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Improved Strength Pareto Evolutionary Algorithm with Local Search Strategies for Optimal Reactive Power Flow

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Abstract: In this study, several versions of Strength Pareto Evolutionary Algorithm (SPEA, SPEA2 and SPEA2+) are adopted and improved for voltage/reactive power control and simultaneously loss reduction in Optimal Reactive Power Flow (ORPF) of power systems. The purpose of ORPF is to provide a solution that minimizes real power loss and improves voltage profile by determining generator voltages, reactive power support of shunt capacitors and tap changing transformers. To enhance the algorithm's exploiting capability, several problem-specific Local Search Strategies (LSSs) are incorporated to formulate three improved versions of SPEA (ISPEA, ISPEA2 and ISPEA2+). A comparative study between original SPEAs and improved SPEAs is also performed for ORPF on standard New England 39-bus test system. Pareto fronts and outer solutions achieved are compared and their nondominated sets are also analyzed using C measure. Experimental results validated the effectiveness of SPEA2+ and also demonstrated the further performance improvement in ISPEA2+ with LSSs. ISPEA2+ was found to be one of the efficient potential candidates in solving power system multiobjective optimization problems.

Key words: Optimal reactive power flow, pareto optimal, strength pareto evolutionary algorithm, local search strategy, multiobjective optimization

INTRODUCTION

For multiple conflicting objectives that represent various competing performance measures in real-world engineering problems, improvement to an optimal solution in one objective may only be reached by degradation in other objectives. It implies that no single optimal solution exists, but rather a set of candidate solutions characterized by tradeoffs in their objectives. Such solutions are said to be Pareto-optimal and their corresponding objective vectors comprise a Pareto front characterized by varying tradeoffs.

To find a set of representative Pareto optimal solutions in a single run, Multi-Objective Evolutionary Algorithms (MOEAs), a class of stochastic optimization techniques that simulate biological evolution to solve multi-objective problems, have been proposed. After the first studies in the mid-1980s (Schaffer, 1985), MOEAs became an important research topic with significant progress, e.g., Niched Pareto Genetic Algorithm (NPGA) by Horn *et al*. (1994), Strength Pareto Evolutionary Algorithm (SPEA) by Zitzler and Thiele (1999), multiobjective genetic algorithm by Deb (1999) and Nondominated Sorting Genetic Algorithm (NSGA) by Deb *et al*. (2002) etc.

Many MOEAs have been successfully applied to solve optimization problems in power system operations. Optimal Reactive Power Flow (ORPF) is one of these optimization problems that have been studied extensively. ORPF can obtain the best performance of reactive-power support to promote economy and security of the power system operation (Benzargua *et al*., 2006; Chettih *et al*., 2008). Many techniques has been used in multiobjective ORPF, such as ε-constraint method by Yuanlin (1996) fuzzy set theory by Venkatesh *et al.* (2001) normalization method by Yousefi *et al.* (2004) weighted-sum method by Zhang and Ren (2004), projection-based method by Chen and Ke (2004) etc. The MOEA-based ORPF is proposed by Abido and Bakhashwain (2005). It uses SPEA, an efficient MOEA that is proposed by Zitzler and Thiele (1999), to solve multiobjective ORPF considering the objectives of voltage deviation and real power loss. According to our experiment, however, SPEA suffer from excessively slow convergence speed, especially in the early stage of the search process. As discussed by Zitzler *et al.* (2001) in the situation that the current generation does not dominate each other, very little information can be obtained from the partial order defined by the dominance relation. Besides, SPEA may lose outer solutions by clustering technique.

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Improved versions of SPEA, named SPEA2 and SPEA2+, are presented by Zitzler *et al.* (2001) and Mifa *et al.* (2004), respectively, to eliminate the potential weaknesses of SPEA. In SPEA2, an improved fitness assignment scheme is used to allocate strength value to each individual in both main population and elitist archive. A nearest neighbor density estimation technique is used to promote solution diversity. For SPEA2+, neighborhood crossover and mating selection are proposed and two archive populations that hold diverse solutions in the objective space and variable space, respectively, are maintained. In this study, a comparison study of SPEA, SPEA2 and SPEA2+, is presented for ORPF on New England 39-bus system. In order to assess the performance of the algorithms, C measure by Zitzler *et al.* (2003) is employed for comparing of Pareto fronts achieved by these three SPEAs.

It is demonstrated in some recent works (Joshua and David, 2005) that the combination of Local Search Strategies (LSSs) and Evolutionary Algorithms (EAs) can combine the global search ability of EAs (Wang *et al*., 2009) with the local refinements advantage from LSS, greatly increasing the convergence speed. SPEA, SPEA2 and SPEA2+ are combined with LSSs and therefore three corresponding improved algorithms, ISPEA, ISPEA2 and ISPEA2+, are proposed for better convergence speed. Several problem-specific LSSs, such as shunt compensator manipulation LSS, generator voltage manipulation LSS, tap manipulation LSS, max-min LSS, swap LSS, etc. (Iba, 1994; Bakirtzis *et al*., 2002) are incorporated into SPEA, SPEA2 and SPEA2+ for better exploiting capability.

PROBLEM FORMULATION

The goal of ORPF is to optimize the steady state performance of power systems in terms of one or more objective functions by optimally setting the reactive power facilities (generators, shunt capacitors and transformers), while maintaining the system voltages within limits. ORPF can be formulated as:

$$\min\ f_{loss} = \sum_{k=1}^{N_L} G_{k(i,j)}[V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}] \tag{1}$$

$$\min\ f_{VD} = \sum_{i=1}^{N}\left|\frac{V_i^* - V_i}{V_i^{max} - V_i^{min}}\right| \tag{2}$$

$$P_i - V_i\sum_{j=1}^{N} V_j[G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij})] = 0, \quad 1 \le i \le N \tag{3}$$

$$Q_i - V_i\sum_{j=1}^{N} V_j[G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}] = 0, \quad 1 \le i \le N \tag{4}$$

$$V_i^{min} \le V_i \le V_i^{max} \qquad i = 1 \ldots N_{PQ} \tag{5}$$

$$Q_{G,i}^{min} \le Q_{G,i} \le Q_{G,i}^{max} \qquad i = 1 \ldots N_G \tag{6}$$

$$V_{G,i}^{min} \le V_{G,i} \le V_{G,i}^{max} \qquad i = 1 \ldots N_G \tag{7}$$

$$Q_{c,i}^{min} \le Q_{c,i} \le Q_{c,i}^{max} \qquad i = 1 \ldots N_c \tag{8}$$

$$T_{k,i}^{min} \le T_{k,i} \le T_{k,i}^{max} \qquad i = 1 \ldots N_T \tag{9}$$

where, in Eq. 1, f_{loss}, N_L, $G_{k(i,j)}$ and θ_{ij} represent, respectively, the real power loss; the number of transmission lines; the conductance of line k that connects bus i to bus j; is the voltage phase difference between bus i and bus j. In Eq. 2, f_{VD} is the total voltage deviation; N is the bus number of the power system; V_i^*, V_i^{max}, V_i^{min} are the desired voltage magnitude, the upper limit voltage magnitude and the lower limit voltage magnitude at bus i, respectively.

Minimization of system loss: Equation 1 represents the system loss objective. This objective is to minimize the power energy loss of power transmission lines. The real power loss on each individual line is calculated and the system loss is calculated by a summation as

Minimization of voltage deviation: Equation 2 represents the voltage deviation objective. This objective is to minimize the voltage deviations from desired voltage magnitudes to improve voltage profile of the whole system. It can be calculated by

Power balance constraints: Equation 3 and 4 represent power balance constraints that represent real and reactive power balance at each bus, where P_i and Q_i are reactive and active power injections at bus i and G_{ij} and B_{ij} is the transfer conductance and susceptance between bus i and bus j respectively. The equality constraints in Eq. 3 and 4 are nonlinear equations that can be solved using NewtonBRaphson method.

Dependent variable constraint: For secure operation, dependent variables are restricted in boundaries. These include the constraints of voltages at load buses and reactive power injection at generator buses as in Eq. 5 and 6, where, N_{PQ} represent the number of PQ buses; $Q_{G,i}$, $Q_{G,i}^{min}$ and $Q_{G,i}^{max}$ denote reactive power generation of generator at bus i and its lower and upper limits, respectively.

Control variable constraint: To optimize the two objectives in Eq. 1 and 2, reactive power facilities are used to adjust the reactive power flow of the network. Control variables of ORPF include voltages of generators, reactive power generation of capacitors and tap ratios of transformers:

$$V_G = [V_{G,1}, V_{G,2} ... V_{G,N_G}]$$

$$Q_c = [Q_{c,1}, Q_{c,2} ... Q_{c,N_c}]$$

$$T_k = [T_{k,1}, T_{k,2} ... T_{k,N_T}]$$

where, V_G, Q_c and T are vectors composed of generator voltages, shunt capacitors and transformer tap ratios respectively, N_G, N_c and N_T are the number of generators, shunt capacitor compensations and transformers, respectively. Control variables are restricted in lower and upper boundaries due to the capacity of the equipments as in Eq. 7-9, where, $V_{G,i}^{min}$, $V_{G,i}^{max}$, $Q_{c,i}^{min}$, $Q_{c,i}^{max}$, $T_{k,i}^{min}$ and $T_{k,i}^{max}$ are minimum and maximum limits of the corresponding variables.

Equation 1-9 represent multiobjective ORPF considering two conflicting objectives. It is inherently a mixed-integer nonlinear programming problem involving multiple objective functions, nonlinear constraints and both continuous variables and discrete variables.

STRENGTH PARETO EVOLUTIONARY ALGORITHM

For multiple objectives, Pareto concept serves as the basis for fitness assignment of SPEAs, which can be defined as follows.

Dominate: A solution x_1 is said to dominate x_2 (denoted by $x_1 \prec x_2$) if and only if:

$$\forall i \in \{1,2...m\}: f_i(x_1) \le f_i(x_2) \quad \wedge$$
$$\exists j \in \{1,2...m\}: f_j(x_1) < f_j(x_2)$$

Usually, the Pareto concepts are defined with respect to the entire control variable space. For SPEAs, however, these concepts are often restricted in a particular set, i.e., $S = \{x_i, i=1..n\}$.

Nondominated solutions: A solution x is said to be a nondominated solution of set S, if $x \in S$ and there is no solution $x' \in S$ for which x' dominates x. A set P contains all these nondominated solutions is the nondominated set of S, which may be denoted by P = Dom(S).

Pareto front: $PF = \{v \mid v = [f_1(x), f_2(x) Y f_m(x)]^T, x \in P\}$ is said to be Pareto front of set S.

If we replace S with populations in evolutionary techniques, e.g., population at generation k, $S^{(k)} = \{x_i^{(k)}, i = 1..n^{(k)}\}$, then $P^{(k)}$ and $PF^{(k)}$ can be called nondominated set and Pareto front at generation k, respectively.

Regarding the tasks of preventing premature convergence and providing decision maker with well distributed solutions, Pareto-based fitness assignment for multiobjective optimization is proposed. It explicitly uses Pareto relations to determine the fitness of each individual solution as by Zitzler *et al.* (2000). Pareto-based fitness assignment scheme of SPEA, SPEA2 and SPEA2+ are introduced briefly.

Fitness assignment of SPEA: Zitzler and Thiele (1999) presented SPEA as a potential algorithm for multi-objective optimization. This elitist algorithm stores all the nondominated solutions discovered so far beginning from the initial population in an external population. Let $T^{(k)}$ be the external population at generation k and then a strength value $s_i^{(k)}$ is set to each individual $x_i^{(k)}$ in $T^{(k)}$ by:

$$s_i^{(k)} = \frac{t_i^{(k)}}{n^{(k)} + 1} \qquad i = 1, 2 ... n_T^{(k)}$$

with,

$$t_i^{(k)} = \left|\{x \mid x_i^{(k)} \prec x \text{ s.t. } x_i^{(k)} \in T^{(k)}, x \in S^{(k)}\}\right| \tag{10}$$

$$T^{(k)} = Dom(S^{(k)} \cup T^{(k-1)})$$

where, $n_T^{(k)}$ denotes the size of $T^{(k)}$, $t_i^{(k)}$ is the number of individuals in $S^{(k)}$ that dominated by $x_i^{(k)}$ in $T^{(k)}$. Then, the fitness can be computed by:

$$f_i^{(k)} = 1 + \sum_{x_j \in T^{(k)} \wedge x_j \prec x_i} s_j^{(k)} \tag{11}$$

The fitness of each individual in SPEA is the sum of the strengths of all external solutions by which it is dominated. The best individual will have the lowest fitness. In addition, A upper limit on the size of $T^{(k)}$ is set and a truncation method based on clustering is adopted when $T^{(k)}$ is oversized.

Fitness assignment of SPEA2: SPEA2 presented by Zitzler *et al.* (2001) is an improved version of SPEA. It allocates strength value $s_i^{(k)}$ to solutions both in $T^{(k-1)}$ and $S^{(k)}$.

$$s_i^{(k)} = t_i^{(k)} \qquad i = 1,2 \ldots n_T^{(k-1)} + n^{(k)}$$

with,

$$t_i^{(k)} = \left|\{x \mid x_i^{(k)} \prec x \ \text{ s.t. } \ x \in T^{(k-1)} \cup S^{(k)}\}\right|$$

Then, the fitness can be computed as:

$$f_i^{(k)} = D_i^{(k)} + \sum_{\substack{x_j \in T^{(k-1)} \cup S^{(k)} \\ x_j \prec x_i}} s_j^{(k)} \tag{12}$$

where, $D_i^{(k)}$ is another density-estimation metric. It equals the inverse of the distance to the k-th nearest neighbor. After calculation of Eq. 12, $T^{(k)}$ is filled with $n_T^{(k)}$ best solutions of $T^{(k-1)}$ and $S^{(k)}$.

Fitness assignment of SPEA2+: SPEA2+ proposed by Mifa *et al*. (2004) allocates fitness in the same way with SPEA2. The modification is that it incorporates new crossover and mating selection scheme and uses two external populations, $T^{(k)}$ and $W^{(k)}$ to store solutions that are diverse in objective space and variable space, respectively.

According to the scheme of fitness assignment, the procedures of SPEA, SPEA2 and SPEA2+ at generation k are demonstrated in Fig. 1. SPEA combines $S^{(k-1)}$ and $T^{(k-1)}$ and then generate $S^{(k)}$ by evolving process. $T^{(k)}$ is selected by filtering process and then enters the next generation together with $S^{(k)}$. For SPEA2, $T^{(k-1)}$ will go through evolving process alone to obtain $S^{(k)}$. $T^{(k-1)}$ and $S^{(k)}$ are filtered and $T^{(k)}$ is generated.

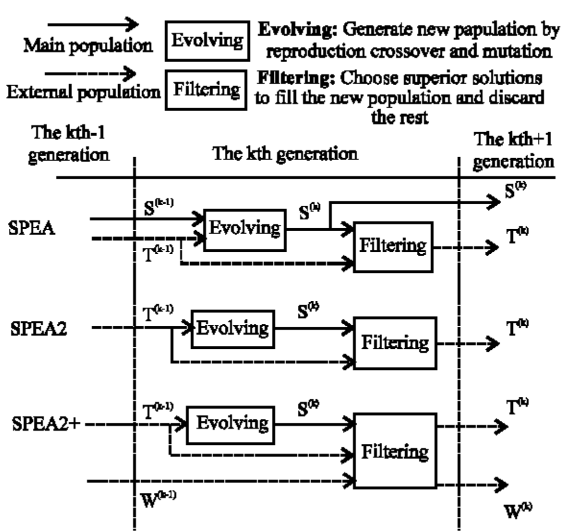

Fig. 1: Procedure of SPEA, SPEA2 and SPEA2+ at generation k

In SPEA2+, three populations are evolving simultaneously. The new population $S^{(k)}$ is generated from $T^{(k-1)}$. Next, filtering process combines $S^{(k)}$, $T^{(k-1)}$ and $W^{(k-1)}$, then chooses superior solutions to form the new external population $T^{(k)}$ and $W^{(k)}$.

IMPROVEMENT OF SPEA FOR ORPF

For ORPF, reactive power and voltage is closed related in the system power flow. According to our experiments, the problem-specific Local Search Strategies (LSSs) can increase the convergence speed of MOEAs (NSGA, NSGA-II, etc.). Here, we use LSSs to improve SPEAs. For Control-Bus LSS and Voltage-Correction LSS, interested readers can refer to Iba (1994).

Controller-random LSS: As shown in Fig. 2, one controller is selected randomly and its tap position is added or dropped for one step (ΔX_i) if it = s a transformer or a capacitor. For generator, one random value change is added to the generator voltage.

Swap-random LSS: Two same type control variables are chosen randomly and their control value are swapped as shown in Fig. 3.

Max-min LSS: One control variable is selected randomly and its output is promoted or reduced to maximum or minimum as demonstrated in Fig. 4.

By incorporating LSSs, improved SPEA (ISPEA), improved SPEA2 (ISPEA2) and improved SPEA2+ (ISPEA2+), are formulated, as demonstrated in Fig. 5.

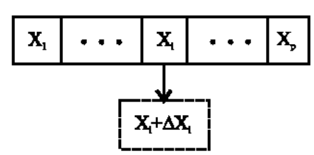

Fig. 2: Controller-random LSS

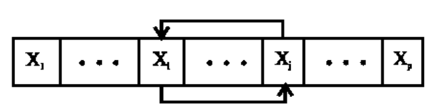

Fig. 3: Swap-random LSS

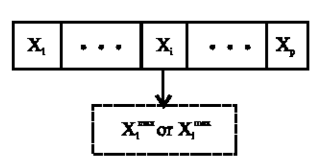

Fig. 4: Max-min LSS

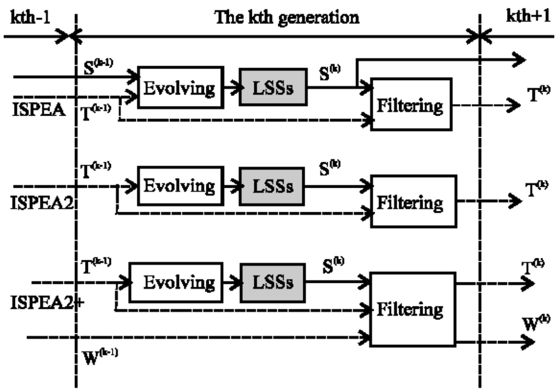

Fig. 5: Procedure of ISPEA, ISPEA2 and ISPEA2+ at generation k

Compared with Fig. 1, an extra LSSs procedure is invoked for local refinement after evolving process. The new population, $S^{(k)}$, can be promoted for better quality with LSSs in Fig. 5 and the optimal solutions can be located more accurately. After LSSs procedure, in SPEA, $T^{(k)}$ is selected by filtering process and then enters the next generation together with $S^{(k)}$. For SPEA2, $T^{(k-1)}$ and $S^{(k)}$ are filtered and $T^{(k)}$ is generated. In SPEA2+, filtering process combines $S^{(k)}$, $T^{(k-1)}$ and $W^{(k-1)}$, then chooses superior solutions for external population $T^{(k)}$ and $W^{(k)}$.

Weighted scalar fitness function method by Joshua and David (2005) is adopted for comparison of nondominated solutions generated by LSSs. For a selected solution that enters LSSs process as in Fig. 5, all the problem-specific LSSs are applied sequentially and several new individuals can be produced. Then a weight vector is randomly generated for fitness calculation. For all the new generated solutions, the one with the best fitness will be accepted.

IMPLEMENTATION OF SPEA FOR ORPF

In the evolving process of SPEAs, genetic operators such as coding, crossover and mutation operators are used to generate new solutions. In coding operator, real-coding scheme is used to deal with continuous search space. A control variable is represented by a real number within its lower limit and upper limit. A blend crossover operator and normally distributed mutation operator is employed for real-coding scheme. In SPEA2+ and ISPEA2+, neighborhood crossover is also used. Based on these genetic operators, the flow chart of the algorithms is shown in Fig. 6 with 5 steps.

- **Step 1:** Input the data of electric power systems; calculate the admittance matrix; randomly generate initial population; configure algorithm parameters; set k = 1

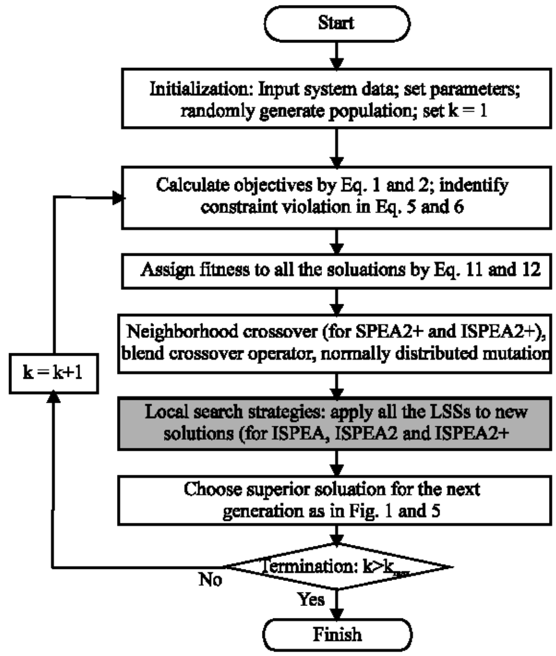

Fig. 6: Flow chart of SPEAs for ORPF

- **Step 2:** A load flow calculation as in Eq. 3 and 4 is performed for each solution and then Eq. 1 and 2 is calculated to obtain real power loss and voltage deviation
- **Step 3:** Based on the objective value calculated in step 2, assign fitness according to Eq. 11 and 12 to each solution in the population
- **Step 4:** Blend crossover operator and normally distributed mutation operator is adopted to generator new solutions; neighborhood crossover is used for SPEA2+ and ISPEA2+
- **Step 5:** For SPEA, SPEA2 and SPEA2+, go to next step; for ISPEA, ISPEA2 and ISPEA2+, the problem-specific LSSs are invoked and performed on all the new solutions for local refinements
- **Step 6:** According to the filter process in Fig. 1 and 5, choose the superior solutions for the next generation
- **Step 7:** Check whether the maximum iteration quantity is reached. If not, k = k + 1 and go to the step 2

CASE STUDY

New England 39-bus system is used as a test system here, as shown in Fig. 7. The detailed system data are listed in Jain *et al*. (2009).

Comparison of nondominated solutions: The population size and generation number are set to 100. Figure 8 shows

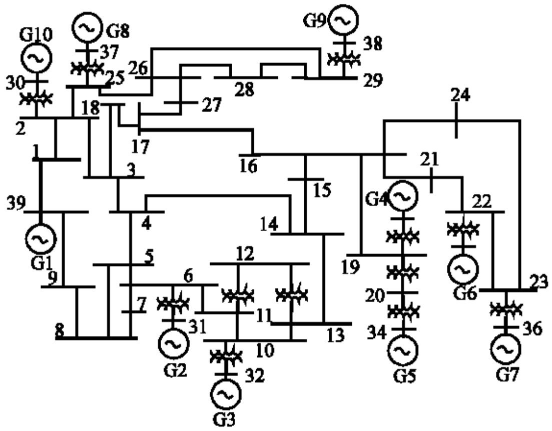

Fig. 7: New England 39-bus system

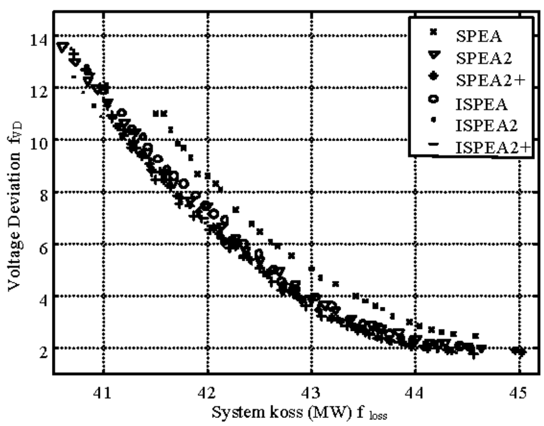

Fig. 8: Pareto fronts with SPEAs

the plots of $PF^{(100)}$ achieved by six SPEAs. Pareto front in the objective space achieved by SPEAs provide the tradeoff information of the two objectives, system loss and voltage deviation. System operator can directly choose the optimal solution according to system states and corresponding protocols. The worst performance is provided by SPEA since, its Pareto front is narrowed down in a smaller region than the others.

Comparison of outer solutions: Outer solutions are the solutions with lowest real power loss or lowest voltage deviation in Pareto front as defined by Zitzler *et al.* (2001). These solutions represent the extreme points of the trade-off surface and can evaluate the diversity characteristics of the Pareto-optimal solutions. Totally 100 trials are performed. For the objective of real power loss, 100 outer solutions can be obtained at generation k for each algorithm. Convergence curves that represent average value are depicted in Fig. 9. Figure 10 provides the information for voltage deviation.

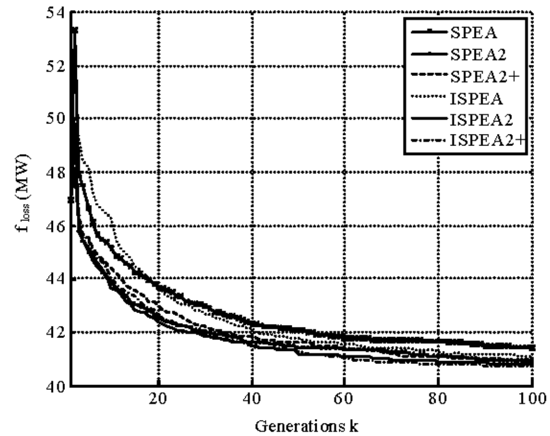

Fig. 9: Convergence of outer solutions for real power loss objective

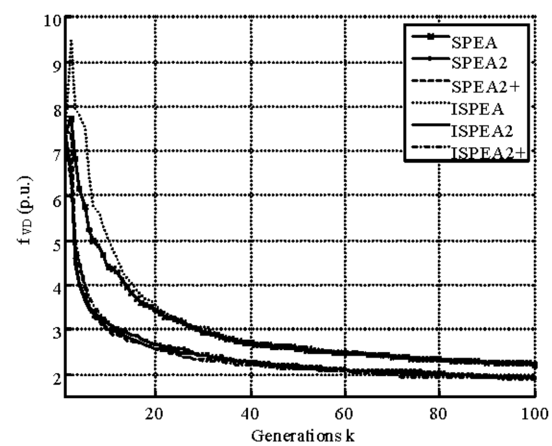

Fig. 10: Convergence of outer solutions for voltage deviation objective

The efficiency of SPEA, SPEA2 and SPEA2+ increase orderly, so does their improved versions, ISPEA, ISPEA2 and SPEA2+. The modifications proposed in SPEA2 and SPEA2+ are proved to be effective to eliminate the disadvantages of SPEA. SPEA converge much slower than SPEA2 and SPEA2+, especially in the early stage. Even its improved version, ISPEA, is less competitive than the original SPEA2 and SPEA2+.

It can be observed that SPEAs with LSSs outperform the original SPEAs. As shown in Fig. 9 and 10, the curves of SPEA, SPEA2 and SPEA2+ converge slower than their corresponding improved versions, ISPEA, ISPEA2 and ISPEA2+, respectively. It implies that the incorporation of LSSs promote the search ability and convergence speed.

The best performances are provided by SPEA2+ and ISPEA2+. SPEA2+ performs well compared with other

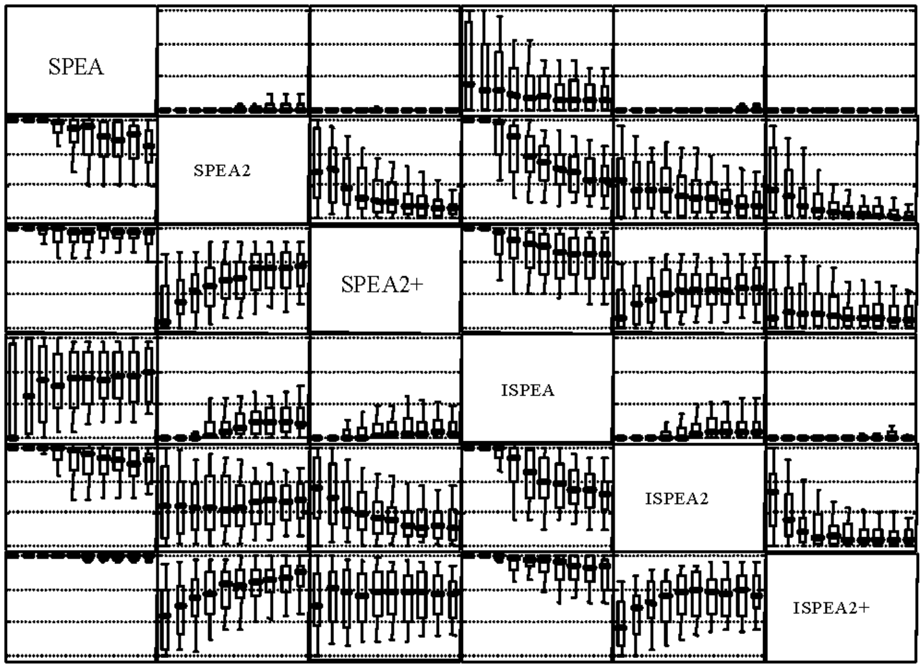

Fig. 11: Box plots based on the C measure. Each rectangle contains ten box plots representing the distribution of the C values for a certain ordered pair of algorithms; the ten box plots relate to generation 10, 20, 30…100. The scale is 0 at the bottom and 1 at the top per rectangle. Each rectangle refers to algorithm A associated with the corresponding row and algorithm B associated with the corresponding column and gives the fraction of B covered by A (C(A, B))

algorithms and it is improved further by the problem-specific LSSs. ISPEA2+ is preferable among all the algorithms.

Comparison by C Measure: Outer solutions only involve two individuals of the population during optimizing. C measure in Zitzler *et al.* (2003) is adopted to compare whole Pareto fronts. For two solution sets, C measure can be computed by

$$C(Q_1, Q_2) = \frac{|\{b \in Q_2; \exists a \in Q_1 : a \prec b\}|}{|Q_2|}$$

$C(Q_1, Q_2)$ represents the proportion of solutions in set Q_2 that are dominated by any solution in set Q_1. The direct comparison of SPEAs based on the C measure is depicted in Fig. 11 by box plot, a classic data analyzing tool used to visualize the distribution of samples. A box plot consists of a box summarizing 50% of the data. The upper and lower ends of the box are the upper and lower quartiles, while, a thick line within the box encodes the median. Appendages summarize the spread and shape of the distribution. In 100 trials, $S^{(i)}$, i= 10, 20, 30…100 for any two of SPEAs are compared. We may focus on the median of 100 trials here. Table 1 lists the median of final C in a similar arrangement as in Fig. 11. The observations in Fig. 11 and Table 1 are largely in agreement with those of Fig. 9 and 10, despite the fact that the method of measurement is quite different.

Table 1: Median of C measure at the final generation

SPEA	0%	0%	10%	0%	0%
73.3%	**SPEA2**	10%	40%	13.3%	0%
96.7%	63.3%	**SPEA2+**	73.3%	40%	8.2%
70%	13.3%	4.7%	**ISPEA**	6.7%	0%
86.7%	46.7%	19.2%	53.3%	**ISPEA2**	8%
100%	83.3%	62%	90%	60%	**ISPEA2+**

The SPEA is proved to be a less efficient algorithm, especially in the early stage of the evolving, when up to 100% of its solutions are covered by the other algorithms at the 20th generation. ISPEA is also less efficient compared with ISPEA2 and ISPEA2+53.3 and 90% solutions of ISPEA is covered by ISPEA2 and ISPEA2+, respectively, while it only dominate 6.7 and 0% solution of them.

The improved SPEAs outperformed original SPEAs. ISPEA covers 70% of SPEA's solutions, which only covers 10% solutions of ISPEA. ISPEA2 covers 46.7% solutions of SPEA2, but only 13.3% of its solution is covered by SPEA2.

It is observed that SPEA2+ and ISPEA2+ clearly outperform other SPEAs. Among these two algorithms, ISPEA2+ is preferable since, only 8.2% of its population is covered by SPEA2+, while it covers 62% population of SPEA2+, at the 100th generation.

CONCLUSION

This paper studies three versions of Strength Pareto Evolutionary Algorithm (SPEA, SPEA2 and SPEA2+) for ORPF and also proposes three corresponding improved SPEAs (ISPEA, ISPEA2 and ISPEA2+) by incorporating several problem-specific Local Search Strategies (LSSs). Based on the case study on New England 39-bus system, SPEA2+ has demonstrated its high efficiency for ORPF and its convergence speed is improved further by LSSs in ISPEA2+. ISPEA2+ can search for Pareto fronts much faster and has provided the best performance on the test system. Its application on an energy control center of large-scale systems should be investigated for future works.

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