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Optimal STATCOM Sizing and Placement Using Particle Swarm Optimization

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Abstract—Heuristic approaches are traditionally applied to find the size and location of Flexible AC Transmission Systems (FACTS) devices in a small power system. Nevertheless, more sophisticated methods are required for placing them in a large power network. Recently, the Particle Swarm Optimization (PSO) technique has been applied to solve power engineering optimization problems giving better results than classical methods. This paper shows the application of PSO for optimal sizing and allocation of a Static Compensator (STATCOM) in a power system. A 45 bus system (part of the Brazilian power network) is used as an example to illustrate the technique. Results show that the PSO is able to find the best solution with statistical significance and a high degree of convergence. A Detailed description of the method, results and conclusions are also presented.

Index Terms—Flexible AC Transmission Systems (FACTS), Particle Swarm Optimization, Static VAR compensators.

I. INTRODUCTION

Power systems components mainly consist of generators, transmission lines, transformers, switches, active or passive compensators and loads. Power system networks are complex systems that are nonlinear, non-stationary, and prone to disturbances and faults. Reinforcement of a power system can be accomplished by improving the voltage profile, increasing the transmission capacity and others. Nevertheless, some of these solutions may require considerable investment that could be difficult to recover. Flexible AC Transmission System (FACTS) devices are an alternate solution to address some of those problems [1].

Simple heuristic approaches are traditionally applied for determining the location of FACTS devices in a small power system. However, more scientific methods are required for placing and sizing FACTS devices in a larger power network. FACTS sizing and allocation constitutes a milestone problem in power systems.

Traditional optimization methods such as mixed integer linear and non-linear programming have been intensely investigated to address this issue; however difficulties arise

due to multiple local minima and the overwhelming computational effort [2], [3].

Recently, Evolutionary Computation Techniques have been employed to solve the optimal allocation of FACTS devices with promising results. Different algorithms such as Genetic Algorithms (GA) [2], [4], [5], [6], and Evolutionary Programming [7] have been tested for finding the optimal allocation as well as the types of devices and their sizes.

Particle Swarm Optimization (PSO) is another evolutionary computation technique that can be used to solve the FACTS sizing and allocation problem. It has been applied to other power engineering problems such as: economic dispatch [8], generation expansion problem [9], short term load forecasting [10], and others, giving better results than classical techniques and with less computational effort. In addition, it has been shown recently that the application of PSO is suitable in principle to optimally place FACTS devices in a multimachine power system [11].

The main goal of this paper is to show the application of PSO for the optimal allocation as well as the sizing of a Static Compensator (STATCOM), shunt FACTS device, in a power system. The criterion used in finding the best solution is to optimize the voltage profile of the system and the STATCOM size such that voltage deviations at each bus do not exceed a predefined set value. A 45 bus system that is part of the Brazilian power network is used as an example to illustrate the methodology. In addition, the effect of the maximum voltage deviation on the PSO performance and STATCOM size is studied.

Section II presents the basic concepts of PSO. The description of the power system used in this study is presented in section III. In section IV the objective function to be optimized is described. Section V presents the implementation of the PSO algorithm. Simulation results are presented in section VI. Conclusions and future work are given in section VII.

II. PARTICLE SWARM OPTIMIZATION

PSO is an evolutionary computation technique developed by Eberhart and Kennedy in 1995, and was inspired by the social behavior of bird flocking and fish schooling [12], [13], [14]. PSO has its roots in artificial life and social psychology as well as in engineering and computer science. It utilizes a population of individuals, called particles, which fly through the problem hyperspace with some given initial velocities. In each iteration, the velocities of the particles are stochastically

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adjusted considering the historical best position of the particles and their neighborhood best position; where these positions are determined according to some predefined fitness function [13], [15]. Then, the movement of each particle naturally evolves to an optimal or near-optimal solution. The name of “swarm” comes from the irregular movements of the particles in the problem space, more similar to a swarm of mosquitoes rather than flock of birds or school of fish [15].

In a real-number space, the position of each particle is given by the vector $\vec{x}_i \in \mathcal{R}^n$. At iteration t , the particle position vector $\vec{x}_i(t)$, given in (1), is determined by the previous position vector $\vec{x}_i(t-1)$ and its movement given by the velocity applied to the particle $\vec{v}_i(t)$ [16].

$$\vec{x}_i(t) = \vec{x}_i(t-1) + \vec{v}_i(t) \quad (1)$$

At each iteration, the velocity of a particle is determined by both the individual and group experience:

$$\vec{v}_i(t) = w_i \cdot \vec{v}_i(t-1) + c_1 \cdot rand_1 \cdot (\vec{p}_i - \vec{x}_i(t-1)) + \dots + c_2 \cdot rand_2 \cdot (\vec{p}_g - \vec{x}_i(t-1)) \quad (2)$$

where:

- w_i is a positive number between 0 and 1.
- c_1, c_2 are two positive numbers called the cognitive and social acceleration constants.
- $rand_1, rand_2$ are two random numbers with uniform distribution in the range of [0, 1].
- p_i is the best position found by the particle i so far.
- p_g is the global best position found by any particle in the swarm

The velocity update equation as given by (2) has three different components [17]:

- i. The first component is sometimes referred to as “inertia”, “momentum” or “habit”. It models the tendency of the particle to continue in the same direction it has been traveling.
- ii. The second component is a linear attraction towards the best position ever found by the given particle (p_{best}). This component is variously referred to as “memory”, “self-knowledge”, “nostalgia” or “remembrance”.
- iii. The third component of the velocity update equation is a linear attraction towards the best position found by any particle (g_{best}). This component is variously referred to as “cooperation”, “social knowledge”, “group knowledge” or “shared information”.

The maximum allowable velocity for the particles is controlled by the parameter V_{max} . If V_{max} is too high, then particles tend to move beyond a good solution; on the other hand, if V_{max} is small, then particles can be trapped in local minima.

Optimization of some real world problems requires to be solved in an integer-number space. In this case, the PSO has

also proven to be effective in this kind of optimization problem; the performance of the PSO could be better than typical techniques such as branch and bound by giving better stability performance and higher success rates [18]. The application of PSO to integer optimization problems is known as the integer PSO. Integer PSO is based on the same principles as the real valued PSO as described before, i.e. computations are carried out in the same way but real values are approximated to the closest integer. The approximation does not seem to significantly affect the performance of the integer PSO [18].

III. MULTIMACHINE POWER SYSTEM

The multimachine power system used for this study is presented in Fig. 1. It corresponds to a part of the Brazilian Power Network and consists of the following [19]:

- 45 Buses.
- 10 Generators.
- 17 Transformers.
- 14 transmission lines at 525 kV.
- 41 transmission lines at 230 kV.
- 24 load buses.
- 7 buses with shunt compensation.
- Generation level at 13.8 kV.
- Total installed capacity of 8,940 MVA.

The distribution and utilization part of the system are represented by equivalent loads at the buses where they are connected.

In such a network, it is desirable to keep the voltage deviations between $\pm 5\%$ to avoid voltage collapses during faulty conditions. In general, if the load requirements increase, the voltages at the corresponding buses may drop below 0.95 p.u. and consequently an additional voltage support is needed at that particular bus. In this study, the voltage support will be provided by a STATCOM, and its optimal location and size will be determined by using PSO. System simulations are carried out using PSAT software [20].

IV. OBJECTIVE FUNCTION

The objective function J in (3) is a weighted sum of the voltage deviation metric and STATCOM size. The STATCOM size is weighted such that the values of the two terms in the objective functions are comparable; the weighting factor is determined by trial and error. The voltage deviations are considered in p.u. and the STATCOM size is considered in MVAR.

$$\text{Min } J = \left(\sum_{i=1}^{45} (V_i - 1)^2 \right)^{1/2} + \frac{\eta}{500} \quad (3)$$

Subject to:

$$|V_i - 1| \leq 0.05 \quad \text{for } i = 1..45$$

$$\eta \geq 0$$

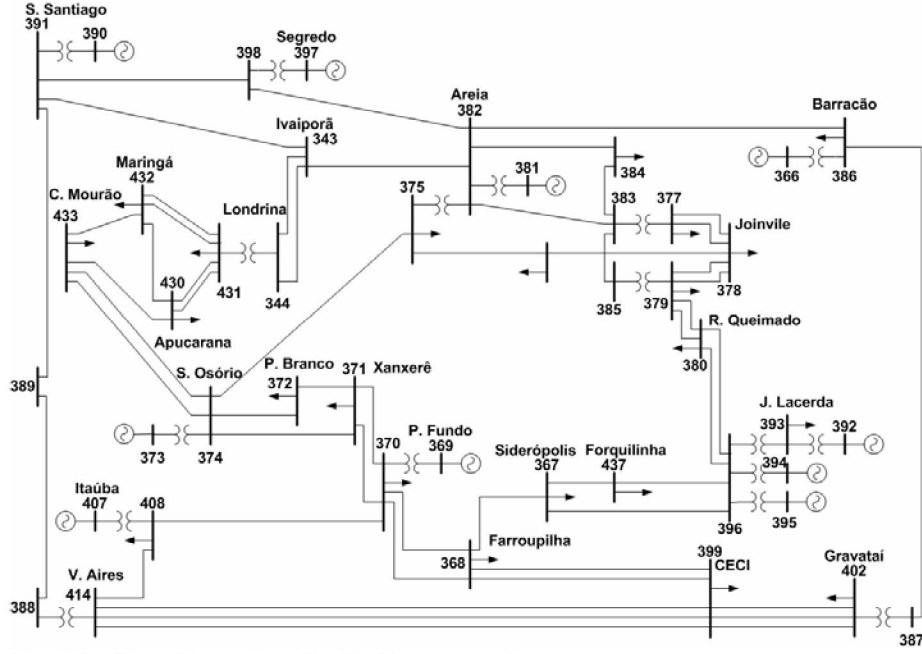


Fig. 1. One line diagram of the 45 bus 10 machine section of the Brazilian power system.

where:

J : is the objective function value.

V_i : is the value of the voltage at bus i in p.u.

V_{i-1} : is the voltage deviation as bus i in p.u.

$\left(\sum_{i=1}^{45} (V_{i-1})^2 \right)^{1/2}$: is the total voltage deviation metric.

η : is the STATCOM size in MVAR.

Since the multimachine power system has 10 generators, and the voltage at each generator bus is regulated by the generator itself, the corresponding generator buses are omitted from the searching process, thus leaving 35 possible locations for the STATCOM.

V. IMPLEMENTATION OF PSO ALGORITHM

The implementation of the PSO algorithm is discussed below and it is illustrated in the flow chart shown in Fig. 2.

A. Particle Definition

The particle is defined as a vector which contains the STATCOM bus location number and its size as shown in (4).

$$\text{Particle} : [\lambda \quad \eta] \quad (4)$$

where:

λ : is the STATCOM bus location number.

η : is the STATCOM size in MVAR.

B. Fitness function

The PSO fitness function used to evaluate the performance of each particle corresponds to the objective function presented in (3).

C. PSO Parameters

The performance of the PSO is affected by the selection of its parameters [12]. Therefore, a way to find a suitable set of parameters has to be chosen. In this case, the selection of the PSO parameters follows the strategy of considering different values for each particular parameter and evaluating its effect on the PSO performance. The different values for the PSO parameters are shown in the next subsections and the performance evaluation is shown in the results section.

1) Number of particles:

There is a trade-off between the number of particles and the number of iterations of the swarm and each particle fitness value has to be evaluated using a power flow solution at each iteration, thus the number of particles should not be large [11] because computational effort could increase dramatically. Swarms of 5 and 10 particles are chosen as an appropriate population sizes.

2) Inertia weight:

From previous results, the inertia weight is linearly decreased [11]. The purpose is to improve the convergence of the swarm by reducing the inertia weight from an initial value of 0.9 to 0.1 in even steps over the maximum number of iterations as shown in (5).

$$w_i = 0.9 - 0.8 \cdot \frac{\text{iter} - 1}{\text{max_iter} - 1} \quad (5)$$

where:

w_i : is the inertia weight at iteration i .

iter : is the iteration number.

max_iter : is the maximum number of iterations.

3) Acceleration constants:

A set of three values for the individual acceleration constants are evaluated to study the effect of giving more importance to

the individual's best or the swarm's best: $c_1 = \{1.5, 2, 2.5\}$. The value for the social acceleration constant is defined as: $c_2 = 4 - c_1$.

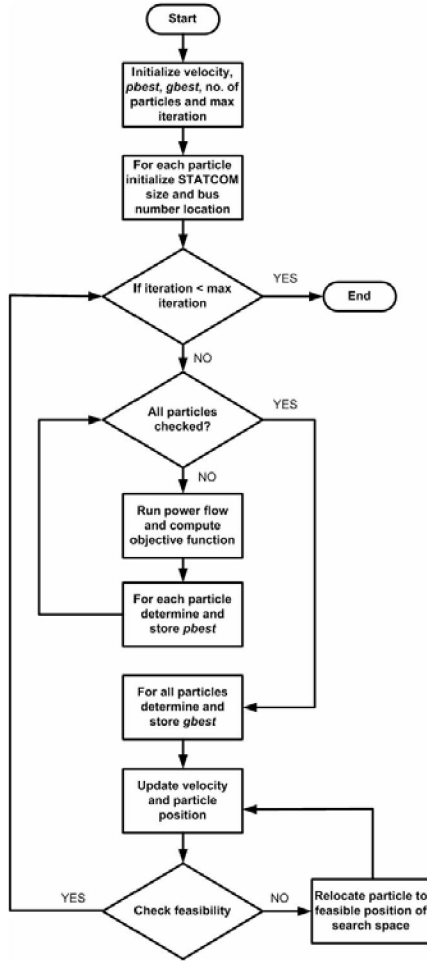


Fig. 2. Flow chart of the implemented PSO.

4) Number of iterations:

Different numbers of iterations $\{10, 15, 20\}$ are considered in order to evaluate the effect of this parameter on the PSO performance.

5) Values for maximum velocity:

In this case, for each particle component, values for the maximum velocity have to be selected. Based on previous results [11], a value of 9 is considered as the maximum velocity for the location bus number. For the STATCOM size maximum velocity values of $\{25, 50, 75\}$ are considered.

Table I presents a summary of the values tested for each parameter.

TABLE I
PSO PARAMETERS

Parameter	Tested values
Number of particles	$\{5, 10\}$
Inertia weight	Linearly decreased inertia weight
Acceleration constant (c_i)	$\{1.5, 2, 2.5\}$
Number of iterations	$\{10, 15, 20\}$
Maximum velocity for STATCOM bus location	9
Maximum velocity for STATCOM size	$\{25, 50, 75\}$

D. Integer PSO

For this particular application, the position of the particle is determined by an integer number (bus location and STATCOM size). Therefore the particles' movement given by (2), are approximated to the nearest integer numbers. Additionally, the location number must not be a generator bus. If the results of (2) imply a generator bus, then the particle component regarding position (λ) is changed to the geographically closest bus without a generator.

VI. SIMULATION RESULTS

A. PSO Parameter Tuning.

In order to find the best set of parameters for the PSO among all the alternatives mentioned before, 50 optimization trials are performed for each possible set. For each combination, the best case final value of the fitness function is registered. From these values, the minimum, maximum, average, and standard deviation (in percentage) values are computed as a statistical indication of the PSO performance.

In addition, a performance index called Convergence Rate (CR) is defined as the number of cases, over the 50 trials in which a feasible solution is found by any particle of the swarm. In practice, high values of CR are desirable. The CR can be understood also as the probability of the PSO to find a feasible solution. A feasible solution is a solution that complies with the objective function constraints as shown in (3).

The criteria used for choosing the best set of PSO parameters is to consider the set that is statistically more significant by evaluating the minimum, maximum, average, and standard deviation values of the fitness function and with high values of CR. The optimal set of parameters found is shown in Table II.

Power flow results considering maximum voltage deviation of $\pm 5\%$ and when the STATCOM is located in its best position at bus 378 are shown in Table III. The values outside the $\pm 5\%$ limits are shown in bold for the cases with and without the STATCOM.

TABLE II
OPTIMAL PSO PARAMETERS

Parameter	Value
Number of Particles	10
Individual Acceleration Constant	2.5
Social Acceleration Constant	1.5
Maximum velocity for STATCOM bus location	9
Maximum velocity for STATCOM size	50
Number of Iterations	20

B. Power Flow Results.

The system without the STATCOM has four buses with voltages below 0.95 p.u.; these buses correspond to one load center. Once the STATCOM is connected to bus 378 the voltage deviations improve at the buses in that load area.

With the STATCOM connected to bus 378, it is providing 62 MVA to the system. Note that after the STATCOM is connected, all the voltages in the system are between the maximum voltage deviation limits of $\pm 5\%$.

Note also that the voltage value of the bus to which the STATCOM is connected is marginally sufficient to keep all other voltages between the limits and keeping the STATCOM size as small as possible. In other words, the size and location of the STATCOM are optimal.

Table IV shows the best case results for the voltage deviation metric before and after the STATCOM placement.

TABLE III
BUS VOLTAGES FROM POWER FLOW RESULTS

Bus number	Voltage p.u. w/o STATCOM	Voltage p.u. with STATCOM
343	1.0341	1.0364
344	1.0244	1.0268
366	1.0200	1.0200
367	0.9589	0.9625
368	1.0054	1.0076
369	1.0400	1.0400
370	1.0130	1.0137
371	0.9836	0.9843
372	0.9769	0.9776
373	1.0200	1.0200
374	0.9932	0.9937
375	0.9956	0.9999
376	0.9646	0.9772
377	0.9692	0.9839
378	0.9215	0.9504
379	0.9405	0.9586
380	0.9491	0.9597
381	1.0220	1.0220
382	1.0237	1.0267
383	0.9710	0.9841
384	0.9737	0.9851
385	0.9485	0.9655
386	1.0228	1.0243
387	1.0181	1.0203
388	1.0315	1.0335
389	1.0408	1.0425
390	1.0180	1.0180
391	1.0354	1.0366
392	1.0300	1.0300
393	0.9911	0.9932
394	1.0300	1.0300
395	1.0300	1.0300
396	0.9907	0.9943
397	1.0200	1.0200
398	1.0283	1.0297
399	1.0246	1.0267
402	1.0334	1.0355
407	1.0000	1.0000
408	0.9860	0.9864
414	1.0366	1.0386
430	0.9891	0.9913
431	1.0086	1.0109
432	0.9767	0.9789
433	0.9665	0.9681
437	0.9573	0.9609

C. Sensitivity Analysis for the Voltage Deviation Constraint.

In order to study the effect of the voltage deviation constraint, simulations considering five different values of the maximum voltage deviations at each bus are carried out. In other words the right hand side constants of the first 45 constraints as shown in (3) are changed. The values for the lower 4.5 %

limit and upper 5.5 % limit are determined by the feasibility of the solution considering generator settings and load conditions.

TABLE IV
BEST CASE RESULTS FOR VOLTAGE DEVIATION METRIC

Parameter	Value
Voltage deviation metric before STATCOM placement	0.2067
Voltage deviation metric after STATCOM placement	0.1811
Minimum voltage deviation metric	0.1823
Maximum voltage deviation metric	0.3070
Average voltage deviation metric	0.2031
Voltage deviation metric standard deviation	6.42 %
Convergence rate (%)	100 %

Fig. 3 shows the voltage deviation metric as defined by (3) and Fig. 4 shows the STATCOM size under these conditions. In all cases the best position for the STATCOM is at bus 378.

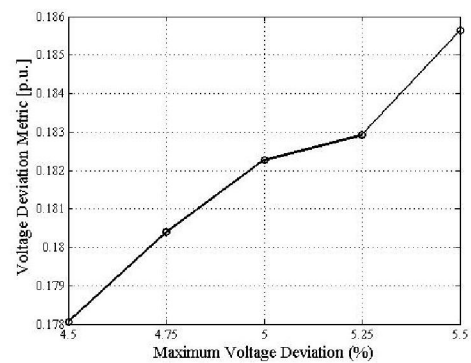


Fig. 3. Voltage deviation metric vs. maximum voltage deviation.

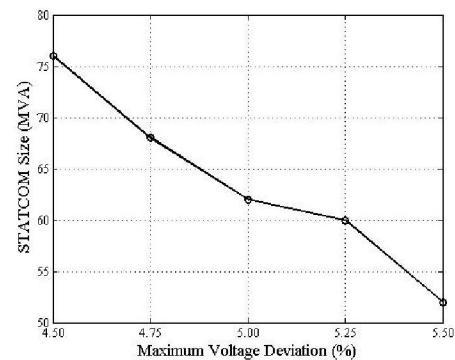


Fig. 4. STATCOM size vs. maximum voltage deviation.

From Figs. 3 and 4 it is observed that as the maximum voltage deviation increases, the voltage deviation metric increases whilst the STATCOM size decreases. Note that a decrease of 0.5 % for the maximum voltage deviation causes a considerable change in the STATCOM size of 22.6% with respect to the case of $\pm 5\%$ limits; which indicates the importance of this parameter in the sizing problem.

VII. CONCLUSIONS AND FUTURE WORK

The paper has demonstrated the application of PSO for sizing and location of a STATCOM in a power system considering at each bus the voltage deviation constraints. Results from the illustrative example show that the PSO is able to find the best size and location solution with statistical

significance when evaluating the minimum, maximum, average, and standard deviation values of the voltage deviation metric, and with a high degree of convergence.

Attention should be paid to the maximum voltage deviation value since the STATCOM size is very sensitive to it. More stringent voltage deviation requirements cause the STATCOM size to increase.

The authors consider the results as promising for the medium size power network used as an example. In large and very large power systems the PSO algorithm could have a significant advantage with respect to exhaustive search and other methods by giving better solutions with less computational effort.

Future work can be done in two different directions. On the one hand, the algorithm could be tested in bigger systems in order to evaluate its performance on more likely real power systems. On the other hand, the allocation and sizing of more than one STATCOM, other types of FACTS devices and combinations of them can be investigated. Additionally, different optimization criteria can be considered such as minimization of losses and stability issues.

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IX. BIOGRAPHIES



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