

# MVMO-based approach for optimal placement and tuning of supplementary damping controller

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## Abstract

This paper introduces an approach based on the Swarm Variant of the Mean-Variance Mapping Optimization (MVMO-S) to solve the multi-scenario formulation of the optimal placement and coordinated tuning of power system supplementary damping controllers (POCDCs). The effectiveness of the approach is evaluated based on the classical IEEE 39-bus (New England) test system. Numerical results include performance comparisons with other metaheuristic optimization techniques, namely, comprehensive learning particle swarm optimization (CLPSO), genetic algorithm with multi-parent crossover (GA-MPC), differential evolution DE algorithm with adaptive crossover operator, linearized biogeography-based optimization with re-initialization (LBBO), and covariance matrix adaptation evolution strategy (CMA-ES).

*Keywords:* Coordinated control, damping controllers, metaheuristics, small-signal stability.

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## 1. Introduction

Traditionally, the placement and tuning of power system damping controllers have been tackled as individual problems based on participation factors, residues, damping torque, sensitivity coefficients and singular value decomposition (Karimpour *et al*, 2005; Pagola *et al*, 1989; Wang *et al*, 1997). Alternatively, the simultaneous solution for both tasks has also been investigated from optimization problem point of view. Particularly, the joint determination of optimal placement and coordinated tuning of power system damping controllers (OPCDC) constitutes a challenging optimization problem due to the mix-integer combinatorial nature as well as to the nonlinearity, multimodality, and no convexity of the search space (Sebaa *et al*, 2010).

Previously reported approaches based on modified versions of genetic algorithm (Sebaa *et al*, 2009), particle swarm optimization (Eslami *et al*, 2009), and differential evolution (Wang *et al*, 2009) highlight the potential of metaheuristic optimization algorithms for solving the OPCDC. Due to the stochastic nature of the underlying evolutionary mechanism, further research is needed to ascertain the robustness of these algorithms, which also motivates the application and extension of emerging metaheuristic optimization algorithms. This paper presents an approach based on the Swarm Mean-Variance Mapping optimization (MVMO-S), which extends the single-solution variant of MVMO to a population based strategy. To achieve efficient and fast search capability, MVMO-S, utilizes swarm intelligence precepts and a multi-parent crossover criterion. The rest of the paper is organized as follows: Section II presents the formulation of the OPCDC and overviews the main features of the MVMO-S algorithm. Section II provides a case study on the IEEE New England 39 bus test system. Finally, conclusions and outlook for future research are summarized in Section IV

## 2. Theoretical Background

### 2.1. Optimization problem statement

Mathematically, the OPCDC problem has the following format (Rueda *et al*, 2014):

Minimize

$$\text{OF} = (\zeta_{\text{sys}}^* - \zeta_{\text{th}})^2 + w_1 (\alpha_{\text{sys}}^* - \alpha_{\text{th}})^2 \quad (1)$$

subject to

$$\mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{x}_{\max} \quad (2)$$

where  $\alpha_{\text{th}}$  is a predefined threshold for minimum acceptable modes' real part (i.e. damping factor).  $\zeta_{\text{sys}}^*$  and  $\alpha_{\text{sys}}^*$  correspond to the global damping ratio and damping factor of the system (among the nm critical OMs) throughout nsc representative scenarios. The vector  $\mathbf{x}$  constitutes the solution of the problem, so it contains the damping controller's tuning parameters (gains  $K_{SDC}$ , and time constants  $T_1$  to  $T_4$ ), which are continuous variables, and their locations, which are coded by using logical variables. The weighting factor  $w_1$  is a positive number that is used for combining the squared difference between  $\alpha_{\text{sys}}^*$  and  $\alpha_{\text{th}}$  with the squared difference between  $\zeta_{\text{sys}}^*$  and  $\zeta_{\text{th}}$ .  $\zeta_{\text{sys}}^*$  and  $\alpha_{\text{sys}}^*$  are determined as follows:

$$\zeta_{\text{sys}}^* = \min_{j=1K \text{ nsc}} \left[ \min_{k=1K \text{ nm}} (\zeta_k) \right] \quad (3)$$

$$\alpha_{\text{sys}}^* = \max_{j=1K \text{ nsc}} \left[ \max_{k=1K \text{ nm}} (\alpha_k) \right] \quad (4)$$

## 2.2. MVMO-S

*Mean-variance mapping optimization* (MVMO) is a recently introduced evolutionary algorithm, which has some basic conceptual similarities to other heuristic approaches, but it constitutes a fundamentally new evolutionary mechanism with two salient features. Firstly, MVMO performs by considering normalized range of the search space for all optimization variables within [0, 1]. This ensures that new values generated for optimization variables in offspring creation stage are always within their bounds. The optimization variables are de-normalized before every fitness evaluation. Secondly, MVMO exploits the statistical attributes of search dynamics by using a special mapping function for mutation operation on the basis of the mean and variance of the n-best solutions attained so far and saved in a continually-updated archive (Rueda *et al*, 2013).

The original MVMO represents a single particle approach, which has shown a great potential for solving different optimization problems. This paper presents a new variant of MVMO, termed as MVMO-S, which adopts a swarm intelligence scheme and incorporates a multi-parent crossover strategy to increase the search diversity while striving for a balance between exploration and exploitation. The overall procedure is described as follows:

– **Step 1:** Define  $N_p$ , the initial and final values ( $f_s^*_{\text{ini}}$  and  $f_s^*_{\text{final}}$ ) for scaling factor  $f_s$ , solution archive size, dynamic shape factor  $\Delta d$ , the initial and final proportion of good particles ( $g_{p,\text{ini}}^*$  and  $g_{p,\text{final}}^*$ ), and the initial and final number of dimensions ( $m_{\text{ini}}^*$  and  $m_{\text{final}}^*$ ) to be selected for mutation operation. Next, generate an initial random population of  $N_p$  particles within the search boundaries and normalize the sampled optimization variables by considering the range of search within [0, 1].

– **Step 2:** De-normalize each particle from [0, 1] range to their original [min, max] boundaries and evaluate its fitness.

– **Step 3:** Fill/update the solution archive associated to each particle. The archive stores the n-best child solutions achieved so far in a descending order of fitness. The archive size is fixed for the entire process. For each particle, an update of its archive takes place only if the new solution is better than those in the archive.

**Step 4:** The first ranked solutions (i.e. local bests) of all solution archives are classified into two groups: A set of GP “good particles”, and the set of remaining  $N_p$ -GP “bad particles”. Local best-based parent assignment is adopted for each particle classified as good, whereas for each bad particle  $\mathbf{x}_p$ , the parent  $\mathbf{x}_p^{\text{parent}}$  is synthesized by using the following multi-parent criteria.

$$\mathbf{x}_p^{\text{parent}} = \mathbf{x}_k + \beta (\mathbf{x}_i - \mathbf{x}_j) \quad (5)$$

where  $\mathbf{x}_i$ ,  $\mathbf{x}_j$ , and  $\mathbf{x}_k$  represent the first (global best), the last, and a randomly selected intermediate particle in the group of good particles, respectively. The factor  $\beta$  is a random number, which is drawn according to

$$\beta = 0.5 - 0.25 \cdot \alpha, \quad \alpha = i / i_{\max} \quad (6)$$

where  $i$  denotes fitness evaluation number, and  $r_n$  is a random number with uniform distribution in [0,1].

An element of  $\mathbf{x}_p^{\text{parent}}$  is set to 1 or 0 if it is outside the range [0, 1].

**Step 5:** Create a child vector  $\mathbf{x}^{\text{new}}$  for each particle by combining a subset of  $N_{\text{var}} - m^*$  directly inherited dimensions from  $\mathbf{x}_p^{\text{parent}}$  and  $m^*$  selected dimensions (via roulette wheel tournament selection) that undergo mutation operation through mapping function based on the means and variances calculated from the particle's solution archive.  $m^*$  is progressively decreased as follows:

$$m^* = \text{round} \left( m_{\text{final}} + \text{rand} \left( m^\dagger - m_{\text{final}} \right) \right) \quad (7)$$

$$m^\dagger = \text{round} \left( m_{\text{ini}} - \alpha (m_{\text{ini}} - m_{\text{final}}) \right) \quad (8)$$

– **Step 6:** The new value of each selected dimension  $x_r$  of  $\mathbf{x}^{\text{new}}$  is determined by

$$x_r = h_x + (1 - h_1 + h_0) \cdot x_r^* - h_0 \quad (9)$$

where  $x_r^*$  is a randomly generated number with uniform distribution between [0, 1], and the term  $h$  represents the transformation mapping function defined as follows:

$$h(\bar{x}, s_1, s_2, x) = \bar{x} \cdot (1 - e^{-x \cdot s_1}) + (1 - \bar{x}) \cdot e^{-(1-x) \cdot s_2} \quad (10)$$

$h_x$ ,  $h_1$  and  $h_0$  are the outputs of the mapping function calculated for

$$h_x = h(x = x_r^*), \quad h_0 = h(x = 0), \quad h_1 = h(x = 1) \quad (11)$$

The shape factors  $s_{r1}$  and  $s_{r2}$  of the variable  $x_r$  are assigned by using a sequential scheme which accounts for mean and variance of  $x_r$ , quadratic decrement of  $f_s$  from  $f_{s\_ini}^*$  to  $f_{s\_final}^*$ , and  $\Delta d$  in order to exploit the asymmetry of  $h$ .

**Step 7:** Stop if the termination criterion is met; else go to **Step 2**.

The above procedure is illustrated in Figure 1.

### 3. Case Study

Numerical experiments were performed on a computer with an Intel® Core™ 2, i7 -3820 central processing unit (CPU), 3.60 GHz processing speed, and 8 GB RAM. The simulation environments MATLAB®, MATPOWER (Zimmerman *et al*, 2011), and DIgSILENT PowerFactory™ were used to accomplish the implementation aspects and to test the proposed approach. The *QR method* is used for full eigenvalue computation. The approach is tested using a slightly modified version of the IEEE New England 39 bus test system (Pai, 2011), which includes two *Thyristor-Controlled Series Capacitors* (TCSCs), as illustrated in Figure 2. All generators are represented by sub-transient model and equipped with static excitation systems as well as thermal turbine governor systems.

Changes have been made in the system to account for different operating conditions. The approach presented in (Rueda *et al*, 2011) was used to determine the representative scenarios from probabilistic model based Monte Carlo simulations.

OPDC is solved by considering the representative scenarios and potential addition of damping controllers at generators G2 to G10 as well as at both TCSCs. The damping controllers at generators are assumed to have speed as input signals from local generators and are superimposed to the excitation control system, whereas those at TCSCs have line currents as inputs and are superimposed on the device's main control loop, whose output signal is the series compensation susceptance. The parameters of each controller were adjusted considering typical limits, i.e.  $K_{SDC} \in [1, 100]$ ,  $T_1$  and  $T_3 \in [0.2, 2]$ ,  $T_1/T_2$  and  $T_3/T_4 \in [1, 30]$ , whereas the location is decided by using logical variables. Therefore, the search space has 66 dimensions, comprising to 55 continuous variables and 11 two-state discrete variables.

A static penalty scheme is defined for MVMO and the compared algorithms in order to properly consider the fulfillment degree of constraints as well as to ensure fair comparison. The fitness  $f^*$  is calculated as follows:

$$f^* = f + \sum_{i=1}^{N_{\text{con}}} \rho_i \max [0, g_i]^2 \quad (12)$$

where  $f$  stands for objective function value,  $N_{\text{con}}$  is the number of constraints,  $g_i$  denotes the  $i$ -th constraint, and  $\rho$  is the penalty coefficient for each constraint.

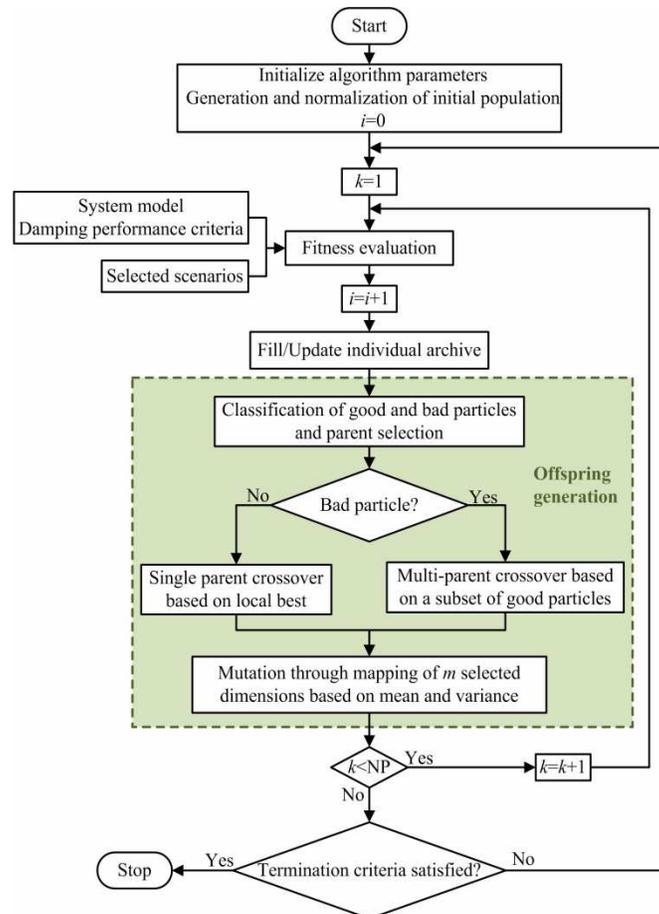


Figure 1. MVMO-S based solution procedure for OPDCD.

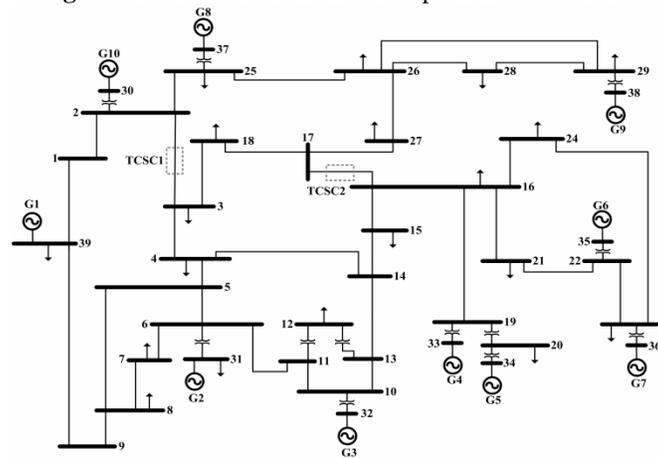


Figure 2. IEEE New England 39 Bus test system.

The average convergence of the fitness, i.e. the OF defined in (1), among 30 independent optimization repetitions is shown in Figure 3, which provides an illustrative comparison between MVMO-S and other emerging metaheuristic optimization algorithms, such as the *comprehensive learning particle swarm optimization* (CLPSO) (Liang *et al*, 2011), *genetic algorithm with multi-parent crossover* (GA-MPC) (Elsayed *et al*, 2011), *differential evolution DE algorithm with adaptive crossover operator* (Reynoso-Meza *et al*, 2011), *linearized biogeography-based optimization with re-initialization* (LBBO) (Simon *et al*, 2014), and *covariance matrix adaptation evolution strategy* (CMA-ES) (Hansen, 2011). By using typical settings provided in the aforesaid references, the goal is to test the suitability of these algorithms as general purpose tools. The stopping criterion was set to 2,000 function evaluations. All algorithms used a population of 40 particles.

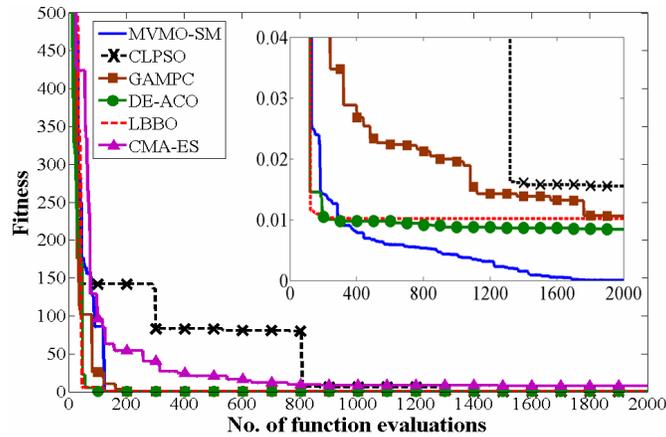


Figure 3. Comparison of average convergence of MVMO-S with other metaheuristic optimization methods.

Table 1. Comparative Performance Statistics

| Fitness (p.u.)               | Algorithm               |                         |                         |                         |                         |                         |
|------------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
|                              | MVMO-S                  | CLPSO                   | GA-MPC                  | DE-ACO                  | LBBO                    | CMA-ES                  |
| Min.                         | $1.6691 \times 10^{-7}$ | $8.8302 \times 10^{-3}$ | $5.0714 \times 10^{-3}$ | $4.9339 \times 10^{-3}$ | $4.7855 \times 10^{-3}$ | $8.5323 \times 10^{-5}$ |
| Max.                         | $1.0659 \times 10^{-4}$ | $4.1739 \times 10^{-2}$ | $1.1517 \times 10^{-2}$ | $9.8407 \times 10^{-3}$ | $1.1517 \times 10^{-2}$ | $6.9723 \times 10^{-1}$ |
| Mean                         | $1.5199 \times 10^{-5}$ | $1.5509 \times 10^{-2}$ | $1.0590 \times 10^{-2}$ | $8.4228 \times 10^{-3}$ | $1.0178 \times 10^{-2}$ | $0.7809 \times 10^{-1}$ |
| Std.                         | $2.9867 \times 10^{-5}$ | $1.1341 \times 10^{-2}$ | $2.1137 \times 10^{-3}$ | $1.3087 \times 10^{-3}$ | $2.2180 \times 10^{-3}$ | $2.1906 \times 10^{-1}$ |
| Average execution time (min) | 26.2537                 | 26.6231                 | 29.7757                 | 26.6538                 | 25.9259                 | 26.5142                 |

From Figure 3, note the excellent performance of MVMO-SM in terms of both convergence speed and the minimum reached, since after the first 1,600 function evaluations, it is able to locate the global optimal solution in the search space (when the thresholds for damping performance are reached, i.e. OF = 0) without being trapped in a local optimum.

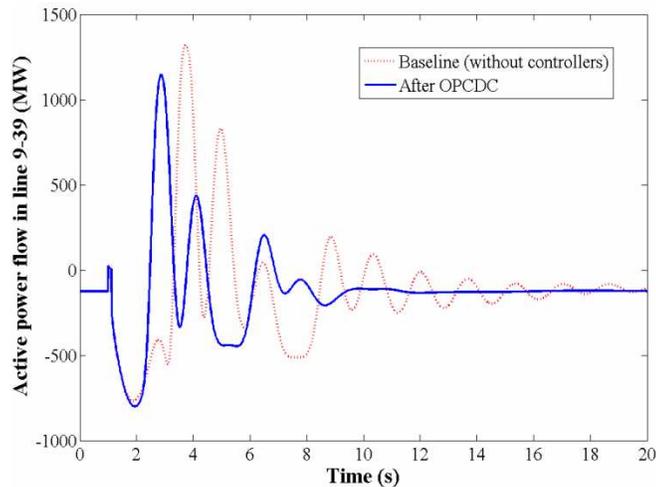


Figure 4. Active power flow in line 9-39.

In the figure, the high nonzero values of fitness observed at the beginning of the convergence progress are due to fact that the global damping factor measure is lower than the threshold, cf. (1). It is also noticed in the figure that all algorithms are capable of finding solutions that entail satisfying the damping factor threshold (i.e. obtaining fitness values that are considerably smaller than those obtained at the beginning of the search process), but finding solutions that simultaneously allow satisfying both damping factor and damping ratio thresholds (i.e. OF=0) is what makes the difference in the performance of the algorithms. A statistical survey of the achieved fitness values for all optimization repetitions is given in Table I, where the outstanding performance of MVMO-S can be more clearly appreciated by comparing different statistical attributes. The table also summarizes the average

execution time of the optimization task for all algorithms. It can be seen that there are some slight differences, which are due to inherent algorithmic characteristics of each method.

Time domain simulation was also performed to confirm the effectiveness of the obtained results. For this purpose, the simulation was conducted for one of the scenarios considered in the OPCDC by applying a three-phase fault at bus 15 at  $t = 1$  s, with a duration of 100 ms. Figure 4 presents the oscillograms corresponding to the active power flow of transmission line 9 – 39, showing the enhancement of damping performance.

#### 4. Conclusions

This paper presents a metaheuristic based approach to tackle the problem of optimal placement and coordinated tuning of power system supplementary damping controllers. The optimization task is solved via MVMO-S. Numerical results attest the outstanding performance of the proposed MVMO-SM in terms of convergence behaviour and lowest statistical attributes associated to optimization repetition. The application of the approach to a real large-size power system is currently being carried out in order to further ascertain its effectiveness. Moreover, the proposed approach can be extended to include other devices in which a damping controller can be added. Ongoing research is also being conducted to evaluate the performance of MVMO-S when solving other power system optimization problems, like the optimal active-reactive power dispatch problem in wind-hydro-thermal systems considering uncertainties and security constraints and the optimal dynamic transmission expansion planning.

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#### Biographical notes

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