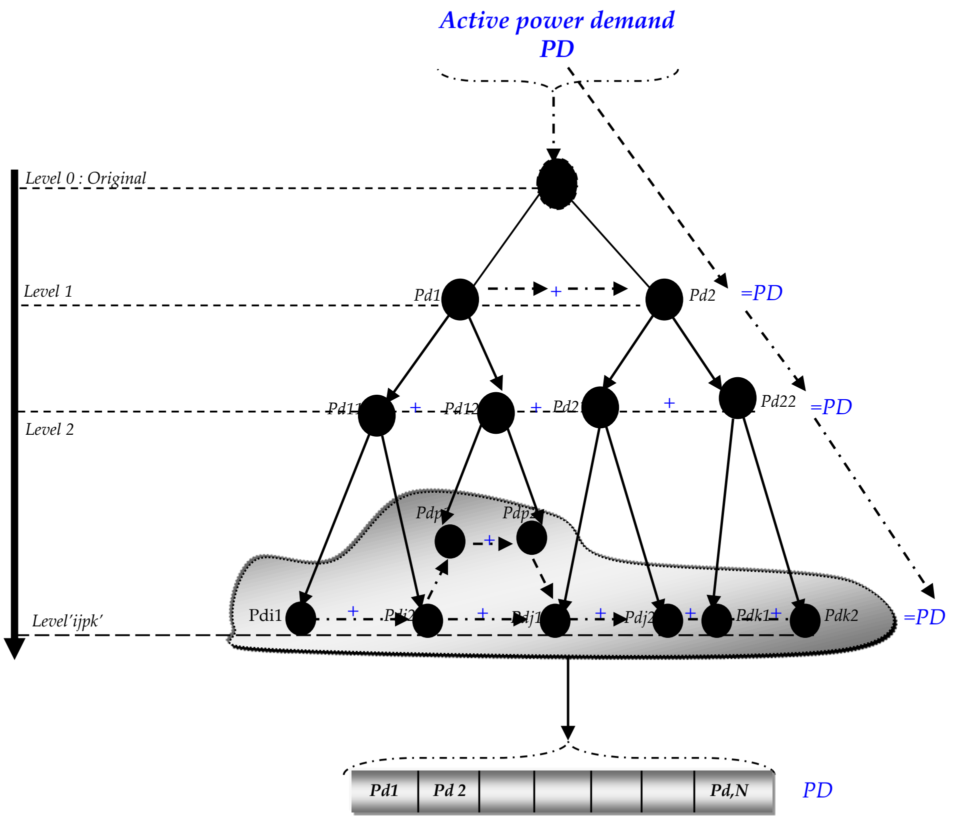

Figure 13. Mechanism of partitioning procedure.

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2. Fitness evaluation based power loss

For all sub-systems generated perform a load flow calculation to evaluate the proposed fitness function. A candidate solution formed by all sub-systems is better if its fitness is higher (low total power loss).

3. A global data base generated containing the best technical sub-systems.

4. Consequently under this concept, the final value of active power demand should satisfy the following equations.

$$\sum_{i=1}^{N_g}\left(Pg_i\right)=\sum_{i=1}^{part_i}\left(Pd_i\right)+ploss \tag{26}$$

$$Pg_i^{\min} \le Pg_i \le Pg_i^{\max} \tag{27}$$

4.2.4. Reactive power dispatch

All the sub-systems are collected to form the original network, global database generated based on the best results found from all sub-populations.

The final solution (Global) is found out after reactive power planning procedure to adjust the reactive power generation limits, and voltage deviation, the final optimal cost is modified to compensate the reactive constraints violations. Fig. 13 illustrates the mechanism search partitioning for active power planning, Fig. 14 shows an example of tree network decomposition.

5. FACTS technology

FACTS philosophy was first introduced by Hingorani [24] from the Electric power research institute (EPRI) in the USA. The objective of FACTS devices is to bring a system under control and to transmit power as ordered by the control centers, it also allows increasing the usable transmission capacity to its thermal limits. With FACTS devices we can control the phase angle, the voltage magnitude at chosen buses and/or line impedances. In general these FACTS devices are classified in three large categories as follows:

5.1. Shunts FACTS controllers (SVC, STATCOM)

Principally designed and integrated to adjust dynamically the voltage at specified buses. Fig 15 shows the basic principle of dynamic shunt FATCS controllers (SVC, and STATCOM).

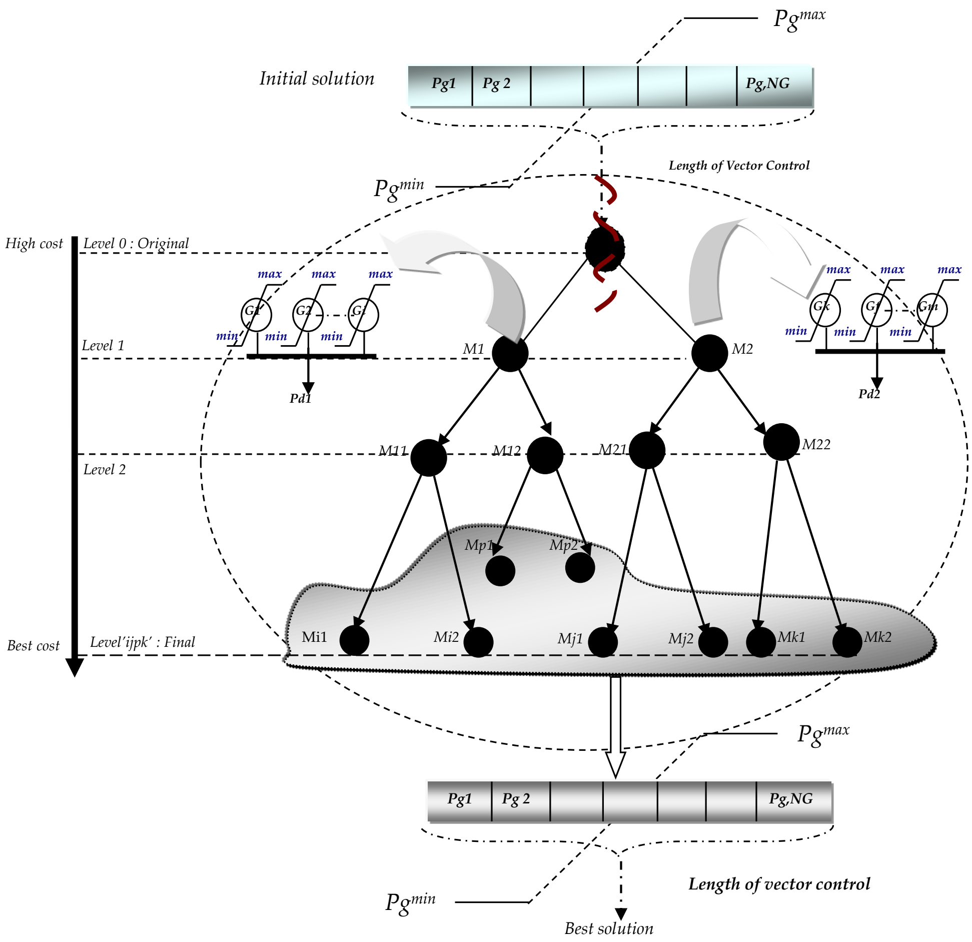

Figure 14. Sample of network in tree decomposition

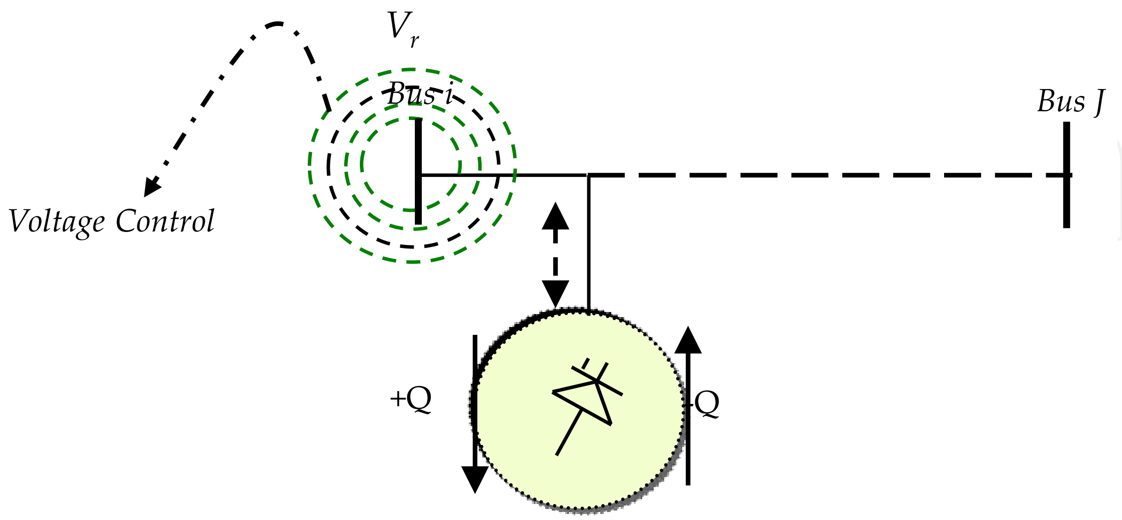

Figure 15. Shunt FACTS Controller.

5.2. Series FACTS controllers (TCSC, SSSC)

Principally designed and integrated to adjust dynamically the transit power at specified lines. Fig 16 shows the basic principle of dynamic series FATCS controllers (TCSC and SSSC).

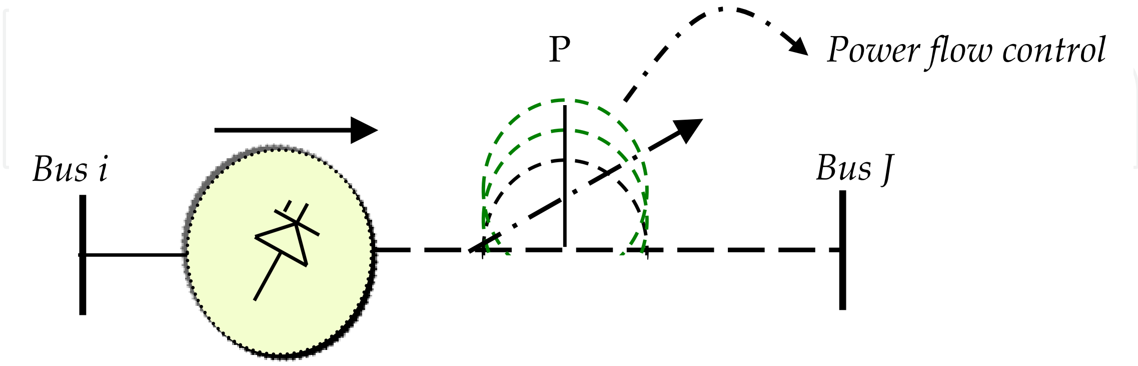

Figure 16. Series FACTS Controllers.

5.3. Hybrid FACTS controllers (UPFC)

Principally designed and integrated to adjust dynamically and simultaneously the voltage, the active power, and the reactive power at specified buses and lines. The basic one line diagram of hybrid controller (UPFC) is well presented in Fig 17.

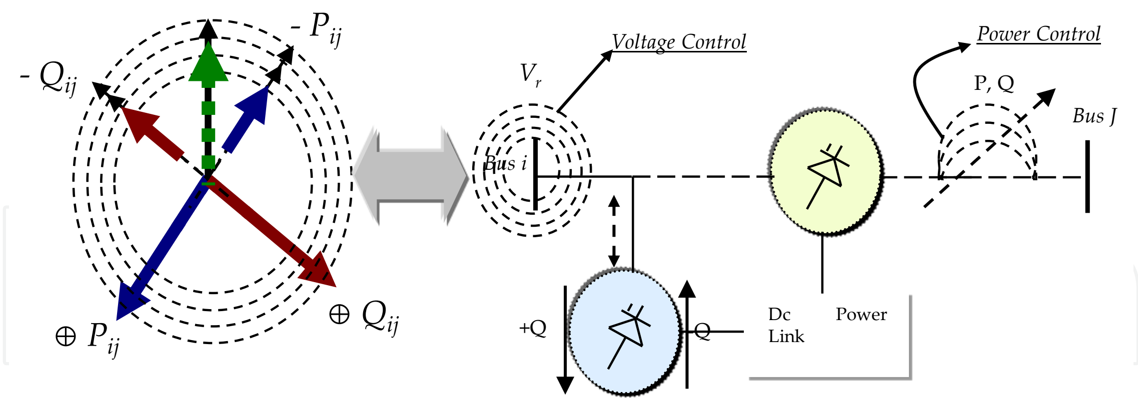

Figure 17. Hybrid FACTS Controller.

5.4. Shunt FACTS modelling

5.4.1. Static VAR Compensator (SVC)

The Static VAr Compensator (SVC) [25] is a shunt connected VAr generator or absorber whose output is adjusted dynamically to exchange capacitive or inductive current so as to maintain or control specific parameters of the electric power system, typically bus voltages. It includes separate equipment for leading and lagging VArs. The steady state model shown in Fig. 18 is used to incorporate the SVC on power flow problems. This model is based on representing the controller as variable susceptance or firing angle control.

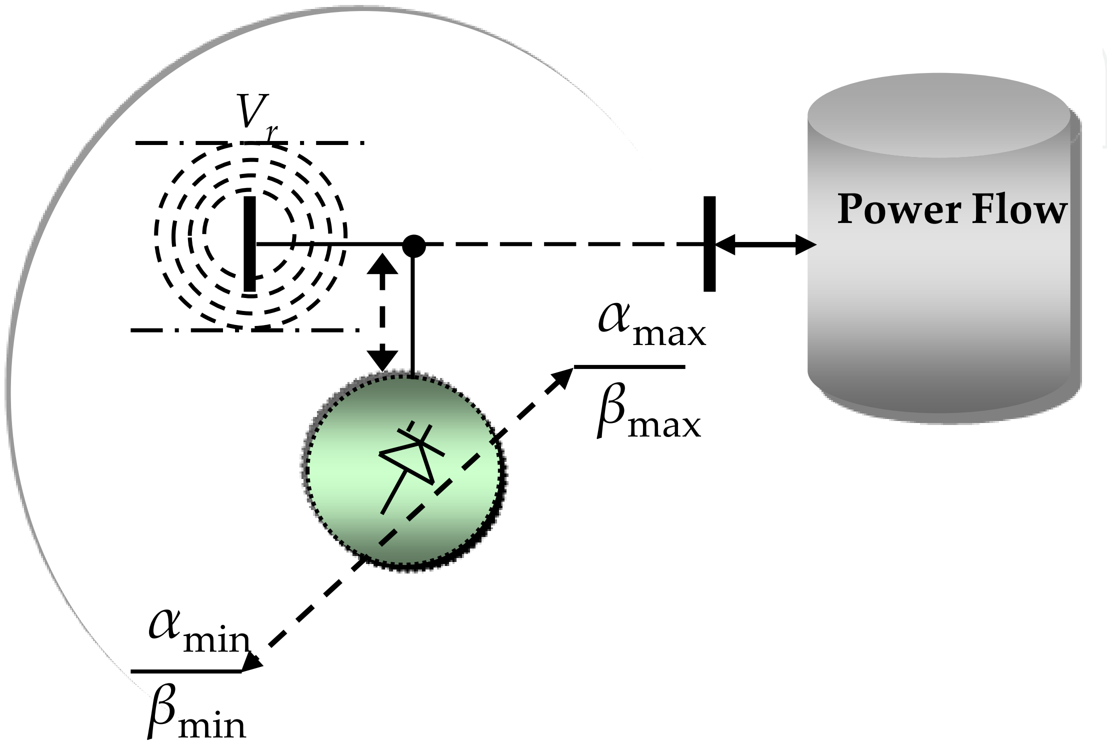

Figure 18. SVC Steady-state model

$$I_{SVC} = jB_{SVC}V \tag{28}$$

$$\left.\begin{aligned} &B_{SVC} = B_C - B_{TCR} = \frac{1}{X_C X_L}\left\{X_L - \frac{X_C}{\pi}\left[2(\pi-\alpha)+\sin(2\alpha)\right]\right\}, \\ &X_L = \omega L,\, X_C = \frac{1}{\omega C}, \end{aligned}\right\} \tag{29}$$

Where, B_{SVC}, α, X_L, X_C, V are the shunt susceptance, firing angle, inductive reactance, capacitive reactance of the SVC controller, and the bus voltage magnitude to which the SVC is connected, respectively. The reactive power Q_i^{SVC} exchange with the bus i can be expressed as,

$$Q_i^{SVC} = B_i^{SVC}.V_i^2 \tag{30}$$

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6. Application

6.1. Test system 1: Algerian electrical network planning

6.1.1. Active Power dispatch without SVC compensators

The proposed algorithm is developed in the Matlab programming language using 6.5 version. The proposed approach has been tested on the Algerian network (1976). It consists of 59 buses, 83 branches (lines and transformers) and 10 generators. Table I shows the technical and economic parameters of the ten generators, knowing that the generator of the bus N°=13 is not in service. Table II shows the generators emission coefficients. The values of the generator emission coefficients are given in Tables 2-3, the generators data and cost coefficients are taken from [23-28], Figs. 19-20 show the topology of the Algerian electrical network test with 59-Bus based one line diagram and in schematic representation. For the purpose of verifying the efficiency of the proposed approach, we made a comparison of our algorithm with others competing OPF algorithm. In [30], they presented a fuzzy controlled genetic algorithm, in [28], authors proposed fast successive linear programming algorithm applied to the Algerian electrical network.

To demonstrate the effectiveness and the robustness of the proposed approach, two cases have been considered with and without consideration of SVC Controllers installation:

Case 1: Minimum total operating cost (α =1).

Case 2: Minimum total emission (α =0).

Bus Number	Pmin [MW]	Pmax [MW]	Qmin [Mvar]	Qmax [Mvar]	a [$/hr]	b [$/MWhr]	c [$/MW2hr]
1	8	72	-10	15	0	1.50	0.0085
2	10	70	-35	45	0	2.50	0.0170
3	30	510	-35	55	0	1.50	0.0085
4	20	400	-60	90	0	1.50	0.0085
13	15	150	-35	48	0	2.50	0.0170
27	10	100	-20	35	0	2.50	0.0170
37	10	100	-20	35	0	2.00	0.0030
41	15	140	-35	45	0	2.00	0.0030
42	18	175	-35	55	0	2.00	0.0030
53	30	450	-100	160	0	1.50	0.0085

Table 2. Technical Admissible paramaters of Generators and the Fuel Cost Coefficients

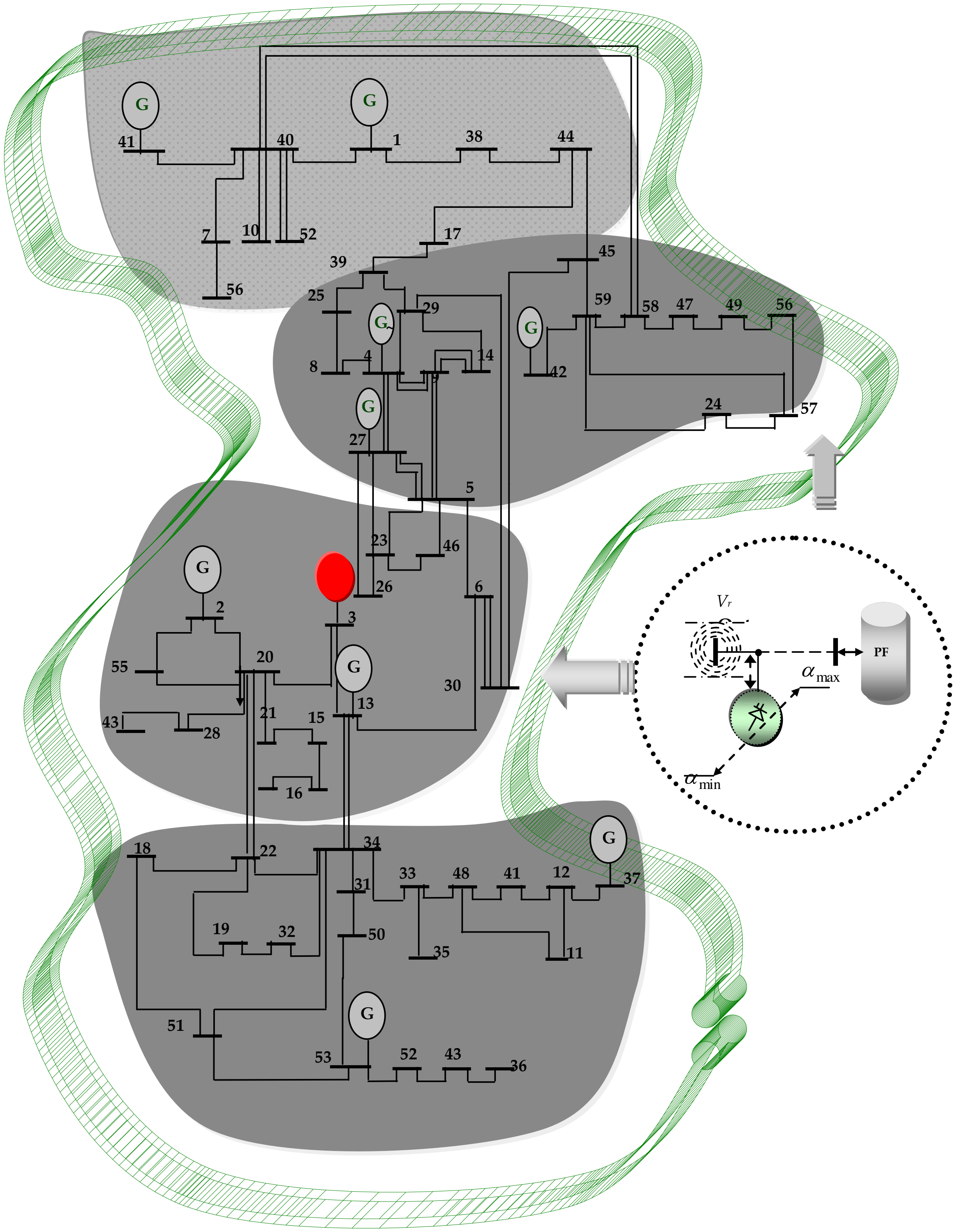

Figure 19. One line representation of the Algerian electrical production and transmission network (Sonelgaz).

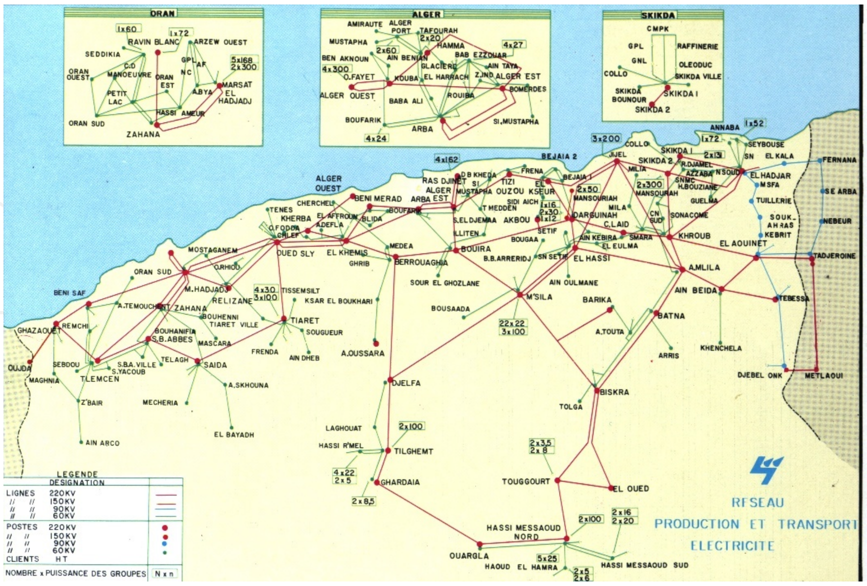

Figure 20. Topology of the Algerian production and transmission network before 1997 (Sonelgaz).

Bus Number	Generator	α	bx1e-2	γ x1e-4	ω	μ x1e-2
1	1	4.091	−5.554	6.490	2.00e-04	2.857
2	2	2.543	−6.047	5.638	5.00e-04	3.333
3	3	4.258	−5.094	4.586	1.00e-06	8.000
4	4	5.326	−3.550	3.380	2.00e-03	2.000
13	5	4.258	−5.094	4.586	1.00e-06	8.000
27	6	6.131	−5.555	5.151	1.00e-05	6.667
37	7	4.091	−5.554	6.490	2.00e-04	2.857
41	8	2.543	−6.047	5.638	5.00e-04	3.333
42	9	4.258	−5.094	4.586	1.00e-06	8.000
53	10	5.326	−3.550	3.380	2.00e-03	2.000

Table 3. Generator Emission Coefficients

	Case1: α =1	Case 2: α =0
***P_{gi}*(MW)**	**Minimum Cost**	**Minimum emission**
P_{g1}	39.5528	28.2958
P_{g2}	37.3190	70.0000
P_{g3}	133.830	109.400
P_{g4}	142.320	79.8000
P_{g5}	**0.00**	**0.00000**
P_{g6}	24.8000	80.5800
P_{g7}	39.7000	34.8600
P_{g8}	39.5400	70.0400
P_{g9}	119.7800	100.6200
P_{g10}	123.4600	128.0200
Cost ($/h)	**1765.9377**	**1850.155**
Emission (ton/h)	**0.530700**	**0.42170**
Power loss (MW)	**16.20180**	**17.51580**

Table 4. Simulation Results for Three Cases with two optimized shunt Compensators

Generators N°	FGA [29]	GA [28]	ACO [28]	FSLP [28]	Our Approach
P_{g1} (MW)	11.193	70.573	64.01	46.579	39.5528
P_{g2} (MW)	24.000	56.57	22.75	37.431	37.3190
P_{g3} (MW)	101.70	89.27	82.37	134.230	133.830
P_{g4} (MW)	84.160	78.22	46.21	137.730	142.320
P_{g5} (MW)	**0.000**	**0.00**	**0.00**	**0.000**	**0.00**
P_{g6} (MW)	35.22	57.93	47.05	23.029	24.8000
P_{g7} (MW)	56.80	39.55	65.56	35.238	39.7000
P_{g8} (MW)	121.38	46.40	39.55	39.972	39.5400
P_{g9} (MW)	165.520	63.58	154.23	117.890	119.7800
P_{g10} (MW)	117.32	211.58	202.36	131.650	123.4600
PD(MW)	684.10	684.10	684.10	684.10	684.1
Ploss (MW)	33.1930	29.580	39.980	19.65	**16.20180**
Cost[$/hr]	1768.50	1937.10	1815.7	1775.856	**1765.9377**

Table 5. Comparison of the Results Obtained with Conventional and Global Methods: Case Minimum Cost

	FSLP [28]		Our Approach	
	Case1	**Case 2**	**Case1**	**Case 2**
P_{gi}(MW)	**α =1**	**α =0**	**α =1**	**α =0**
P_{g1}	46.579	28.558	39.5528	28.2958
P_{g2}	37.431	70.000	37.319	70.000
P_{g3}	134.230	114.200	133.83	109.40
P_{g4}	137.730	77.056	142.32	79.800
P_{g5}	**0.000**	**0.000**	**0.00**	**0.00**
P_{g6}	23.029	87.575	24.80	80.580
P_{g7}	35.238	32.278	39.70	34.860
P_{g8}	39.972	63.176	39.54	70.040
P_{g9}	117.890	95.645	119.78	100.62
P_{g10}	131.650	135.540	123.46	128.02
Cost ($/h)	1775.856	1889.805	**1765.9377**	**1850.155**
Emission (ton/h)	0.5328	0.4329	**0.5307**	**0.4217**
Power loss (MW)	19.65	19.93	**16.2018**	**17.5158**

Table 6. Comparison of the results obtained with conventional methods

Table 4 shows simulation results obtained by the proposed approach for the two cases (α =1, α =0), the comparison of the results obtained by the application of the decomposed parallel GA proposed with those found by global optimization (GA, FGA, and ACO) and conventional methods are reported in the Table 5 and Table 6 The proposed approach gives better results for all cases. For example at the case corresponding to the minimum total operating cost (α =1), the fuel cost is 1765.9377 $/h, and power losses 16.2018 MW which are better compared with the results found by the global and conventional methods.

It is important to note that all results obtained by the proposed approach do not violate the physical generation capacity constraints (reactive power). The security constraints are also satisfied for voltage magnitudes (0.9<V<1.1 p.u). Fig 18 shows distribution voltage profile with and without two optimized shunt compensators installed at bus 27 and bus 36. Fig 19 shows the voltage phase profiles, it is clearly identified that all voltage phase profiles are within the constraint limit.

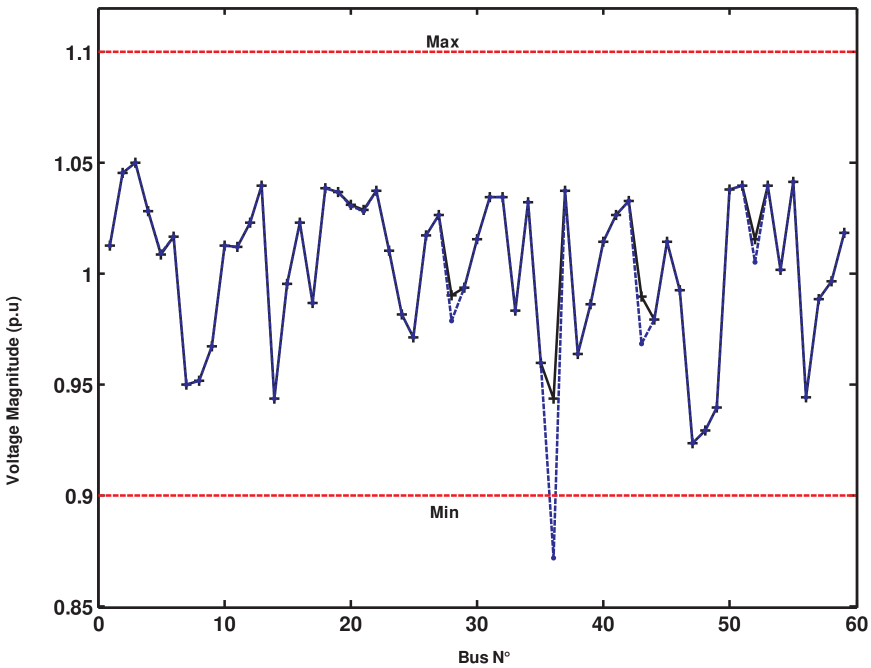

Figure 21. Voltage magnitude profiles with and without compensation: case: minimum cost

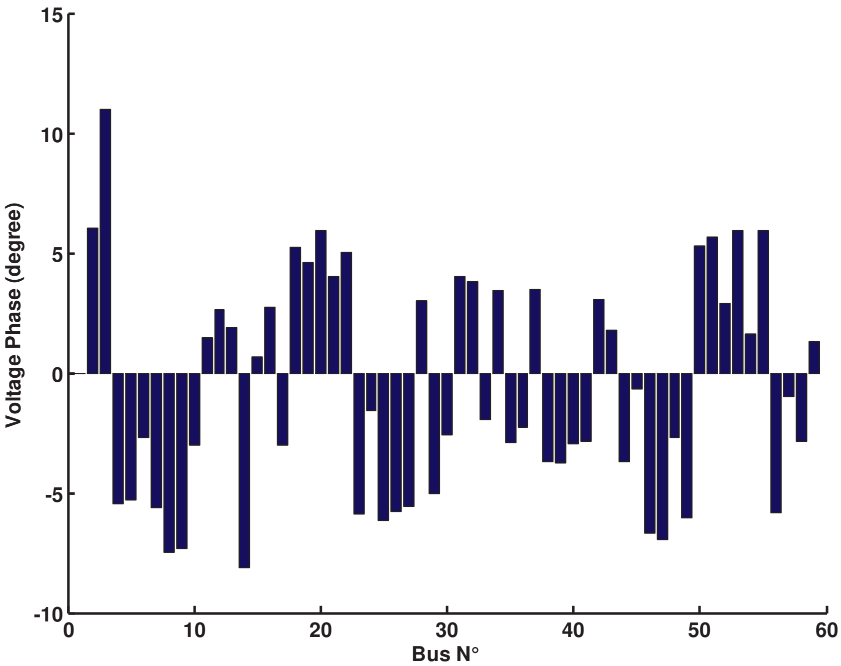

Figure 22. Voltage phase profiles of the Algerian network 59-bus: case 1: minimum fuel cost: with two optimized shunt compensators.

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	Case 1	Case 2	Qmax	Qmin
Bus	**Qg (Mvar)**	**Qg (p.u)**	**Q max**	**Q min**
1	3.6462	7.62240	15.00	-10
2	36.9832	31.8128	45.00	-35
3	12.6903	14.1747	55.00	-35
4	57.312	80.745	90.00	-60
13	1.5281	2.6443	48.00	-35
27	11.7001	-9.7079	35.00	-20
37	21.2983	25.378	35.00	-20
41	37.8163	28.8672	45.00	-35
42	20.3931	23.2128	55.00	-35
53	0.59601	-1.80110	160.00	-100

Table 7. Simulation Results for two Cases: Reactive Power Generation with optimized two shunt compensators

6.1.2. Reactive power dispatch based SVC controllers

For a secure operation of the power system, it is important to maintain required level of security margin, system loadability, voltage magnitude and power loss are three important indices of power quality. In this stage, dynamic shunt compensation based SVC Controllers taken in consideration. The control variables selected for reactive power dispatch (RPD) are the generator voltages, and reactive power of the SVC compensators installed at critical buses.

6.1.3. Optimal location of shunt FACTS

Before the insertion of SVC devices, the system was pushed to its collapsing point by increasing both active and reactive load discretely using continuation load flow [5]. In this test system according to results obtained from the continuation load flow, buses 7, 14, 17, 35, 36, 39, 44, 47, 56 are the best location points for installation and coordination between SVC Compensators and the network. Table 8 gives details of the SVC Data. Table 8, shows results of reactive power generation with SVC Compensators for the minimum cost case, the active power loss and the total cost are reduced to **15.1105 MW, 1763.5771 ($/h)** respectively compared to base case considering two optimized shunt compensators. It is important to note that the system loadability improved to **1.9109 p.u** compared to the base case (**1.8607 p.u**) with two shunt compensators, reactive power of generating units are within their admissible limits.). Fig 20 shows distribution voltage profile considering two fixed shunt compensators and multi SVC compensators. Fig 21 shows the voltage phase profiles, it is clearly identified that all voltage phase profiles are within the constraint limit.

	B_{min} (p.u)	B_{max} (p.u)	B_{init} (p.u)
Susceptance SVC Model	-0.5	0.5	0.025

Table 8. SVCs data.

Bus	B_{SVC}(p.u)	V (p.u) with SVC	Fixed Shunt Capacitors
7	0.04243	1.00	
14	0.23974	1.00	
17	0.01790	1.00	
35	0.01790	1.00	
36		1.00	
39	-0.01116	1.00	
44	0.05846	1.00	
47	0.12876	1.00	
56	0.08352	1.00	
27			
Ploss MW	15.1105		
Cost ($/hr)	1763.5771		
Voltage deviation	0.95<Vi<1.05		
Loading Factor (p.u): without SVC	1.8607		
Loading Factor (p.u): with 8 SVC Controllers	1.9109		

Table 9. Results of the Reactive power dispatch based two static shunt compensators and multi -SVC Controllers: Case 1: Minimum Cost

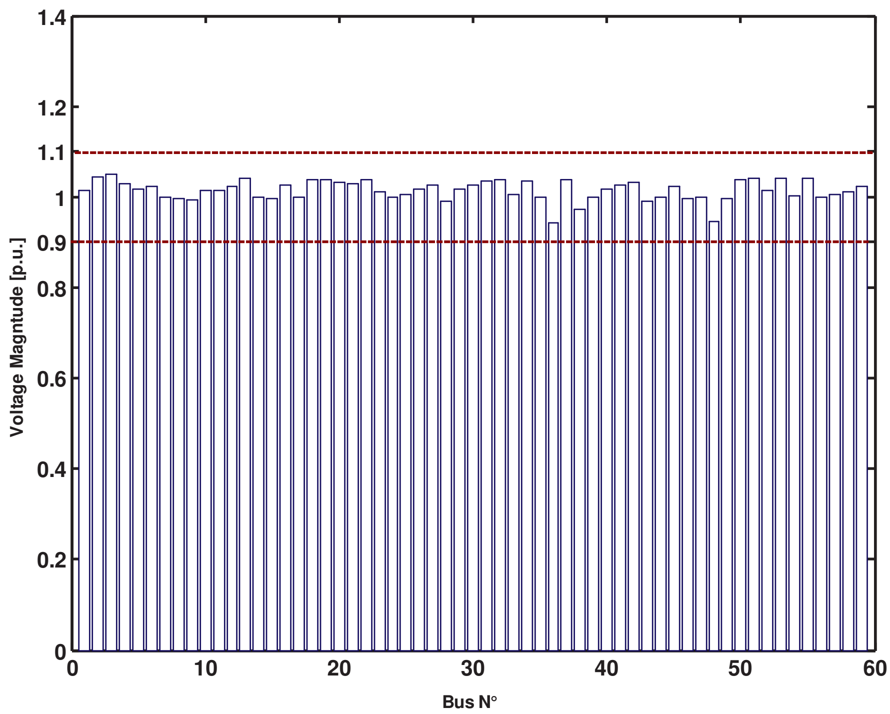

Figure 23. Voltage magnitude profiles with optimized SVC compensation: case: minimum fuel cost

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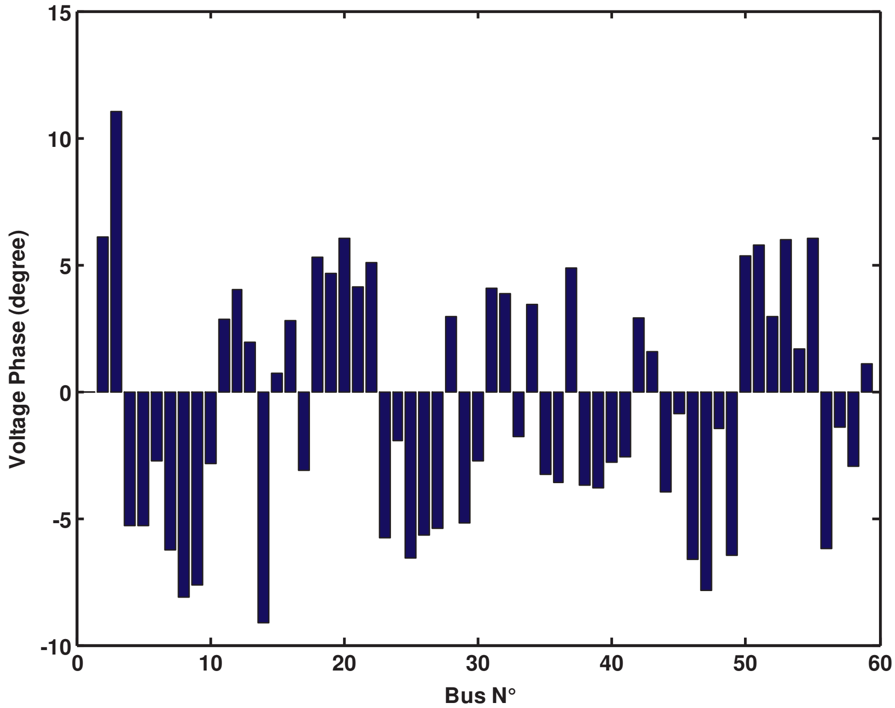

Figure 24. Voltage phase profiles of the Algerian network 59-bus with optimized SVC compensation: case 1: minimum fuel cost:

7. Conclusion

The multi objective power quality management consists in optimizing indices of power quality in coordination with FACTS devices considering fuel cost. In this chapter two techniques based metaheuristic methods have been proposed to solving the multi objective power management problem, many objective functions related to power quality have been proposed like power loss, voltage deviation, system loadability, and pollution constraint. The first proposed method called Firefly research algorithm is used to solve the combined economic emission problem, the algorithm applied to 6 generating units. The second method is a new variant based GA named parallel GA (PGA) proposed as an alternative to improve the performances of the standard GA to solving the security combined economic dispatch considering multi shunt FACTS devices. The proposed PGA applied to solving the security OPF of the Algerian power system (59-Bus) considering three indices of power quality; power loss, voltage deviation and gaz emissions. From simulation results, it is found that the two proposed approaches, FFA and PGA can converge to the near global solution and obtain competitive results in term of solution quality and convergence characteristic compared to the others recent optimization methods.

Due to these efficient properties, in the future work, author will still to apply these two methods to solving the multi objective optimal power flow based multi FACTS devices considering practical generator units (valve point effect and prohibited zones).

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