Performance Assessment of a Modified Multi-objective Cuckoo's Search Algorithm for Microgrid Planning considering uncertainties

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ABSTRACT

The implementation of the microgrid concept is expected to bring multiple advantages on the sustainability and reliability of electric power systems. In this paper, the performance of a modified Cuckoo's Search (CS) algorithm with parameter control is evaluated for solving a planning optimization problem which considers uncertainties of non dispatchable energy resources and both operations modes of a microgrid. The results show that the Cuckoo's Search algorithm offers advantages in terms of exploration of the search space.

CCS CONCEPTS

• Hardware → Power and Energy; • Energy distribution → Power networks;

KEYWORDS

Microgrid planning, Cuckoo, Multi-objective optimization, Bioinspired optimization, CS, Parameter tuning

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1 INTRODUCTION

A microgrid is a self controled cluster of micro-sources, storage systems, and loads that can operate in two different modes: gridconnected mode and islanded mode. In this way, microgrids are intended to improve the reliability, efficiency and sustainability in the electric energy supply [1]. Nothwithstanding, its implementation leads to challenges regarding planning methodologies.

The microgrid's planning optimization problem (POP) can require more than one objective function. Thus, a multi-objective CS algorithm with parameter control is used for solving a POP which

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considers uncertainties of non dispatchable energy resources, both operations modes of a microgrid and three objectives functions. The optimal location and sizing of Distributed Generators in a distribution system is obtained with the modified CS algorithm and its results are compared with the ones of the NSGA-II Algorithm.

2 PLANNING METHODOLOGY AND OPTIMIZATION PROBLEM

The planning methodology used in this paper was proposed by [2], and was selected due to its consideration of uncertainties associated with non-dispatchable DG units and the load-shedding scenario in islanded mode, which isn't considered in other methodologies. The planning methodology and optimization problem remain the same as proposed by the authors of [2] in order to compare the results of the two optimization techniques.

The objective functions are: minimization of the power mismatch in islanded mode (MPM), maximization of the residual active power in grid-connected mode (MRAP) and minimization of the annual energy losses in grid-connected mode (MAEL). The optimization problem solves the POP by locating and sizing the DGs in a test system. The location variables are discrete and the sizing variables can be continuous or discrete depending on the DG technology.

3 MULTI-OBJECTIVE CS ALGORITHM

The multi-objective CS Algorithm was formulated in 2013 [5]. Each solution moves between generations by the Levy Flights operator and after every iteration a percentage p_a of the worst solutions is discarded and new solutions are created from the remaining ones.

The stepsize is defined according the equation (1) where it is included a constant stepsize α_0 and the comparison between two random solutions *i* y *j*.

$$\alpha = \alpha_0 (x_i^{(t)} - x_j^{(t)}) \tag{1}$$

3.1 Parameter control: stepsize α and abandon probability p_a

The CS algorithm has the advantage of only needing as input two parameters. However, the algorithm has as a disadvantage: his slow convergence [4]. The parameter control proposed by [3] was chosen to mitigate this phenomenon. However, it is proposed for the mono-objective version. In order to adapt the parameter control functions to the multi-objective version, it was decided that the stepsize control is only applied to α_0 (1) instead of α (as proposed

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by [3]), since it is expected to maintain the idea of similar eggs being less likely to be discovered. The parameter control functions are shown in (2):

$$p_{a}(gn) = p_{amax} - \frac{gn}{NI}(p_{amax} - p_{amin})$$

$$\alpha_{0}(gn) = \alpha_{0max} \exp(c \cdot gn)$$

$$c = \frac{1}{NI} \log \frac{\alpha_{0min}}{\alpha_{0max}}$$
(2)

where,

 $\begin{array}{ll} \alpha_{0max} = \text{Upper limit for } \alpha_0 & \alpha_{0min} & = \text{Lower limit for } \alpha_0 \\ p_{amax} = \text{Upper limit for } p_a & p_{amin} & = \text{Lower limit for } p_a \\ gn = \text{Dynamic number of iterations} \\ NI = \text{Total number of iterations} \end{array}$

3.2 Parameter tuning

The multi-objective CS algorithm with parameter control was tested on the ZDT set of problems and the global optima was found for every problem tested. The ZDT4 problem was chosen to show the impact of changing the parameter limits in the convergence for the problem. The problem was solved for 81 different cases, the number of iterations (2000), the number of nests (2000), and the range for $p_a (p_{amax}=0.9, p_{amin}=0.2)$ were kept constant. The values of α_{0min} and α_{0max} were modified from 0.01 to 0.09 with a 0.01 step and from 0.1 to 0.9 with a 0.1 step, respectively.

The results of the 81 cases are shown in Fig. 1.a; it is clear that the parameter tuning has a clear impact on the performance of the algorithm since some cases reach the global optimum and some other cases cannot even converge to one of the many local optimum. Quantitatively, 11% of the cases converged to the global optimum.



Table 1: Objective function values for selected solutions

	3					
Objective	Units	Solutions				
Function		А	В	С	D	Base
MPM	[MW]	1.21	3.644	1.728	2.876	-
MRAP	[MW]	0.86	-1.589	0.3597	-0.8606	-
MAEL	[MWh]	53.51	567.1	40.35	710.2	740.2

The settings with which the best three solutions were obtained are shown in Fig. 1.b. Note that there is no pattern or region where the best settings are (See blue dots).

4 RESULTS AND ANALYSIS

The study case is the one proposed by [2]. The simulation was made for 100 nests during 20 generations. The parameters were set at $p_{amin} = 0.2$, $p_{amax} = 0.9$, $\alpha_{0min} = 0.01$ and $\alpha_{0max} = 0.6$ based on the parameters tuning and successful experiences in similar areas found in the state of the art.



Figure 2: Pareto fronts obtained by CS and NSGAII

The results obtained by the CS algorithm (grey dots) were compared with those obtained by NSGAII (blue dots), as shown in 2. It can be seen that the CS front has a better diversity across the feasible region than the NSGAII front.

The hypervolume indicator was applied to the solution sets of Fig. 2. The NSGAII front dominates 31.5% of the volume defined by the reference point and the CS front dominates 55.5% of the same space, therefore, the CS front is more diverse than the NSGAII front.

5 CONCLUSIONS

The CS algorithm offers advantages in terms of exploration of the search space when compared to the NSGA-II for solving a microgrid planning problem.

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