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Optimization of Multi-FACTS Devices for Multi-objective Voltage Stability Problem: A Comparative Study

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***Abstract*— This paper deals with the problem of optimal location of FACTS devices in power systems. The problem is formulated as a mixed discrete-continuous real multi-objective optimization problem. Where, the location, settings, and number of static compensator (STATCOM) and static synchronous series compensator (SSSC) are considered as the decision variables of the optimization problem. The STATCOM and SSSC are optimized in the way increase the static voltage stability margin (SVSM) and decrease the real power losses (RPL) of the power system. To solve this multi-objective optimization problem, three multi-objective evolutionary algorithms are proposed namely strength Pareto Evolutionary algorithm (SPEA 2), Non-dominated sorting genetic algorithm (NSGA-II) and Non-dominated sorting particle swarm optimization (NSPSO). The three algorithms are improved in order to handle the discrete as well as the continuous decision variables. The proposed methods are applied on IEEE 30-bus. The obtained results show the capability of STATCOM and SSSC to enhance voltage stability and all power system performance. Furthermore, the proposed methods show a great efficiency to solve the mixed discrete-continuous multi-objective optimization problem.**

***Index Terms*— FACTS devices, STATCOM, SSSC, voltage stability, real power losses, multi-objective optimization. Multi-objective genetic algorithm**

1. INTRODUCTION

In the last few years, many electric utilities in the world are paying attention at voltage stability problem in the power systems [1]. The voltage instability can occurs when a power system is heavily loaded in transmission lines and ⁄or lacks in local reactive power sources [2].

Several efforts have been made to find the ways to ensure the security of the system in terms of voltage stability. It is found that Flexible Alternating Current Devices (FACTS) are a good choice to improve the Static Voltage Stability Margin and power systems performances. Taking advantages of the FACTS devices depends greatly on how these devices are placed in the power system, specifically on their type, location, and settings.

In a practical power system, allocation of FACTS devices depends on a comprehensive analysis of steady state analysis, small signal stability, voltage stability, and other practical factors such as cost and installation conditions also need to be considered [3]. In the literature, several mathematics methods are proposed to optimal location of FACTS devices, such as modal analysis, continuation power flow, optimal power flow in, and sensitivity analysis [2].

Rather than the mathematical techniques cited above, population based heuristic methods have been also applied with success to the problem of location of FACTS devices in power systems. In [3], the authors applied the Genetic algorithms (GA) to optimize four types of FACTS devices, in order to enhance the power system loadability. The optimizations were performed on three parameters: locations, types, and settings of these devices. In [4] Particle Swarm Optimization (PSO) techniques were proposed to find the optimal location of multi-types of FACTS in order to minimize the installation cost and to improve the system loadability. The two objectives were aggregated to a single objective function. In [5] GA was used to find the optimal number and location of FACTS devices that maximize the compromise between three objectives using fuzzy logic. The proposed objective functions are: power system capability, social welfare, and to satisfy contractual requirements in an open market power.

From the previous works, we can conclude that the problem of optimal location of FACTS devices is generally formulated as a mono-objective optimization problem. Unfortunately, the formulation of FACTS location problem as a mono-objective optimization is not quite practical. While, planners the power systems aim to take advantages of FACTS devices considering several objectives at the same time.

In contrary to the previous cited works, Benabid et al. [6, 7] formulates the optimal location and settings of SVC and TCSC as a real mixed integer continuous multi-objective optimization problem. Where, the problem is formulated as a bi-objective and a three-objective optimization problem. The FACTS devices are optimized in order to optimize the voltage stability,

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real power losses and load voltage deviation of power systems.

In this paper, the optimal location and settings of STATCOM, SSSC is formulated as multi-objective optimization problem. Where, three evolutionary algorithms are proposed to fulfill this purpose, namely: strength Pareto Evolutionary algorithm (SPEA 2) and Non-dominated sorting genetic algorithms (NSGA-II) and Non-dominated sorting particle swarm optimization (NSPSO). The three algorithms are specialized in the continuous multi-objective optimization. In this paper, we propose an enhancement of these methods in order to handle the continuous as well as the discrete decision variables.

The remainder of this paper is organized as follows. Section 2 is allowed for STATCOM and SSSC modeling. The problem formulation is presented in the section 3. In section 4, we will present a description of the proposed methods. The results and discussions are presented in section 5. Finally the main gained conclusions are presented in section 6.

2. STATCOM AND SSSC MODELING

As we already mentioned, this paper focus on the impacts of three types controllers on voltage stability and overall power systems performance such as real power system losses and buses voltage profile. So to do these purposes an appropriate modeling of these devices is required. The STATCOM and SSSC behavior can be generally modeled by a set of differential and algebraic equation as follows:

$$\dot{x} = f\left(x, y, u\right) \tag{1}$$

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

Where,
x is the vector of FACTS state variables;
y is the vector of network algebraic variables;
u is the FACTS input variables.

The following subsections describe the models of STATCOM and SSSC devices used in this paper.

2.1 STATCOM model

STATCOM is a shunt compensator device based on voltage source inverter (VSI), which converts a DC input voltage into AC output voltage in order to compensate the active and reactive power by controlling the bus voltage where is installed [8]. In this paper, the STATCOM is modeled by the current injection model [9]. The injected current is remaining in quadrature with the bus voltage where the STATCOM is installed. Thus, only the reactive power is exchanged between the ac system and the STATCOM. The differential and algebraic equations of STATCOM are presented as follows.

$$\dot{i}_{STATCOM} = \left(K\left(V - V_{ref}\right) - i_{STATCOM}\right) \big/ T \tag{3}$$

$$Q = i_{STATCOM} V \tag{4}$$

During the power flow calculation; the STATCOM is considered as *PV* generator with *P*=0, and without reactive power limits. After the convergence of power flow program, the STATCOM will be initialized. The STATCOM is equipped with non-windup limiter presented by the equation (5). Thus the current is locked when its limits are reached and therefore the equation (3) will be equal to zero.

$$i_{STATCOM}^{Min} \le i_{STATCOM} \le i_{STATCOM}^{Max} \tag{5}$$

2.2 SSSC model

SSSC is a series connected compensator device that controls the current and thus the power flowing through the line. The SSSC is modeled by a series voltage source injected in quadrature with line current. Therefore, the only controlled parameter is the magnitude of the output voltage.

$$\dot{v}_{SSSC} = \left(v_{SSSC}^{0} - v_{SSSC}\right) \big/ T \tag{6}$$

$$v_{SSSC}^{Min} \le v_{SSSC} \le v_{SSSC}^{Max} \tag{7}$$

The advantage of SSSC is that it does not affect the impedance of the line, thus, there is no danger of having resonance problem [8].

3. PROBLEM FORMULATION

As we already mentioned, the optimal location of STATCOM and SSSC devices problem is formulated as multi-objective optimization problem. This last involve an optimization of several conflicting and non-consumable objectives at the same time to obtain a set of non-dominated solutions. The general form of a multi-objective optimization minimization problem can be formulated as follows [16]:

$$\text{Minimize} f_i\left(x\right),\ i = 1,\ldots,N_{obj} \tag{8}$$

$$\text{Subject to constraints: } \begin{cases} g_j\left(x\right) = 0 & j = 1,\ldots,M \\ h_k\left(x\right) \le 0 & k = 1,\ldots K \end{cases} \tag{9}$$

where, f_i is the i^{th} objective function; x is the decision vector, N_{obj} is the number of objectives, g_j is the j^{th} equality constraint, and h_k is the k^{th} inequality constraint.

In this paper, the main objective behind the optimization of STATCOM and SSSC is to increase static voltage stability margin (SVSMS) and decrease the real power losses (RPL). The detail of these objectives is presented below.

3.1 Static Voltage Stability Margin (SVSM)

Static Voltage stability Margin (SVSM) is the most widely accepted index for proximity of voltage collapse. SVSM is defined as the largest load change that the power system may sustain at a bus or collective of buses from a well defined operating point (base case). The SVSM is calculated considering STATCOM and SSSC using Power System Analysis Toolbox (PSAT) [9].

The maximization of SVSM can be presented as follows:

$$Max\{\lambda\} \tag{10}$$

Where, λ is the *SVSM* or the loading margin.

3.2 Real Power Losses (RPL)

This objective consists of minimizing the real power loss in the transmission lines and which can be expressed as:

$$Min\left\{\sum_{k=1}^{nl} g_k\left[V_i^2+V_i^2-2V_iV_j\cos(\delta_i-\delta_i)\right]\right\} \tag{11}$$

where, nl is the number of transmission lines; g_k is the conductance of the kth line; $V_i\angle\delta_i$ and $V_j\angle\delta_j$ are the voltages at the end buses i and j of the k^{th} line, respectively.

3.3 Equality and Inequality Constraints

The equality and inequality constraints must be satisfied during the optimization procedure. The equality constraints represent the typical load flow equations. The inequality constraints represent the reactive power limit of generators, and the operating limits of the STATCOM and SSSC. Moreover, two security limits are considered, namely the thermal limits of the transmission lines and the bus voltage limits, which are applied on *RPL* only. For the *SVSM* objective, the security limits are not considered, because the voltage collapse is generally occurs, after the violation of the security limits. In this work, if the security limits are not satisfied the current solution is rejected.

4. PROPOSED METHODS

Three multi-objective optimization methods are proposed to solve the optimal location of FACTS devices problem. These methods are improved in the way to handle the discrete as well as the continuous decision variables. In the above subsection the main loop and principle of these methods is presented.

4.1 Strengthen Pareto Evolutionary Algorithm 2 (SPEA 2)

Strength Pareto evolutionary algorithm (SPEA) is a multi-objective optimization evolutionary algorithm developed by Ziztler et al. [10]. SPEA has shown very good performance in comparison to other multi-objective evolutionary algorithms. SPEA 2 [11] is the improved version of SPEA; it is proposed to overcome the drawbacks existing in the old version SPEA. SPEA 2 algorithm has the following enhancements: a fine-gained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method [11].

The SPEA 2 function has three input parameters namely: population size N, Archive sizes $\overline{N}$, maximum number of generations T. and the non-dominated set A as the output of the function.

The main loop of SPEA2 is as follows [11]:

Step1: *Initialization*

Generate an initial population P_0 and create the empty archive (external set) $\overline{P}_0=\varnothing$. Set t=0.

Step2: *Fitness evaluation*

Calculate fitness values of individuals in P_t and $\overline{P}_t$.

Step3: *Environmental selection*

Copy all non-dominated individuals in P_t and $\overline{P}_t$ to $\overline{P}_{t+1}$. If size of $\overline{P}_{t+1}$ exceeds $\overline{N}$ then reduce $\overline{P}_{t+1}$ by means of the truncation operator, otherwise, If size of $\overline{P}_{t+1}$ is less that $\overline{N}$ then fill $\overline{P}_{t+1}$ with dominated individuals in P_t and $\overline{P}_t$

Step4: *Termination*

If t > T then set A to the set of decision vectors represented by the non-dominated individuals in $\overline{P}_{t+1}$. Stop.

Step5: *Mating selection*

Perform binary tournament selection with replacement on $\overline{P}_{t+1}$ in order to fill the mating pool.

Step6: *Variation*

Apply recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population. Increment generation counter (t=t+1) and go to Step 2.

4.2 Non-dominated sorting genetic algorithm 2 (NSGA-II)

Non-dominated sorting genetic algorithm NSGA [12] is an evolutionary algorithm specialized in multi-objective optimization. It is a very effective algorithm but has been criticized for its computational complexity. An enhanced version NSGA-II [13] which has a better sorting algorithm incorporates elitism and crowding distance algorithm instead of sharing parameter. The main loop of NSGA-II is presented bellow.

For each iteration k do:

1. $R^k=P^k\cup Q^k$ (*combine parent and offspring population*)

2. $F = non\_dom\_sort\left(R^k\right)$ (*Application the non-dominated sorting on* R^k)
3. $P^{k+1} = \phi \,\&\, i = 1$
4. until $\left|P^{k+1}\right| + \left|F_i\right| \le N$ (*until the parent population is filled*)
    a. $i=i+1$
    b. Calculate the crowding distance for each particle in F_i
    c. $P^{k+1} = P^{k+1} \cup F_i$
5. Sort *(Fi)* (*sort in descending order*)
6. $\left|P^{k+1}\right| = \left|P^{k+1}\right| \cup F_i\left(N - \left|P^{k+1}\right|\right)$
   (*Choose the first* $N - \left|P^{k+1}\right|$ *elements of* F_i)
7. Q^{k+1} (use selection, crossover and mutation to create a new population with using P^{k+1} .
- *k=k+1*

4.3 Non-dominated sorting particle swarm optimization (NSPSO)

Non-dominated sorting Particle Swarm optimization (NSPSO) [14] is based on the same non-dominated sorting, elitism and crowding distance proposed in NSGA-II. Instead of comparing each particle with its *pbest*; NSPSO combine the *N* particles with its *N pbest* to a temporary set of population of *2N* particles. After this, the non-dominated sorting will be applied to store the particles in various fronts considering Pareto domination concept.
The original NSPSO proposed in [14] is improved in order handle the discrete as well as the continuous variables. Where we used the same methodology proposed in [15].

The main loop of NSPSO is presented bellow.

For each iteration k do:
1. $R^k = x^k \cup pbest^k$ (combine the current solution and all personal best)
2. $F = non\_dom\_sort\left(R^k\right)$ (Application the non-dominated sorting on R^k)
3. $pbest^{k+1} = \phi \,\&\, i = 1$
4. until $\left|pbest^{k+1}\right| + \left|F_i\right| \le N$ (until the *pbest* set is filled)
    a. $i=i+1$
    b. Calculate the crowding distance for each particle in F_i
    c. $pbest^{k+1} = pbest^{k+1} \cup F_i$
5. Sort *(Fi)* (*sort in descending order*)
6. Select randomly *gbest* for each particle from a specified top part *(e.g. top 5%)* of the first front F_1
7. $\left|pbest^{k+1}\right| = \left|pbest^{k+1}\right| \cup F_i\left(N - \left|pbest^{k+1}\right|\right)$
   (*Choose the first* $N - \left|pbest\right|$ *elements of* F_i)
8. x^{k+1} (Update the velocity and position of all particles with using the new *pbest* and *gbest*.
- *k=k+1*

4.4 The best compromise solution

5. RESULTS AND DISCUSSIONS

The impact STATCOM and SSSC on voltage stability, real power losses and load buses voltage profiles is tested on IEEE 30-bus 6 generators test system [17]. The system has six generators located at buses 1, 2, 5, 8, and 13 and four transformers with off-nominal tap ratio in line 6-9, 6-10, 4-12, and 27-28. The lower voltage magnitude limits at all buses are 0.95 pu for all buses and the upper limits are 1.1 pu for generators 2, 5, 8, and 13, and 1.05 pu for the remaining buses including the reference bus 1. Moreover, the apparent power limits of lines are considered. The total active and reactive powers of system load are respectively: 283.4 MW, and 126.2 MVAR.

5.1 Analysis and assessment of voltage instability

The voltage stability margin of the IEEE 30-bus without FACTS devices is depicted in fig.1.

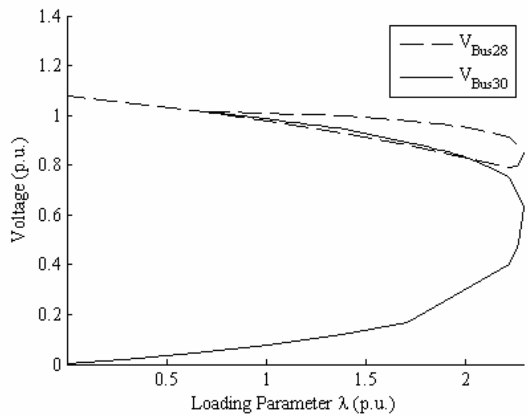

Fig. 1 *PV* curves.

The figure 1 depicts the static voltage stability or the loading margin of the system that is 2.289 pu. From this figure, we can observe the voltage stability and collapse mechanisms. Where the voltage is decreases with the increase of loading parameter. At the nose point of the *PV* curve, the voltage decreases rapidly in incontrollable way, and this phenomenon is the voltage collapse.

Regarding the *PV* curve of bus 28, the voltage collapse is occurred at voltage value is very near to the nominal voltage. Thus we can conclude that the voltage value is not an efficient indicative of voltage collapse.

5.2 Impacts of STATCOM, SSSC on Static voltage stability

The figure 2 depicts the SVSM for STATCOM installed in bus 30, and for the SSSC installed in the line 1-2. The results are compared to the case without FACTS. From fig. 2, it is clear that the STATCOM provides the best SVSM of 2.545 pu. Furthermore, the voltage at bus 30 is remained at the reference point until the voltage collapse. These, approve the capability of STATCOM to control the Voltage at the bus where is installed. We can remark also from fig. 2 that the SSSC, it is clear that this last enhances the SVSM to 2.424 pu.

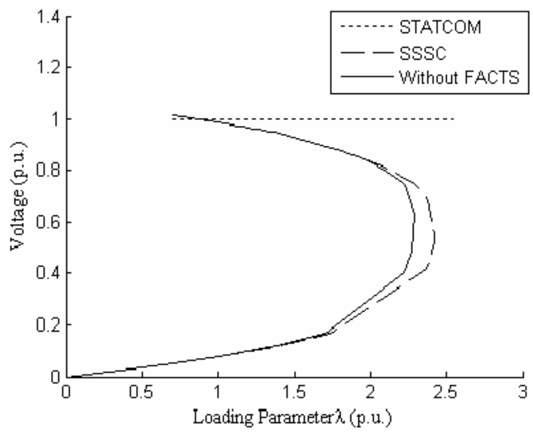

Fig.2. Impact of STATCOM and SSSC on static voltage stability margin.

5.3 Impacts of STATCOM and SSSC on real and reactive power losses

From figure 3 and 4 we can conclude that the STATCOM and the SSSC decrease both real and reactive power losses. Otherwise the SSSC is the best that reducing both real and reactive losses. This is due to the reason that the SSSC influence directly on the current flow in the line consequently on power losses. So we can conclude that the SSSC is better than the STATCOM in the viewpoint power flow control and thus reducing of power losses.

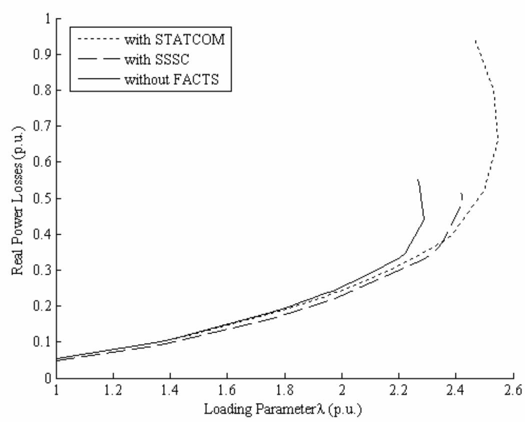

Fig.3. Impact of STATCOM and SSSC on real power losses

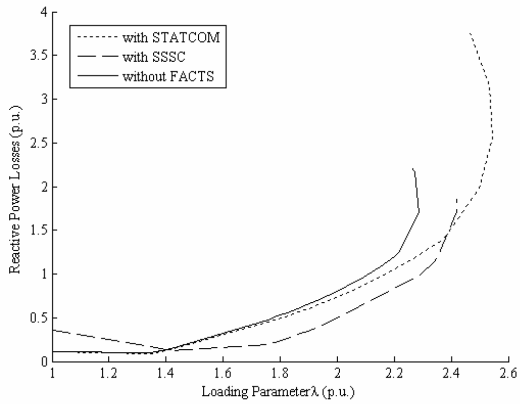

Fig.4. Impact of STATCOM and SSSC on reactive power losses

5.4 Impacts of STATCOM and SSSC on buses voltage profiles

The figure 3 illustrates the voltage profiles in the presence of SATATCOM, SSSC, and in the case without FACTS. From fig. 5, we remark that the STATCOM provides the best voltage profile at the nose curve. Otherwise, the SSSC enhance also the voltage profile compared to the case without FACTS. These results approve the main purpose of the STATCOM that is the voltage control.

5.5 optimal location, number and setting of STATCOM and SSSC

An appropriate location, setting and number of STATCOM and SSSC is necessary for a good effectiveness of these devices. In the following subsections, we will apply and compare the proposed SPEA 2, NSGA-II and NSPSO to optimize the multi-objective problem.

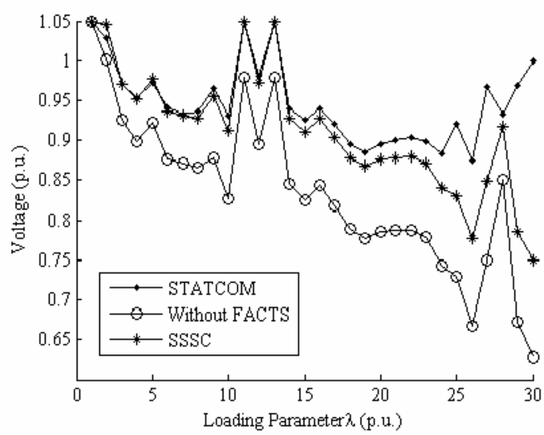

Fig.5. Impact of STATCOM and SSSC on voltage profile.

The decision variables of the problem are presented as follows:

1) Decision variables of STATCOM

Firstly, we install one STATCOM at each load bus. Thus in our problem, we are 24 STATCOMs in the system. And during the optimization the decision variables of STATCOM are the voltage reference $V_{STATCOM}^{ref}$, and activation of STATCOM $Act_{STATCOM}$. The two decision variables are limited as follows:

$$0.95pu \le V_{STATCOM}^{ref} \le 1.05pu \qquad (12)$$

$$Act_{STATCOM} = \begin{cases} Act_{STATCOM} = 0 \\ Act_{STATCOM} = 1 \end{cases} \qquad (13)$$

where, $Act_{STATCOM}$ is a discrete variable. If $Act_{STATCOM}$ =0, i.e. the STATCOM is not activated, otherwise, if $Act_{STATCOM}$ =1 i.e. the STATCOM is activated. So, the number STATCOM is the sum of the activated STATCOMs and the emplacement of STATCOM is the emplacement of the activated STATCOM.

2) Decision variables of SSSC

Firstly and like STATCOM, we install one SSSC at each line. So, we have 41 SSSCs installed in the system. The decision variables of the SSSC are selected as follows. Cp_{SSSC} is the percent compensation of line and Act_{SSSC} is a discrete variable that presents the state of the SSSC; activates or not. The two decision variables are limited as follows.

$$-0.2Xline \le Cp_{SSSC} \le 0.80Xline \qquad (14)$$

$$Act_{SSSC} = \begin{cases} Act_{SSSC} = 0 \\ Act_{SSSC} = 1 \end{cases} \qquad (15)$$

where, Act_{SSSC} is a discrete variable that present the state of the SSSC. If Act_{SSSC}=0, i.e. the SSSC is not activated, otherwise, if Act_{SSSC} =1 i.e. the SSSC is activated. So, the number SSSCs is the sum of the activated SSSCs and the emplacement of SSSCs is the emplacement of the activated SSSCs.

3) Trade-off surfaces of the multi-objective optimization problem.

This multi-objective optimization problem has two objective functions namely SVSM and RPL and 130 decision variables presented by the number, placement, and settings of STATCOM and SSSC. The security operating limits such apparent power flow limit of lines and load buses voltage limits are considered during the optimization. We noticed that, the size of the non-dominated solution archive is not limited during the optimization.

The trade-off surface of the three algorithms is depicted in fig.6. From fig.6, we can conclude that the three proposed algorithms are successfully solving the optimal location of FACTS devices formulated as mixed discrete-continuous optimization problem. Compared the three trade-off surfaces, we can remark that the SPEA 2 provides the best non-dominated solutions. Also, NSPSO is more efficient than NSGA-II in terms of Pareto dominance.

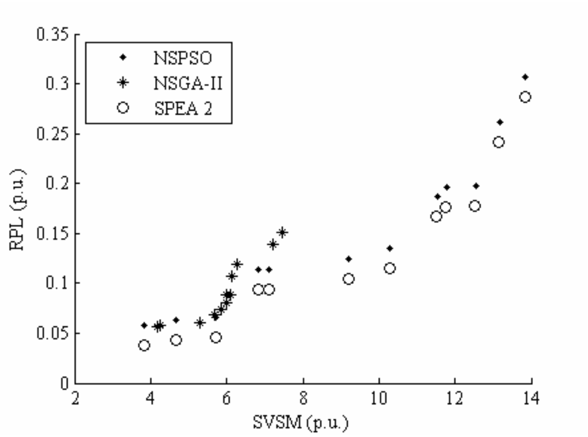

Fig. 6 Trade-off surface of NSPSO, NSGA-II and SPEA 2.

6. CONCLUSION

In this work, we investigate the impacts of STATCOM and SSSC on power systems. Firstly, the impacts of STATCOM and SSSC on voltage stability margin, power losses and buses voltage profile are investigated. The results show that both STATCOM and SSSC enhance voltage stability, improve buses voltage profiles, and also reduce the real and reactive power losses in the system. Compared the STATCOM and SSSC; the STATCOM shows its superiority in terms of static voltage stability and voltage profile enhancement. In addition, the SSSC is better than STATCOM in terms of power losses decreasing.

Second, a new formulation of the optimal location of FACTS devices is proposed. Where, we consider the optimal location of STATCOM and SSSC as a mixed discrete-continuous real multi-objective optimization problem. The decision variables of the problem are: location, setting and number of STATCOM and SSSC. To solve this optimization problem, three multi-objective optimization evolutionary algorithms namely SPEA 2, NSGA-II and NSPSO are proposed and enhanced in order to handle the discrete and the continuous variables. The results show that the proposed methods are effective tools to find the optimal location and setting of STATCOM and SSSC devices for multi-objective problem. Furthermore, the methods do not impose any limitation on the number of objectives and beings applied to other FACTS devices like UPFC.

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