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# Multiple STATCOM Allocation and Sizing Using Particle Swarm Optimization

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***Abstract*-- This study shows step by step the application of the Particle Swarm Optimization (PSO) method to solve the problem of optimal allocation and sizing of multiple Static Compensators (STATCOM) in a medium size power network (45 bus system, part of the Brazilian power network). The PSO is proposed as an alternative methodology for traditional heuristic approaches and complicated mixed integer linear and non linear programming methods. Simulation results show the suitability of the PSO technique in finding multiple optimal solutions to the problem (Pareto front) with reasonable computational effort. As a part of this study, the optimal setting of PSO parameters is investigated and different power system load conditions are tested to determine the impact over the location and size of each STATCOM unit.**

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

## I. INTRODUCTION

At the present time, there is a consensus that the power grid has to be reinforced and to make it smart and aware, fault tolerant and self-healing, and dynamically and statically controllable. Flexible AC Transmission System (FACTS) devices, such as a STATCOM, a SVC, a SSSC and a UPFC can be connected in series or shunt (or a combination of the two) to achieve numerous control functions, including voltage regulation, system damping and power flow control [1].

In the case of voltage support, shunt FACTS devices, such as STATCOMs and SVCs, are typically used. While designing and installing these devices, two basic issues have to be addressed: (i) steady state performance and (ii) transient performance. This study is focused on the steady state performance of multiple STATCOM units in a medium size power system. Particularly, it is desired to determine their optimal location (bus number) and power rating (MVA).

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Heuristic approaches are traditionally applied to determining the location of FACTS devices, for instance, shunt FACTS devices are usually connected to the bus with the lowest voltage. These heuristics are sufficiently accurate in a small power system; however, more scientific methods are required in larger power networks.

Traditional optimization methods such as mixed integer linear and non linear programming have been investigated to address this issue; however difficulties arise due to multiple local minima and overwhelming computational effort [2], [3].

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

Particle Swarm Optimization (PSO) is an evolutionary computation technique that has been applied to other power engineering problems (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.

This paper introduces the application of PSO for the optimal allocation and sizing of multiple shunt FACTS devices: Static Compensators (STATCOMs), in a 45 bus system that is part of the Brazilian power network. The problem statement is presented in section II along with the description of the power system used in this study. Section III introduces the particle swarm optimization principles and describes the classical formulation in real number space and integer number space (integer PSO). In section IV the implementation of the PSO algorithm is presented step by step: the fitness function and particle definition, constrained search space and parameter setting are described in detail. Section V shows the simulation results in terms of power flow results, multiple optimal solutions and impact of load profile in the power system. Finally, conclusions and future work are given in section VI.

## II. PROBLEM DESCRIPTION

The problem to be addressed consists of finding the optimal placemen (bus number) and power rating (MVA) of multiple STATCOM units in a medium size power system, based on their steady state performance. Such a problem can be stated as a constrained optimization problem in which the main objective is to find the best positions of the STATCOM units to minimize the bus voltage deviations throughout the power system, using a minimum (cost efficient) size for each STATCOM. In addition, other operating conditions can be imposed such as keeping all voltage deviations within ±5% of the corresponding nominal values.

The multimachine power system used for this study appears in Fig. 1. It corresponds to a part of the Brazilian power network [12] and has two distinctive load centers, one of them located among buses 377-380 and the other in buses 430-433. The existence of these two load centers suggests that the voltage support should be done through two STATCOM units. All simulations are carried out using PSAT software [13].

## III. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is an evolutionary computation technique inspired by the social behavior of bird flocking and fish schooling [14], [15], [16]. It utilizes a population of individuals, called particles, which fly through the problem hyperspace with some given initial velocities.

At each iteration, each particle's position is evaluated according to a predefined fitness function. Then the particle's velocities are stochastically adjusted considering the historical best position of each particle itself and the neighborhood best position [15], [17].

### *A. Original PSO formulation*

Mathematically, in a real-number space, the PSO algorithm considers that each particle is given by a vector $\vec{x}_i \in \Re^n$ At iteration $t$, the particle position vector $\vec{x}_i(t)$, is determined by the sum of the previous position vector $\vec{x}_i(t-1)$ and its velocity $\vec{v}_i(t)$ [18]:

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

The velocity of the particle is determined by both the individual and group experiences:

$$\begin{aligned} \vec{v}_i(t) = w_i \cdot \vec{v}_i(t-1) + c_1 \cdot rand_1 \cdot (\vec{p}_i - \vec{x}_i(t-1)) + ... \\ c_2 \cdot rand_2 \cdot (\vec{p}_g - \vec{x}_i(t-1)) \end{aligned} \tag{2}$$

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]. |

The velocity update equation as given by (2) has three different components [19]. The first one, known as "inertia" or "momentum", models the tendency of the particle to continue in the same direction it has been traveling. The second component is the linear attraction towards the best position ever found by the given particle (*pbest*), thus receives the name of "memory" or "self-knowledge". Finally, the third term, referred to as "cooperation" or "social knowledge", can be described as the linear attraction towards the best position ever found by any particle in the swarm (*gbest).*

In the case of a two-dimensional space, the particle's movement is illustrated by Fig. 2.

In order to avoid the divergence of the swarm, the maximum allowable velocity for the particles is controlled by

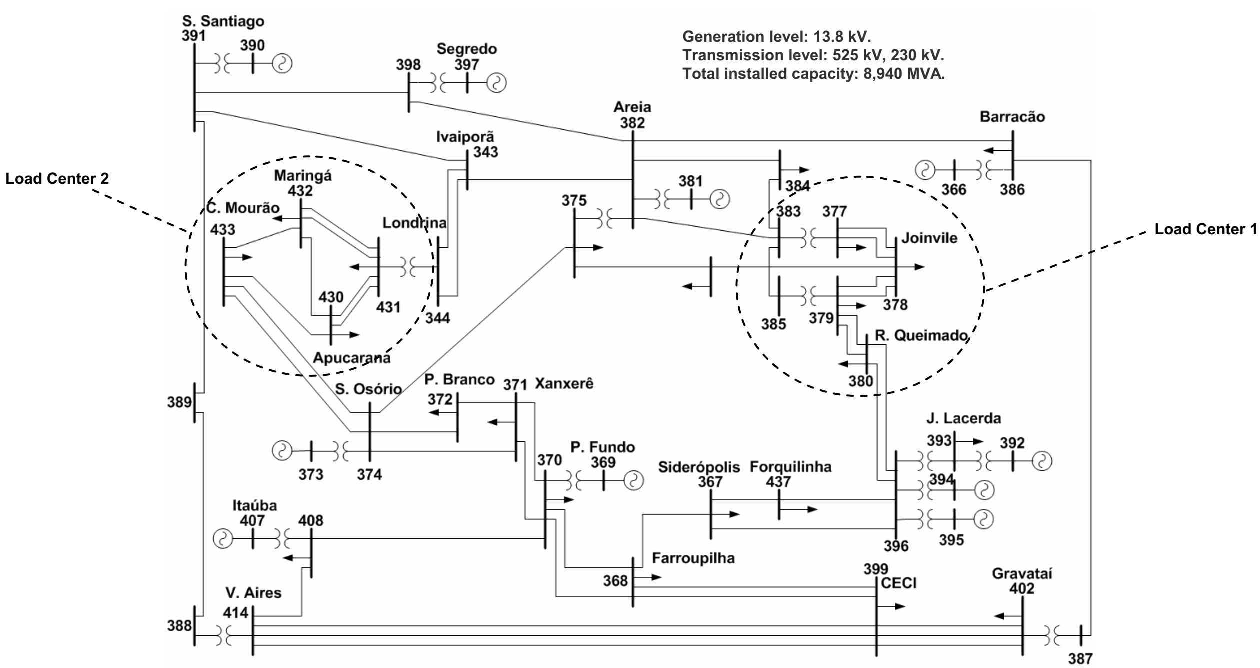


Fig. 1. One line diagram of the 45 bus 10 machine section of the Brazilian power system.

the parameter *Vmax*. If *Vmax* is too high, the particles tend to move erratically; on the other hand, if *Vmax* is small, then the particle's movement is limited and the optimal solution may not be reached.

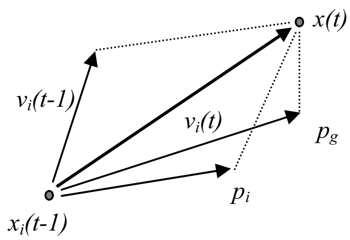


Fig. 2. A particle's movement in a two-dimensional space

*B. Integer PSO formulation*

In the case where integer variables are included in the optimization problem, the formulation of the PSO algorithm can be reformulated by rounding off the particle's position to the nearest integer [20]. Mathematically, (1) and (2) are still valid but once the new particle's position is determined in the real-number space, the conversion to the integer number space must be done[1]:

$$\begin{aligned} &\mathrm{X}_{id}(t) = \left[x_{id}(t)\right], \quad d: 1 \rightarrow n \\ &x_{id}(t) \in \Re \ \textit{and} \ \mathrm{X}_{id}(t) \in \mathrm{Z} \end{aligned} \tag{3}$$

where $d$ corresponds to the dimension index.

## IV. Implementation of PSO algorithm

In order to correctly implement the PSO algorithm, several aspects have to be considered: (i) to define a proper fitness function to evaluate the performance of each individual in the population, (ii) to define the particle vector such that each individual represents a potential solution to the optimization problem, (iii) to characterize the search space taking into account feasible solutions and discarding infeasible ones, and (iv) to tune parameters, such as inertia and acceleration constants, to have an optimal performance of the algorithm (less computational effort, more accuracy, etc.).

*A. Fitness Function Definition*

To evaluate each particle's position it is necessary to define a fitness function that can properly take into account the main objectives that are pursued.

In this case there are two goals that have to be accomplished: (i) to minimize the voltage deviations in the system and (ii) to have the minimum possible STATCOM sizes. Thus, two metrics $J_1$ and $J_2$ are defined as in (4) and (5).

$$J_1 = \sqrt{\sum_1^{45} \left(V_i - 1\right)^2} \tag{4}$$

where:
$J_1$ is the total voltage deviation metric.
$V_i$ is the value of the voltage at bus $i$ in p.u, and

[1] Bracket function rounds off the argument to its nearest integer

$$J_2 = \eta_1 + \eta_2 \tag{5}$$

where:
$J_2$ is the STATCOM size metric.
$\eta_1$ is the size of the first STATCOM in MVAr.
$\eta_2$ is the size of the second STATCOM in MVAr.

The multi-objective optimization problem can now be defined using the weighted sum of both metrics $J_1$ and $J_2$ to create the fitness function $J$ shown in (6). The best solution is one for which $J$ is a minimum.

$$J = \omega_1 \cdot J_1 + \omega_2 \cdot J_2 \tag{6}$$

where:
$J$ is the PSO fitness function.

The weight that multiplies each metric is adjusted to reflect the relative importance that each goal has with respect to the other. In this case, it is decided to give equal importance to both metrics, giving values of $\omega_1 = 1$ and $\omega_2 = 1/500$, so that the two terms in the fitness function are comparable in magnitude.

*B. Particle Definition*

The particle is defined as a vector containing the location (bus number) of the two STATCOM units and their sizes as shown in (7).

$$x_i = \left[\lambda_1 \quad \eta_1 \quad \lambda_2 \quad \eta_2\right], \quad x_i \in \mathrm{Z}^4 \tag{7}$$

where:
$\lambda_1$ is the location (bus number) of the first STATCOM.
$\lambda_2$ is the location (bus number) of the second STATCOM

All components of the particle vector (bus numbers and sizes) are integer numbers, thus $x_i \in Z^4$.

*C. Search Space Definition*

There are several constraints in this problem regarding the characteristics of the power system and the desired voltage profile. Each of these constraints represents a limit in the search space; therefore the PSO algorithm has to be programmed so that the particles can only move over the feasible region.

For instance, the network in Fig. 1 has 10 generators buses where voltages are regulated by the generator AVRs. These generator buses do not need a STATCOM and are omitted from the PSO search process, leaving 35 other possible locations for the STATCOM. In terms of the algorithm, each time that a particle's new position includes a generator bus, the position is changed to the geographically closest load bus.

Also, considering the topology of the system, the bus numbers are limited to the range from 1 to 45, thus the two constraints shown in (8) have to be considered.

$$\begin{aligned} 1 \le \lambda_1 \le 45 \\ 1 \le \lambda_2 \le 45 \end{aligned} \tag{8}$$

To solve this issue, if either $\lambda_1$ or $\lambda_2$ are outside this range, their values are re-randomized, i.e. the particle moves to a randomly selected bus.

Additionally, the event of having the two STATCOM units connected to the same bus is considered infeasible, giving the restriction in (9). This is solved by relocating the second STATCOM to the nearest bus.

$$\lambda_1 \neq \lambda_2 \tag{9}$$

The desired voltage profile required that 45 restrictions have to be defined as in (10).

$$0.95 \leq V_i \leq 1.05\ , \quad i : 1 \rightarrow 45 \tag{10}$$

Each solution which does not satisfy the above restrictions is considered infeasible, thus its fitness function value is set to infinity.

Finally, in order to limit the sizes of the STATCOM units the restrictions in (11) are applied to the particles. If the maximum size of the STATCOM is exceeded (or if a negative value is encountered) then the particle is re-randomized.

$$\begin{aligned} 0 \leq \eta_1 \leq 250 \\ 0 \leq \eta_2 \leq 250 \end{aligned} \tag{11}$$

### *D. PSO Parameters*

In the PSO algorithm, there are five different parameters to be tuned for optimal performance: (i) type and value of inertia constant, (ii) acceleration constants, (iii) maximum velocity for each dimension of the problem hyperspace, (iv) number of particles in the swarm, (v) maximum number of iterations.

In the author's previous work [11], it has been shown that the most suitable type of inertia constant corresponds to a linearly decreasing scheme shown in (12).

$$w_i = 0.9 - 0.8 \cdot \frac{iter - 1}{\max\_iter - 1} \tag{12}$$

where:

$w_i$ is the inertia weight at iteration $i$.

*iter* is the iteration number.

*max_iter* is the maximum number of iterations.

Under this scheme, the convergence of the swarm is improved by reducing the inertia weight from an initial value of 0.9 to 0.1 in even steps over the maximum number of iterations.

The optimal individual and social acceleration constants for this type of application are $c_1$ = 2.5 and $c_2$ = *1.5*, which indicates that giving more importance to the individual's knowledge with respect to the social information improves the performance of the PSO in this particular type of application [11], [21].

The value for maximum velocity has been determined to be equal to 9 in the case of the bus number (rapid changes are allowed) [11], and equal to 50 in the case of the STATCOM size [21]. Accordingly, the maximum velocity vector is:

$$v_{\max} = \begin{bmatrix} 9 & 50 & 9 & 50 \end{bmatrix} \tag{13}$$

In the case of the number of particles in the swarm and the maximum iteration number, there is no previous work to guide the setting of these parameters; different values are therefore tried according to Table I. It is important to note that there is a trade-off between the number of particles, the number of iterations, and the computational effort; it is therefore preferred to keep the values of these two parameters as small as possible.

TABLE I
PSO PARAMETERS

| Parameter | Tested values |
|---|---|
| Number of particles | {15, 20} |
| Number of iterations | {50, 75, 100} |
| Inertia weight | Linearly decreased |
| Social acceleration constant ($c_1$) | 2.5 |
| Social acceleration constant ($c_2$) | 1.5 |
| $V_{max}$ for bus location | 9 |
| $V_{max}$ for STATCOM size | 50 |

The final implementation of the PSO algorithm is illustrated in the flow chart shown in Fig. 3.

## V. SIMULATION RESULTS

### *A. PSO Parameter.*

In order to find the best set of parameters for the PSO, 50 trials are performed for each possible set of parameters. For each trial the best fitness function value is recorded and once all 50 trials have been performed, the minimum, maximum, average, and standard deviation 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 the swarm converges to any feasible solution (optimal or near optimal).

The simulation results indicate that the choice of the number of particles equal to 20 and the maximum number of iterations equals to 100, gives the best performance in terms of the standard deviation (more accuracy in finding the best solution) and CR. Other simulations were carried out with a larger number of individuals (up to 50 particles) and iterations (up to 500) without finding any significant improvement in the PSO performance; however the computational time was, as expected, considerably larger.

The optimal set of parameters appears in Table II.

TABLE II
OPTIMAL PSO PARAMETERS

| Parameter | Tested values |
|---|---|
| Number of particles | 20 |
| Number of iterations | 100 |
| Inertia weight | Linearly decreased |
| Social acceleration constant ($c_1$) | 2.5 |
| Social acceleration constant ($c_2$) | 1.5 |
| $V_{max}$ for bus location | 9 |
| $V_{max}$ for STATCOM size | 50 |

### *B. Power Flow Results.*

The solution found by the PSO algorithm, in terms of bus location and size for each STATCOM unit, is shown in Tables

III and IV. Additionally the power flow results, with and without the STATCOM units is shown in Table V.

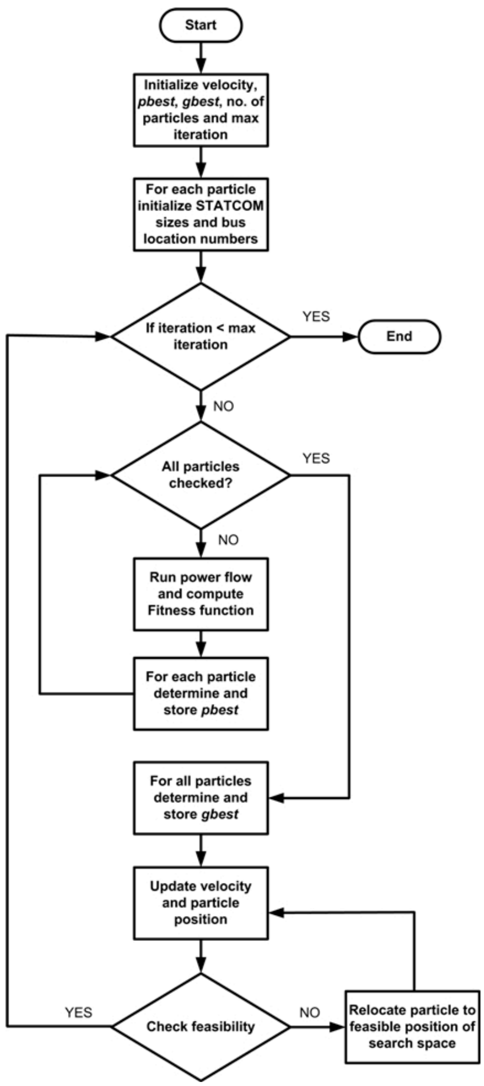


Fig. 3. Flow chart of the implemented PSO.

TABLE III
SOLUTION FOUND BY PSO ALGORITHM

| STATCOM Unit | Location (Bus number) | Size (MVA) |
|---|---|---|
| 1 | 378 | 95 |
| 2 | 430 | 137 |

TABLE IV
RESULTS FOR VOLTAGE DEVIATION METRIC ($J_I$)

| Parameter | Value |
|---|---|
| $J_I$ without STATCOM units | 0.2481 |
| $J_I$ with STATCOM units | 0.1753 |
| Minimum $J_I$ | 0.1753 |
| Maximum $J_I$ | 0.2265 |
| Average $J_I$ | 0.2076 |
| Standard deviation $J_I$ | 0.028% |
| Convergence rate (%) | 60% |

The system without the STATCOM has 7 buses with voltages below 0.95 p.u., these buses correspond to the two load centers described in section II. Once the STATCOM units are connected to buses 378 and 430, the voltage deviations improve in the respective closest load area.

TABLE V
BUS VOLTAGES FROM POWER FLOW RESULTS

| Bus number | Voltage p.u. w/o STATCOM units | Voltage p.u. with STATCOM units |
|---|---|---|
| 343 | 1.0088 | 1.0342 |
| 344 | 0.9902 | 1.0244 |
| 366 | 1.0200 | 1.0200 |
| 367 | 0.9565 | 0.9683 |
| 368 | 1.0014 | 1.0106 |
| 369 | 1.0400 | 1.0400 |
| 370 | 1.0125 | 1.0158 |
| 371 | 0.9826 | 0.9870 |
| 372 | 0.9743 | 0.9794 |
| 373 | 1.0200 | 1.0200 |
| 374 | 0.9876 | 0.9929 |
| 375 | 0.9903 | 1.0068 |
| 376 | 0.9567 | 0.9975 |
| 377 | 0.9607 | 1.0074 |
| 378 | **0.9126** | 1.0000 |
| 379 | **0.9321** | 0.9885 |
| 380 | **0.9440** | 0.9771 |
| 381 | 1.0220 | 1.0220 |
| 382 | 1.0175 | 1.0298 |
| 383 | 0.9625 | 1.0046 |
| 384 | 0.9652 | 1.0027 |
| 385 | **0.9399** | 0.9933 |
| 386 | 1.0190 | 1.0256 |
| 387 | 1.0118 | 1.0216 |
| 388 | 1.0234 | 1.0338 |
| 389 | 1.0317 | 1.0421 |
| 390 | 1.0180 | 1.0180 |
| 391 | 1.0275 | 1.0360 |
| 392 | 1.0300 | 1.0300 |
| 393 | 0.9899 | 0.9967 |
| 394 | 1.0300 | 1.0300 |
| 395 | 1.0300 | 1.0300 |
| 396 | 0.9888 | 1.0000 |
| 397 | 1.0200 | 1.0200 |
| 398 | 1.0233 | 1.0302 |
| 399 | 1.0183 | 1.0282 |
| 402 | 1.0272 | 1.0370 |
| 407 | 1.0000 | 1.0000 |
| 408 | 0.9848 | 0.9868 |
| 414 | 1.0292 | 1.0391 |
| 430 | **0.9354** | 1.0000 |
| 431 | 0.9690 | 1.0102 |
| 432 | **0.9203** | 0.9679 |
| 433 | **0.9150** | 0.9544 |
| 437 | 0.9550 | 0.9667 |

## C. Alternative Solutions

The nature of the problem defined in section II (constrained multi-objective optimization problem) allows the possibility of having more than one solution. In this case the PSO algorithm is able to find different options for both placement and sizing of the STATCOM units that gives similar fitness function values ($J$) and voltage deviation metric ($J_I$). The existence of these multiple solutions constitutes the Pareto front for this particular problem and gives more flexibility to take the final decision about the locations and sizes of the STATCOM units.

The multiple results obtained for this problem are shown in Table VI.

TABLE VI
ALTERNATIVE SOLUTIONS FOUND BY PSO ALGORITHM

| Solution | STATCOM #1 (Bus, Size) | STATCOM #2 (Bus, Size) | ($J$, $J_1$) |
|---|---|---|---|
| 1 | (377, 154) | (432, 144) | (0.767, 0.171) |
| 2 | (378, 95) | (430, 137) | (0.639, 0.175) |
| 3 | (378,150) | (433,103) | (0.667, 0.162) |

*D. Analysis under Different Load Conditions.*

In order to study the effect of the load conditions in the optimal solution found by the PSO algorithm (solution number 2 on Table VI), simulations are carried out by changing the load in each load center in a range from 90% to 110%.

In the case of load center 1 (buses 377-380) the load change is applied to buses 378, 379 and 380; while in the case of load center 2 (430-431) the variations involve buses 430, 432 and 433. It is important to note that the geographical distance between the two load centers is relatively large, thus the change in the load conditions in one center has a minimum impact in the other center.

The results obtained by the different load conditions in center 1 are shown in Table VII. The same results in the case of load center 2 are presented in Table VIII.

TABLE VII
LOCATION AND SIZE OF STATCOM UNIT 1 FOR DIFFERENT LOAD CONDITIONS

| Load (%) | Location (Bus) | Size (MVA) |
|---|---|---|
| 90 | 378 | 18 |
| 95 | 378 | 53 |
| 100 | 378 | 95 |
| 105 | 378 | 112 |
| 110 | 378 | 189 |

TABLE VIII
LOCATION AND SIZE OF STATCOM UNIT 1 FOR DIFFERENT LOAD CONDITIONS

| Load (%) | Location (Bus) | Size (MVA) |
|---|---|---|
| 90 | 433 | 20 |
| 95 | 433 | 50 |
| 100 | 430 | 137 |
| 105 | 430 | 181 |
| 110 | 431 | 242 |

From Table VII, the location of the STATCOM doesn't change under different load conditions, however the requirements in terms of reactive power do change. Fig. 4 illustrates the relationship between the load conditions in center 1 and the STATCOM unit located in this load center.

In the case of load center 2, the position of the STATCOM varies under different load values. For relaxed load conditions (90% and 95% of load in load center 2), the STATCOM is located at the bus with the lower bus voltage (bus 430). However, if the load increases (cases of 105% and 110% loading) the location moves to buses 430 and 431, thus it is not possible to establish a strict correlation between load conditions and STATCOM size.

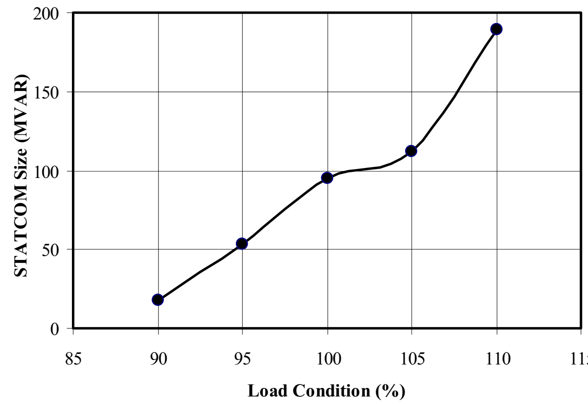


Fig. 4. STATCOM size for different load conditions in load center 1

Finally, Table IX and Fig. 5 show the impact of the two STATCOM units on the voltage deviation metric ($J_1$) for different load conditions.

TABLE IX
IMPROVEMENT ON $J_1$ FOR DIFFERENT LOAD CONDITIONS

| Load (%) | $J_1$ w/o STATCOM | $J_1$ with STATCOM | Improvement (%) |
|---|---|---|---|
| 90 | 0.1868 | 0.1786 | 4.4 |
| 95 | 0.2120 | 0.1776 | 16.2 |
| 100 | 0.2481 | 0.1753 | 29.3 |
| 105 | 0.2952 | 0.1771 | 40.0 |
| 110 | 0.3540 | 0.1696 | 52.1 |

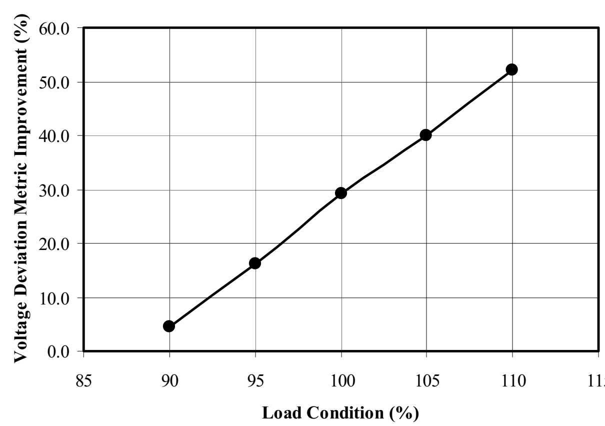


Fig. 5. Improvement on $J_1$ for different load conditions

Considering the information presented in Table IX, the improvement in the voltage deviation metric ($J_1$) changes dramatically as the loading is increased. In fact, an improvement greater that 50% is achieved for the highest load condition (110% loading). Fig 5 shows that the improvement in $J_1$ changes linearly with respect to the load condition.

## VI. Conclusions and Future Work

This study has shown step by step the application of the Particle Swarm Optimization method to solve the problem of optimal placement and sizing of multiple STATCOM units in a medium size power network.

The algorithm is easy to implement and it is able to find multiple optimal solutions to this constrained multi-objective problem, giving more flexibility to take the final decision about the location and sizes of the STATCOM units.

The settings of the PSO parameters are shown to be optimal for this type of application; the algorithm is able to find the optimal solutions with a relatively small number of iterations and particles, therefore with a reasonable computational effort.

The load profile has been modified in the main load centers in order to measure the impact on the size and location of each STATCOM unit. The results indicate that in one of the load centers the location of the STATCOM does not change but its size decreases linearly below 100% loading and tends to have a quadratic shape above this condition. In the other load center the optimal location changes, moving from the bus with the lowest voltage to a central bus in the same area. Additionally, the impact of the two STATCOM units in the power system, in terms of the improvement of the voltage profile, becomes more significant as the loading increases.

The results as promising for the medium size power network used as an example. For large power systems, the PSO algorithm could have a significant advantage compared to exhaustive search and other methods by giving better solutions with less computational effort. Future work can be done by testing the algorithm on larger power systems and including other types of FACTS devices. Additionally, different optimization criteria can be considered such as minimization of transmission losses and stability issues.

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## VIII. Biographies

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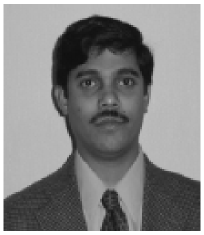

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