CE+EPSO: a merged approach to solve SCOPF problem*

Extended Abstract†

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ABSTRACT

This work discusses the solution of a Large-scale global optimization problem named Security Constrained Optimal Power Flow (SCOPF) using a method based on Cross Entropy (CE) and Evolutionary Particle Swarm Optimization (EPSO). The obtained solution is compared to the Entropy Enhanced Covariance Matrix Adaptation Evolution Strategy (EE-CMAES) and Shrinking Net Algorithm (SNA). Experiments show the approach reaches competitive results.

CCS CONCEPTS

• **Theory of computation → Mixed discrete-continuous optimization**.

KEYWORDS

CE+EPSO, LSGO, SCOPF

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1 INTRODUCTION

Large-scale global optimization (LSGO) problems can be easily found in countless practical applications such as industrial control, aerospace, logistics and biomedicine. Typically, these problems are hard to be solved due to the inherent difficulty in finding the optimum in high-dimensional spaces. Hence, new optimization methods, which are mostly metaheuristic-based, are being proposed to overcome the curse of dimensionality [1]. Given the vast range of the metaheuristics available nowadays, it is common to organize international competitions not only to find the most promising algorithms but also to encourage original research and gain new insights on how to tackle these difficult problems. For instance, the Working Group on Modern Heuristic Optimization under the IEEE Power and Energy Society (PES) Analytic Mehtods in Power System aims at identifying emerging developments in metheuristics for solving power system problems. One example can be seen in the IEEE PES 2018 competition described in [2]. This paper reports the application of an algorithm based on Cross Entropy (CE) and Evolutionary Particle Swarm Optimization (EPSO), named CE+EPSO, to solve the Security Constrained Optimal Power Flow (SCOPF) problem (see, [2, 3]).

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2 CE+EPSO OPTIMIZATION METHOD

The CE+EPSO algorithm is a metaheuristic based on EPSO [4] and CE method [5]. EPSO has an interesting feature: it can be seen as a variant of PSO or as a variant of Evolutionary Algorithms (EA). On the other hand, the CE method is a versatile heuristic tool for solving difficult estimation and optimization problems, based on Kullback-Leibler minimization. The CE method collaborates with EPSO in the first generations by finding promising regions of the state space to be exploited by EPSO. This structure works in each class of variables of problem [5].

3 SCOPF – MATHEMATICAL MODELING

This work addresses the SCOPF problem described in [3] considering only one objective function: the minimization of total operation cost,

$$\min\ F(P_g) = \sum_{i=1}^{N}(a_i + b_i P_{Gi} + c_i P_{Gi}^2)\ (\$/h), \tag{1}$$

in which $F(P_g)$ is the total fuel cost of the system; P_{Gi} is the power output of the i th unit; N indicates the number of generators; a_i, b_i and c_i are the cost coefficients associated with each generation unit. The problem must also satisfy the following constraints:

$$P_i = \sum_{j=1}^{n} V_i V_j [G_{ij} cos(\theta_i - \theta_j) + B_{ij} sen(\theta_i - \theta_j), \tag{2}$$

$$Q_i = \sum_{j=1}^{n} V_i V_j [G_{ij} cos(\theta_i - \theta_j) + B_{ij} sen(\theta_i - \theta_j), \tag{3}$$

$$V_i^{min} \leq V_i \leq V_i^{max}, \tag{4}$$

$$P_g^{min} \leq P_g \leq P_g^{max}, \tag{5}$$

$$Q_i^{min} \leq Q_i \leq Q_i^{max}, \tag{6}$$

$$P_{ij}^{min} \leq P_{ij} \leq P_{ij}^{max}, \tag{7}$$

$$T_k^{min} \leq T_k \leq T_k^{max}, \tag{8}$$

$$Q_{ci}^{min} \leq Q^{ci} \leq Q_{ci}^{max}. \tag{9}$$

4 EXPERIMENTS AND RESULTS

The first experiment, Test bed (A), aimed to minimize the total fuel cost of traditional generators (buses: 1,3,8,12), plus the expected uncertainty cost for renewable energy generators (buses 269) and the compensation cost for controllable loads (buses: 8, 12, 18 47) in the IEEE 57 bus system test bed. This problem has 35 variables, comprising 13 continuous (generators power outputs), 15 discrete variables (to adjustable on-load transformers tap positions), 3 binary variables (shunt compensation devices) and 4 controllable loads. In this problem, 179 contingencies (N-1 conditions) and outages at branches 8 and 50 are considered. Five cases with distinct combinations of renewable energy generations were considered in Test Bed (A), according [2]:
Case 1: with Wind generators and controllable loads;
Case 2: with Wind/Solar generators and controllable loads;
Case 3: with Wind/Solar/Small-Hydro generators and control. loads;
Case 4: using an analytical uncertainty cost function considering Wind generators and controllable loads;
Case 5: using an analytical uncertainty cost function considering Wind/Solar generators and controllable loads.

The second experiment, Test Bed (B), considered the electric vehicles as dissociable units in the IEEE 118 bus system, considering the probability distribution of the possible injected or consumed power (vehicle to grid or grid to vehicle). The idea was to minimize the total fuel cost of traditional generators plus the expected uncertainty cost for renewable energy generators and the uncertainty cost for electric vehicles. This problem has 6×130 optimization variables: 107 continuous (generators), 9 discrete (stepwise transformers) and 14 binary (shunt compensation). This problem considers 492 constraints for each N-1 contingency condition in: 21, 50, 16 and 48 buses.

The CE+EPSO algorithm has two initialization parameters inside the EPSO, the mutation (τ) and recombination (P) rates [4]. For the experiment, one factorial design (see [3, 5]) was made and the best configuration indicated the use of $\tau = 0.8$ and $P = 0.8$. In the CE method, the following parameters were used: $\sigma = 0.8$ and $\beta = 0.1$ rates [5]. The CE+EPSO was compared with the Entropy Enhanced Covariance Matrix Adaptation Evolution Strategy (EE-CMAES) ([2]) in Test bed (A) and with the Shrinking Net Algorithm (SNA) ([2]) in Test bed (B). Each algorithm was executed 12 times with a budget of 30000 fitness function evaluations (FFEs). For Test Bed (A) within IEEE 57 bus system scenario, the CE+EPSO was used to optimize costs of generation system for five case test scenarios. Figure 1 shows the convergence curve of CE+EPSO for Case 3.

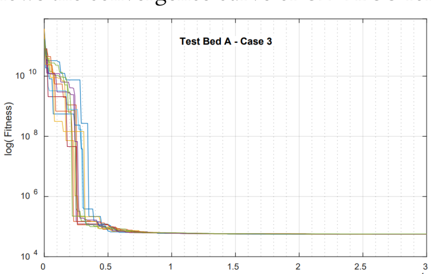

Figure 1: Convergence curve of CE+EPSO in IEEE 57.

It is possible to see a convergence pattern around 10000 FFEs. Table 1 shows the results showing CE+EPSO is competitive approach. The mean difference in relation of EE-CMAES is 331,96 $/h. In a annual projection CE+EPSO saves approximately US $3 million compared to EE-CMAES.

Table 1: Test Bed (A) - Results of five test cases in $/h. Total costs represents the sum of cases.

		Best	Worst	Mean
Case 1	CE+EPSO	80.732,46	81.547,19	81.077,07
	EE-CMAES	80.594,10	81.430,00	81.382,61
Case 2	CE+EPSO	67.709,06	68.923,91	68.473,43
	EE-CMAES	68.522,97	68.861,47	68.519,13
Case 3	CE+EPSO	55.245,86	56.683,60	55.935,62
	EE-CMAES	55.720,55	56.316,68	56.043,48
Case 4	CE+EPSO	84.382,21	84.880,76	84.442,94
	EE-CMAES	84.342,95	84.347,42	84.348,35
Case 5	CE+EPSO	71.044,22	71.128,74	71.065,91
	EE-CMAES	71.030,54	71.034,54	71.033,36
Total cost	CE+EPSO	**359.113,81**	363.164,20	**360.994,97**
	EE-CMAES	360.211,11	**361.990,28**	361.326,93

Table 2 shows the results obtained for Test bed (B). SNA found a higher average solution that corresponds the double of CE+EPSO value in this test case scenario. The results shows that the combination of methods (CE method and EPSO) to address different stages of the search can greatly improve accuracy and robustness of heuristic methods. CE+EPSO showed be a competitive technique to solve the SCOPF problem in all tested scenarios.

Table 2: Results of Test Bed (B) in $/h.

		Best	Worst	Mean
Test Bed 2	CE+EPSO	**773.193,77**	**823.684,44**	**789.719,58**
	SNA	1.172.100,00	1.878.123,00	1.518.700,00

5 FINAL REMARKS

This work investigated CE+EPSO for solving SCOPF problems. CE+EPSO is single-objective metaheuristic that incorporates some features of evolutionary algorithms, swarm intelligence and cross entropy methods. The results indicated that the CE+EPSO algorithm is an efficient and competitive technique to tackle large-scale problems as SCOPF problem. The experimental results also showed that the proposed approach reached competitive results when compared to the other algorithms considered as state-of-art for solving the proposed test beds.

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