Optimal Management of FACTS Units for Voltage Stability Enhancement in Power Networks with High Wind Energy Penetration

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Abstract— This paper presents a methodology for optimal management of FACTS units in power networks to improve the voltage profile as well as to maximize the voltage loadability under normal and/or contingency conditions. The methodology is based on Genetics Algorithms which are applied in the reactive power planning process in order to achieve the desired system reliability requirements taking into account stability limits. Study results, widely shown in the paper, indicate that the proposed formulation could be used to determine the optimal points in which the connection of FACTS devices would get to a great enhancement of both, the voltage stability of the whole network and the voltage stability margin under normal and contingencies situations.

***Keywords*—FACTS, Wind Energy, Genetic Algorithm, Voltage Stability, Contingency.**

I. Introduction

Over the last decades, wind energy has experimented a great growing due to several factors such as: fuel saving, supplying remote places and environmental considerations. According to the International Energy Agency (IEA) renewable sources shall provide about 35% of the European Union's (EU) electricity by 2020, and within this context, wind energy is set to contribute the most - nearly 35% - of all the power coming from renewable sources. Moreover, as it is stated in [1], from 2006 till 2030 around 60% of the increased capability of whole European power system will find its origin in new wind capability incorporations. This evolution is based on sustainability of scenarios, like the BLUE one [2] related to the reduction of greenhouse emissions. Presenting a panoramic view of the Spanish case, during the last five years wind energy capability has been duplicated and as a result, at the end of 2010 Spanish wind energy capability is around 20.000 MW [3]. However, the appropriate integration of such renewable energy into power systems grids still presents major challenges to Power Systems Operators (PSO) and planners.

Incorporation of wind energy units into distribution networks not only modifies power flows but, in some situations could also result in under or over-voltage on specific points of the network [4].

Additionally, the electric system's planning with high wind energy penetration requires the definition of several factors, such as: the best technology to be used, the optimal number of units to be connected and the optimal size to be chosen.

Following the same path as the growth of wind power, there has been an upward trend in demand, which has led to a relocation of operating point closer to their physical limits of operation within the power systems. There are many examples of voltage stability problems caused mainly because of this increase in demand throughout the world [5].

Reactive power compensation systems such as FACTS units are presented as a good alternative to alleviate problems related to voltage stability. Therefore reactive power planning in large power systems has become a particularly important point in recent years since it is necessary to develop new techniques to solve any problem that may arise.

Moreover, metaheuristic techniques have come up to be a good alternative to face the question of optimal management of reactive power, which involves operation, location and optimal size of these units [6]-[8]. The main reason is because of their ability to reach a satisfactory solution of the problem; furthermore they are very fast and they have low computation complexity. Among all these techniques genetic algorithms stand out because of their speed of calculation and simplicity, sum up to their robustness and the fact that they can find a global optimal solution in complex multi-dimensional search spaces [9].

The paper is organized as follows: section 2 presents the objective of the work; sections 3 and 4 present a brief review of voltage stability and Reactive Power Planning (RPP) methodology respectively; section 5 describes genetic algorithm technique which will be further implemented in section 6. In section 7 numerical results are presented to prove the suitability of the proposed methodology. Conclusions are shown in section 8.

II. Objective

Main objectives of this analysis are to find out the best allocation and the most appropriate reactive power injection of SVC units as well as to determine the allowable wind energy penetration level in order to maximize the loadability of the system. This study has been carried out with the intention of improving voltage stability under contingency situations by implementing heuristic methods. The methodology put into practice in the application is based on the two following processes (Fig. 1):

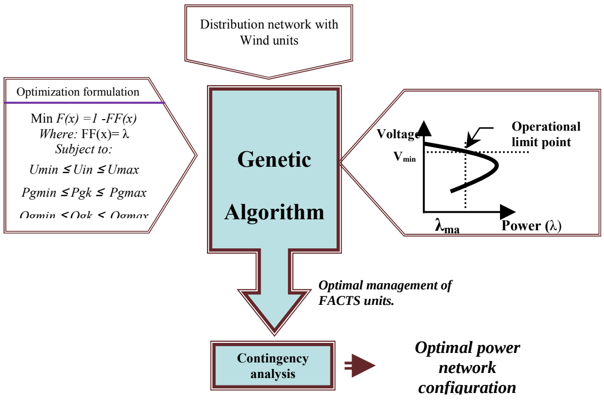

Fig. 1. Scheme of the algorithm

- Optimal Allocation Process: The aim of this method is to optimally locate SVC units on distribution networks in order to maximize the loadability conditions of the system as well as to provide potential candidates to the problem. This task will be properly fulfilled by the application of Genetic Algorithms (GA) to evaluate possible solutions to the optimization problem (Fig. 2).
- Evaluation of Contingency Situations: This second process evaluates the reliability of the distribution network with FACTS units and wind energy optimally located under N-1 contingencies. At this point an evaluation of voltage profile and voltage stability is taking place.

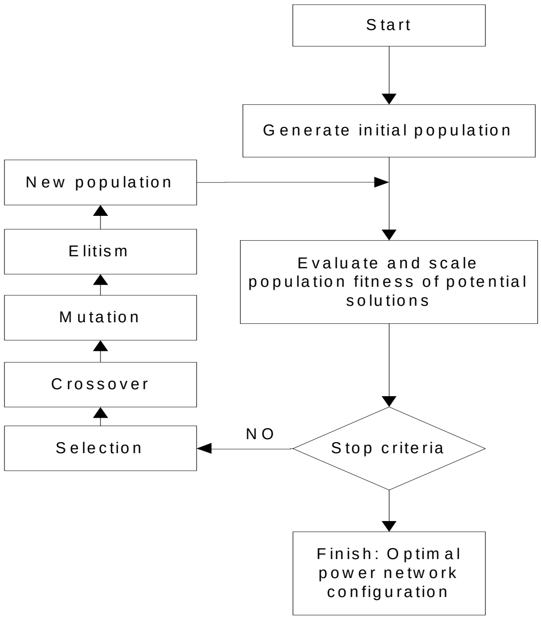

Fig. 2. Implementation of the optimization algorithm

III. Voltage Stability

Voltage Stability is defined as the ability of a power system to maintain steady-state voltage at all buses in the system after being subjected to a disturbance from a given initial operating condition [10]. In the literature, two voltage stability problems are analysed:

- Estimation of the maximum loadability.
- Computation of the critical power system loading that could lead to voltage collapse.

Voltage stability is usually represented by a P-V curve. In Fig. 3 the point in which the load parameter becomes tangent to the P-V characteristic defines the Point of Collapse (PoC). Classical power-flow methodologies fail to converge beyond this limit, which indicates voltage instability and could be easily associated with a saddle-node bifurcation point [10].

In spite of the fact that voltage instability is a local phenomenon, the problem of voltage stability concerns the whole power system being essential for its operation and its control. This aspect turns to be even more critical in power networks which are heavily loaded, faulted, or with insufficient reactive power supply.

Voltage Collapse is a sudden catastrophic transition that is usually due to an instability occurring in a faster time-scale than the one considered. Voltage collapse may, or may not be the final outcome of voltage instability [10].

As a solution, renewable energy sources coupled to the network through power converters offer the ability to provide a very fast dynamic Var injection, and thus, their optimal allocation in the power network could alleviate the voltage instability or even prevent the voltage collapse.

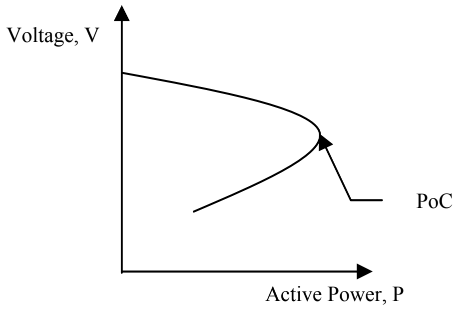

Fig. 3. P-V curve

IV. Reactive Power Planning

Optimal allocation of Var sources happens to be one of the most challenging problems in power networks. The incorporation of shunt reactive power compensation devices in power networks provides voltage support, and reduces the danger of voltage instability or voltage collapse. In the past years, locations of Var sources were barely determined by estimation or by approach [12]; however, neither of both methodologies proved to be effective [13].

Traditionally the Reactive Power Planning (RPP) methodology is based on the one hand on the definition of complex objective functions and network constrains, and on the other hand on the use of optimization algorithms.

RPP of large-scale power systems is a complex, nonlinear and multimodal optimization problem with a mixture of discrete and continuous variables. For decades, conventional gradient-based optimization methods have been widely used to solve this problem [12], [14], [15]. However, RPP is a global optimization problem with several local minima, and thus conventional optimization methods are not suitable to solve it.

Furthermore, conventional optimization techniques require several mathematical assumptions of the problem to be solved, such as linear and continuous functions and constraints differentiable properties of the objective function [16]. In the literature related to the reactive power planning, it could be observed that stochastic non-conventional search methods offer a good alternative to solve this combinatorial optimization problem because of their easy implementation and their capacity to reach global solutions [17], [18].

In this paper, optimal locations of DG units with reactive power capability are determined by using the proposed optimal reactive power planning model. Moreover, Genetic algorithms (GA) are used to solve the optimization problem. The methodology proposed could be successfully applied to any RES inverted based unit offering reactive power capability (DFIG or PV). If dealing with fixed speed wind turbines, it will be assumed that the Var injection is supplied by external Var sources located at the wind farm terminal (STATCOM or SVC).

V. Genetic Algorithms

Genetic algorithms (GA) are a family of computational optimization models invented by Holland (1975) [19] and firstly implemented by Goldberg (1989) and Hopgood (2001) [20] to solve both constrained and unconstrained optimization problems. GA are based on natural evolution process, as it could be deduced from the employed operators, which are clearly inspired by these natural sequences, and from the main driver of the GA, which would be defined as a biological selection. One of the main advantages of the GA is that they work with a set of possible solutions, called population, which will be modified on each step (generation) of the algorithm according to genetic operators.

The main advantages of GA to be stressed over conventional optimization methods are:

- They do not need any prior knowledge about issues such as space limitations or any other special properties of the objective function of the problem to be optimised.
- They do not deal directly with the parameters of the problem. They work only with codes, which represent the parameters and the evaluation of the fitness function to afterwards, be able to assign a quality value to every solution produced.
- They work with a set of solutions from one generation to the next making the process likely to converge into a global minimum.

The solutions obtained are randomly based on the probability rate of the genetic operators such as mutation and crossover.

This technique is very useful for solving optimization problems such as the one proposed in this paper. The optimisation problem would be formulated as:

Min F(x)
Subject to:

$$Aeq(x) = Beq$$
$$A(x) \leq Beq$$
$$x \in S$$

where:

- F(x) is the objective function to be optimised
- Aeq is equality constraint
- A is inequality constraint
- x is the vector of variables
- S is the search space.

I. *Representation*

A population is formed by a set of individuals that correspond with a possible solution of the problem. Each individual is represented by a set of variables to be optimized and they are usually represented in a string form called chromosome.

Indeed, the method of chromosome's representation has a major impact on the performance of the GA. There are two common representation methods for numerical optimization problems: binary string or vector of integers and real numbers. Each element (bit, integer or real number) in a chromosome is called gene.

II. *Initial Population*

Instead of facing a single solution each time, GA work with a group of initial solutions to start the process of optimization This initial population could be created in two ways. The first one consists in using randomly produced solutions which have been preciously created by a random generator; this method would be preferable in those cases in which no prior knowledge existed. The second method employs a set of known solutions able to satisfy the requirements of the problem. This method does require a previous knowledge about the optimization problem and converges to an optimal solution in less time than the first one.

III. *Fitness Evaluation Function*

The formulation of the fitness function (FF) is a major aspect of the optimization problem. FF assigns a quality value to each individual of the population depending on how well the solution performs the desired functions and satisfies the given constraints. Moreover, it allows to determinate which individuals of the population will survive for the next generation. The fitness values of individuals in a given population are employed to drive the evolution process. In the case of a GA, this calculation must be automatic and the problem lies in how to devise an effective procedure to compute the quality of the solution. These characteristics enable the GA to present excellent results even when optimizing complex, multimodal or discontinuous functions.

IV. *Genetic operators*

After implementing the fitness function, three basic genetic operators are applied to the population, in order to create a new population: selection, crossover and mutation,. All of these three generators are inspired by natural process, as we pointed out above; however, it is not necessary to employ all the operators in a GA simultaneously. The choice or design of the operators depends on the problem to be analyzed and the representation scheme to be employed.

Selection: The aim of the selection procedure is to copy individuals whose fitness values are higher than those whose fitness values are lower in the next generation. Besides this, the operator allows transmitting the best individual's genetic material in the next generations in order to drive the search towards a promising area and finding optimal solutions in a very short time.

Crossover: This operator is considered the most important one of GA method because it is responsible for the genetic recombination. It is used to create two new individuals (children) from two existing ones (parents), which are picked from the current population through the selection operator. There are several ways of doing this, but the most common crossover operations are: one point, two point, cycle and uniform crossovers.

Mutation: During this procedure all individuals of the population are checked, gene by gene, and this gene value is randomly reversed according to a specified rate. This operation introduces new information in the algorithm to force it to search new areas. Additionally, this operator helps GA to avoid premature convergence due to genetic material that has been lost during the selection operation. In addition to that already mentioned, it helps to find out a global optimal solution.

V. *Control parameters*

The most important control parameters of a simple GA are:

- Population size: It allows a better exploration of the solution space during the search, so that the probability of convergence to the global optimal solution will be higher.
- Crossover rate: It determines the frequency of the crossover operation. It is used to discover a promising area at the start of the simulation.
- Mutation rate: It controls the mutation operation. In general, an increase in the mutation rate helps the GA to reach the global solution avoiding the local minimum. However, if this mutation rate parameter is too high, it could result in a wide diversity in the population and, so that the global solution will not be reached.

VI. Optimization methodology for optimal management of FACTS units

I. *Encoding*

The target is how to find the best location for the “N” FACTS units. Each chromosome has (1 + 2 N) representing the system variables. The first one represents the loadability parameter of the system (λ); the other ones represent the bus number location (PC) in which SVCs units could be connected, and the Var injection from each device respectively.

Gen 1	Gen 2	Gen 3	…	Gen 2*N	Gen 1+2*N
λ (p.u.)	PC1	Q_1 (Mvar)	…	PC_N	Q_N (Mvar)

II. *Fitness Function*

According to this paper, the fitness function deals with the loadability of the system. Load growth is modelled as a homothetic growth in all distribution load nodes. That is, the same load growth rate is used in every load node [21]. For this purpose a load change scenario is considered in which P_d and Q_d can be represented as:

$$P_{di}(\lambda) = P_{di0}(1+\lambda) \tag{1}$$

$$Q_{di}(\lambda) = Q_{di0}(1+\lambda) \tag{2}$$

Where:

- P_{di0} and Q_{di0} are the original power load (base case) on each node.
- λ represents the percentage of load homothetic increase definition, defines as:

  $\lambda = (P_{dTot}*100)/P_{d0Tot}$

  where P_{dTot} and P_{d0Tot} are, respectively, the total system load after an increment of λ and at the base case [22].

In this scenario of load change, λ_{max} corresponds to the maximum power transferred under voltage constraints.

To maximize the system loadability through the load parameter λ, The FF function used will be:

$$FF(x) = \lambda$$

Where:

- x is a vector of variables.
- λ loadalability value Constraints

The main constraints considered in the optimization process are the following:

- Voltage level at all buses should be held within established limits.
- Active and reactive power generation are limited by the generator capabilities.

III. *Optimisation Formulation*

According to the fitness function objective and the constraints equations, the optimization problem could be formulated as:

$$Min\,F(y) = 1 - FF(y) \tag{3}$$

- *Load flow constraints:*

$$\Delta P_i = P_{gi} - P_{di} - P_i \tag{4}$$

$$\Delta Q_i = Q_{gi} - Q_{di} - Q_i \tag{5}$$

where:

$$Y_{ik} = G_{ik} + B_{ik} \tag{6}$$

$$\boldsymbol{V}_i = V_i \llcorner \theta_i \tag{7}$$

$$\boldsymbol{V}_k = V_k \llcorner \theta_k \tag{8}$$

Active and reactive power injections at the node “i” are given by:

$$P_i = V_i \sum_{i=1}^{N} V_k (G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}) \tag{9}$$

$$Q_i = V_i \sum_{i=1}^{N} V_k (G_{ik}\sin\theta_{ik} - B_{ik}\cos\theta_{ik}) \tag{10}$$

- *Voltage constraints*

$$V_{i,mín} \le V_i \le V_{i,máx} \tag{11}$$

Where N_B is the number of buses

- *Active and reactive power generation*

$$P_{gi,mín} \le P_{gi} \le P_{gi,máx} \tag{12}$$

$$Q_{SVCi,mín} \le Q_{SVCi} \le Q_{SVCi,máx} \tag{13}$$

- *Physical constrains at the generation units connection point*

The potential connection point from the generation units to the grid is limited to the several geographical area in which the power system has been divided.

$$PC_{gi,mín} \le PC_{gi} \le PC_{gi,máx} \tag{14}$$

Where N_G is the number of generation units

- *Limits on Power Flow and maximum current at each branch*

$$S_l \le S_{l,máx} \tag{15}$$

$$I_l \le I_{l,máx} \tag{16}$$

VII. Case Studied

Recently, grid code requirements at distribution networks state that renewable energy sources should be able to inject reactive power according to the DSO demands, as can be seen in [23],[24].

This section analyzes two different power networks where two applications of the GA have been studied.

In the first case, a 34 bus distribution system (Fig. 4) is considered and the objective of the study is to determine the optimal location of the SVC units and their optimal Var injection. In this case, two different situations are analyzed:

- the first one is to maximize the system loadability ,
- and the second one tries to maximize system loadability increasing at the same time the wind penetration level by means of a multiobjective function .

Once the application of the GA to optimal management of FACTS units has been successfully demonstrated, the methodology will be applied to a real 140 bus power network.

Finally, a contingency analysis of the 34 bus systems will be made in order to demonstrate that an optimal management of FACTS units could improve the system reliability.

Voltage profile and reliability studies are performed with PowerWorld® [25] and Matlab® [26].

I. *Optimal allocation of FACTS units in a distribution network.*

In this case an optimal management of FACTS units in a distribution system is studied (Fig. 4) [27]. Initially (base case) there are no SVC units connected to the distribution network. The GA will indicate the optimal allocations of SVC units and their Var injection.

Four different wind energy penetration scenarios are considered: base case, in which no wind energy units and FACTS units are connected to the network, and the other ones (case 1 to 3) correspond to a wind penetration level of 23.9%, 47.2% y 71.7% and a connection of 1, 2 or 3 FACTS devices respectively.

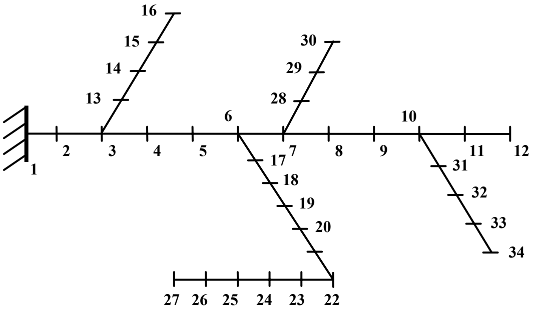

Fig. 4. Modified IEEE 34 bus system

Table I shows the obtained results by the algorithm: the bus number where each FACTS unit should be located, the injected reactive power and the maximum loadability for low limit operational voltage ($\lambda_{máx}$). For each scenario

Fig. 5 shows the voltage profile at the base loadability of the case studied (λ=0), and after the application of the optimisation algorithm.

TABLE I.
RESULTS OF GA

Case	Penetration level	FACTS bus location	Q_{inj} (Mvar)	$\lambda_{máx}$
Case 0	Base case	-	-	0
GA solution case 1	23.9%	27	2.77	0.06
GA solution case 2	47.8%	11	2.95	0.30
		25	2.79	
GA solution case 3	71.7%	10	2.15	0.74
		23	2.45	
		26	2.71	

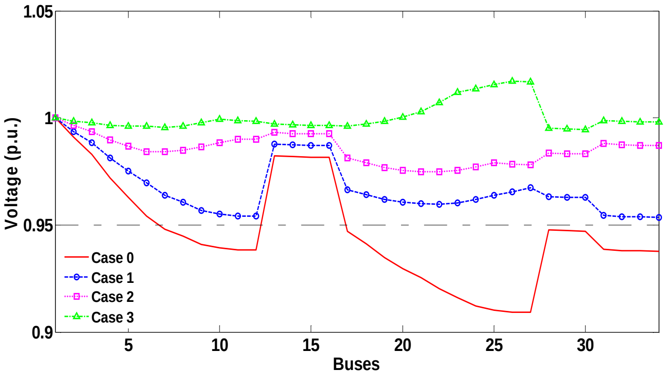

Fig. 5. Voltage profile of the m modified IEEE 34 bus system

It is shown that the optimal management of FACTS units in distribution networks with high wind energy enhances the voltage profile and increases the maximum loading of the system. Most specifically, if adding three FACTS units to the power network, the maximum loading of the system for operational voltage limit will increase by 74% (Fig. 6).

II. *Optimal management of FACTS units to maximize both the loadability of the system and the wind penetration level.*

As it has been demonstrated in the previous section, optimal management of SVC units in distribution system with high wind penetration level improves the loadability condition. For that reason, it would be interesting to develop an algorithm to solve a new multiobjective optimization problem able to find out the optimal allocation and proper sizing of SVC units in order to maximize, at the same time the loadability of the system and the wind penetration level as shown in (14) and (15).

$$FF(x) = ½(1 - \lambda) + ½(1/g(x)) \qquad (17)$$

$$g(x) = \frac{\sum_{i=1}^{n} P_{GD_i}}{P_{load}} \qquad (18)$$

Regarding the previous consideration, four wind units of 1.5 MW and four FACTS units associated to them will be optimally included in the distribution systems according to the GA results.

Table II shows the results of the GA for the multiobjective optimization problem. It could be observed that the maximum penetration level (70.09%) corresponds to an overload of 62% in the distribution system.

TABLE II.
RESULTS OF GA MULTIOBJECTIVE OPTIMIZATION PROBLEM

$\lambda_{máx}$	Penetration level
0.62	70.09

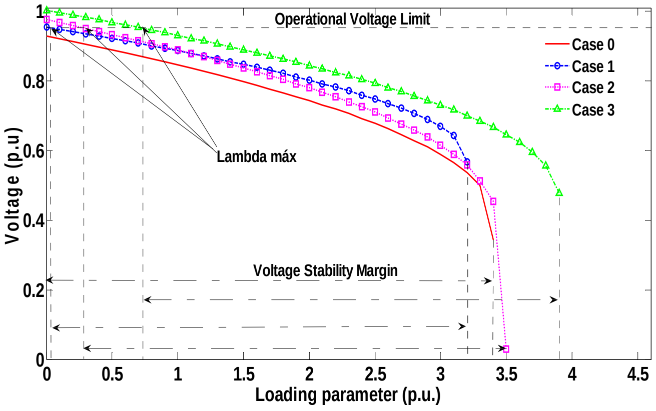

Fig. 6. Maximum loading parameter and voltage stability margin

Table III shows the optimal location, the proper active and reactive power injection of wind and FACTS units respectively for the maximize loadability and penetration level.

TABLE III.
OPTIMAL ALLOCATION, REACTIVE POWER AND VAR INJECTION OF WIND AND SVC UNITS

Wind + SVC	Wind + SVC bus location	$P_{inj.}$(MW)	$Q_{inj.}$(Mvar)
1	10	1.49	1.8
2	25	1.5	1.72
3	21	1.44	1.94
4	22	1.42	2

III. *Optimal location of FACTS units in a real 140 bus system*

In this section GA have been applied upon a real power system. The power systems is made up of 140 buses with different voltage level varying between 380 kV and 380 V. Fig. 7 shows the sub-network corresponding to voltage levels between 380 kV and 45 kV for the sake of clarity. The load has been distributed across all the voltage level, although most of them (40%) are connected to low voltage [28]. There is only one generator, slack bus, which represents the connection with the rest of the national power system. In this case, the main objective of the GA is to maximize the loadability of the systems by optimally locating the five FACTS units being two of them associated to wind farms.

Results of the GA are shown in Table IV. Due to optimal management of SVC units in the 140 network, maximum loadability of the systems will increase by 17% and the loadability at the point of collapse ($\lambda_{crit.}$) will increase by 120% (Table V).

TABLE IV.
RESULTS OF GA 140 BUS POWER SYSTEM

#1	Q_1 (Mvar)	#2	Q_2 (Mvar)	#3	Q_3 (Mvar)	#4	Q_4 (Mvar)	#5	Q_5 (Mvar)
13	0.42	11	0.18	31	0.42	14	8	21	9

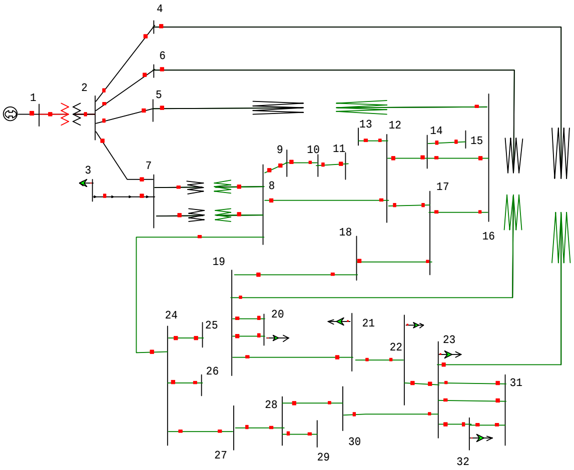

Fig. 7. 140 Bus power network corresponding to 380 kV to 45 kV

TABLE V.
MAXIMUM LOADABILITY OF THE 140 BUS SYSTEM

$\lambda_{máx}$	$\lambda_{crít.}$
0.17	1.2

IV. *Contingency analysis*

Contingency analysis is one of the most important tools to determine preventive or corrective actions to be taken in the power system. In this paper a single line outage (N-1 Contingency) has been studied in the modified IEEE-34 bus power network for the sake of clarity and simplicity. The severest contingencies scenarios were determined based on the overloaded lines and on bus voltage violations by using PowerWorld®. The worst situation corresponds to the disconnection of line 10-31. This failure produces an overload of lines 22-21 and 22-23 of 104% and 109 % respectively. Fig. 6 shows the voltage profile of the power network under a single N-1 contingency considering the base case (without wind farm and Var injection) and case 3 (three SVC units). Fig. 7 shows the post-contingency voltage profile for maximum loadalibity. It could be observed how the installation of FACTS units, optimally located and with the proper sizing, improves the system reliability after contingency N-1.

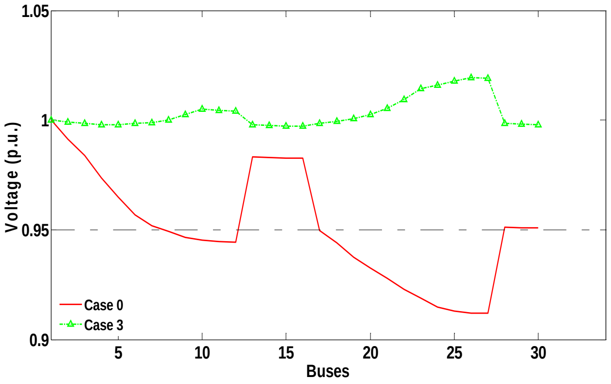

Fig. 6. Voltage profile under single N-1

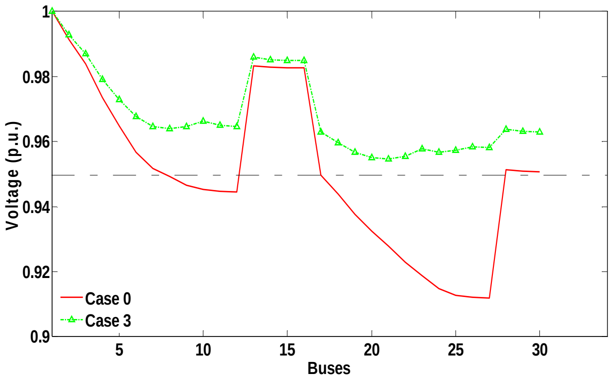

Fig. 7. Maximum loadability voltage profiles under single N-1 contingency

VIII. Conclusions

In this paper a method based on GA for optimal location of FACTS units has been successfully developed. The pursued target of the methodology focuses on maximizing the loadability of the system, increasing the wind penetration level, and improving, at the same time, the security of the power network under single N-1 contingencies. Therefore GA have been tested in distribution networks and they have widely proved their ability to reach a global optimal solution for the allocation of several FACTS units. Moreover it has been demonstrated the ability of GA to optimally locate and manage the reactive power injection of FACTS units upon a realistic power system with140 buses. The obtained results related to the algorithm show that the optimum allocation of FACTS devices in power networks with high wind energy penetration could enhance voltage stability as well as maximize voltage stability margin in the whole network.

IX. ACKNOWLEDGEMENT

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