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OPTIMAL LOCATION AND SETTING OF FACTS DEVICES USING NON-DOMINATED SORTING PARTICLE SWARM OPTIMIZATION IN FUZZY FRAMEWORK

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Abstract- FACTS devices allocation and assessing its optimal capacity is one of most discussed subject in scheduling and utilization of the power system. According to value of the matter such as power loss reduction, enhance of the stability margin and also, less cost imposition need to create a partial balance between these several goals, FACTS allocation problem established as a multiobjective optimization problem. It postulates that the achievement of those registered goals simultaneously, implicates the use of the multiobjective optimization methods and finally, reaches the Pareto optimal sets. A hybrid approach based on non-dominated sorting particle swarm optimization (NSPSO) algorithm and Fuzzy logic is presented in this paper that is able to present the Pareto optimal sets in the meantime to attend the technical and economic aspects. In this paper, the efficiency of this approach's performance in test IEEE 14-bus and 30-bus systems is analyzed.

Keywords: FACTS Devices Allocation, NSPSO Algorithm, Fuzzy Logic, Multiobjective Optimization.

I. INTRODUCTION

Nowadays the nations is becoming ever more dependent on its electrical power grid and due to the load demand is increasing, so because of the difficulty of the new line construction, and its environmental and economic considerations, the utilities are now forced to increase the utilization of existing transmission facilities while at the same time, whilst the power grid is becoming increasingly vulnerable to both natural and intentional disturbance, some problems such as power loss enhancement, voltage profile decay and stability margin decrement appear more.

Resolving these problems and improvement of the system's performance is therefore of paramount importance. The need for more efficient electricity system has given rise to innovative technologies in power generation and transmission. Flexible AC transmission systems is a good example of a new development in transmission systems, FACTS as they are generally known, are new devices that improve transmission systems. These devices cause the Transmission systems could be flexible to react to more diverse generation and load patterns. Flexible AC Transmission Systems (FACTS) is a technology that significantly alters the way transmission systems are developed and controlled together with improvements in asset utilization, system flexibility and system performance.

However, to obtain good performance from these controllers, proper placement of these devices in the grid is important [1-14]. In the past, various optimization techniques have been used for the placement of FACTS devices. In [1] a sensitivity based method is proposed for finding the optimal placement of FACTS devices in the system. S.H. Song et al. [2] have applied an analytical method which is implemented to minimize the security indices. Ref. [3] introduces a PSO based approach to find the optimal location of FACTS devices with minimum cost of installation to improve system loadability. The optimal location of FACTS devices in power system using genetic algorithm is suggested in [4]. This method optimizes the type and rated value of the FACTS devices simultaneously.

In [5], a genetic algorithm is presented to seek the optimal location of multi-type FACTS devices. In this method the system loadability is applied as measure of power system performance. In [6], the authors proposed an approach for optimal placement of STATCOM which is based on simultaneous application of PSO and CPF to optimize the objective functions. In [7], FACTS devices are optimally allocated to achieve optimal power flow solution. In this approach, the performance of the power network is improved by a Bacterial Swarming Algorithm (BSA). In order to enhance voltage profile and reduce total real power losses, PSO and GA are used for SVC planning in [8]. In [9], a Micro-Genetic based method which is conjunction with Fuzzy logic, is used to optimize the type and rated value of the FACTS devices. In [10], a harmony search heuristic method and GA have been suggested to optimally locate the UPFC, TCPAR and SVC. From a comprehensive solution development point of view, in the procedure of transforming the multi-objective function problem to mono objective function, it is very difficult to choose appropriate weighting parameters. Considering a range of possible solutions to this problem and that a single best numerical solution may not be applicable in real-life systems due to various not-technical and non-quantifiable constraints, it would be better to identify groups of feasible solutions using multi-objective optimization algorithms, i.e. In [11], a multiobjective genetic algorithm is used to characterize the Non-dominated solutions. In this method, the optimization process is focused on three parameters: location, type and size of Facts devices.

In [12], the authors have proposed a multiobjective Particle Swarm optimization (MOPSO) to find optimal location of SVC. R. Benabid et al. [13] applied Non-dominated Sorting Particle Swarm Optimization for find the optimal location and rating of SVC and TCSC. But the procedure of the allocation is done in one load level. In [14], M. Gitizadeh has presented a multi-objective genetic algorithm (MOGA) to solve FACTS devices problem. A review of these methods reveals that most of these studies have taken into account the methods oriented towards technical criteria or to economical approach. And both technical and economic criteria are not considered in the selection procedure of the best compromise solution.

In this paper, a hybrid approach which is composed of NSPSO algorithm and Fuzzy logic is proposed to solve multiobjective FACTS devices allocation problem. Here, active power loss and L index voltage stability are optimized simultaneously in FACTS device equipped power systems while maintaining power balance constraints, active and reactive power generation limits, voltage limits, transmission line limits, and physical limits of FACTS devices. Thyristor controlled series capacitor (TCSC) and Static VAR compensator (SVC) are integrated in Power Flow equations using through the reactance model and injected power model respectively.

The optimization procedure is performed for two objective functions. The problem is formulated as a bi-objective optimization problem, considering only the minimization of active power loss and L voltage stability index. In order to demonstrate the effectiveness of the proposed approach, the modified IEEE 14-bus and 30-bus systems are taken as test systems Results obtained from the proposed approach have been compared to those obtained by PSO algorithm. In both algorithms the parameters are the same.

In section II, the bi-objective function and problem statement is discussed. Then the proposed hybrid approach will be introduced, also objective functions are described in section III. Steady state model of FACTS devices and decision algorithm are given in section IV and V, respectively. Finally the implementation of the hybrid algorithm is done at the IEEE 14-bus and 30-bus test systems and the results are analyzed in section VI. The paper closes with the conclusions in section VII.

II. MULTIOBJECTIVE OPTIMIZATION OVERVIEW

Many real world problems involve simultaneous opti mization of several objective functions. Generally, these functions are non-commensurable and often conflicting objectives. Multi-objective optimization with such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that no one can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as Pareto-optimal solutions. A general multi-objective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows:

$$\text{minimize } (F(x)) = \min[F_1(x), F_2(x), ..., F_M(x)]^T$$

$$\begin{cases} h_L(x) = 0 & L = 1, 2, \dots, e \\ g_j(x) \le 0 & j = 1, 2, \dots, N \end{cases} \tag{1}$$

where x represents the feasible search space. The objective functions are conflicting one another and the aim is optimizing them simultaneously (without loss of generality it is assumed that the objectives are to be minimized). The decision vector x belongs to the feasible region. It is the decision vector representing a solution. In order to compare candidate solution in multiobjective optimization problems, the concept of Pareto dominance is used [7, 11, 12, 13].

Definition 1: A solution x_1 is said to dominate x_2 (denoted by $x_1 < x_2$) if and only if:

$$\forall\ F_i(x_1) \le F_i(x_2) \wedge \exists\ i \in \{1, 2, ..., M\} : F_i(x_1) < F_i(x_2)$$

This means that the decision vector x_1 is not worse than x_2 in all objectives and is strictly better than x_2 in at least one objective.

Definition 2: For $S = \{x_i, i=1, ..., n\}$, solution x is said to be a non-dominated solution (Pareto solution) of set S if $x \in S$ and there is no solution $x' \in S$ for which x' dominates x.

Definition 3: Assume that set P contains all the non-dominated solutions of S, then $PF = \{v|v = [f_1(x), f_2(x) \dots f_m(x)]^T,\ x \in P\}$ is a Pareto front of set S.

The goals of multi-objective optimization are: (1) to guide the search toward the true Pareto front (non-dominated solutions) or approximate the Pareto optimal set and (2) to generate a well-distributed Pareto front.

A. Problem Statement

Many areas in power systems, including the FACTS devices placement, sizing and control, require solving one or more nonlinear, multi-objective optimization problems. While analytical methods might suffer from slow convergence and the curse of dimensionality, heuristics based evolutionary computation techniques can be an efficient alternative to solve these complex optimization problems. In this paper, the optimization problem includes basically two aspects: finding the optimal location of the device in the network, finding its optimal size, such that maximum benefit can be obtained in steady state.

Considering these two aspects, the problem becomes a multiobjective optimization problem which involves a very complex formulation and it is certainly difficult to solve in an efficient manner. Non-dominated Particle Swarm optimization (NSPSO) is one of evolutionary algorithms (EAs) that are used to explore the different parts of the Pareto front simultaneously. NSPSO algorithm is developed by Xiaodong Li in 2003, which is an extended form of PSO. Similar to PSO algorithm, NSPSO is known to effectively solve large scale nonlinear optimization problems. It is not largely affected by nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge. It can therefore be effectively applied to optimal location, sizing and control of FACTS devices in the power systems.

Moreover, NSPSO has some advantages over other similar multi-objective optimization techniques since: (i) it is easier to implement and there are few parameters to adjust, (ii) it has an effective elitism capability and (iii) NSPSO maintains the diversity of the particles with crowding distance mechanism. Thus it is capable to avoid getting trapped in local minima [13, 18]. NSPSO algorithm is based on the same non-dominated sorting concept used in NSGA-II and presented in [17] in detail. In particular, this research proposed a hybrid algorithm which is composed of NSPSO algorithm and Fuzzy logic. The task of NSPSO is to find the Pareto optimal solutions and Fuzzy system's one is to select the best compromise solution among optimal solutions. It is able to solve multiobjective problem related to FACTS devices allocation. In order to attain Pareto optimal solutions following fitness assignment scheme is considered.

In the fitness assignment procedure, NSPSO allocates a rank value r_i to each solution. The non-dominated solutions are identified and assigned the rank value 1. After removing those solutions from the population, new non-dominated solutions are assigned rank value 2. This procedure continues iteratively. In this way, non-dominated particles are always assigned the same rank. Assignment of fitness according to rank is as follows:

For the each t generation, sort population in descendent order according to rank (p, t) of the particle p. The particles rank is given by:

$$\text{rank}(p,t) = 1 + n_p^t \tag{2}$$

Dominance count is equal to the number of particles, in current population, which dominate the particle p. All non-dominated particles are assigned rank 1. Figure 1 provides a graphic example. It represents rank values for a population (size 10). First, the non-dominated solutions 1, 2 and 3 receive rank value 1, then solutions 4, 5 and 6 receive rank value 2 and the procedure continues. To promote the solutions in the sparse region, crowding distance D_i is assigned to each candidate solution. D_i is the average distance of two points on either side of the solution i along each of the objectives. With assigned r_i and D_i, any two solutions in the population can be compared. Solution i is superior than solution:

$$j \Leftrightarrow \{r_i < r_j\} \text{ or } \{r_i = r_j \text{ and } D_i > D_j\} \tag{3}$$

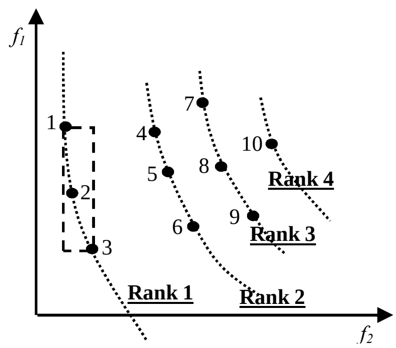

Figure 1. Fitness assignment of NSPSO in a two-objective space

The initial population of particles is initialized with random solutions. For every generation, whole the solutions move toward the Pareto Optimal Front (POF) by updating its velocity, *Pbest* and *Gbest*. This remarkable performance of NSPSO can be attributed to its use of Non-dominated sorting approach to sort the solutions. Using this principle, whole the solutions sort in different fronts. For these types of problems the Proposed Algorithm can converge in parallel to the Pareto front. While optimizing, different solutions in the population converge to different areas of the Pareto front, and thus an approximation of the Pareto front can be obtained in a single optimization run (trade-off surface) [16-18].

In absence of additional information, it is not possible to distinguish any one of the Pareto solutions as being objectively better than any others with respect to all the objectives concerned (i.e. there is no uniquely "best" solution); therefore, each of them is an acceptable solution. Once the set of optimal solutions is identified, designer has owns freedom to choose one solution out of many possible solutions based on their experience and prior knowledge and other criteria or constraints. In this paper, the choice of the optimal solution among the POF points remained to Fuzzy Inference system (FIS).

B. Brief Discussion about NSPSO

Similar to PSO algorithm, in each iteration of NSPSO's Implementation, each agent is updated with reference of two "best" values: *Pbest* and *Gbest*. Each agent seeks to modify its position using the current positions, the current velocities, the distance between the current position and *Pbest*, and the distance between the current position and *Gbest*. In NSPSO those parameters need to be tuned are: the number of particles; weighting factors; and the maximum change for a particle. In order to attaining the Pareto optimal solutions, usually the number of particles is set high.

The weighting factors, C_1 and C_2, are often to 2, though other settings are used in different papers, typically with $C_1 = C_2$ and in the range [1, 2]. Instead of comparing solely on a particle's personal best with its potential offspring, the entire population of N particles' personal bests and N of these particles' offspring are first combined to form a temporary population of $2N$ particles. After this, the non-dominated sorting concept is applied, where the entire population is sorted into various non-domination fronts. In order to ensure the best distribution of the non-dominated solutions, a new parameter called crowding distance is introduced.

It is a measure of how close an individual is to its neighbors. The global best $Gbest_i$ for the ith particle X_i is selected randomly from the top part of the first front. Based on rank value of the points, N particle are selected to play the role of *Pbest*. It should be noted that, *Pbest* is selected from the fronts which has smaller rank value and if the number of the solutions in one front is bigger than N, the selection criterion is based on the crowding distance (D). After the determination procedure of *Pbest* and *Gbest*, the position of the particles must be updated. It is done based on following equations [13, 18, 19, 20].

$$X_i^{k+1} = X_i^k + V_i^{k+1}$$
$$V_i^{k+1} = WV_i^k + C_1\text{rand1}\times(Pbest_i - X_i^k) + \quad (4)$$
$$+C_2\text{rand2}\times(Gbest_i - X_i^k)$$

where, V_i^{k+1} is current velocity of agent i at iteration k+1, X_i^k is current position of agent i at iteration k and X_i^{k+1} is current position of agent i at iteration k+1. Also, in this paper, the following weighting function is used:

$$W = W_{\max} - \left(\frac{W_{\max} - W_{\min}}{iter_{\max}}\right).\ iter \quad (5)$$

where, $W_{\max}$, $W_{\min}$ are initial/initial weight, $iter_{\max}$ is max. iteration number and $iter$ is current iteration number.

III. PROBLEM FORMULATION

The FACTS devices allocation problem using SVC and TCSC can be formulated as a mixed continues-discrete multiobjective optimization problem. The optimization parameters are FACTS locations and the levels of compensations. In this paper, these objectives include active power loss minimization and L voltage stability index minimization. They depend strongly on the available control variables. Attaining to this goal, could be achieved by placing SVC and TCSC considering the following objective functions.

A. Real Power Loss

The first objective is related to real power loss. This term, called RPL, is computed by active power flow through the transmission lines of the system and can be expressed as:

$$F_1 = \min\{\sum_{k=1}^{N_l} g_k[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j]\} \quad (6)$$

where, N_l is the number of transmission lines; g_k is the conductance of the kth line; $V_i<\delta_i$, $V_j<\delta_j$ are the voltages at the end buses i and j of the kth line, respectively.

B. Voltage Stability Index

The second objective function concerns voltage stability of the system. The voltage stability index is based on the hybrid matrix of circuit theory. It is assumed all of the system's nodes are divided in to generator nodes (indicated by index G) and load nodes (indicated by index L). Then transmission system is written as:

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} = H\begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (7)$$

For a given system operating condition, using the load-flow (state estimation) results, the voltage-stability L index at load node j is obtained as:

$$L_j = \left|1 + V_{oj} / V_j\right| \quad (8)$$

where,

$$V_{oj} = -\sum_{i\in\alpha_G} F_{ji}V_i \quad (9)$$

and i indicate the generator buses. Therefore, the voltage stability index for whole network may be expressed as:

$$L = \max(L_j) \quad (10)$$

where Index L varies between 0 and 1 where 0 means a power network without load and L=1 shows a voltage collapse. Hence the introduced index allows the operator to estimate a margin to voltage instability. The third objective which is minimized is the L voltage stability index. This index is calculated for all load buses and the maximum amount of all buses is the objective. It can be expressed as:

$$F_2 = \min\{\max(L_j)\} \quad (11)$$

A.

C. Equality Constraints

These constraints represent the typical load flow equations as follows:

$$P_{Gi} - P_{Di} - V_i\sum_{j=1}^{N_b} V_j[G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)] = 0 \quad (12)$$

$$Q_{Gi} - Q_{Di} - V_i\sum_{j=1}^{N_b} V_j[G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)] = 0 \quad (13)$$

$$i = 1, 2, ..., N_b$$

where, N_b is the number of buses; P_G and Q_G are the generator real and reactive power, respectively; P_D and Q_D are the load real and reactive power, respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively.

D. Inequality Constraints

These constraints represent the system operating limits as follows:

- Generation Constraints: The generator reactive power output Q_G is restricted by its lower and upper limits as :

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \quad , \quad i = 1, 2, ..., N_G \quad (14)$$

- Operating Constraints: The constraints of voltage at load buses and line loadings.

$$V_i^{\min} \le V_i \le V_i^{\max} \quad , \quad i = 1, 2, ..., N_b$$
$$|S_{Li}| \le S_{Li}^{\max} \quad , \quad i = 1, 2, ..., N_l \quad (15)$$

- FACTS Devices Constraints:

$$Q_{SVCi}^{\min} \le Q_{SVCi} \le Q_{SVCi}^{\max} \quad , \quad i = 1, 2, ..., N_S$$
$$X_{TCSCi}^{\min} \le X_{TCSC\ i} \le X_{TCSCi}^{\max} \quad , \quad i = 1, 2, ..., N_{TC} \quad (16)$$

where, Q_{SVCi} is reactive power injection at bus i by SVC, N_S is number of SVC in the system, X_{TCSC} is reactance of TCSC and N_{TC} is number of TCSC in the system.

IV. FACTS DEVICES MODELING

As the intention is to improve the steady state operation, the power system as well as the FACTS devices is modeled using static equations. The steady state models of the selected FACTS devices and their models are briefly discussed below [4, 5, 9, 10, 13, 14].

A. TCSC Steady State Model

Thyristor Controlled Series Capacitor (TCSC) is an important FACTS component that is able to alter the value of the transmission line reactance by adding either a capacitive or inductive component to the main transmission line reactance as shown in Figure 2. In this study, the reactance of the transmission line is adjusted by TCSC directly. The rating of TCSC depends on the reactance of the transmission line where the TCSC is located.

$$X_{TCSC} = r_{TCSC} . X_{Line} \tag{17}$$

where X_{Line} is the reactance of the transmission line and r_{TCSC} is the coefficient which represents the degree of compensation by TCSC. To avoid overcompensation, the working range of the TCSC is chosen between ($-0.8X$ line and $0.2X$ line). By optimizing the reactance values between these ranges, Optimal setting of reactance value can be achieved.

B. SVC Steady State Model

While the previous device is a series connected, an SVC is shunt connected devices. It is installed in parallel with a bus and has the ability to generate or absorb reactive power at the point of connection. In this paper, the SVC is modeled as a generator (or absorber) of reactive power like is presented in Figure 3 the reactive power provided is limited as presented in the equation below:

$$Q_{SVC}^{\min} \le Q_{SVC} \le Q_{SVC}^{\max} \tag{18}$$

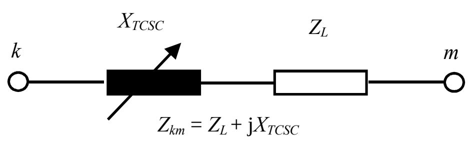

Figure 2. Steady State model of TCSC

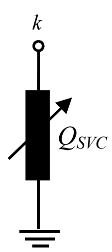

Figure 3. Steady State model of SVC

V. DECISION ALGORITHM

The problem of FACTS devices allocation which is described in the past section is a multiobjective optimization problem so it is necessary to use a multiobjective technique for solving it. Thus using a multiobjective technique gives a set of optimal solutions. Selection of the Best Compromise Solution is a crucial step in such algorithms.

In this paper, the optimization problem is solved by NSPSO algorithm and the choice of the optimal solution among the optimal Pareto solutions is based on Fuzzy inference system (FIS). Due to the importance of this matter, a Fuzzy logic technique is proposed to achieve a tradeoff between the conflicting multiple objective functions.

In resolution procedure of the problem, in the first step, NSPSO algorithm is implemented, and the pareto optimal solutions are attained. Then at the second step two indexes those called Preference Index (*PI*) and Cost Index (*CI*) are calculated. These indexes are inputs of the FIS. Similar to *PI* and *CI*, an index is introduced as the output of the FIS. This index is called Satisfaction Index (*SI*). The inputs should be fuzzified by the membership functions shown in Figures 4 and 5.

The membership function of the output is shown in Figure 6 the inference engine uses the rules defined in Table 1 and develops fuzzy outputs from the fuzzy inputs. The fuzzy output is defuzzified to yield a crisp value for the Satisfaction Index. Table 1 shows the fuzzy rules for solving the problem where, *G* stands for good, *M* stands for moderate, *B* stands for bad, *PG* stands for partly good and *PB* stands for partly bad.

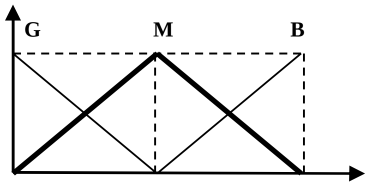

Figure 4. Cost index membership function

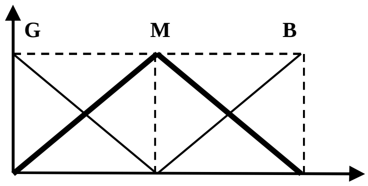

Figure 5. Preference index membership function

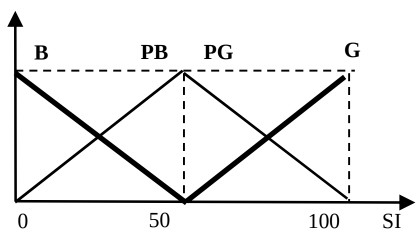

Figure 6. Satisfaction Index membership function

Table 1. Fuzzy rules

		PI		
		G	M	B
CI	G	G	PG	B
	M	PG	PG	B
	B	PG	PB	B

In the proposed hybrid algorithm, the solution with the highest Satisfaction Index (*SI*) is the best compromise solution in the Pareto optimal set. Sorting the optimal solutions based on Preference Index (*PI*) and Cost Index (*CI*), allows DM, to have a high capability of decision in the selection procedure of the solution. It should be noted that, in the selection of the best compromise solution, the decision's criterion is based on *SI* value. Also it is necessary to mention that, the solution with lowest value of *PI* has technical justification and the solution with the lowest CI has economic justification. Best compromise solution which has the highest value of *SI* is capable to balance between two these aspects. Once the Pareto optimal set is obtained, it is practical to calculate the *PI* and *CI*. In order to reach this important Goal, the functions of these parameters are presented as bellows:

A. Preference Index (PI)

As the algorithm yields a set of the optimal solutions, always there is a challenge to balance between the objects which regarded in the multiobjective function. From the technical aspect, *PI* function is introduced to represent the ranking of the non-dominated solutions. The solution which attains the minimum value of *PI* has more technical justification.

$$PI(X_i) = \sum_{j=1}^{M} mo_j(X_i)$$

$$mo_j(X_i) = \begin{cases} 0 & F_j(X_i) \le F_j^{\min} \\ \dfrac{F_j(X_i) - F_j^{\min}}{F_j^{\max} - F_j^{\min}} & F_j^{\min} < F_j(X_i) \le F_j^{\max} \\ 1 & F_j(X_i) > F_j^{\max} \end{cases} \quad (19)$$

where $F_j^{\min}$ and $F_j^{\max}$ are the minimum and the maximum value of the *j*th objective function among all non-dominated solutions, respectively and *M* is the number of the objective functions.

B. Cost Index (CI)

Due to the high investment and operating costs of FACTS devices, it is important to consider the economic aspects related to these devices. Hence, in order to attain this goal, the *CI* function introduced and it is presented as bellows:

$$CI = K_i C_{investment} - K_e \sum_i (\Delta P_i) \cdot T_i$$

$$K_i = \frac{(1+B)^{n\ facts} \cdot B}{(1+B)^{n\ facts} - 1}$$

$$C_{investment} = \sum_i IC_i^{SVC} + \sum_j IC_j^{TCSC} \quad (20)$$

$$\Delta P_i = P_{loss\ t}^{base\ case} - P_{loss\ t}^{new\ case} \quad , \quad P_{loss\ t} = \sum_i P_{loss\ i}$$

Using Siemens AG database, the investment cost functions of SVC and TCSC are developed as follows:

$$IC_m = (aS_m^{\ 2} + bS_m + c) \times S_m \times 1000 \quad (21)$$

Table 2. Cost coefficient for SVC and TCSC

Type	C	B	A
SVC	0.0003	0.3051	127.38
TCSC	0.0015	0.7130	153.75

C. Constraint Handling Scheme

In order to handle constrained optimization problem, the proposed algorithm is adapted the constraint handling mechanism used by NSGA-II due to its simplicity in using feasibility and non-dominance of solutions when comparing solutions. A solution *i* is said to constrained-dominate a solution *j* if any of the following conditions is true:

1. Solution *i* is feasible and solution *j* is not.
2. Both solutions *i* and *j* are infeasible, but solution *i* has a smaller overall constraint violation.
3. Both solutions *i* and *j* are feasible and solution *i* Dominates solutions *j*.

Comparing two feasible particles, the particle which dominates the other one is considered as a better solution. On the other hand, if both particles are infeasible, the particle with a lesser number of constraint violations is a better solution. In this paper, the overall constraints violations can be computed as:

$$F_v = \omega_v . \sum_{i=1}^{N_{PQ}} M(i) \ + \ \omega_s . \sum_{j=1}^{N_l} L(j) \quad (22)$$

where,

$$M(i) = \begin{cases} \dfrac{\left|V_i - V_i^{\min}\right|}{V_i^{\max} - V_i^{\min}} & V_i < V_i^{\min} \\ 0 & V_i^{\min} \le V_i \le V_i^{\max} \\ \dfrac{\left|V_i - V_i^{\max}\right|}{V_i^{\max} - V_i^{\min}} & V_i > V_i^{\max} \end{cases} \quad (23)$$

$$L(j) = \begin{cases} 0 & \left|S_j\right| \le S_j^{\max} \\ \dfrac{\left|S_j - S_j^{\max}\right|}{S_j^{\max}} & \left|S_j\right| > S_j^{\max} \end{cases} \quad (24)$$

where $S_j^{\max}$ is thermal limit of *j*th transmission line and V_i is the voltage magnitude at bus *i*. The $V_i^{\max}$ and $V_i^{\min}$ denote the violated upper or lower limits, ω_V and ω_S are weighting coefficients which are set to 0.5 here. The flowchart of the proposed algorithm is shown in Figure 7.

VI. RESULTS AND DISCUSSIONS

In order to investigate its effectiveness of the proposed algorithm, it is implemented using IEEE 14-bus and 30-bus systems. Data of these systems is taken from [14] and [15], respectively. Since, the voltage limits of load buses and are not considered in IEEE data format; the maximum and minimum voltage load buses are considered 1.1 pu and 0.9 pu, respectively.

The thermal limits of lines are taken from [21]. In this work the generators are modeled as PV buses with Q limits; the loads are typically represented by constant PQ loads; the decision variables considered are the location and setting of TCSC and SVC. The number of FACTS and their constraints are chosen at the beginning; where the number of FACTS is fixed at one for each type, also the reactance of TCSC is considered as continuous variable which varies between 20% inductive and 80% capacitive of the line reactance.

The placement of TCSC is considered as a discreet variable, where all the lines of the system are selected to be the optimal location of TCSC. Similarly, the SVC considered as a generator (or an absorber) of reactive power which varies continuously between -2 pu and 2 pu. The optimal location of SVC is, also, considered as a discreet decision variable, where all load buses are selected to be the optimal location of SVC.

In this paper, the optimal location and setting of SVC and TCSC is performed considering three cases in term of use of FACTS:

- Case 1: SVC only
- Case 2: TCSC only
- Case 3: Coordinated SVC and TCSC

Also, the performance of the proposed algorithm is compared with PSO's one. The parameters of both algorithms for all optimizations cases are summarized in Table 3. It should be noted that, in the hybrid approach, the selection mechanism of the final solution is based on both technical and economical consideration, but in PSO algorithm, this procedure is done based on technical aspect of problem. The necessary information for economic study is listed in Table 4.

Table 3. NSPSO and PSO parameters

C_j	W_{max}	W_{min}	Number of generation	Population size
2.0	0.9	0.4	50	100

Table 4. Information for economic study

Parameters	Values
Factor and duration of load level 1	0.81, 2136 hours
Factor and duration of load level 2	1.00, 2832 hours
Factor and duration of load level 3	0.90, 4392 hours
Interest rate	15 %
K_e	0.16 $/KWh
Life time of FACTS devices	30 years
Base cost	100000 $

Table 5. Hybrid and pso solutions of case1 for bi-objective optimization

	Corresponding Solution to:		Solution found by:	
	Best L Index	Best Losses	PSO	Hybrid approach
Location [1] (Bus No.)	11	9	13	9
Setting [2] (p.u)	-16.0475	-16.5854	-19.8916	-16.5854
L index	0.0748	0.0782	0.0765	0.0782
Losses [3] (p.u)	0.346712	0.342475	0.351711	0.342475

1: Bus data in [14]
2: Generated reactive power: positive means operation in capacitive mode
3: Base Power = 100 MVA

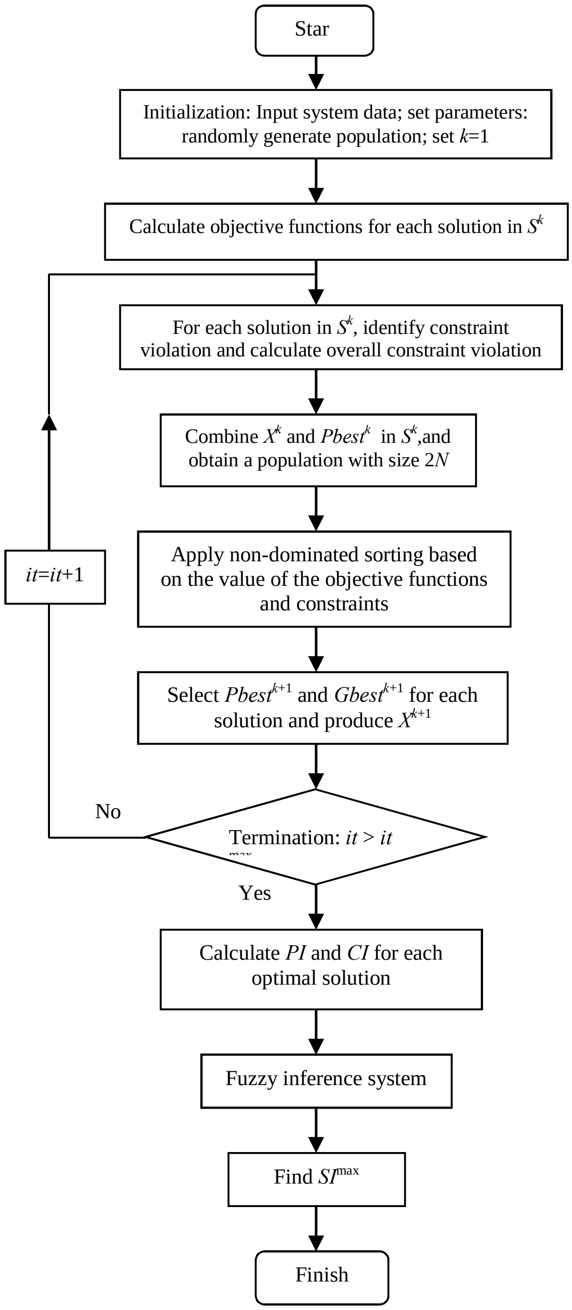

Figure 7. Flowchart of hybrid approach for FACTS devices allocation

A. IEEE 14-BUS

A.1. Case 1: SVC Only

Figures 8 and 9 show the graphical results produced by hybrid approach in case 1. The Pareto optimal set has 4 points and it can be seen that the obtained solutions are well distributed on trade-off surface; except some discontinuity, caused by discrete optimization. The solutions for giving the best objective functions are presented in Table 5. As it can be seen from this table, the solution of PSO and hybrid algorithms is exhibited. From Table 5, we can conclude that the placement of SVC at bus 11 with the reference set at -16.0475 MVAR presents the best L index of 0.0748. The installation of SVC at bus 9 with -16.5854 MVAR of the reference presents the minimum real power loss of 0.342475 pu.

Based on the value of *SI*, the installation of SVC at bus 9 with -16.5854 MVAR of the reference, is considered as the best compromise solution throughout the Non-Dominated solutions set. In order to compare the performance of the hybrid approach and PSO algorithm it can be seen that the proposed algorithm is able to decrease real power loss more, but to decrease the *L* stability index of the system, PSO algorithm has better performance. Table 6 shows the numerical results corresponding to the best *CI*, *PI* and *SI* values. It can be seen that, the *PI* value of both solutions with minimum *CI* and *PI* value is equal to 1. Since the *PI* values of these solutions are the same, consequently, that solution with smaller *CI* is selected as the best compromise solution. This solution is considered as the solution which has the biggest *SI* value. Also in the term of *CI* comparison between hybrid approach and PSO algorithm, we can conclude the hybrid algorithm has better performance than PSO's one. The presented results are verified in Table 7.

Table 6. Corresponding objectivefunctions to those solutions with the best *CI*, *PI* and *SI* for case 1

		CI^1 (p.u)	*PI*	*SI* (%)	*L* index	Losses[2] (p.u)
Corresponding Result to Best:	*CI*	4.3971	1.0000	83.6667	0.0782	0.342475
	PI	5.6984	1.0000	33.6667	0.0748	0.346712
	SI	4.3971	1.0000	83.6667	0.0782	0.342475

1: Base Cost = 100000 $, 2: Base Power = 100 MVA

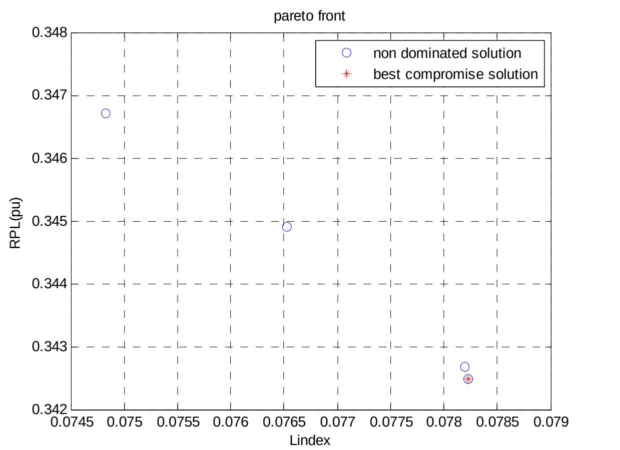

Figure 8. Pareto front of case 1 for IEEE 14-bus test system

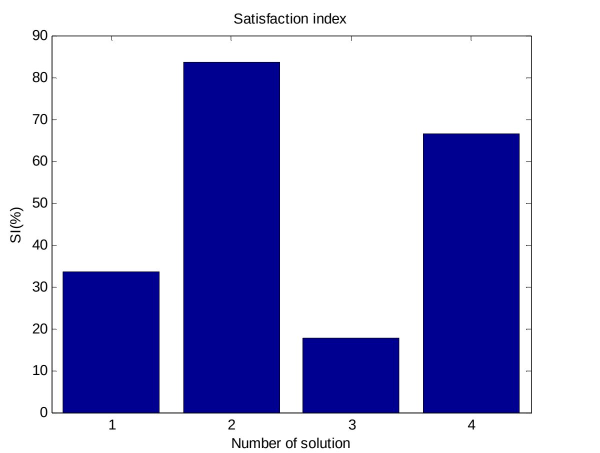

Figure 9. Output of fuzzy system, *SI* in case 1 for IEEE 14-bus test system

Table 7. Calculated cost index with hybrid and PSO algorithms

Cost index[1] (p.u)	
Hybrid approach	PSO
4.3971	8.2198

1: Base Cost = 100000 $

A.2. Case 2: TCSC Only

In order to find the best setting and placement of TCSC, both hybrid and PSO approach are executed with three different size of population. The size of the population is 100, 500 and 1000. In these cases both algorithms converge to the solution which is shown in table 8. Due to the constraint reversal, solution which is attained with both PSO and hybrid algorithms, is infeasible.

Table 8. Hybrid and PSO solutions of case 2 for bi-objective optimization

	Solution found by:	
	PSO	Hybrid approach
Location[1] (Branch)	6-12	6-12
Compensation Ratio[2]	-0.0833	-0.0833
L index	0.0700	0.0700
Losses[3] (p.u)	0.340241	0.3402

1: Line data in [14] , 2: Negative means operation in capacitive mode
3: Base Power = 100 MVA

A.3. Case 3: Coordinated SVC and TCSC

Figures 10 and 11 show the graphical results produced by hybrid approach in case 3. The Pareto optimal set has 9 points and it can be seen that the obtained solutions are well distributed on trade-off surface; except some discontinuity, caused by discrete optimization. The solutions for giving the best objective functions are presented in Table 9. As it can be seen from this table, the solution of PSO and hybrid algorithms is exhibited. From Table 9, we can conclude that the placement of SVC at bus 11 with the reference set at -16.6385 MVAR and TCSC in line 7-9 with considered compensation ratio to -0.5033, presents the best *L* Stability index with the reference of 0.0697.

Table 9. Hybrid and PSO solutions of case 3 for bi-objective optimization

	Corresponding Solution to:		Solution found by:	
	Best *L* Index	Best Losses	PSO	Hybrid approach
Location[1] (Bus No.)	11	9	13	9
Setting[2] (p.u)	-16.6385	-11.8641	-18.2010	-12.7478
Location[3] (Branch)	7-9	7-8	10-11	6-13
Compensation Ratio[4]	-0.5033	-0.3002	-0.0076	-0.3699
L index	0.0697	0.0741	0.0759	0.0725
Losses[5] (p.u)	0.346954	0.340687	0.350783	0.341615

1: Bus data in [14] , 2: Positive means operation in capacitive mode
3: Line data in [14] , 4: Negative means operation in capacitive mode
5: Base Power = 100 MVA

The installation of SVC at bus 9 with -11.8641 Mvar of reference and TCSC in line 7-8 provides the minimum Real power loss of 0.34068 pu. Based on the value of SI, the installation of SVC at bus 9 with -12.7478 Mvar and TCSC in line 6-13 with considered compensation ratio to -0.3699, is introduced as the best compromise solution throughout the Non-Dominated solutions set. In order to compare the performance of the hybrid approach and PSO algorithm, it can be seen that to decrease the active power loss and *L* index, the performance of the proposed algorithm is better than the PSO's one. Table 10 shows the numerical results corresponding to the best *CI*, *PI* and *SI* values. It can be seen that, the solution with the minimum *CI* value has maximum *PI* value and solution with the minimum PI value has the maximum *CI* value.

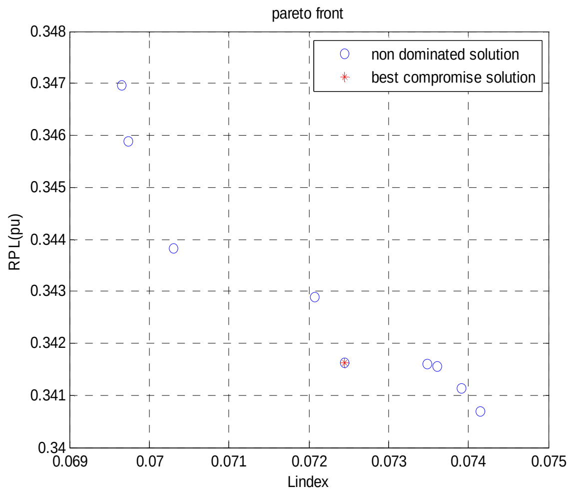

Figure 10. Pareto front of case 3 for IEEE 14-bus test system

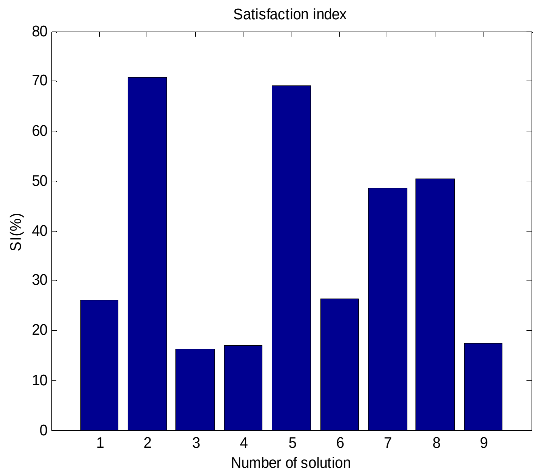

Figure 11. Output of fuzzy system, *SI* in case 3 for IEEE 14-bus test system

Also it can be concluded that, the compromise solution with the maximum *SI* value has the *CI* value bigger than the best *CI* value and smaller than *CI* value which the solution with the best *PI* value has. The converse matter is established between *PI* value of the final solution and its corresponding values in this table. So it can be concluded that the hybrid algorithm has a good ability to maintain a relative balance between technical and economic aspects of the problem. It should be noted that the solution with the minimum *CI* value is justified from economical viewpoint and the solution with the minimum *PI* value is justified from technical viewpoint. Also in term of *CI* value comparison between hybrid approach and PSO algorithm, we can conclude hybrid algorithm has better performance than PSO algorithm. The presented results are verified in Table 11.

Table 10. Corresponding objectivefunctions to those solutions with the best *CI*, *PI* and *SI* for case 3

		CI[1] (p.u)	*PI*	*SI* (%)	*L* index	Losses[2] (p.u)
Corresponding Result to Best:	*CI*	2.8856	1.0196	16.3333	.0739	0.341124
	PI	4.0397	0.6453	69.0680	0.0703	0.343823
	SI	3.3908	0.7706	70.8319	0.0725	0.341615

1: Base Cost = 100000 $, 2: Base Power = 100 MVA

Table 11. Calculated cost index with hybrid and PSO algorithms

Cost index[1] (p.u)	
Hybrid approach	PSO
3.3908	7.4626

1: Base Cost = 100000 $

B. IEEE 30-Bus

B.1. Case 1: SVC Only

Figures 12 and 13 show the graphical results produced by hybrid approach in case 1. The Pareto optimal set has 135 points and in order to simplify the solutions demonstration, only 100 points are displayed. It can be seen that the obtained solutions are well distributed on trade-off surface; except some discontinuity, caused by discrete optimization. The solutions for giving the best objective functions are presented in Table 12. As it can be seen, the solution of PSO and hybrid algorithms is exhibited. From Table 12, we can conclude that the placement of SVC at bus 27 with the reference set at 12.1456 MVAR presents the best *L* stability index with the reference of 0.1252. The installation of SVC at bus 27 with 10.6168 MVAR of reference presents the minimum real power loss of 0.434268 pu. Based on the value of *SI*, the installation of SVC at bus 27 with 11.0170 MVAR is considered as the best compromise solution throughout the Non-Dominated solutions set.

In order to compare the performance of the hybrid approach and PSO algorithm, it can be seen that the proposed algorithm is able to decrease Real power loss more, but to decrease the *L* stability index of the system, PSO algorithm has better performance. Table 13 shows the numerical results corresponding to the best *CI*, *PI* and *SI* values. It can be seen that, the solution with the minimum CI value has the maximum *PI* value and the solution with the minimum *PI* value has the maximum *CI* value. Also it can be concluded that, the compromise solution with the maximum *SI* value has the *CI* value bigger than the best *CI* value and smaller than *CI* value which the solution with the best *PI* value has.

The converse matter is established between *PI* value of the final solution and its corresponding values. So it can be concluded that the hybrid algorithm has a good ability to maintain a relative balance between technical and economic aspects of the problem. It should be noted that the solution with the minimum *CI* value is justified from economical viewpoint and the solution with the minimum *PI* value is justified from technical viewpoint. From Table 14, in order to compare the performance of both hybrid an PSO algorithms based on *CI* value, it is observed that hybrid algorithm has a better performance than to PSO's one.

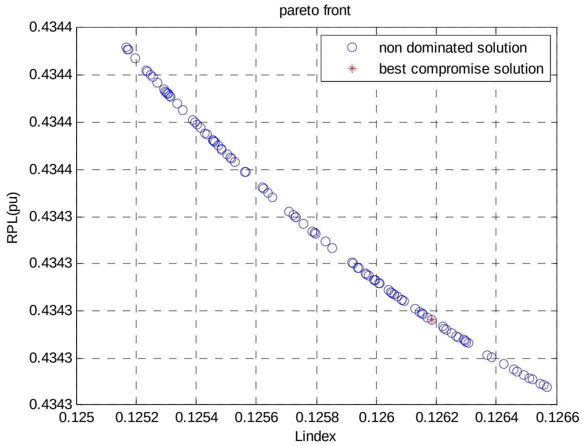

Figure 12. Pareto front of case 1 for IEEE 30-bus test system

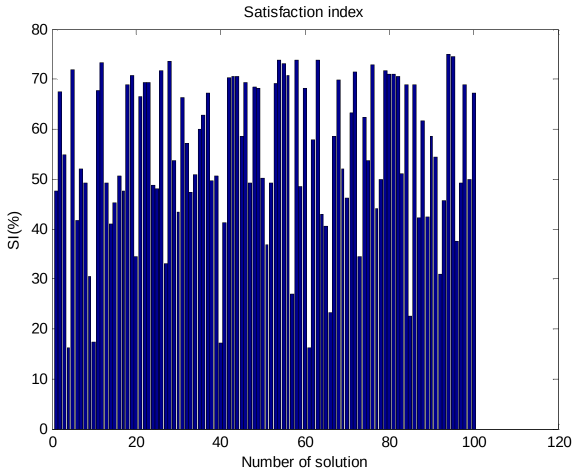

Figure 13. Output of fuzzy system, *SI* in case 1 for IEEE 30-bus test system

B.2. Case 2: TCSC Only

Figures 14 and 15 show the graphical results produced by hybrid approach in case 2. The Pareto optimal set has 157 points and in order to simplify the solutions demonstration, only 100 points are displayed.

Table 12. Hybrid and PSO solutions of case 1 for bi-objective optimization

	Corresponding Solution to:		Solution found by:	
	Best *L* Index	Best Losses	PSO	Hybrid approach
Location [1] (Bus No.)	27	27	27	27
Setting [2] (p.u)	12.1456	10.6168	11.8236	11.0170
L index	0.1252	0.1266	0.1254	0.1262
Losses [3] (p.u)	0.434412	0.434268	0.434373	0.434296

1: Bus data in [15] , 2: Positive means operation in capacitive mode
3: Base Power = 100 MVA

Table 13. Corresponding objectivefunctions to those solutions with the best *CI*, *PI* and *SI* for case 1

		CI [1] (p.u)	PI	SI (%)	*L* index	Losses [2] (p.u)
Corresponding Result to Best:	*CI*	0.0586	1.0000	16.3333	0.1266	0.434268
	PI	0.2172	0.8998	66.4390	0.1259	0.434327
	SI	0.1417	0.9224	74.8814	0.1262	0.434296

1: Base Cost = 100000 $, 2: Base Power = 100 MVA

Table 14. Calculated cost index with hybrid and PSO algorithms

Cost index [1] (p.u)	
Hybrid approach	PSO
0.1417	0.3160

1: Base Cost = 100000 $

It can be seen that the obtained solutions are well distributed on trade-off surface; except some discontinuity, caused by discrete optimization. The solutions for giving the best objective functions are presented in Table 15. As it can be seen, the solution of PSO and hybrid algorithms is exhibited. From Table 15, we can conclude that the placement of TCSC in line 27-28 with considered compensation ratio to -0.3409 presents the best *L* index of 0.1226. The installation of TCSC in line 25-26 with considered compensation ratio to -0.2743 presents minimum Real power loss of 0.440607 pu. Based on the value of *SI*, the installation of TCSC in line 27-28 with considered compensation ratio to -0.1232 is considered as the best compromise solution throughout the Non-Dominated solutions set.

In order to compare the performance of the hybrid approach and PSO algorithm, it can be seen that the proposed algorithm is able to decrease Real power loss more, but to decrease the *L* stability index, PSO algorithm has better performance. Table 16 shows the numerical results corresponding to the best *CI*, *PI* and *SI* values. It can be seen the solution with the minimum CI value, has the maximum *PI* value and the solution with the minimum *PI* value has the maximum *CI* value. Also it can be concluded that, the compromise solution with the maximum *SI* value has the *CI* value bigger than the best *CI* value and smaller than *CI* value which the solution with the best *PI* value has.

The converse matter is established between *PI* value of the final solution and its corresponding values. So it can be concluded that the hybrid algorithm has a good ability to maintain a relative balance between technical and economic aspects of the problem. It should be noted that the solution with the minimum *CI* value is justified from economical viewpoint and the solution with the minimum *PI* value is justified from technical viewpoint. From Table 17, in order to compare the performance of the foregoing algorithms based on *CI* value, it is observed that hybrid algorithm has a better performance than to PSO's one.

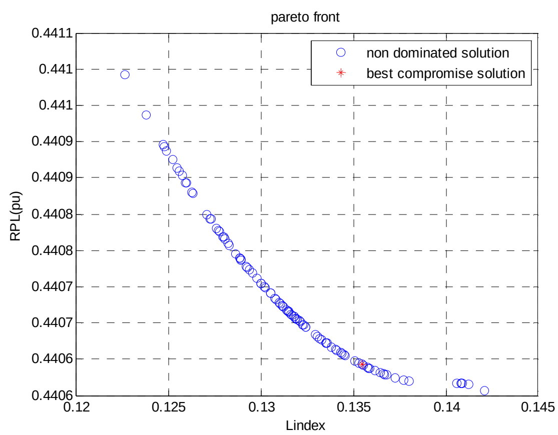

Figure 14. Pareto front of case 2 for IEEE 30-bus test system

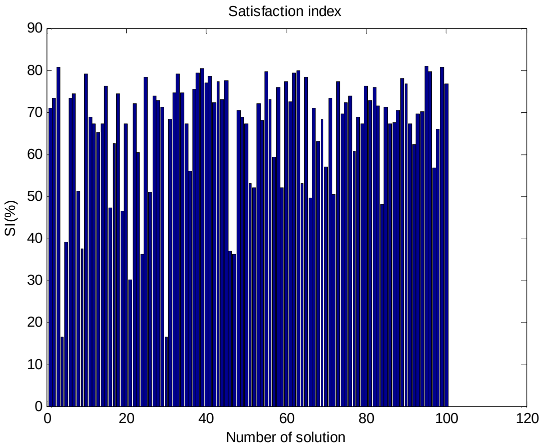

Figure 15. Output of fuzzy system, *SI* in case 2 for IEEE 30-bus test system

Table 15. Hybrid and PSO solutions of case 2 for bi-objective optimization

	Corresponding Solution to		Solution found by	
	Best *L* Index	Best Losses	PSO	Hybrid approach
Location [1] (Branch)	27-28	25-26	27-28	27-28
Compensation Ratio [2]	-0.3409	-0.2743	-0.2417	-0.1232
L index	0.1226	0.1421	0.1286	0.1354
Losses [3] (p.u)	0.441042	0.440607	0.440795	0.440642

1: Line data in[15] , 2: Negative means operation in capacitive mode
3: Base Power = 100 MVA

Table 16. Corresponding objectivefunctions to those solutions with the best *CI*, *PI* and *SI* for case 2

		CI [1] (p.u)	*PI*	*SI* (%)	*L* index	Losses [2] (p.u)
Corresponding Result to Best:	*CI*	0.0004	1.0000	16.3333	0.1421	0.440607
	PI	0.0515	0.7024	73.8404	0.1321	0.440701
	SI	0.0238	0.7397	80.8496	0.1354	0.440642

1: Base Cost = 100000 $
2: Base Power = 100 MVA

Table 17. Calculated cost index with hybrid and PSO algorithms

Cost index [1] (p.u)	
Hybrid approach	PSO
0.0238	0.0912

1: Base Cost = 100000 $

B.3. Case 3: Coordinated SVC and TCSC

Figures 16 and 17 show the graphical results produced by hybrid approach in case 3. The Pareto optimal set has 25 points and Iit can be seen that the obtained solutions are well distributed on trade-off surface; except some discontinuity, caused by discrete optimization. The solutions for giving the best objective functions are presented in Table 18. As it can be seen, the solution of PSO and hybrid algorithms is exhibited. From Table 18, we can conclude that the placement of SVC at bus 27 With the reference set at 12.0752 MVAR and TCSC in line 22-24 with considered compensation ratio to -0.2300, presents the best *L* index of 0.1248. The installation of SVC at bus 27 with 10.6471 MVAR of reference and TCSC in line 15-23 with considered compensation ratio to -0.1913 presents the minimum Real power loss of 0.434252 pu.

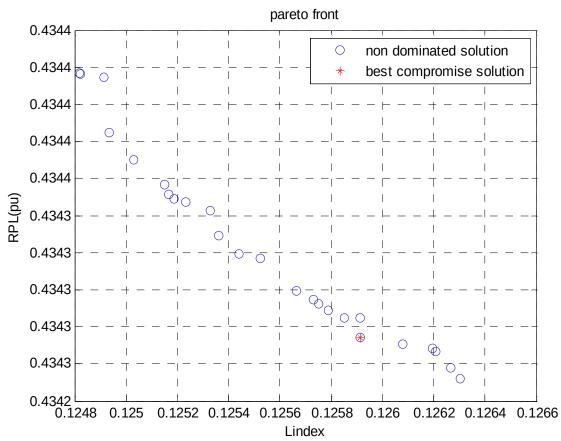

Figure 16. Pareto front of case 3 for IEEE 30-bus test system

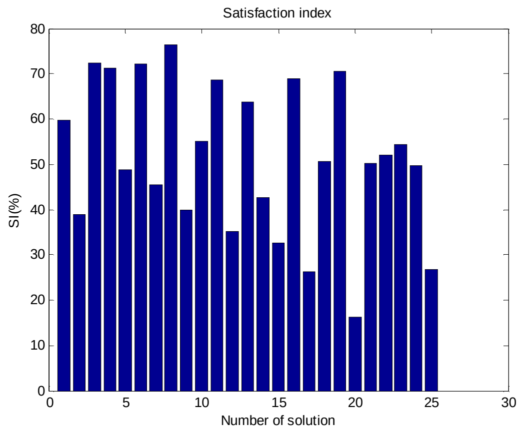

Figure 17. Output of fuzzy system, *SI* in case 3 for IEEE 30-bus test system

Table 18. Hybrid and pso solutions of case 3 for bi-objective optimization

	Corresponding Solution to		Solution found by	
	Best *L* Index	Best Losses	PSO	Hybrid approach
Location [1] (Bus No.)	27	27	27	27
Setting [2] (p.u)	12.0752	10.6471	11.3568	10.9990
Location [3] (Branch)	22-24	15-23	27-28	15-23
Compensation Ratio [4]	-0.2300	-0.1913	-0.2716	-0.2313
L index	0.1248	0.1263	0.1129	0.1259

1: Bus data in [15] , 2: Positive means operation in capacitive mode
3: Line data in [15] , 4: Negative means operation in capacitive mode
5: Base Power = 100 MVA

Table 19. Corresponding objectivefunctions to those solutions with the best *CI*, *PI* and *SI* for case 3

		CI [1] (p.u)	*PI*	*SI* (%)	*L* index	Losses [2] (p.u)
Corresponding Result to Best:	*CI*	0.0647	1.0000	42.7558	0.1263	0.434252
	PI	0.2463	0.8257	59.7350	0.1254	0.434319
	SI	0.1373	0.8720	76.4498	0.1259	0.434274

1: Base Cost = 100000 $, 2: Base Power = 100 MVA

Table 20. Calculated cost index with hybrid and PSO algorithms

Cost index [1] (p.u)	
Hybrid approach	PSO
0.1373	0.4137

1: Base Cost = 100000 $

Based on the value of the *SI*, the installation of the SVC at bus 27 with 10.9990 Mvar and TCSC in line 15-23 with considered compensation ratio to -0.2313, is considered as the best compromise solution throughout the Non-Dominated solutions set. In order to compare the performance of the hybrid approach and PSO algorithm, it can be seen that the proposed algorithm is able to decrease *L* stability more, but to decrease the Real power loss of the system, PSO algorithm has better performance. Table 19 shows the numerical results corresponding to the best *CI*, *PI* and *SI* values. It can be seen that, the solution with the minimum CI value has the maximum *PI* value and the solution with the minimum *PI* value has the maximum *CI* value.

Also it can be concluded that, the compromise solution with the maximum *SI* value has the *CI* value bigger than the best *CI* value and smaller than *CI* value which the solution with the best *PI* value has. The converse matter is established between *PI* value of the final solution and it's corresponding values So it can be concluded that the hybrid algorithm has a good ability to maintain a relative balance between technical and economic aspects of the problem. It should be noted that the solution with the minimum *CI* value is justified from economical view point and the solution with the minimum *PI* value is justified from technical viewpoint. From the table 20, in order to compare the performance of both hybrid an PSO algorithms based on *CI* value, it is observed that hybrid algorithm has a better performance than to PSO's one.

VII. CONCLUSIONS

So far, the implemented method for the resolution of the FACTS allocation problem has been oriented to economical or technical aspects separately. The present paper makes use of recent advances in bi-objective evolutionary algorithms to develop a method for the combinatorial optimal allocation of FACTS into power systems. Optimizations were performed on two parameters: the locations of FACTS devices, and their rates. The implementation of the proposed hybrid algorithm has performed well when it was used to characterize POF of the FACTS optimal location problem.

The diversity of non-dominated solutions is maintained by using the mechanism of crowding distance. In order to select the best compromise solution a novel regime which is based on Fuzzy mechanism was proposed. Three cases of FACTS device placement are conducted using the IEEE 14-bus and 30-bus systems. As an illustrative example, an optimal location solution was compared using conventional PSO algorithm which confirmed the effectiveness of the proposed method.

The results show that hybrid approach provides well-distributed non-dominated solutions and well exploration of the research space. Moreover the method does not impose any limitation on the number of objectives.

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