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Improved Cuckoo Optimization Algorithm for Excitation Control of Synchronous Generators

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Abstract**—** In this paper, a new modified Cuckoo optimization algorithm (MCOA) is used for the excitation control of a synchronous generator (SG). The performance of the MCOA is examined and tested on such an engineering application system with cost minimization based on system error between system outputs and reference values. Then, the application of an adapted MCOA, evolutionary-based approach, to design a state feedback controller is proposed; and this is adopted for adjusting and determining the optimal settings of a state controller to cancel the oscillations in synchronous generators. A compression is performed between MCOA and Ant Colony Optimization algorithm (ACO) where the results show that the MCOA-based state feedback controller has obtained good performance as compared to ACO for excitation control of SG through the reduction of the effect of the unwanted low frequencies oscillations.

Keywords**—** Ant colony optimization, Cuckoo optimization algorithm, Excitation control, On-line control, Synchronous generator.

Nomenclature

i	Armature current
i_d	d-axis component of armature current, A
M	Inertia constant
P_e	Electrical output power, W
P	Mechanical input power, W
V_t	Generator terminal voltage, V
V_d	d-axis component of V_t
V_F	Field voltage
V_o	Infinite bus voltage
V_q	q-axis component of V_t
X	Transmission line reactance
X_d	d-axis synchronous reactance
$X_d\sum$	Sum of d-axis transient reactance
D	Damping constant
X_d`	d-axis transient reactance
X_q	q-axis synchronous reactance
δ	Torque angle, p.u.
Δ	Deviation from initial value of a variable
$\tau`_{do}$	Open circuit time constant of field, s
τ_e	Exciter time constant
τ_s	Voltage control feedback loop time constant
ψ_F	Field flux linkage, Wbt
ω	Rotor speed, rad/s
ω_d	Damped frequency of oscillation
ω_n	Natural frequency
ω_o	Synchronous speed, 314.15 rad/s

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I. INTRODUCTION

In recent years, some optimization methods that are conceptually different from the traditional techniques have been developed. These methods are considered modern methods of optimization. Most of these methods are based on certain characteristics and behaviors of biological, annealing, swarm of insects, and neurobiological systems [1]. Genetic algorithms (GA) [2], Simulated annealing (SA) [3], [4], Particle swarm algorithms (PSO) [5], [6], Fuzzy logic (FL) [7] and artificial neural networks (ANN) [8] are examples of intelligent optimization modern methods applicable for solving different types of optimization. The genetic algorithms are based on the principles of natural genetics and natural selection [2]. Simulated annealing is based on the simulation of thermal annealing of critically heated solids [3]. The particle swarm optimization is based on the social behavior of a flock of migrating birds trying to reach an unknown destination [5]. Fuzzy methods have been developed to map an input space to an output space through adopting a list of if-then statements called rules for solving problems. In neural-network-based methods, the problem is modelled as a network consisting of several neurons; and the network is trained suitably to solve the optimization problem efficiently [9].

In this work, some characters of cuckoo are mathematically modelled in order to design a modified optimization algorithm. MCOA, which is applied to solve different multi modal non-linear problems, has proven its excellent capabilities such as faster convergence, better global minimum achievement and good capability in diverse optimization tasks rather than other meta-heuristic algorithms [10]. This algorithm has been tested so far on different types of practical problems such as noise canceller design, chemical machine process, and machine process [11]-[15]. However, the synchronous generator application is adopted in the present work since it is considered to be one of the most essential power system components which has various kinds of power system dynamic problems: high-or low frequency oscillations, and large or small (fast and slow varying) disturbances. It, therefore, needs to be controlled and cancelled. In the main, an ACO meta-heuristic algorithm [16], [17] is used for controlling the adopted application optimization problem; its results are compared to those obtained with the MCOA. The inspiring sources of ACO algorithms, which belong to the class of meta-heuristics, are real ant colonies. More specifically, ACO behavior is mainly based on the indirect communication between ants by means of chemical pheromone trails, which enables them to find short paths between their nest and destinations.

The main goal and motivation of the present work is to modify the original COA and then to apply the modified (MCOA) in optimization processes to control and attain the optimal cancellation of oscillations in the adopted engineering system. These control schemes contribute to preventing system instability by suppressing the low-frequency oscillations arising from power grid fault disturbances.

II. MODIFIED CUCKOO OPTIMIZATION ALGORITHM

Cuckoo optimization algorithm, which was originally proposed by Rajabioun [10] in 2011, is based on the behavior of initial population of cuckoos which has some eggs to lie in some host birds' nests. In the proposed algorithm, COA, the initial population is formed by an asset of randomly generated solutions called "habitat". In *N* D-dimensional optimization problem (or population size), the position of i^{th} cuckoo is presented as follow:

$$x_i = \{x_{i1}, x_{i2},.....,x_{iD}\} \qquad \text{where } i=1, 2, \ldots, N \tag{1}$$

To use COA in cost minimization problems, the cost (profit or fitness value) of each habitat can be computed by evaluating the cost function as follows:

$$\text{Profit} = -\text{cost(habitat)} = -f\{x_{i1}, x_{i2}, \dots \dots \dots .., x_{iD}\} \quad (2)$$

Then, a randomly produced number of eggs is supposed for each of these initial cuckoo populations. In nature, each cuckoo lays from five to twenty eggs. These values are used as the upper and lower limits of egg dedication to each cuckoo at different iterations. Another habit of real cuckoos is that they lay eggs within a maximum distance from their habitat. This maximum range is called the egg laying radius (ELR). In an optimization problem with an upper limit of var_{hi} and a lower limit of var_{low} for the variables, for each cuckoo, ELR, which is proportional to the total number of eggs, number of current cuckoo's eggs, and also variable limits of var_{hi} and var_{low} is determined. The ELR is defined as follows:

$$ELR = \propto \frac{\text{Number of current cuckoo's eggs}}{\text{total number of eggs}} (var_{hi} - var_{low}) \quad (3)$$

where α is an integer, supposed to handle the maximum value for ELR.

Therefore, these initial cuckoos have some eggs to lie in some host birds' nests. Some of these eggs, which are like eggs of most bird's eggs, have the opportunity to grow up and become mature cuckoos. Other eggs are revealed and killed by host brides. The mature cuckoos live in their own area and make a community for some time. After some repetitions, each cuckoo migrates to an optimal point with the most similarity to the hosts' eggs where it has an access to the richest food sources. In this location, we have the lowest numbers of eggs were killed. The convergence of more than 95% of all cuckoos to a single point puts the COA at its end. Fig. 1 demonstrates the flowchart of the whole process of the original COA [10].

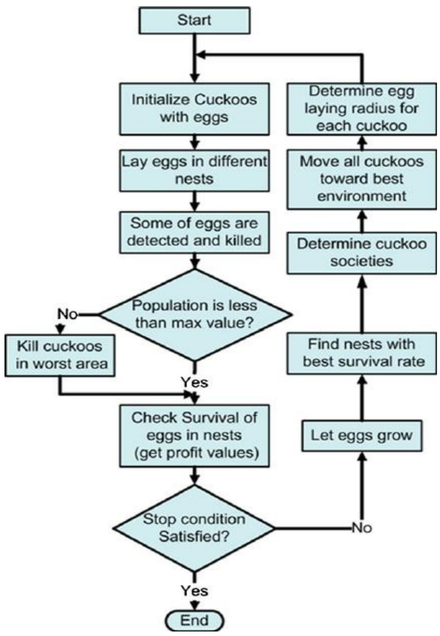


Fig. 1. Flowchart of Cuckoo optimization algorithm

In this work, to improve the converging rate and the algorithm performance, a study method of inserting noise into (3) is introduced. It shows that applying a controlled amount of noise during searching process may improve the convergence. In addition, the effects of each additive noise parameters are chosen. The best overall performance can be achieved by injecting such noise at each time step. In this condition, injection of extra noise works as a regularizer in the sense of statistical learning theory where cost values will converge globally to its final value; and therefore the test error will go down. In the modified COA with a noise (MCOAN) method, which is corrupted by Gaussian noise, the ELR formulation is used with an injected additive noise in order to improve and speed the convergence of the algorithm performance. In the COA method, the ELR for each cuckoo is more fixed and better though the *ELR* is large at first with injected noise to avoid being stuck in local minimum and giving rise to move the search to global minimum or iteratively move to the nearest deepest value. Therefore, this new formulation causes the variation of the optimization parameters and the reduction of their ranges at each time step. It can be given as:

$$factor=\frac{\text{var}_{\text{hi}}-\text{var}_{\text{low}}}{MaxIter} \times iter \tag{4}$$

$$\text{var}_{old}= \text{var}_{hi}\ \tilde{}\ \text{var}_{low} \tag{5}$$

$$\text{var}_{new} = \frac{\text{var}_{old}-swgn}{factor} \tag{6}$$

where *awgn* is the additive white Gaussian noise (awgn). This value is generated by the awgn is Matlab inbuilt function with which one can add an Additive Gaussian White Noise to obtain the desired Signal−to−Noise Ratio (S/N). The main usage of this function is to add AWGN to a clean signal (infinite S/N) in order to get a resultant signal with a given S/N ratio (usually specified in dB). Therefore, the new *ELR* will be given as:

$$ELR=\propto \frac{\text{Number of current cuckoo's eggs}}{\text{total number of eggs}} \times \text{var}_{new} \tag{7}$$

For evaluation of the efficiency of the MCOAN with the new *ELR* formula, a benchmark function is studied [18]. The adopted function, which is utilized as a test function for assessment, has the following form:

$$f(x, y)= x \times \sin(4x)+ 1.1y \times \sin(2y) \tag{8}$$

where the search space of x:[−10, 10], and global minimum:-18.5547 for $f(9.039, 8.668)$. Therefore, the benchmark function in (8) is utilized for comparing the evaluation and utility of original COA algorithm and the modified MCOAN. The Meta-Heuristic algorithms are very sensitive for their parameters; and the setting of the parameters can affect their efficiency. The parameters settings cause more reliability and flexibility of the algorithm. So, settings of the parameters are one of the crucial factors to gain the optimized solution in all optimization problems. Table 1 shows the selected parameters for COA and MCOAN algorithms.

TABLE 1
PARAMETERS SETTINGS OF COA AND MCOAN ALGORITHMS

Number of Cuckoos	8
Minimum Number of Eggs	2
Maximum Number of Eggs	4
Maximum Iteration	200
Number of Clusters	2
Lower Band of Parameter	-10
Higher Band of Parameter	10
Maximum Number of Cuckoos	10
Radius Coefficient	5

The Modified COA algorithm has been run for 200 iterations; and the results, when the cuckoo COA and MCOAN algorithms are run 10 successive times, are presented in Table 2. Table 2 shows the cost value as well as the statistical results values of the mean, standard deviation, and the worst run.

TABLE 2
COMPARISON OF RESULTS BETWEEN COA AND MCOAN
A) RUN RESULTS

Run #	1	2	3	4	5	6	7	8	9	10
COA	-18.531	-18.531	-18.505	-18.526	-18.426	-18.515	-18.355	-18.467	-18.5546	-18.0991
MCOAN	-18.5547	-18.5547	-18.5547	-18.5547	-18.5547	-18.5547	-18.5547	-18.5547	-18.5547	-18.5547

B) STATISTICAL RESULTS ANALYSIS

	Average	Worst Values	Standard deviation
COA	-18.53	-18.4515	0.249206
MCOAN	-18.5547	-18.5547	0

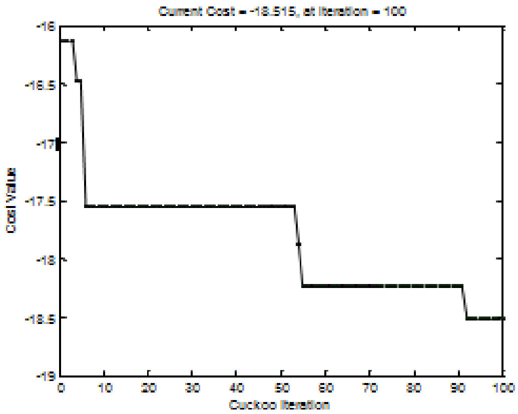
Fig. 2 shows the cost function results when searching simulations for one run are conducted for 100 and 200 iterations using COA and MCOAN. It is clear that the runs without adding noise in Fig. 2a and 2c are stuck in local minimum with cost values of -18.515 and -18.554 respectively, where the numerical global solution is -18.5547. The results of Table 2 and Fig. 2 demonstrate that using the MCOAN algorithm makes the optimized solution possible and, the function of the algorithms is in convergence toward the global optimal solution in appropriate number of iterations mostly in all simulations runs.

In this work, the best value of the signal-to-noise ratio (S/N), for the purpose of finding the best egg laying radius (ELR) factor, must be verified. To determine the factor to be selected in order to reach the best result, different plots at difference S/N ratios, which illustrate the values of the cuckoo cost, at each iteration, are shown in Fig. 3. This figure and Table 3 show the speed of responses to catch the global minima with different values of S/N. The best value for all our next applications in this work is 20 dB.

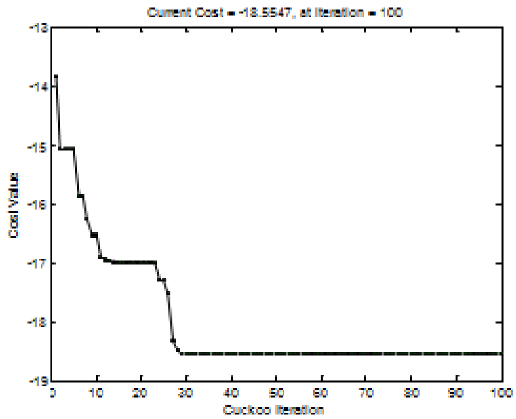
III. IMPLEMENTING THE MCOAN MODEL FOR EXCITATION CONTROL OF A SYNCHRONOUS GENERATOR

In this part, the power system considered in this study is a synchronous generator connected to an infinite bus bar as presented in Fig. 4. For such a system, the online MCOAN is implemented to determine the optimal settings of a state controller to cancel the oscillations in synchronous generators. Synchronous generator excitation control system is a closed loop control circuit composed by excitation regulation unit, power unit, synchronous generator and voltage measuring unit. In this paper, the problem of oscillations in a synchronous generator connected to an infinite bus through transmission lines is considered, where the controller is based on excitation control to improve the performance of the synchronous generator.

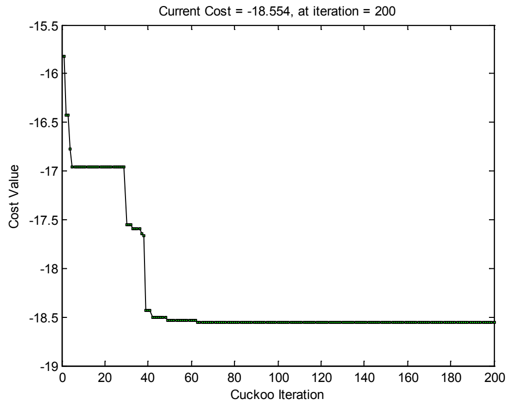
For the purpose of studying and controlling a synchronous machine, it is necessary to have a mathematical model in the form of a set of differential equations. The state-space representation is the most suitable method for computer applications in a synchronous machine control. In addition, one can get this form of knowledge from the actual behavior of the system or from the input-output data. Appendix A indicates all the symbols and abbreviations of the SG parameters that are used in this work. The system investigated has the parametric and initial values, which are given in Tables A1 and A2 in Appendix.



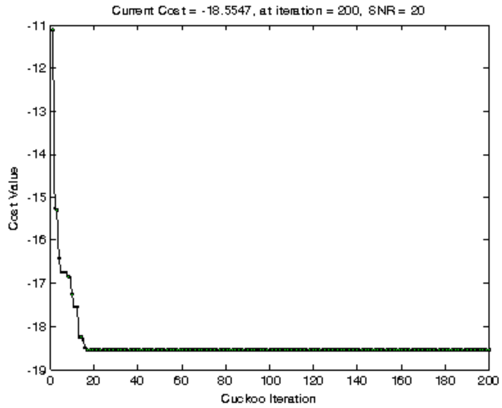
Run without injected noise (COA)



Simulation run with adding noise (MCOAN)



Run without injected noise (COA) for 200 iterations



Simulation run with adding noise (MCOAN) for 200 iterations

Fig. 2. Cost values without and with injected noise

TABLE 3
NUMBER OF ITERATIONS TO REACH GLOBAL MINIMUM VALUE AT DIFFERENT S/N RATIOS

S/N Ratio, dB	No. of Iterations to Reach Global Minimum Value
1	72
5	73
10	70
15	67
20	47
25	65
30	68
40	73

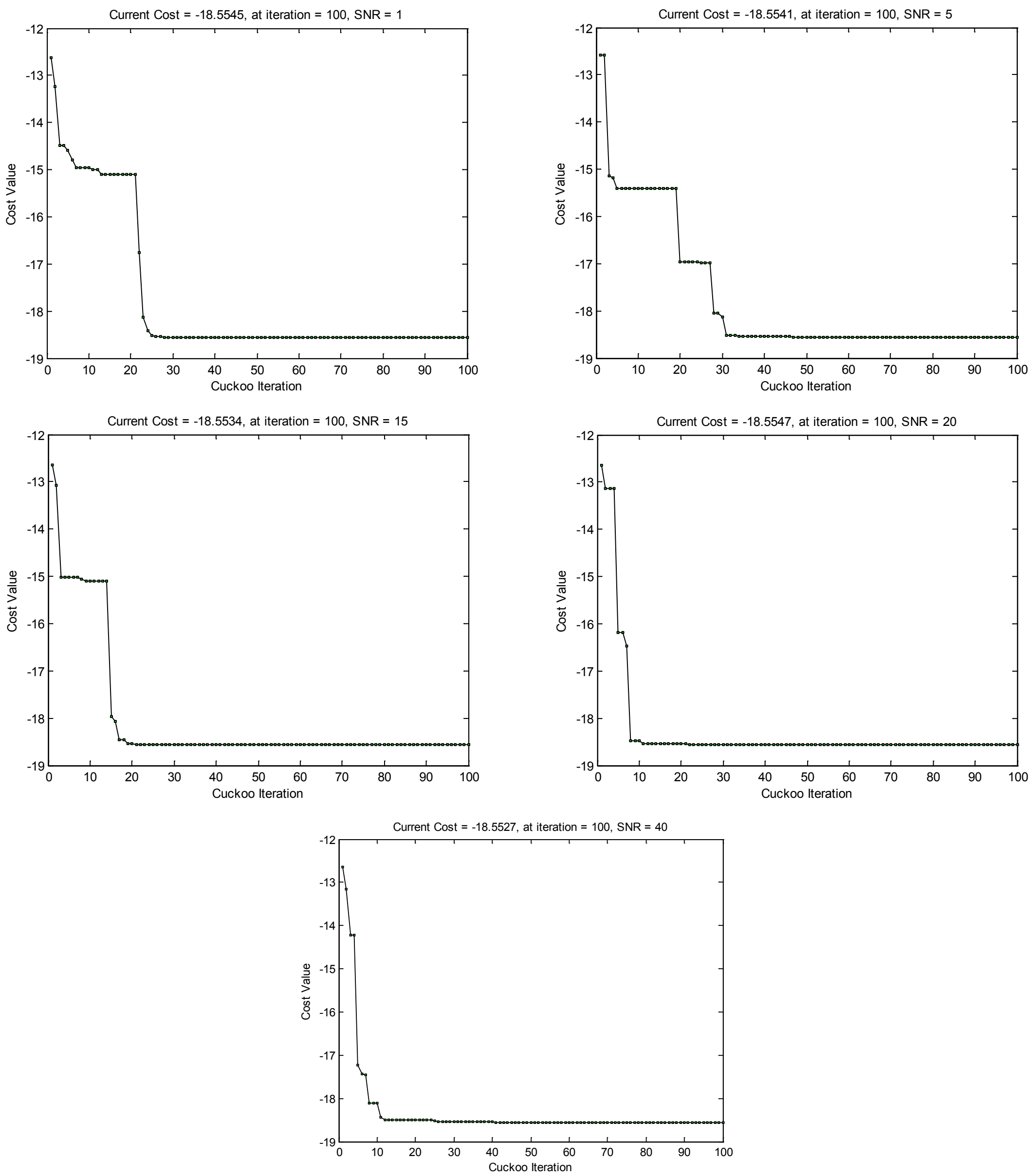


Fig. 3. Simulation runs with different S/N ratio

Therefore, the overall state-space equation of the synchronous generator, whose its parametric and initial values are obtained from reference [19], will be:

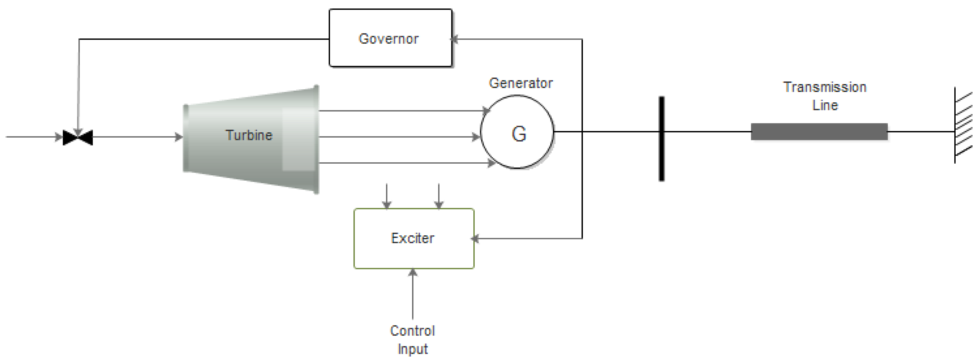


Fig. 4. Power system configuration

$$\begin{bmatrix} \dot{\Delta\delta} \\ \dot{\Delta\omega} \\ \dot{\Delta V_t} \\ \dot{\Delta\psi_F} \\ \dot{\Delta V_F} \\ \dot{\Delta Vs} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & a_{24} & 0 & 0 \\ a_{31} & a_{32} & 0 & a_{34} & a_{35} & 0 \\ a_{41} & 0 & 0 & a_{44} & 1 & 0 \\ a_{51} & 0 & 0 & a_{54} & a_{55} & a_{56} \\ 0 & 0 & 0 & 0 & 0 & a_{66} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta V_t \\ \Delta\psi_F \\ \Delta V_F \\ \Delta V_s \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} U_{ex} \\ P_m \end{bmatrix} \tag{9}$$

where

$a_{21} = -\left(\frac{1}{M}\right)\left[\frac{V_o cos\delta_o \Psi_{Fo}}{\grave{X}_{d\Sigma}\,\acute{\tau}_{do}} + \frac{(\acute{X}_d - X_d)V_o^2 cos2\delta}{X_{q\Sigma}\acute{X}_{d\Sigma}}\right]$, $a_{22} = \frac{-D}{M}$; $a_{24} = \left(\frac{V_o sin\delta_o}{M\grave{X}_{d\Sigma}\,\acute{\tau}_{do}}\right)$;

$a_{31} = \frac{V_{do}X_qV_o}{V_{to}X_q}cos\delta_o - \frac{V_{qo}\acute{X}_dV_o}{V_{to}\acute{X}_d}sin\delta_o$; $a_{32} = K$; $a_{34} = a_{44} \times K$;

$K = \frac{V_{do}X_qV_o}{V_{to}X_q}cos\delta_o - \frac{V_{qo}\acute{X}_dV_o}{V_{to}\acute{X}_d}sin\delta_o$; $a_{35} = \frac{V_{qo}X}{V_{to}\tau_{do}\acute{X}_d}$; $a_{41} = \left(\frac{-V_o(X_d - \acute{X}_d)}{\acute{X}_{d\Sigma}}\right)sin\delta_o$;

$a_{44} = \frac{X_{d\Sigma}}{\acute{X}_{d\Sigma}\acute{\tau}_{do}}$; $a_{51} = \left(\frac{-G_d V_o}{\tau_d V_{to}}\right)\left[\frac{V_{do}X_q}{X_{q\Sigma}}cos\delta_o - \frac{V_{qo}\acute{X}_d}{\acute{X}_{d\Sigma}}sin\delta_o\right]$; $a_{54} = \left(\frac{-G_d}{\tau_d V_{to}}\right)\left[\frac{V_{qo}X}{\acute{X}_{q\Sigma}\tau_{do}}\right]$;

$a_{55} = -\left(\frac{1}{\tau_d}\right)$; $a_{56} = \frac{G_d}{\tau_d}$; and $a_{66} = -\left(\frac{1}{\tau_s}\right)$

The synchronous generator under study is tested for (10 %) change in the input signal to study the open loop performance (the system without controller). The deviations of output states ($\Delta\delta$, $\Delta\omega$, ΔV_t, $\Delta\psi_F$, and ΔV_F) are oscillated before reaching their steady-state values. These are shown in Fig. 5, which shows that the system is stable but with significant amount of oscillations in the state variables. These oscillations are not acceptable in power system stability considerations; therefore, the stability of the system needs to be improved [20]-[22].

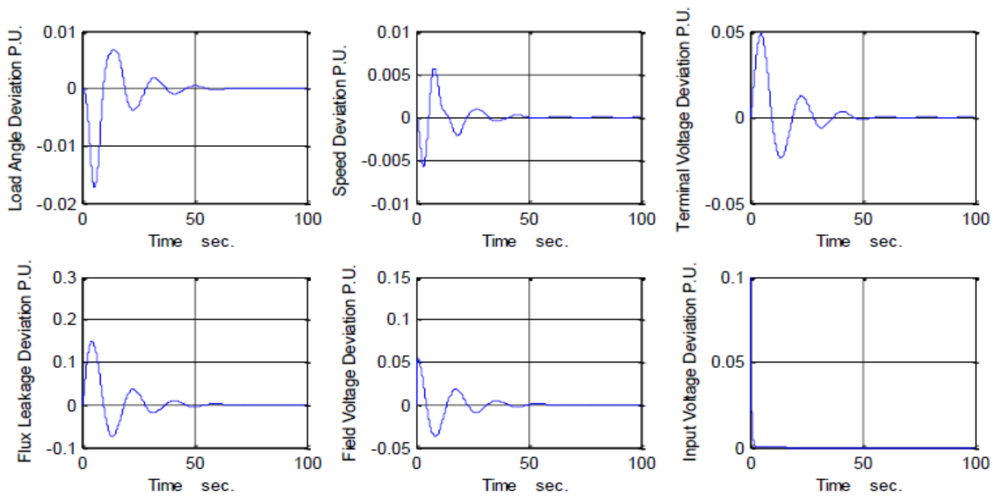


Fig. 5. The SG variables without control due to a step (10%) change in the input excitation

For improving stability in a synchronous generator system, stabilizers (PSS) are widely installed on a large scale power system [22]. With the development of power systems, and the occurrence and expansion of interconnected power systems and applications, there is a need to adopt intelligent and fast automatic excitation controllers systems. Fluctuation of power at low frequency occurs in power systems, seriously affecting the safe and stable operation of power systems. This has been one of the most important factors for the improvement of transmission power. The new cuckoo optimization algorithm (MCOAN) can be utilized to optimize feedback state-space controller parameters in order to suppress the low-frequency oscillation and improve the dynamic stability of the adopted system.

At present, the MCOAN has been applied in an excitation system of SG with the parameters settings as presented in Table 1 to improve the excitation regulation under different circumstances and change in system variables. Consequently, the complete structure of the controller based state-space feedback gain parameters estimation is shown in the block diagram of Fig. 6. As in the state controller, the gain vector F improves the level of damping the unwanted oscillations, to keep the SG system output voltage within an appropriate range of values. More specifically, the MCOAN optimizes the linear feedback gains by minimizing the steady state error between a reference value and the GS system outputs through a cost function. The steady state values of the MCOAN based state controller's gains must be picked up and used as feedback gains in the proposed system; thus, the cuckoo controller will operate as a state feedback controller. The state feedback controller in the system model can be defined as:

$$u_c(t) = [f_{11} \quad f_{12} \quad f_{13} \quad f_{14} \quad f_{15} \quad f_{16}] \begin{bmatrix} \Delta\delta & 0 & 0 & 0 & 0 & 0 \\ 0 & \Delta\omega & 0 & 0 & 0 & 0 \\ 0 & 0 & \Delta V_t & 0 & 0 & 0 \\ 0 & 0 & 0 & \Delta\Psi_F & 0 & 0 \\ 0 & 0 & 0 & 0 & \Delta V_F & 0 \\ 0 & 0 & 0 & 0 & 0 & \Delta V_S \end{bmatrix} \tag{10}$$

where $\Delta\delta$, $\Delta\omega$, ΔV_t , $\Delta\psi_F$, and ΔV_F are the system states.

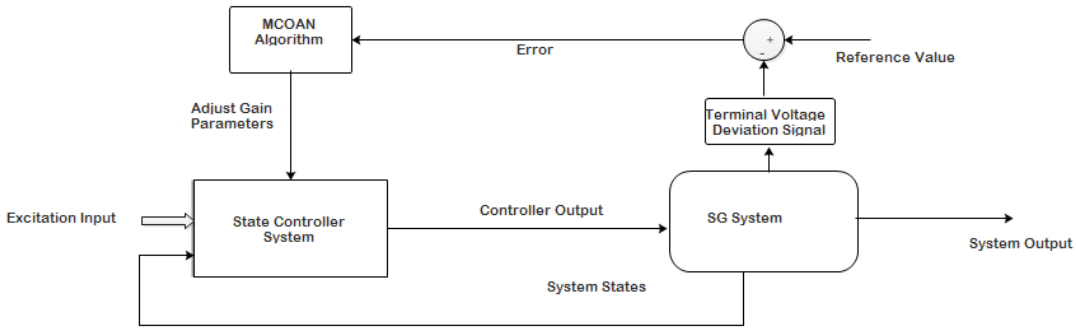


Fig. 6. Block diagram of control system of GS

In this work, firstly the controller was implemented using the on-line optimized feedback gains in the control system design, where the convergence of the error parameters and the value of the gain parameters correspond to the best of all habitats. The simulation results presented in Fig. 7 are a result of changing the input signal of the system by a step of (10%) when the controller is turned on immediately after starting. This gives the overall results in time and frequency domains, which are obtained for all deviations of output states ($\Delta\delta$, $\Delta\omega$, ΔV_t, $\Delta\psi_F$, and ΔV_F) of the GS system as shown in Fig. 7. This figure demonstrates the controlled time-domain response of the system, where the reference value is assumed to be equal zero. System response to the reference value appears to have good agreement with each other. It is noted that the system needs less than 3 seconds to reach a stable condition; and the performance of the algorithm in the oscillation cancellation control process is significant. Such a significant reduction is reflected throughout all the system variables. The corresponding frequency-domain description of the SG system behavior as compared to uncontrolled behavior is shown in Fig. 8. This figure illustrates the average power spectral density before and after oscillations cancellation. The results demonstrated a clear reduction in the oscillations levels of all system variables. The controller was effective for obtaining global minimization. Basically, Fig. 5 and 6 reflect the efficiency of the MCOAN based-controller in reducing oscillations in synchronous generator systems. The absolute average attenuations are found to be approximately 55.48 dB for load angle deviation, 33.66 dB for speed deviation, 33.28 dB for terminal voltage deviation, 27.79 dB for field voltage deviation, and 6.48 dB for flux linkage deviation.

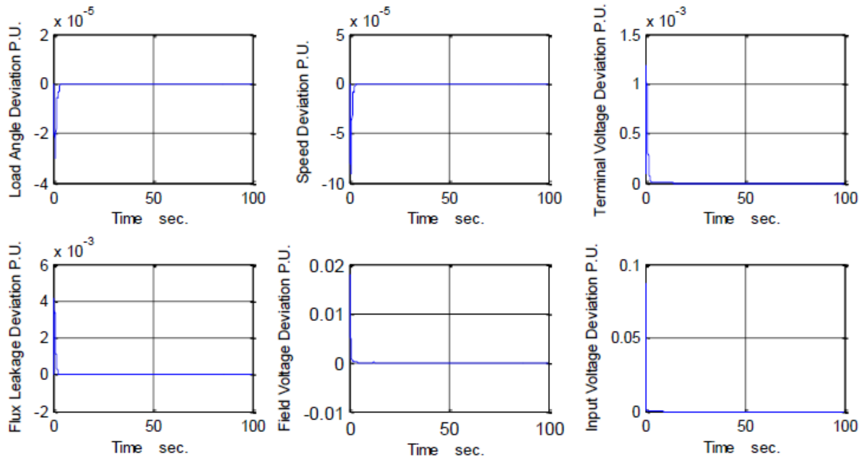


Fig. 7. System controlled variables responses when the controller is tuned on at starting

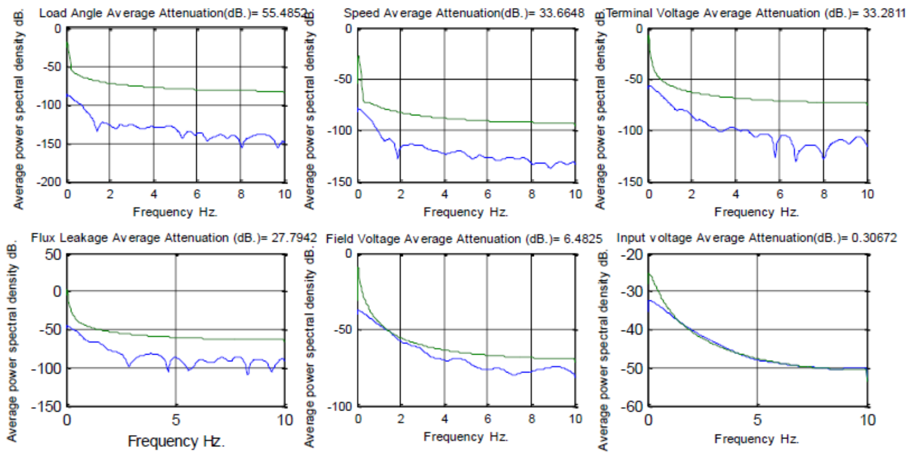


Fig. 8. Power spectral density of un-controlled and control system variables

To show the robustness of the presented control approach, the exponential disturbance, with constants c=2×106, and k=1.75 are arbitrary chosen, is assumed after 50 seconds when the controller is conducted in the control system. The form of the excitation signal disturbance in time domain is given as:

$$U_{ex}=c\times exp^{(-kt)} \tag{11}$$

Fig. 9 and 10 demonstrate the time responses of the deviations of the system variables before and after applying the control rule when the system is injected by the disturbance as presented in (11).

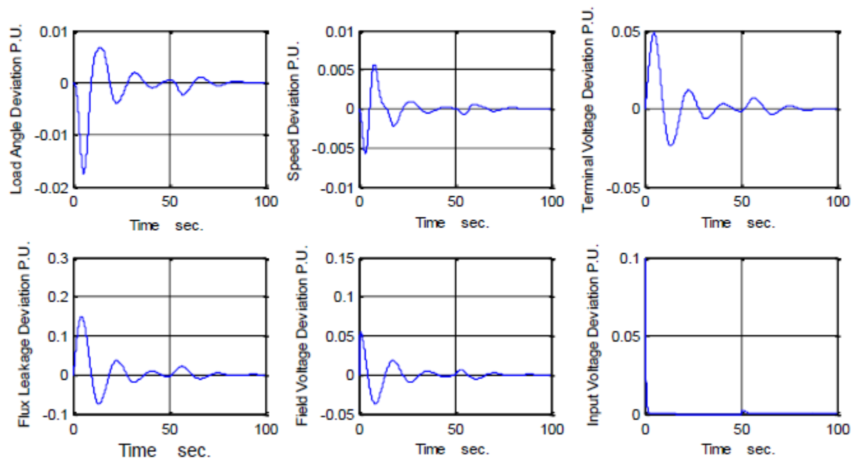


Fig. 9. The uncontrolled system variables responses

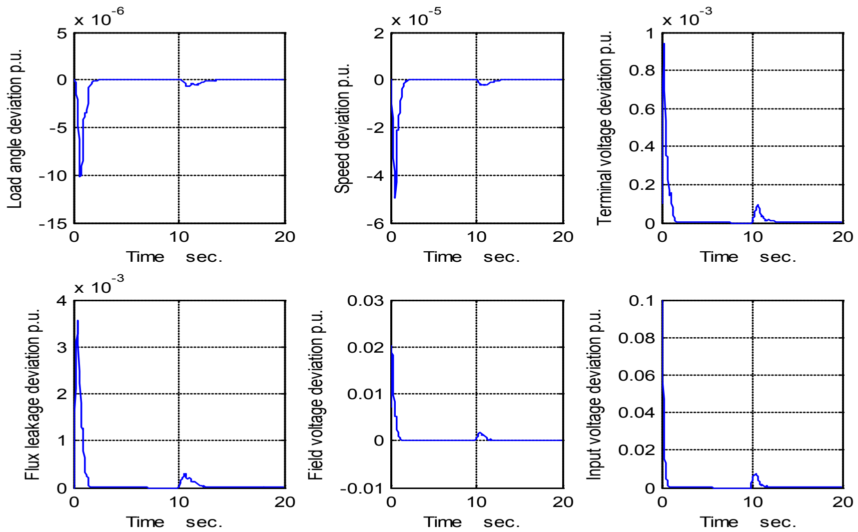


Fig. 10. The controlled system variables responses when the controller is turned on at starting

Fig. 10 that the controller is robust to disturbance; and since the system performance returns to steady-state values with acceptable over shoot and settling time where the controller is conducted to the system.

IV. Implementing the ACO Model for Excitation Control of a Synchronous Generator

Ant colony optimization (ACO) is one of the most recent techniques for optimization purposes [16]-[18]. The core of this optimization algorithm is each ant gets a start nest. Beginning from this nest, the ant chooses a path to food sources according to algorithm rules. After reaching the new location, the ant returns to its original nest. The ants might travel concurrently or in sequence; and each ant deposits some amount of pheromone on its path. The amount of pheromone depends on the quality of the ant's path: a shorter path usually results in a greater amount of pheromone. Moreover, ACO deals with an important process, i.e. trail pheromone evaporation that is decreasing in amount of pheromone deposited on every path by the time. The ant colony optimization process can be explained by representing a multilayered optimization problem, where the number of layers is equal to the number of design variables, and the number of nodes in a particular layer is equal to the number of discrete values permitted for the corresponding design variable. In the present application, the total number of variables is chosen to be six according to (10). The PSO procedure, which is used here for optimizing the state feedback controller gains, is shown as a flowchart in Fig. 11.

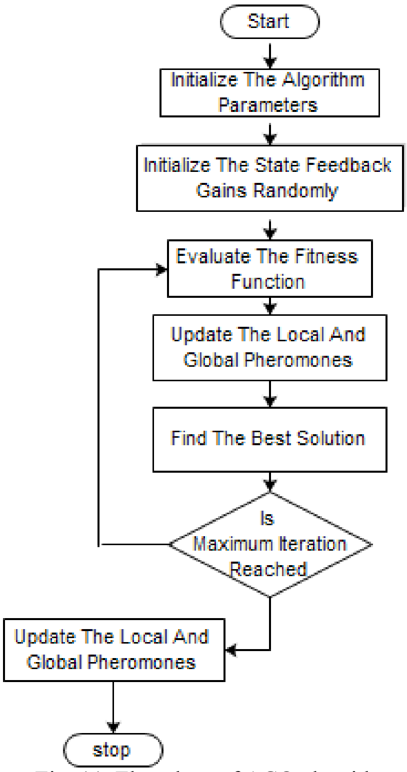


Fig. 11. Flowchart of ACO algorithm

The number of nodes in a particular layer is equal to the number of discrete values permitted for the corresponding design variable. In the present application, the total number of variables is chosen to be six according to (10). The PSO procedure, which is used here for optimizing the state feedback controller gains, is shown as a flowchart in Fig. 11.
The ACO method procedure starts when an ant k, that is located at node i, uses the pheromone trail τ_{ij} to compute the probability of choosing the next node j by applying the following probabilistic transition rule:

$$P_{ij}^{k}\ (t)=\begin{cases}\frac{[\tau_{ij}(t)]^{\alpha}[\eta]^{\emptyset}}{\Sigma_{j\to N_i^{(k)}}[\tau_{ij}(t)]^{\alpha}[\eta]^{\emptyset}} & if\ j\to N_i^{(k)}\\ 0 & otherwise\end{cases} \tag{12}$$

where N_i^k indicates the set of neighborhood nodes which remain to be visited when the ant k is at node i. α and β are two adjustable positive parameters that control the relative weights of the pheromone trail and of the heuristic visibility. After each ant completes its tour, the pheromone amount on each path will be adjusted according to (13):

$$\tau_{ij}=(1-\rho)\times\tau_{ij}+\Delta \tag{13}$$

where (1-ρ) is the pheromone decay parameter (0<ρ<1), where it represents the trail evaporation when the ant chooses a node and decides to move; and

$$\Delta\tau_{IJ}=\begin{cases}\frac{Q}{L_k} & if\ (i,j) belongs\ to\ best\ tour\\ 0 & otherwise\end{cases} \tag{14}$$

where L_k is the length of the tour performed by ant k; and Q is an arbitrary constant related to the quality of pheromone trails laid by ants [1]. To adopt the ant colony algorithm and to tune the controller parameters, the following steps should be followed:

- Step 1: Create n layers and li nodes inside the i^{th} layer (i=2,...,n); (n–1) is the number of parameters to be optimized by the algorithm; and li values must cover the range of variations of the i^{th} parameter with the specified resolution.
- Step 2: Generate m ants and put them in layer 1 (layer 1 is the start point with only one node).
- Step 3: Each ant chooses only one node among the cities in the layer based on the rule in (12).
- Step 4: Repeat Step 3 for all parameters (layers).
- Step 5: After the tour was completed, the pheromone is updated by (13) and (14), with the difference that Lk is the value of the objective function.
- Step 6: If the convergence criteria are not met, return to Step 1; otherwise, the algorithm is finished.

In this work, the algorithm is tested for different values of parameters by simulating the model for different operating conditions. According to the trials, the optimum parameters used for verifying the performance of the ACO-based state feedback controller are listed in Table 4.

TABLE 4
ACO PARAMETERS

ACO Parameters	
Number of ants	100
Number of nodes	2000
Number of iteration	2000
Evaporation rate	0.7
α and β	0.7 and 0.2 respectively

The simulated waveforms in time domain responses to step (10%) in the input signal are depicted in Fig. 12. Fig. 13 compares the average power spectral density of the system variables oscillations before and after oscillations cancellation. This is further evidenced in the corresponding frequency- domain description of Fig. 11, where a clear indication about the reduction in the oscillations and in the peaks of the frequency response for the synchronous generator can be observed. The absolute average attenuation is found to be approximately 34.89 dB for load angle deviation, 21.54 dB for speed deviation, 31.3 dB for terminal voltage deviation, 15.6 dB for field voltage deviation, and 4.56 dB for flux linkage deviation.

Compared to the MCOAN, the ant colony algorithm offers a less significant improvement in tuning the controller parameters. While the controllers tuned by the MOCAN provide better performance than the ACO ones, they exhibit a superior performance in terms of faster response and less oscillation.

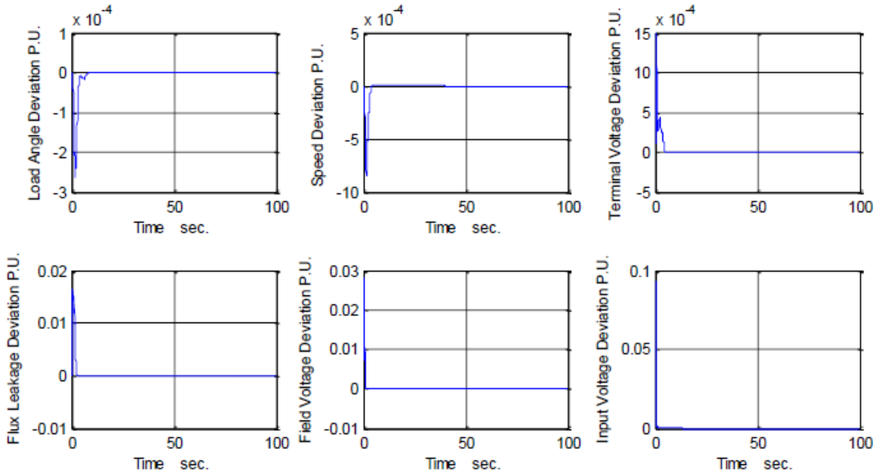


Fig. 12. The controlled system variables responses when the controller is turned on at starting using ACO

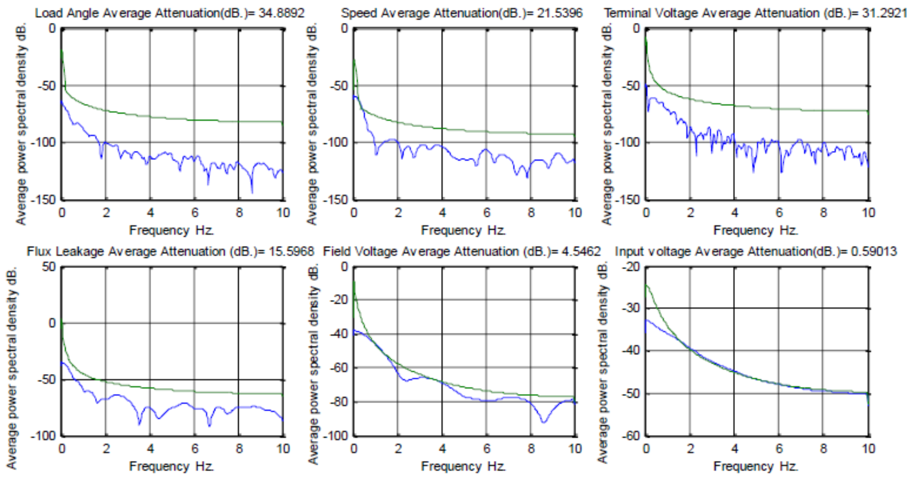


Fig. 13. Power spectral density of un-controlled and controlled system variables when ACO algorithm is adopted

V. CONCLUSIONS

This paper analyzes the characteristics of a modified COA for solving engineering problems. A hybrid algorithm combining the state feedback controller with the good global search ability of MCON has been proposed. Generally speaking, a parameter estimation of the state controller is performed based on the use of a modified MCOA where a noise signal is injected to improve the converging rate and the algorithm performance. Consequently, a procedure of inserting noise into *ELR* is introduced. It shows that applying a controlled amount of noise during the searching process improves the convergence. In addition, the effects of each noise parameters are analyzed to achieve the best performance. Based on the obtained results, it is shown that the best value of the objective (cost) function is achieved by the MCOAN algorithm compared to the original one (COA). Then, the application of the ant colony algorithm to tune the controller parameters of the converter was proposed. The MCOAN-optimized linear state controller is compared to ACO-based controller. One finds that the MCOA is much more effective; and a considerable improvement in suppressing the unwanted oscillations was achieved. This indicates that the signifying controlled behavior in a synchronous generator is performed; and therefore in general it can be adopted for a wide range of engineering applications, and for multimodal responses.

APPENDIX

TABLE A1
SYSTEM PARAMETERS IN P.U. VALUES

System Parameters	Value, p.u.
x	0.71417
Xd	1
Xd'	0.27
Xq	0.6
$\tau`do$	9 sec
M	0.1534
Ge	10
τe	1s
τs	0.5s

TABLE A2
INITIAL VARIABLES OF THE SG SYSTEM

SG System variables	Value, p.u.
Po	0.735
Qo	0.034
vto	1.050
ido	0.286
iqo	0.640
vdo	0.384
vo	1.058
ΨFo	9.491
δo	0.887

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