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Cuckoo Search Optimisation – Modifications and Application

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9.1 Introduction

The cuckoo search optimization (CSO) algorithm is one of the recently developed bio-inspired meta-heuristic algorithms which is capable and very effective in solving complex combinatorial optimization problems. It is inspired from the cuckoo's aging behavior based on the parasitized breeding mechanism of the cuckoos egg and Levy flight search principle. The algorithm was developed by Yang and Deb [1], inspired by the obligate brood parasitism of some the cuckoo species. The cuckoo is a very pretty bird that not only has an attractive and sweet voice but is also intelligent enough to have a forceful reproduction strategy by which adult cuckoos lay their eggs in the nests of other host birds or species. The implementation of Levy flight behavior in CSO, makes this algorithm superior over other meta-heuristic optimization techniques such as genetic algorithm and particle swarm intelligence. In this chapter, a brief of the CSO algorithm is discussed and then some of the improved variants of this algorithm are also discussed.

The organization of this chapter is as follows. In Section 9.2, a brief of the standard CSO algorithm is presented including the explanation of cuckoo breeding behavior and Levy flights. All steps of the CSO algorithm are also presented. Some of the modified variants of CSO algorithm suggested in literature, to overcome some of the limitations observed in its standard variant, are also discussed in Section 9.3. The sections include modified cuckoo search by varying step size only, and improved cuckoo search by varying both step size and probability index. In Section 9.4, the application of the modified CSO algorithm is demonstrated to optimally design the power system stabilizer (PSS) parameters of a multi-machine power system (MMPS).

9.2 Original CSO algorithm in brief

9.2.1 Breeding behavior of cuckoo

Cuckoos are fascinating birds with a sweet voice and aggressive reproduction strategy. Some cuckoo species like the Ani and Guira lay their eggs in common nests, though they may remove other eggs to increase the hatching probability of their own eggs. There are large numbers of cuckoo species that engage in the obligate brood parasitism by laying their eggs in the nests of other host birds, often other species.

In cuckoo search optimization, three main types of brood parasitism are adopted: intra-specific brood parasitism, cooperative breeding, and nest takeover. A little host bird can engage in direct conflict with the interfering cuckoos. If a host bird discovers that some or all eggs are not their own, they will either throw out these unknown eggs or simply leave their nest or build a new nest somewhere else. Some cuckoo species such as the new world brood-parasitic Tapera have evolved in such a way that female parasitic cuckoos are often very specialized to mimic egg colors and patterns of a few chosen host species [1, 2]. This reduces the probability of their eggs being abandoned and thereby increases their reproduction.

9.2.2 Levy flights

Levy flight is a random walk where step size has a Levy tailed probability distribution. The term Levy flight was coined by Benoit Mandelbrot who used a specific definition for distribution of step sizes. Ultimately, the term Levy flight has been used to refer to a discrete grid rather than continuous space. It gives a scale invariant property that is used to model the data for exhibiting clusters. In nature, many animals and insects follow the Levy flight properties. Recent studies by Reynolds and Frye demonstrated the behavior of fruit flies (Drosophila Melanogaster) which explore their landscape by using numerous series of straight flight paths/routes, followed by a sudden right angle turn which is a Levy-flight-style intermittent scale free [3, 4].

9.2.3 Cuckoo search optimization algorithm

In beginning of the algorithm, each egg of the nest represents a solution whereas cuckoo egg represents a new solution. The algorithm has been described by the breeding strategy of some cuckoo species in conjunction with Levy flight behavior of a few birds. In this study also, if a host bird searches the eggs that are not its own then they either throw these foreign eggs away or just abandon the nest and construct a new nest at other places. The standard version of CSO algorithm follows three rules, listed here.

- Each cuckoo places one egg at a time and drops it in an arbitrarily selected nest.
- The best nests with excellence fitness or eggs will carry forward to the next generation.
- The number of host nests is fixed and the egg laid by a cuckoo is detected by the host bird with a probability index $p_a \in (0, 1)$.

The new solution (cuckoo) $x_i^{(t+1)}$ is generated by application of Levy flight as

$$x_i^{(t+1)} = x_i^{(t)} + a \oplus Levy(\lambda) \tag{9.1}$$

where, $\epsilon > 0$ is a step size that should be related to the scale problem of interest. Mostly, the value of step size $a = 1$ is chosen. The product $\oplus$ means an entry wise walk during multiplication. A Levy flight is an arbitrary walk in which the steps are defined in terms of step length, which have a definite probability distribution with the direction of steps being isotropic and random. It can be defined as

$$Levy \sim u = t^{-\lambda}, (1 < \lambda \leq 3) \tag{9.2}$$

Here, the steps essentially form a random walk process that follows a power law step-length distribution with a heavy tail. To speed up the local search, some of the new solutions should be generated by a Levy walk around the best solution obtained so far. Before starting the iteration process, CSO identifies the best fitness x_{best}. Equation (9.2) has infinite mean with infinite variance. The detection step Φ is expressed as

$$\Phi = \left[\frac{\Gamma(1+\beta) \cdot \sin\left(\pi \frac{\beta}{2}\right)}{\Gamma\left(\left(\frac{1+\beta}{2}\right) \cdot \beta \cdot 2^{\frac{\beta-2}{2}}\right)} \right]^{\frac{1}{\beta}} \tag{9.3}$$

where, Γ denotes the gamma function. In this algorithm, the value of β is taken as 1.5 and the evolution phase of x_i begins by defining v as $v = x_i$ [2]. After this step, the required step is evaluated as

$$stepsize_i = 0.01 \left(\frac{u_i}{v_i} \right)^{\frac{1}{\beta}} \cdot (v - x_{best}) \tag{9.4}$$

However, a substantial fraction of new solutions generated by far field randomization are located far enough from the current best solution. It ensures that the algorithm will not be trapped in a local optima. The control parameters of the algorithm are scale factor (β) and probability index (p_a).
The pseudo-code of standard CSO is presented in Algorithm 12.

Algorithm 12 Pseudo-code of standard CSO.

```
Define objective function F(x), x = x^1, x^2, x^3, ..., x^d;        ▷ d=dimension
set CSO algorithm parameters such as total number of host nests n, step
size a, scale factor β, the probability index p_a, and maximum generation
T^max;
generate initial but feasible population of n host nests and compute fitness
function f_i = F(x_i) for each individual solution i ∈ n;
while gen < T^max do                                  ▷ generation starts here...
    randomly select a cuckoo i and change its solution by using Levy
flights;
    compute its fitness value or function f_i = F(x_i);
    select a nest j among available n nests;
    if f_j > f_i then                                   ▷ for maximization
        replace the solution x_i with x_j and f_i with f_j;
    end if
    a fraction (p_a) of worse nests are rejected and new nests are created;
    retain the most best/excellent nests with better fitness value;
    rank the nests and determine the current best solution;
end while
```

9.3 Modified CSO algorithms

In this section, some of the popularly known improved variants of CSO algorithms are discussed.

9.3.1 Gradient free cuckoo search

The standard variant of CSO algorithm is able to find an optimum solution for most of the complex optimization problems however a fast convergence cannot be guaranteed because its search entirely depends on random walks. In order to overcome the limitation, a modified cuckoo search (MCS) was proposed in [5]. Two modifications have been suggested to improve the convergence rate that makes the method more useful for wide-range applications.

In the first modification, the Levy flight step size a is adjusted. In basic CSO [1], the step size a is considered as a constant with value $a = 1$. In this modification, the value of a decreases as the number of generations increases to enforce more localized search so that individuals or the eggs get closer to the optimal solution. Initially, the value of Levy flight step size $a = 1$ is chosen and, at every generation, a new Levy flight step is evaluated by using $\alpha = a/\sqrt{G}$, where G is the current generation. This exploratory search is only executed on the fraction of nests to be rejected. In the second modification, the information exchange between the eggs is also introduced to speed up the convergence. This information exchange between eggs is missing in the standard CSO algorithm; essentially, the searches are completed independently [2].

In this modified CSO version, a part of the eggs with the greatest fitness will be placed into a set of top eggs. For each of the top eggs, a second egg in this set is randomly chosen and a new egg is then created on the line connecting these two top eggs. An inverse of the golden ratio $\phi = (1 + \sqrt{5})/2$ is used to evaluate the distance along this line at which a new egg is placed. In a case when both eggs have the same fitness, a new egg is created at the midpoint. Here, a random fraction is used in place of the golden ratio.

There is a possibility that the same egg is picked twice in this step [5]. In this case, a local Levy flight search is implemented from the randomly picked nest with step size $\alpha = a/G^2$. There are two parameters, a fraction of nests to be abandoned and a fraction of nests supposed to create the top nests. For most of the benchmark functions, the fraction of nests to be abandoned and the fraction of nests located in the top nests are set to 0.75 and 0.25 respectively [5].

9.3.2 Improved cuckoo search for reliability optimization problems

In the original CSO algorithm, the parameters p_a, λ and a are presented to find global and local improved solutions [6]. For varying the convergence rate of the CSO algorithm, the parameters p_a and a play an important role in fine tuning of solutions. The values of both p_a and a are assumed to be constant in the standard version of CSO. The performance of this algorithm is usually found poor for a high value of a and low value of p_a. It also requires a considerably high number of generations. Alternatively, the convergence speed increases for a lesser value of a and high values of p_a however increases the chances of premature convergence. The main advantage of improved cuckoo search (ICS) over basic CSO is its control on the values of p_a and a. In early iterations, the values of p_a and a should be sufficiently high to increase the diversity. However, the values of these parameters should decrease in final generations for fine tuning of solution vectors [6].

In ICS, the values of p_a and a are dynamically changing with generations, as expressed in (9.5)-(9.7).

$$P_a(gen) = \frac{(p_a^{\max} - p_a^{\min})}{NI} \times gen \tag{9.5}$$

$$\alpha(gen) = \alpha^{\max} exp(c \cdot gen) \tag{9.6}$$

$$c = \frac{Ln\left(\frac{\alpha_{\min}}{\alpha_{\max}}\right)}{NI} \tag{9.7}$$

where, NI and gen are denoting the total number of generations and current generation respectively.

9.4 Application of CSO algorithm for designing power system stabilizer

9.4.1 Problem description

In recent years, low frequency electromechanical oscillations is one of the most frequently encountered problems in small-signal stability analysis of interconnected power systems [7]. A small disturbance can significantly affect the characteristic of electromechanical oscillations of generators, irrespective of its origin. These oscillations produce oscillatory instability and cause system separation if system damping is insufficient. The electromechanical oscillations are generally controlled by a power system stabilizer (PSS)[5]. The PSS parameters are optimally designed to improve the system damping.

9.4.2 Objective function and problem formulation

In this section, an eigenvalue-based multiobjective function is devised for simultaneous control of damping factor and damping ratio of a two-area four machine (TAFM) power system [7]. PSS parameters are designed in such a way that unstable and/or poorly damped open-loop (without PSS) eigenvalues are shifted to a specified D-shape zone in the left-half of the s-plane for a wide range of operating conditions tested under different scenarios of severe disturbances.

In order to damp out the low frequency oscillations, the parameters of PSS are designed in such a way that the eigenvalue-based multiobjective function expressed in (9.8) should be minimum. This will place the unstable and/or poorly damped eigenvalues of all operating conditions to a D-shape zone characterized by $\sigma_{i,j} \geq \sigma_0$ and $\zeta_{i,j} \leq \zeta_0$ in the left-half of the s-plane, as shown in Fig. 9.1.

$$J = \sum_{j=1}^{np} \sum_{\sigma_{i,j} \geq \sigma_0} \left(\sigma_0 - \sigma_{i,j}\right)^2 + \sum_{j=1}^{np} \sum_{\zeta_{i,j} \leq \zeta_0} \left(\zeta_0 - \zeta_{i,j}\right)^2 \tag{9.8}$$

subjected to:

$$K_i^{\min} \leq K_i \leq K_i^{\max} \tag{9.9}$$

$$T_{1i}^{\min} \leq T_{1i} \leq T_{1i}^{\max} \tag{9.10}$$

$$T_{3i}^{\min} \leq T_{3i} \leq T_{3i}^{\max} \tag{9.11}$$

where, np is the number of operating points considered in the design problem. $\sigma_{i,j}$ and $\zeta_{i,j}$ denote the damping factor (real part) and damping ratio of the ith eigenvalue of the jth operating point. The value of the desired damping factor σ_0 and damping ratio ζ_0 are selected according to the problem requirement. The aim of CSO is to determine the optimal set of PSS parameters so that the minimum settling time and overshoots of the system are achieved.

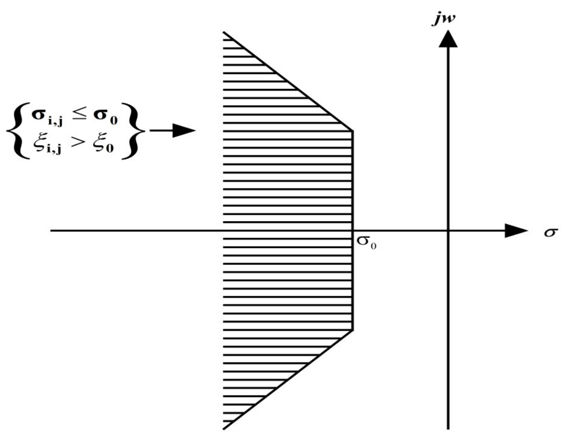

FIGURE 9.1
A D-shape zone in the left half of the s-plane where $\sigma_{i,j} \geq \sigma_0$ and $\zeta_{i,j} \leq \zeta_0$.

9.4.3 Case study on two-area four machine power system

This system comprises two generating areas connected by a 220-Km, 230-KV double circuit tie-line. The two areas 1 and 2 consist of two generators G_1, G_2 and G_3, G_4 respectively [7]. All generators' mechanical and electrical parameters are the same, except their inertia constants. These generators are represented by a fourth order non-linear model with a fast static excitation system. The single-line diagram and other details of the system are given in Fig. 9.2. Three test cases with different loading conditions have been considered to tune the PSS parameters for small-signal stability analysis, i.e., Case-1 as normal loading, Case-2 as light loading and Case-3 as high loading [8], as summarized in Table 9.1.

9.4.4 Eigenvalue analysis of TAFM power system without and with PSSs

The PSAT [9] is used for eigenvalue analysis of the system. Usually, a PSS is not required for the swing generator; therefore the PSS parameters of only

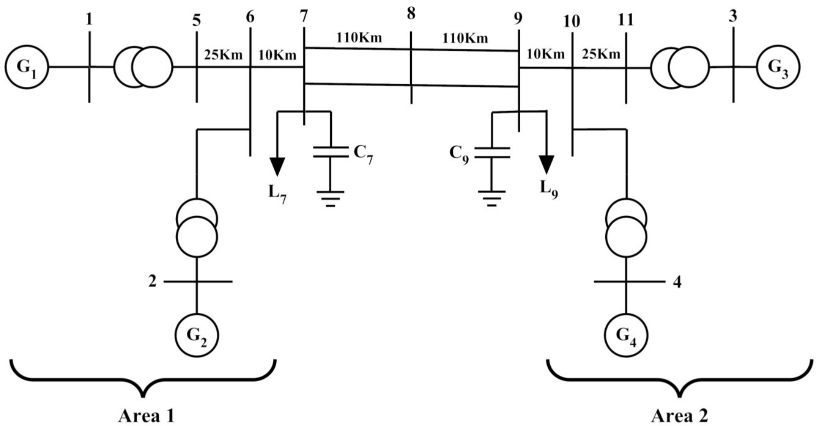

FIGURE 9.2
A single-line diagram of two-area four machine power system.

TABLE 9.1
Three operating conditions of TAFM power system.

Case-1	Case-2	Case-3
Nominal active power	Total active power decreasing by 20%	Total active power increasing by 20%
Nominal reactive power	Total reactive power decreasing by 15%	Total reactive power increasing by 15%

three generators G_1, G_2, G_4 are to be optimized as G_3 is the swing generator. The open-loop eigenvalues and damping ratios are calculated for only unstable and/or poorly damped modes of the system. Now, nine parameters of three generators $3 \times (K, T_1, T_2)$ are optimized by minimizing the objective function J by using CSO. The optimal values of these design parameters are presented in Table 9.2. The typical convergence characteristic of CSO is shown in Fig. 9.3. The figure shows that the algorithm is able to find the desired solution for which fitness function J is zero.

TABLE 9.2
Optimal values of PSS design parameters for three generators.

Generators	K	T1	T3
G1	99.421	0.014	0.116
G2	41.590	0.059	0.010
G4	36.781	0.049	0.035

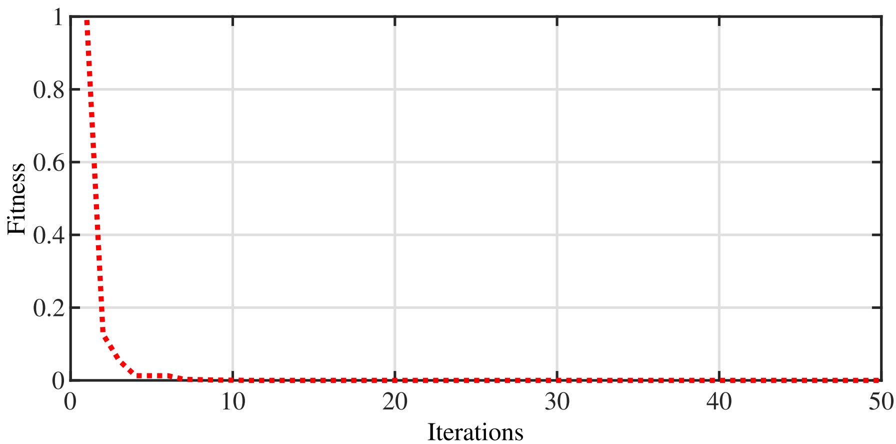

FIGURE 9.3
Convergence characteristic of CSO.

Furthermore, the comparison of eigenvalues and their damping ratios with and without PSSs for loading cases 1-3 is shown in Table 9.3. The table shows that all eigenvalues are shifted to a specified D-shape zone in the left half of the s-plane with improved damping factor and ratio.

9.4.5 Time-domain simulation of TAFM power system

In order to examine the performance of previously designed PSS controllers in terms of speed deviations under different scenarios of severe disturbances on

TABLE 9.3
Eigenvalues and damping ratios with and without PSSs for all operating cases.

Cases	Without PSS	With CSO designed PSS
Case-1	0.026±j3.803, -0.070	-1.157 ± j4.275, 0.26
	-0.541±j7.027, 0.076	-6.742±j4.788, 0.81
	-0.543±j6.810, 0.079	-7.733±j2.332, 0.95
Case-2	-0.068±j3.279, 0.021	-1.090±j3.595, 0.29
	-1.010±j6.380, 0.156	-7.472±j2.563, 0.94
	-0.535±j6.786, 0.078	-6.237±j4.167, 0.83
Case-3	0.160±j3.751, -0.042	-1.119±j5.322, 0.20
	0.042±j7.129, -0.005	-4.343±j2.917, 0.83
	-0.545±j6.803, 0.079	-5.049±j0.353, 0.99

TABLE 9.4
Scenarios of disturbances for testing the performance of designed PSSs on TAFM power system.

Scenarios	Detail
Scenario-1	A 9-cycle, 3-phase fault occurs at $t = 1$ sec on bus 7 without tripping the line 7-8 for Case-2
Scenario-2	A 12-cycle, 3-phase fault occurs at $t = 1$ sec on bus 9 without tripping the line 8-9 for Case-3

the TAFM power system are considered as shown in Table 9.4. For the sake of robustness, the number of cycles of operation increases with three-phase faults until designed controllers for the system fail.

Due to space limitation, specimen results for the comparison of speed deviations Δw_1, Δw_3 for Scenario-1 of Case-2 and the Δw_2, Δw_4 for Scenario-2 of Case-3 with designed PSS controllers are only shown in Fig. 9.4 (a)-(b) and 9.4(c)-(d) respectively. From this figure, it is clear that the system performance with designed PSSs is significantly improved for all severe loading cases and oscillations are quickly damped out. This illustrates that the CSO technique is capable of damping out the low frequency oscillations rapidly for a wide range of loading cases under severe scenarios of disturbances.

9.4.6 Performance indices results and discussion of TAFM power system

In addition to time-domain simulations, the effectiveness of designed PSS controllers is also analysed by determining two indices, known as integral

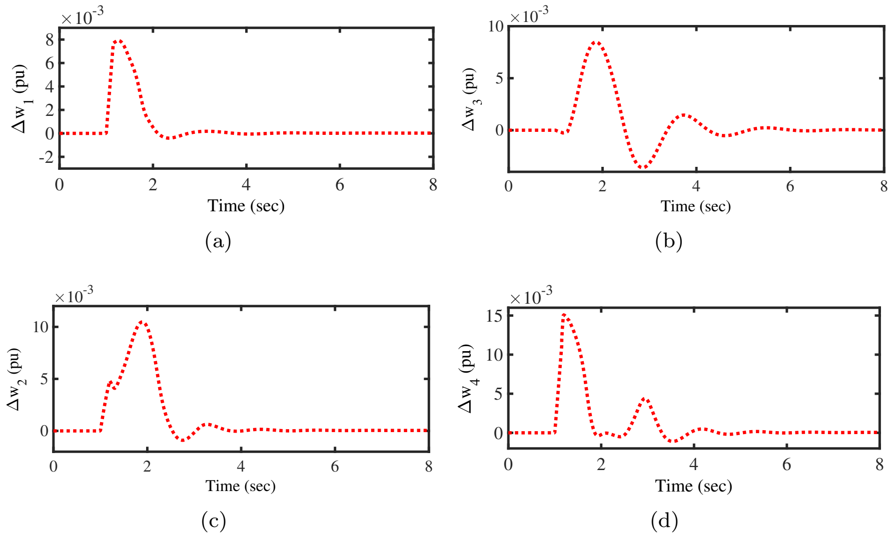

FIGURE 9.4
Comparison of speed deviations: (a) Δw_1 in scenario-1 of case-2; (b) Δw_3 in scenario-1 of case-2 ; (c) Δw_2 in scenario-2 of case-3 ; and, (d) Δw_4 in scenario-2 of case-3.

TABLE 9.5
Values of IAE and ITAE of the system for all scenarios and cases.

Cases	Scenario-1		Scenario-2	
	IAE	ITAE	IAE	ITAE
Case-1	15.8×10^{-3}	27.6×10^{-3}	20.7×10^{-3}	36.5×10^{-3}
Case-2	25.3×10^{-3}	50.2×10^{-3}	12.7×10^{-3}	21.4×10^{-3}
Case-3	12.3×10^{-3}	19.3×10^{-3}	44.4×10^{-3}	84.6×10^{-3}

of absolute error (IAE) and integral of time multiplied absolute value of error (ITAE), for two observed scenarios of different disturbances. These indices with designed PSS controllers are evaluated for each scenario of disturbances for loading cases 1-3 and presented in Table 9.5. From the table, it may be concluded that the designed PSS controllers provide enhanced damping to damp out low frequency local and inter-area modes of oscillations with less overshoot and settling time.

9.5 Conclusion

In this chapter, the CSO algorithm is presented to solve various optimization problems. In order to overcome some of the limitations observed in its standard variant, two modified variants have also been discussed. Finally, the application of the CSO algorithm to solve a real-life complex combinatorial problem is demonstrated. A modified CSO algorithm is used to optimally design PSS parameters for a wide range of operating conditions under severe scenarios of disturbances for damped out low frequency oscillations of a TAFM power system. The eigenvalue analysis, eigenvalue maps, time-domain simulations results and performance indices demonstrate that designed PSS controllers are capable of guaranteed robust performance of TAFM for a wide range of loading conditions under different scenarios of severe disturbances.

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