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IFAC-PapersOnLine 48-30 (2015) 276–281

MVMO for Optimal Reconfiguration in Smart Distribution Systems

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Abstract: This paper introduces an approach based on the mean-variance mapping optimization algorithm (MVMO) to solve the optimal reconfiguration of radial distribution systems (ORRDS). MVMO is an emerging evolutionary algorithm, whose search procedure performs within a normalized range of the search space for all optimization variables, and by following either a single parent-offspring pair or a population based procedure. Remarkably, its main trait resides in the use of a special mapping function for mutation operation, which allows a controlled shift from exploration priority at early stages of the search process to exploitation at later stages. Numerical tests on the IEEE 33-bus test system, including performance comparison with other state-of-art algorithms, show the effectiveness of the MVMO-based approach to get the optimal switching combination in the network which results in total minimum active power losses.

1. INTRODUCTION

Broadly speaking, distribution networks are structured in mesh, but generally operated in radial tree configuration in order to reduce the fault level and to ensure effective coordination of the protection scheme. Due to continuous change of operating conditions, the topological layout of the distribution feeders is often modified for different purposes, for instance, to ensure suitable reliability level, improve the voltage profile, tackle load congestion, and reduce overall network losses [Swarnkar et al. (2011)].

Since feeder reconfiguration can be done by considering many different strategies (i.e. candidate switching combinations), finding the most desirable radial operating configuration constitutes a mathematically complicated optimization problem, due to the underlying combinatorial, non-convex, and constrained solution search space [Srinivasa et al. (2011)]. The problem is henceforth referred to as optimal reconfiguration of radial distribution systems (ORRDS).

Classical optimization algorithm based solution techniques do not lend themselves to acceptable outcomes, even though these are computationally efficient. [Lee et al. (2008)]. These features have motivate the exploration of new solution strategies, for which heuristic optimization framework has become a promising alternative due to conceptual simplicity, easy adaptability, and open feasibility of hybridization with additional algorithms (e.g. local search) to improve the search process performance [Camargo et al. (2014)]. Exemplary pioneer applications include Genetic Algorithm [Duan et al. (2015)], Particle Swarm Optimization [Andervazh et al. (2015)], Simulated Annealing [Jeon et al. (2002)], Harmony search [Srinivasa et al. (2011)], Ant Colony [Swarnkar et al. (2011)], Tabu Search [Hayashi et al. (2004)], and plant growth simulation [Wang et al. (2008)], whereas recent applications include Fireworks Algorithm [Imran et al. (2014)], Shuffle Frog Leaping Algorithm [Behdad et al. (2014)], Artificial Immune Systems Optimization [Alonso et al. (2015)], and Cuckoo Search Algorithm [Nguyena et al. (2015)]. Due to their stochastic nature, these heuristic optimization algorithms do not strictly guarantee global optimality, especially for high-dimensional problems (i.e. large-scale distribution systems), but usually provide near-to-optimal or good enough solutions in reasonable time. Moreover, they all might involve a large number of computation requirements, and tuning their parameters to ensure robust performance might become a cumbersome task.

Mean-variance mapping optimization (MVMO), is an emerging evolutionary algorithm, which was initially conceived as a single-solution based approach (i.e. evolution of a single candidate solution), and whose evolutionary mechanism performs on a normalized search space (i.e. within the range [0,1]) for all optimization variables [Pham et al. (2014)]. Furthermore, MVMO uses a solution archive as an adaptive memory to record the n-best solutions found so far. Like other state-of-art evolutionary mechanisms, MVMO adopts an elitism criterion to select the parent solution (i.e. first ranked solution in the archive), from which a child solution (offspring) is created. Moreover, some dimensions of the child solution inherit the values from the parent, whereas the remaining dimensions are mutated through a special mapping function which accounts for the corresponding mean and variance. The mapping function is

10.1016/j.ifacol.2015.12.390

defined in the interval [0, 1] and its shape is adapted throughout the progress of the search process in order to shift the focus from exploration (at initial stages of the process) to exploitation (at later stages). De-normalization (i.e. conversion to the original dimension) of each dimension of a candidate solution is only performed for each fitness evaluation.

Recently, MVMO has been extended to a population-based approach, which is also hybridized to include the possibility launching a local search strategy. Due to these two extensions, the new variant is hereafter denoted as MVMO-SH. Broadly speaking, each solution is evolved like in the single-solution approach, but multi-parent crossover is incorporated into the offspring creation stage in order to force the individuals with worst fitness to explore other sub-regions of the search space [Erlich et al. (2014)]. Due to the fast convergence characteristics and successful application in other power system problems [Rueda et al. (2014)], both MVMO variants (single parent-offspring pair and population based procedures), are used in this paper to tackle the ORRDS problem with the aim of determining the optimal radial operating configuration that entails minimum losses while satisfying all operational constraints.

Following this introduction, the rest of the paper is organized as follows: Section 2 introduces the formulation of ORRDS problem and overviews the theoretical background behind MVMO-SH based approach. Numerical results are provided in Section 3. Finally, conclusions are summarized in Section 4.

2. PROPOSED APPROACH

2.1 Problem statement

The mathematical model of the ORRDS problem, with the aim of minimizing the total active power losses of a distribution system, has the following format [Rost. (2006)]:

Minimize

$$P_{\text{loss}} = \text{Re}\left(V_{\text{ss}} \sum_{j\in \text{N}_\text{b}} \left[\left(V_{\text{ss}} - V_j \right) Y_{\text{ss},j} \right]^* \right) - \sum_{k\in \text{N}_\text{d}} P_{\text{D}} \tag{1}$$

subject to

$$\sum_{i\in \text{S}_\text{L}} sw_i = N_{\text{S}_\text{L}}^{\text{SE}} - 1, \quad \forall \text{S}_\text{L} \in \text{M} \tag{2}$$

$$\mathbf{p}(\mathbf{v},\boldsymbol{\theta}) = \mathbf{0} \tag{3}$$

$$\mathbf{q}(\mathbf{v},\boldsymbol{\theta}) = \mathbf{0} \tag{4}$$

$$\mathbf{v}_{\text{min}} \le \mathbf{v} \le \mathbf{v}_{\text{max}} \tag{5}$$

where P_D stands for nodal active power demand, whereas N_b and N_d denote total number of buses attached to the substation and total number of demand buses. $Y_{\text{ss},j}$ is the admittance between the substation bus and any bus attached to the substation, V_{ss} is the substation bus voltage phasor, and V_j is the voltage phasor at any bus attached to the substation bus. S_L and M stand for loop and number of possible loops, whereas *sw* and $N_{\text{S}_\text{L}}^{\text{SE}}$ denote switch-state-vector and number of switchable elements within a specific loop S_L, respectively. The vectors $\mathbf{p}$(.) and $\mathbf{q}$(.) refer to the nodal active and reactive power balance, respectively, whereas $\mathbf{v}$ and $\boldsymbol{\theta}$ denote bus voltage magnitude and phase angle vectors, respectively. Finally, the vectors $\mathbf{v_{min}}$, $\mathbf{v_{max}}$, comprise the lower and upper bounds of all bus voltages.

Equation (2) is defined so as to ensure a radial layout of the feeders, whereas (3) to (5) consider fulfillment of active and reactive power nodal balance as well voltage constraints for each bus of the system.

2.2 Candidate solution

A candidate solution (i.e. vector of optimization variables) is defined as $\mathbf{x} = [x_1, x_2, \ldots, x_\text{M}]$, where each element x is associated to a loop S_L, and is represented by an integer number that varies between 1 and the length of *sw*. Thus, considering that the elements of *sw* correspond to the switch state (i.e. 1=on or 0=out) of the switchable line segments for the loop S_L, it is defined that a sampled value of x throughout the optimization procedure indicates the element of *sw* that will be set to 0 (i.e. the associated line segment is switched out), whereas the remaining elements are equal to 1. Therefore, equation (2) is satisfied at every function evaluation in the optimization procedure, since only one line segment will be switched out (i.e. radial feeder layout), and the sum of *sw* will always equal $N_{\text{S}_\text{L}}^{\text{SE}} - 1$.

2.3 Solution procedure

The flowchart of MVMO-SH based solution procedure is schematically shown in Fig. 1. The procedure begins with an initialization stage where the algorithm parameter settings are defined and samples of the optimization variables are randomly drawn within their search boundaries for a population of N_P candidate solutions. Besides, the optimization variables are normalized at this stage, that is, the range of the search space for all variables is transformed from [min, max] to [0, 1] range. This is a precondition for the subsequent mutation operation via mapping function; on top of this, it guarantees that the generated offspring will never violate the search boundaries. The optimization variables are only de-normalized when performing fitness evaluation. The core of the algorithm is contained in the inner loop of the flowchart, in which, after execution of fitness evaluation for a given candidate solution, updating the solution archive, fitness based classification of candidate solutions into good or bad solutions, parent selection and offspring generation are performed. The process is terminated upon completion of a specified number of iterations. It is worth pointing out that the single parent-offspring MVMO variant is equivalent to the execution of MVMO-SH with $N_P = 1$.

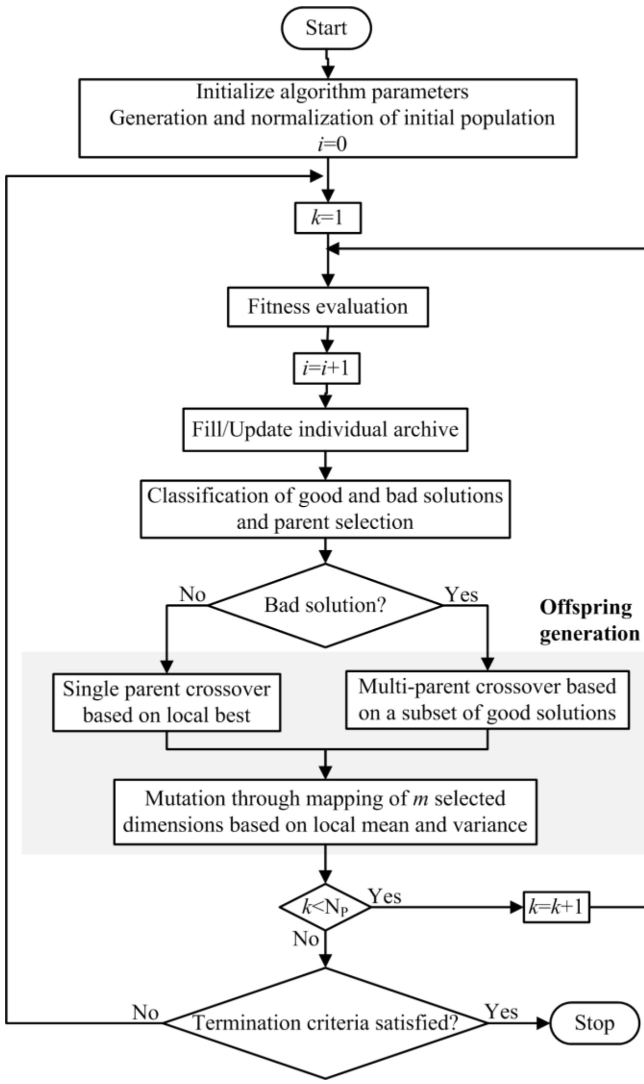

Fig. 1. MVMO-SH based solution procedure for ORRDS. The fitness evaluation and candidate solution counters are denoted by *i* and *k*, whereas N_P, ΔFE, and *rand* stand for number of candidate solutions, number of fitness evaluations, and uniform random number between [0, 1], respectively

2.4 Fitness evaluation

The elements of the candidate solution array are de-normalized from [0, 1] range to their original [min, max] boundaries before fitness evaluation or local search is performed. A static penalty scheme is adopted, where the fitness is computed as follows:

$$f = P_{\text{loss}} + p_1 + p_2 \tag{6}$$

$$p_1 = \sum_{i=1}^{N_{\text{icon}}} \rho_i^{\dagger} \cdot \max\left[0, g_i(\mathbf{x})\right] \tag{7}$$

$$p_2 = \sum_{j=1}^{N_{\text{econ}}} \rho_j^{\dagger\dagger} \cdot \max\left[0, \left|h_j(\mathbf{x})\right| - \varepsilon\right] \tag{8}$$

where N_{icon} is the number of inequality constraints, N_{econ} is the number of equality constraints, and ε is a tolerance parameter for equality constraints. Furthermore, g_i denotes the i-th inequality constraint (excluding boundary constraints), and h_j the j-th equality constraint. $\rho_i^{\dagger}$ and $\rho_j^{\dagger\dagger}$ stand for penalty coefficient (factor) for each constraint.

2.5 The evolutionary mechanism

Each candidate solution has a compact and continually updated solution archive associated to it, which stores its n-best offsprings in a descending order of fitness and serves as the knowledge base for guiding the search direction. The archive size is fixed for the entire process. For each candidate solution, and after every execution of fitness evaluation, an update of its archive takes place only if the child solution is better than those in the archive. Besides, the mean $\bar{x}_i$, shape s_i, and d-factor d_i associated to each optimization variable are recalculated whenever an update of the archive takes place.

In the early stage of the search process, each candidate solution is independently drawn for at least two function evaluations, and the solution that produced the individual best fitness achieved so far (i.e. the one corresponding to the first ranked position in its particular solution archive) is chosen as the parent for the next offspring. Afterwards, the candidate solutions are classified into the set of GP "good solutions", and N_P-GP "bad solutions" based on the individual best fitness. Individual best-based parent assignment is adopted for each solutions classified as good, whereas for each bad solution $\mathbf{x}_k$, the parent $\mathbf{x}_k^{\text{parent}}$ is determined by a following multi-parent criterion:

$$\mathbf{x}_k^{\text{parent}} = \mathbf{x}_{\text{RG}}^{\text{best}} + \beta\left(\mathbf{x}_{\text{GB}}^{\text{best}} - \mathbf{x}_{\text{LG}}^{\text{best}}\right) \tag{9}$$

where $\mathbf{x}_{\text{GB}}^{\text{best}}$, $\mathbf{x}_{\text{LG}}^{\text{best}}$ and $\mathbf{x}_{\text{RG}}^{\text{best}}$ represent the first (global best), the last, and a randomly selected intermediate solution in the group of good solutions, respectively. The vector of mean values associated to $\mathbf{x}_k$, which are required later for mutation and mapping by the mapping function is also set to $\mathbf{x}_k^{\text{parent}}$. The factor β is a random number, which is determined from:

$$\beta = 2.5\left(rand + 0.25 \cdot \alpha^2 - 0.5\right) \tag{10}$$

β is re-drawn and (10) is recalculated for any element of $\mathbf{x}_k^{\text{parent}}$ going outside the range [0, 1]. For the class of "good solutions" the mean used for mapping is selected randomly from the same group. The relative number *GP* of solutions belonging to the group of good solutions is linearly decreased throughout the iterations from an initial predefined value $g_{\text{p\_ini}}^{*}$ to a smaller one $g_{\text{p\_final}}^{*}$.

For the next generation, a child vector (array) $\mathbf{x}^{\text{new}}=[x_1,x_2,x_3,\ldots,x_D]$, where D is the number of problem dimensions, is created for each solution by combining a subset of D-m directly inherited dimensions from $\mathbf{x}_{\text{p}}^{\text{parent}}$ (i.e. crossover) and m selected dimensions that undergo mutation operation through mapping function based on the actual values of the parameters $\bar{x}_i$, s_i, and d_i associated to each solution. The number m of dimensions to be selected for mutation operation is also linearly decreased throughout the iterations from an initial value m_{ini} to a smaller one m_{final}.

The new value of each selected dimension x_{r} of $\mathbf{x}^{\text{new}}$ is determined by

$$x_{\text{r}} = h_{\text{x}} + (1 - h_1 + h_0)\cdot x_{\text{r}}^* - h_0 \tag{11}$$

where x_{r}^* is a randomly generated number with uniform distribution between [0, 1], and the term h (subscripts specified below) represents the transformation mapping function defined as follows.

$$h(\bar{x},s_1,s_2,x) = \bar{x}\cdot(1-e^{-x\cdot s_1}) + (1-\bar{x})\cdot e^{-(1-x)\cdot s_2} \tag{12}$$

h_{x}, h_1 and h_0 are the outputs of the mapping function calculated for

The shape factor s_{r} is calculated as follows:

$$s_{\text{r}} = -\ln(v_{\text{r}})\cdot f_{\text{s}} \tag{13}$$

where v_{r} is the variance computed from the stored values of x_{r} in the solution archive, and f_{s} is a scaling factor. Recalling (12), the shape factors s_{r1} and s_{r2} of the variable x_{r} are sequentially assigned by using the following procedure:

$$\begin{array}{l}
s_{\text{i1}} = s_{\text{i2}} = s_{\text{i}} \\
\text{if } s_i > 0 \text{ then} \\
\quad \Delta d = (1+\Delta d_0) + 2.5\cdot\Delta d_0\cdot(rand - 0.5) \\
\quad \text{if } s_{\text{i}} > d_{\text{i}},\ d_{\text{i}} = d_{\text{i}}\cdot\Delta d, \text{ else } d_{\text{i}} = d_{\text{i}}/\Delta d \text{, end} \\
\quad \text{if } d_{\text{i}} > s_{\text{i}} \text{ then} \\
\qquad s_a = d_{\text{i}};\ \ s_b = s_{\text{i}} \\
\quad \text{else} \\
\qquad s_a = s_{\text{i}};\ \ s_b = d_{\text{i}} \\
\quad \text{end if} \\
\quad \text{if } rand < 0.5 \text{ then} \\
\qquad s_{\text{i1}} = s_a;\ \ s_{\text{i2}} = s_b \\
\quad \text{else } s_{\text{i1}} = s_b;\ \ s_{\text{i2}} = s_a \\
\quad \text{end if} \\
\text{end if}
\end{array} \tag{14}$$

Initially, the value of d_{i} is set to 1 for all variables. Thereafter, each d_{i} is scaled up or down over the iterations by the factor Δd, which is randomly varied between 1 and $1+2\cdot\Delta d_0$. If $d_{\text{i}} > s_{\text{i}}$, the current d_{i} is divided by Δd which is always larger than 1.0 and thus leads to reduced value of d_{i}. In case $d_{\text{i}} < s_{\text{i}}$, d_{i} will be multiplied by Δd resulting in increased d_{i}. In this way d_{i} will always oscillate around the current shape factor s_{i}. The assignment of s_{i} and d_{i} to s_{i1} or s_{i2} depends on the actual values of s_{i} and d_{i} and $\bar{x}_{\text{i}}$. It is recommended to take a non-zero value equal to or smaller than 0.4 for Δd_0. A high value of Δd_0 will indirectly entail wider global search diversification over the entire space whereas a smaller one would lead to concentrated local search aiming at accuracy improvement.

3. NUMERICAL RESULTS

Numerical experiments were performed on a Dell personal computer equipped with Intel® Core™ i7 4600U CPU, 2.70 GHz and 8 GB RAM, under Windows 7 enterprise, 64 bit OS. The implementation of the optimization task and the MVMO-SH based approach was done in Matlab® Version R2014b. The IEEE 33-bus test distribution system was used to evaluate the performance of the proposed approach. Detailed description of the system and parameter data can be found in [Rost. (2006)].

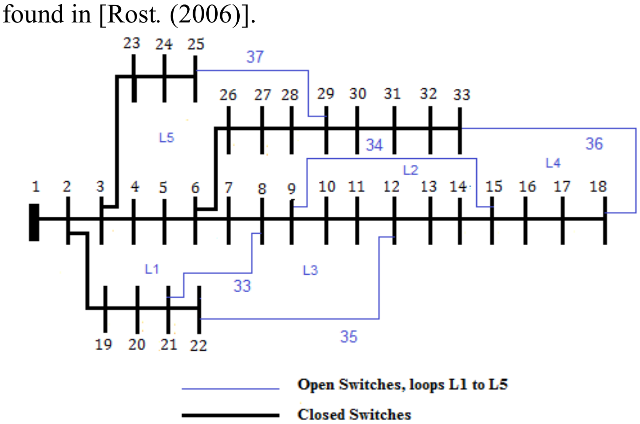

Fig. 2. IEEE 33-bus test system: Initial configuration

The initial configuration is shown in Fig. 2, where the tie switches 33, 34, 35, 36 and 37 are open, and the radial layout consists of the line sections numbered from 1 to 32. The load flow calculation algorithm presented in [Rost. (2006)] is used to determine the load flow profile associated to the initial configuration. The total active and reactive power demands are 3715 kW and 2300 kVAr, respectively, whereas the active power losses are 202.67 kW. The lowest voltage magnitude is 0.9131 p.u, and occurs at bus 18.

The parameter settings used for MVMO-SH were: N_{p}=5, and N_{p}=1 (single-parent offspring MVMO classical approach), archive size=5, $g^*_{\text{p\_ini}} = 0.7$, $g^*_{\text{p\_final}} = 0.2$, m_{ini}=D/4, $\text{m}_{\text{final}} = 1$, Δd_0=0.2, $f_{\text{s}} = 1$. Random initialization is adopted. The penalty factors $\rho_i^{\dagger}$ and $\rho_j^{\dagger\dagger}$ used in (7) and (8) are set to 10, since sensitivity analysis with respect to the variation of these parameters under optimization repetition evidenced that similar effect is obtained by using any other penalty value above 10. For equality constraints, the tolerance parameter is set to ε=0.0001. The MVMO-SH based approach was executed for 200 independent optimization repetitions. The best optimization repetition entailed a configuration with the switches [7 14 9 32 37] being open, and the total active power losses equal to 139.55 kW, which corresponds with a decreases of the losses of approximately 31.14 %. The optimal reconfiguration is shown in Fig. 3. For this reconfiguration, the lowest voltage magnitude was 0.9378 p.u, which occurs at bus 32. No violation of the upper voltage bounds occurred (cf. Fig. 4).

Table 1 provides a summary of the statistics of the MVMO-SH based approach, including a comparison with the results obtained by MVMO (i.e. MVMO-SH executed with N_P =1) and the results obtained by using different state of the art heuristic optimization algorithms, namely, Harmony search (HSA) [Srinivasa et al. (2011)], evolutionary programming [Rost. (2006)], genetic algorithm with multi-parent crossover (GA-MPC) [Elsayed et al. (2014)], covariance matrix adaptation evolution strategy (CMA-ES) [Hansen (2011)], and linearized biogeography-based optimization (LBBO) [Simon et al. (2014)]. All algorithms were run for 200 independent optimization repetitions and were set to stop if there is no improvement of fitness after two consecutive evaluations. Note that similar outcomes are obtained if MVMO-SH is run with one or more candidate solutions. Thus, in light of lower computing effort, it would be desirable to use the single parent-offspring MVMO approach. Nevertheless, additional tests with larger systems are needed to further ascertain if this finding also holds for such systems. Note that EP also allows obtaining similar statistics, but the calculations involved in the algorithmic procedure entail a higher computing effort. HAS allows obtaining the reconfiguration with lower losses than those obtained by MVMO and EP, but the average and std measures indicate that the algorithm entails a considerably higher variability under optimization repetition. It is worth pointing out that none of the algorithms were tuned. Thus, further analysis by using optimized parameters of each optimization algorithm is needed in order to corroborate whether the same performance can be achieved.

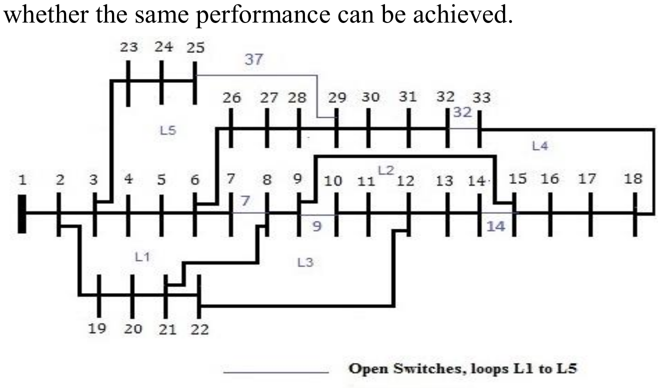

Fig. 3. IEEE 33-bus test system: optimal reconfiguration.

Fig. 4 illustrates the improvement in the bus voltage profile that is achieved by solving ORRDS based on EP, MVMO, and MVMO-SH algorithms. Note that the solutions obtained by using any of these algorithms entails preventing the risk of violation of the allowed low voltage boundary. Recalling the findings from the statistical performance measures shown in Table 1, there will be a high confidence level that, despite of the random factors involved in the evolutionary mechanism of these optimization algorithms, they will provide similar results in any optimization repetition, particularly, when applied to small-size distribution systems. Although not shown here due to space constraint, it is worth pointing out that MVMO algorithm was able to reach the minimum value of losses after 45 function evaluations, whereas EP needed 1000 function evaluations. Thus, this algorithm is attractive for online implementation of ORRDS.

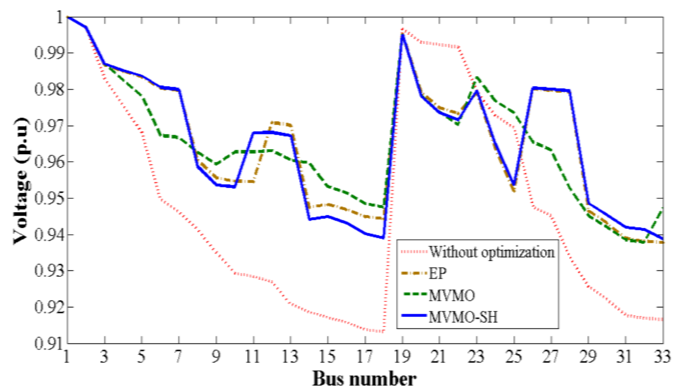

Fig. 4. Improvement of voltage profile by ORRDS.

4. CONCLUSIONS

An approach based on the MVMO algorithm to solve the ORRDS problem was presented in this paper. The rationale behind MVMO and its application to properly tackle ORRDS was thoroughly discussed. Numerical results, based on the IEEE 33-bus test distribution system, including performance comparison with other emerging heuristic optimization algorithms, illustrated the potential of MVMO for successfully finding the optimal reconfiguration that entails minimum active power losses and enhanced voltage profile. The tests were conducted by using typical parameters for the compared algorithms and evidenced that MVMO entails less variability of the obtained optimization outcomes, which is in agreement with the findings from other applications of MVMO to different power system problems. Nevertheless, it is worth pointing out further analysis must be carried out in order to ascertain if the conclusions drawn in this paper are still valid when the compared algorithms are optimally tuned. Moreover, unlike other approaches reported in existing literature concerning ORRDS, in which the optimization algorithms were mixed with other techniques, e.g. graph theory considerations, MVMO was used in its pure algorithmic form. Future research work will be also focused on hybridization of MVMO with other techniques to solve ORRDS, and also considering different formulations and targets for ORRDS, e.g. reliability. The application of MVMO to other combinatorial problems in power system field, and the comparison of algorithms by using non-parametric statistical tests are currently being investigated.

Table 1. Comparative statistics

		HAS	EP	GA-MPC	LBBO	CMA-ES	MVMO	MVMO-SH
Tie Switches		7,10,14,37,36	7,9,14,32,37	7,9,14,32,37	7,9,14,36,37	7,9,14,37,32	7,9,14,32,37	7,9,14,32,37
Loss (kW)	Best	138.06	139.55	139.55	139.28	141.60	139.55	139.55
	Average	152.33	144.74	164.90	163.5	166.20	146.314	145.82
	STD	11.28	2.50	13.34	12.11	14.53	3.43	3.19
Minimum Voltaje (p.u)		0.91	0.93	0.93	0.92	0.92	0.93	0.93
CPU Time (s)		7.20	167.50	13.80	8.10	19.10	9.79	10.03

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