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A Hybrid Self-Adaptive Spider Monkey Optimization for Automatic Generation Control

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Abstract : A hybrid self-adaptive Spider Monkey Optimization (SaSMO) with Tournament selection is proposed in this paper to design 2 Degree of Freedom Fractional Order PID controllers for Automatic Generation Control (AGC). This work presents a self-adaptive Spider Monkey optimization (SaSMO) algorithm for optimization problems. The proposed strategy is self-adaptive in nature and therefore no manual parameter setting is required.The modification in Spider Monkey Optimization proposed by replacing the fitness proportionate probability scheme of Spider Monkey optimization. The modification in Spider Monkey optimization algorithm proposed by introducing a strategy in which tournament selection based probability scheme has been used instead of fitness proportionate probability scheme of SMO during the iterations. At beginning, the approach is applied to an interconnected two equal area thermal power system and the improvement of the proposed approach has been demonstrated by comparing the results with some recently reported approaches like Differential Evolution (DE), Spider monkey Optimization for the two identical test case.
Keywords: Automatic Generation Control (AGC);Tournament Selection; 2 Degree of Freedom Fractional Order PID; self-adaptive Spider Monkey Optimization (SaSMO).

1. INTRODUCTION

In present days due to increase in power demand with the modern power system being increase in network size, uses an intelligent control systems with latest methodologies for the real-time control of power systems. The tie-line flows and the system frequency are monitored by an Automatic Generation Control (AGC), to maintain the time average of frequency deviations and the deviations of tie-line at a low which computes the generation net change required and the set position changes of the generators within the area[1, 2]. In order to keep the line flow and system frequency during normal operating and various disturbance conditions with their scheduled values, number of control strategies for AGC are designed in present days. In [3], literature review on the Load Frequency Control of power systems with different control techniques are compared. In [4], for AGC system controllers like PID and Integral Double Derivative have been proposed. In[5], the PI controller parameters are optimized by Differential Evolution algorithm. In [6], the DE was applied for a multi-area multi source power system. In [7], $PI^{\lambda}D^{\mu}$ controller is designed by using improved DE technique.

Intelligent food foraging behavior of Spider Monkeys inspired J. C Bansal and his colleagues to develop a new algorithm. J. C. Bansal *et al.* [8] proposed Spider Monkey Optimization algorithm in year 2013. A Tournament selection Spider Monkey optimization is a new meta-heuristic optimization technique which is purposed in 2015 [9]. There are very few research papers on SMO algorithm in literature as it

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is very young algorithm. Recently S. Kumar *et al.* proposed a couple of variants of SMO algorithm. First is Modified Position Update in Spider Monkey Optimization Algorithm (MPU-SMO)[10]. Fitness of a solution play very important role in population based stochastic algorithms. It denotes quality of solution, that how much they are suitable for next iteration. FPSMO update position based on the individual's fitness. It assumes that best fitted solution has good neighbors and modifies the step size according to its fitness. It takes a large step for high fitted solution and a small step for low fitted solutions. FPSMO move away from bad solutions and keep searching in proximity of good solutions. In [10], the basic concepts of self-adaptive spider monkey (SaSMO) algorithm for numerical computation was discussed.

2. SYSTEM UNDER STUDY

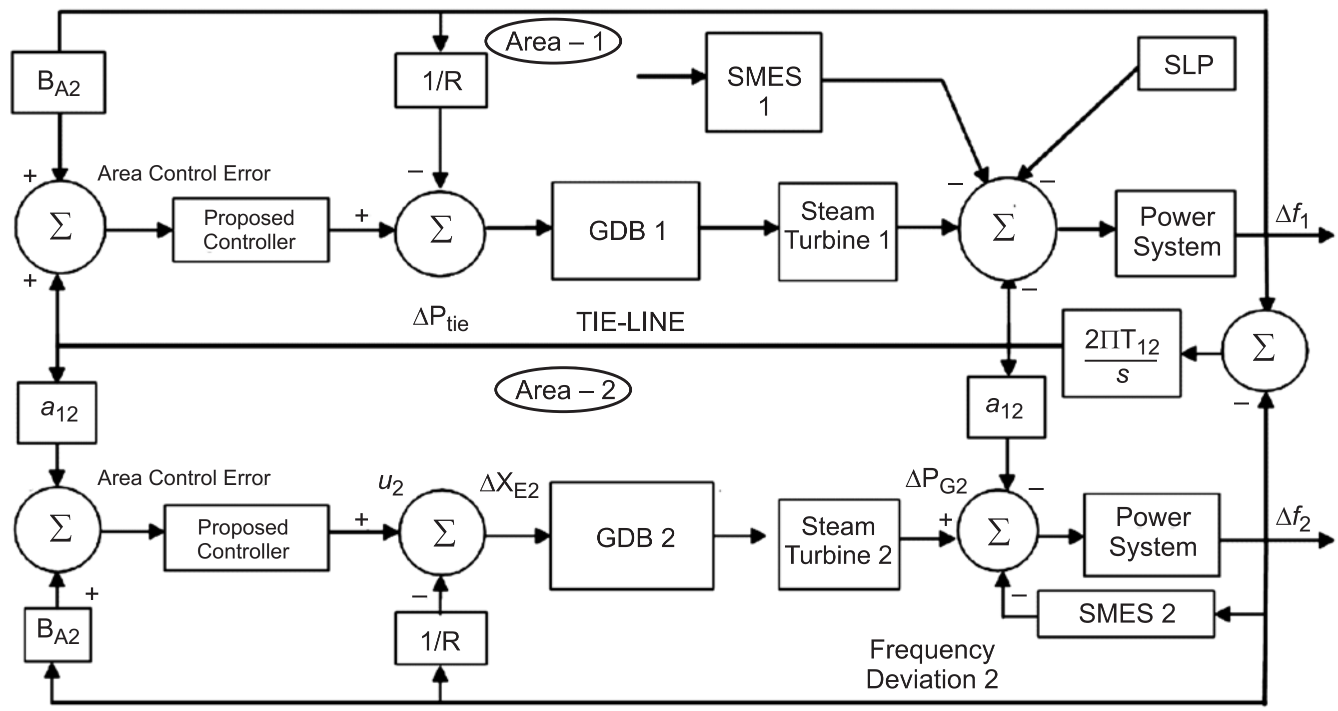

Figure 1: Transfer function model of two-area non reheat thermal system

For design and analysis consider thermal plants with two area interconnected power system as shown in Fig.1. Each area has a rating of 4000 MW with a nominal load of 1500 MW. The system is widely used in literature for the design and analysis of automatic load frequency control of interconnected areas. In Fig. 1, frequency bias parameters are represented by B_1 and B_2; area control errors are represented by ACE_1 and ACE_2; the controller control outputs are u_1 and u_2 respectively. The relevant parameters are given in appendix.

In two area system each area consists of speed governing system, turbine and generator as shown in Fig. 1. The controller inputs are ΔP_{ref}, ΔP_{Tie} represents load disturbances and tie-line power error. The generator frequency deviations outputs and Area Control Errors (ACE) given by [2].

$$ACE_1 = A_1 \Delta f_1 + \Delta P_{Tie} \quad (1)$$

$$ACE_2 = C_1 \Delta f_2 - \Delta P_{Tie} \quad (2)$$

Where C is the frequency bias parameter.

Turbine is represented by the transfer function [2]:

$$G_T(s) = \frac{\Delta P_{TR}(s)}{\Delta P_V(s)} = \frac{1}{1 + sT_C} \quad (3)$$

From [2], the transfer function of a governor is:

$$G_G(s) = \frac{\Delta P_V(s)}{\Delta G_V(s)} = \frac{1}{1+sT_G} \quad (4)$$

The speed governing system has two inputs ΔP_{ref} & ΔSf with one out put $\Delta G_V(s)$ given by [2]:

$$\Delta G_V(s) = \Delta P_{ref}(s) - \frac{1}{R}\Delta F(s) \quad (5)$$

The transfer function [2] represents the generator and the load:

$$G_P(s) = \frac{K_P}{1+sT_P} \quad (6)$$

where $K_P = 1/D$, $T_P = 2H/f D$.

The two inputs of generator load system $\Delta P_{TR}(s)$ & $\Delta P_{LD}(s)$ with one output $\Delta f(s)$ given by [2]:

$$\Delta f(s) = G_P(s)\,[\Delta P_{TR}(s) - \Delta P_{LD}] \quad (7)$$

The tuning parameters of fractional order PID controller transfer function is given by

$$G_b(s) = K_P + \frac{K_I}{s^{\lambda}} + K_D s^{\mu} \quad (8)$$

Select $\lambda = \mu = 0.8$, for a classical PID controller.

Fig 2. shows the structure of ideal 2-DOF-FOPID controller which is proposed.

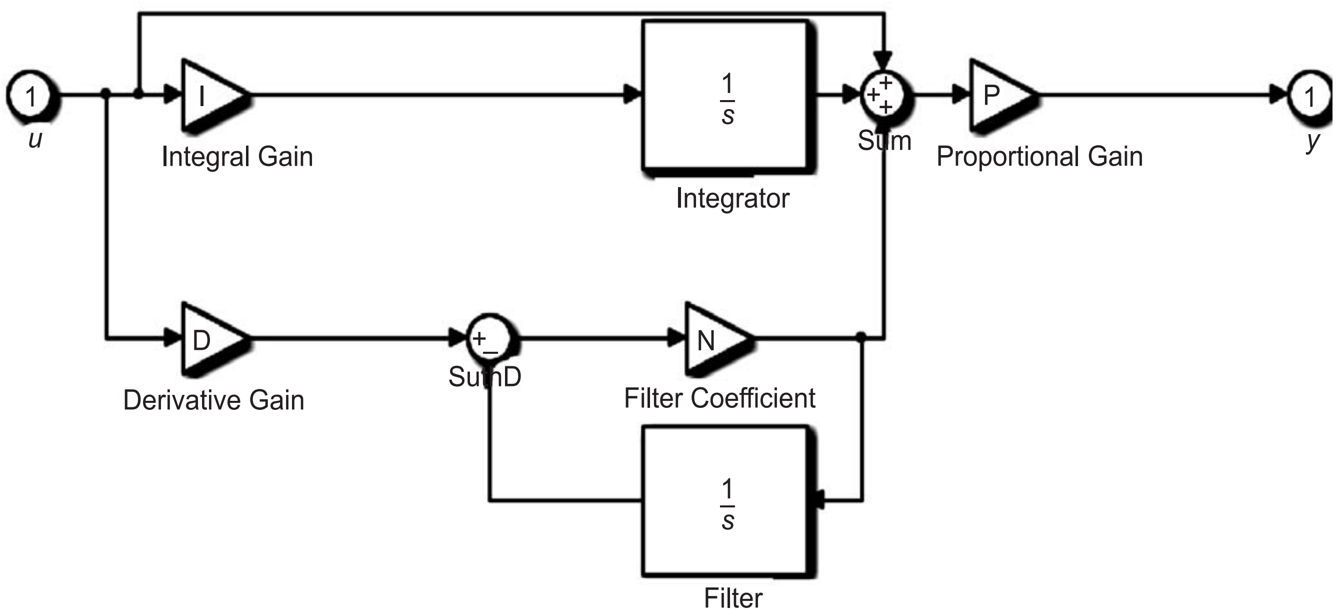

Figure 2: Two Degree of Freedom Fractional Order PID controller structure

The proposed controllers are designed to give less overshoot and settling times compared with Integral of Time multiplied Absolute Error (ITAE) based objective function given in Eq. (9).

$$W = ITAE = \int_0^{tr_{sim}} \left(|\Delta Sf_1| + |\Delta Sf_2| + |\Delta P_{tie}|\right)\cdot t \cdot dt \quad (9)$$

Where, the system frequency deviations are ΔSf_1 and ΔSf_1 ; ΔP_{tie} is the incremental change in tie-line power and tr_{sim} is the time range of simulation.

The design problem can be formulated as the following optimization problem.

Minimize SM (10)

Subject to

$$G_{Pmin} < G_P,\ G_{Pmax} > G_P,\ G_{Imin} < G_I,\ G_{Imax} > G_I \text{ and } G_{Dmin} < G_D,\ G_{Dmax} > G_D \quad (11)$$

The minimum and maximum values of controller parameters and set point weights are taken as -3.0 & 3.0 and 0.2 & 4.5. respectively. The integrator (λ) and differentiator (μ) minimum order is 0 and maximum value are chosen as 3 respectively.

3. OVERVIEW OF TOURNAMENT SELECTION SPIDER MONKEY OPTIMIZATION

Tournament selection Spider Monkey Optimization (TS-SMO) is a recently proposed meta-heuristic optimization technique inspired by the food searching strategy of Spider Monkeys [9]. Spider Monkeys belong to the class of fission-fusion social structure phases in each iteration which are responsible for updating the swarm. There are seven main steps in food searching.

1. Initialization of population
2. Local leader phase.
3. Global leader phase
4. Local leader learning phase.
5. Global leader learning phase
6. Local leader decision phase.
7. Global leader decision phase

3.1. Initialization of population

Let N be spider monkey early population the vector of dimension R for every monkey is TM_j (j = 1, 2 .. , N). In an optimization problem quantity of variables represented by R and the position of j^{th} spider monkey is given by TM_j. For the problem TM represents the probable solution of each spider monkey.

$$TM_{jk} = TM_{\min k} + \phi \times (TM_{\max\ k} - TM_{\min\ k})$$

where $$\phi \in (0, 1) \quad (12)$$

3.2. Local leader phase

Here TM update its existing location from the information received from the local leader. The fresh location of fitness value is considered for update. Here the new location and new fitness value is considered for TM updates.

$$TM_{newjk} = TM_{jk} + \phi \times (LL_{rl} - TM_{jk})$$

where $$\phi \in (0, 1) \quad (13)$$

else $$TM_{newjk} = TM_{jk} + \text{rand}\,[0, 1] \times (LL_j - TM_{jk})$$

$$+ (TM_{ij} - LL_{kj}) \times (\omega_{max} - \frac{\text{iter}}{max\_\text{iter}}(\omega_{max} - \omega_{min}))$$

A. Global leader phase

Here each and every TM's bring up their location by understanding the local group members and global leader.

$$TM_{newjk} = TM_{jk} + \phi \times (GL_k - TM_{jk}) + \phi_2 \times (TM_{jk} - TM_{jk})$$

where ϕ_1 (0, 1) and $$\phi_2 \in (-1, 1) \quad (14)$$

Where, GL_k represents global leader location of k^{th} dimension.

With higher fitness there are more number of chances and for lower fitness there are less number of chances.The fitness function is given by

$$p_i = 0.95 \times \frac{\text{fittness}_j}{\text{fittness}_{max}} + 0.12 \quad (15)$$

Here $fitness_j$ and $fitness_{max}$ represent the fitness value of the j^{th} TM and in a group of maximum fitness respectively.

3.4. Global leader learning phase

In this phase the global leader is modernized in the population by applying the starving selection approach. Here according to the fitness the best fitted candidate is considered as global leader. The global counter limit gets advanced if the location is not updated.

3.5. Local leader learning phase

By applying the starving approach within that group If the location of local leader is not updated then local limit counter has to advanced.

3.6. Local leader Decision phase

Here the individual locations in group of local leader decides their locations either by arbitrary initialization from global leader and local leader through preoccupation rate. Local Leader Limit (LL_{limit}) used if not updated for a predefined threshold.

$$TM_{newjk} = TM_{jk} + \phi \times (GL_k - TM_{jk}) + \phi \times (TM_{ij} - TM_{jk})$$

where $$\phi_1 \in (0, 1) \quad (16)$$

(15) shows that the simplified measurement of this TM is involved with global leader and outlined from local leader.

3.7. Global leader Decision phase

The minor groups are formed in this phase which divides by global leader if locations of individuals are not modernized up to a predefined number of iterations known as global leader limit GL_{limit}. Upto forming maximum number of groups the division process continues. The process of local leader limit is initiated to decide the local leader in the newly formed groups of each time in global leader decision phase.

Self-Adaptive Spider Monkey Optimization (SaSMO) Algorithm

Step 1: Initialize all parameters

Step 2: Calculate fitness

Step 3: Choose leaders (global and local both)

Step 4: Repeat till the extermination criterion is not fulfilled.

Step 5: Generate the fresh locations for the entire group members

Step 6: Apply the greedy selection mechanism between existing position and newly computed position.

Step 7: Compute the probability *pi* (*pi* denote probability of i^{th} solution) for every group member.

Step 8: Engender new positions for the every member of group. Modernize local and global leader's position.

If position of a Local leader is not updating after LL_{limit} then apply following steps.

$$TM_{newjk} = TM_{min\,j} + \text{rand}\,[0, 1] \times (TM_{max\,j} - TM_{min\,j})$$

else

$$TM_{newjk} = TM_{ij} + \text{rand}\,[0, 1] \times (GL_j - TM_{Ij}) + (TM_{ij} - LL_{ij}) \times ((\omega_{max} - \frac{\text{iter}}{max\_\text{iter}}(\omega_{max} - \omega_{min}))$$

Step 9: If position of Global Leader is not updating after GL_{LIMIT} then apply following steps.

If(Global_limit_count > GL_{Limit})

then

Set Global_Limit_count = 0

If(number of groups < MG)

then

Divide the population into groups

else

Merge all the groups into single large group

Bring upto date position of leader.

4. RESULTS AND DISCUSSIONS

4.1 Application of SaSMO algorithm

MATLAB/SIMULINK environment is used to model the system under study by considering identical controller in each areas. The change in step load in area-1 is considered as 20%.. For the proposed controller parameters the optimization solution was repeated 20 times and the best final fit solution. To demonstrate the advantage of proposed SaSMO optimization algorithm, results of SaSMO are compared with Differential Evolution, and Spider monkey algorithm. In this algorithm, number of iterations and search agents are chosen as 35and 65 respectively. Initially for 75 iterations are applied.

4.2. Results Analysis

To demonstrate the effectiveness of the proposed approach results are compared with some recently published modern heuristic optimization methods such as Differential Evolution (DE), for the same interconnected power system. Minimum settling times in frequency deviations are also obtained with proposed SaSMO optimized 2-DOF-FOPID controller compared to the other two approaches.

At different locations the simulations of time domain analysis are carried out for step load change. At area –1 when $t = 0$ sec, a step increase demand of 2 % is applied. The system dynamic responses are shown in Figs. 3&4.

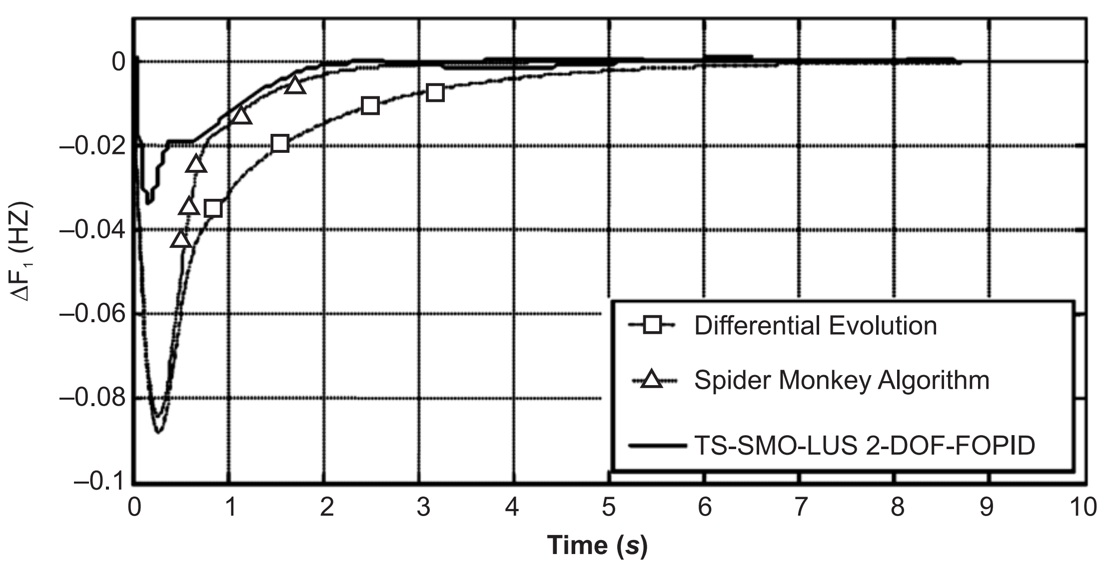

Figure 3: Area -1 frequency deviation for 2 % step load change in area-1

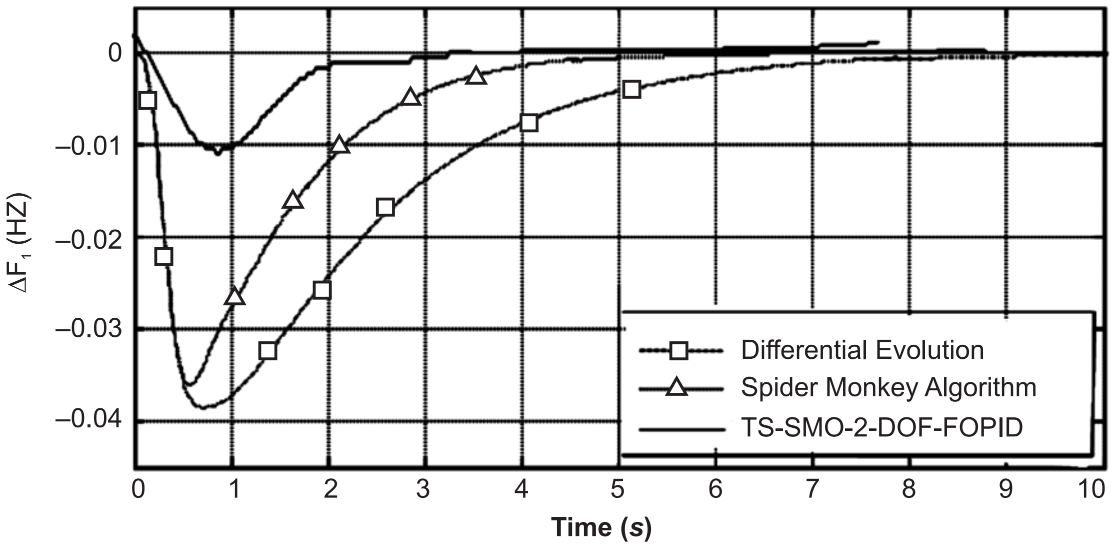

Figure 4: Area -2 frequency deviation for 2 % step load change in area-1

The dynamic responses of critical analysis shows that significant improvement is observed with proposed Sa SMO optimized compared other literature reported approaches. For the given all system cases, it is found that dynamic performance is achieved with proposed SaSMO algorithm with other discussed approaches are shown in Fig.1. and Table. 1 shows the comparative performance indexes.

Table 1
Comparative performance indexes with recent AGC approaches

Performance/Technique: Control Structure	*ITAE Value x10^{-2}*	*Settling times T_s(Sec)*	
		ΔF_1	ΔF_2
Diffferential Evolution	125.51	8.96	8.16
Spider Monkey Algorithm	103.7	7.92	6.57
SaSMO Algorithm	10.14	1.98	2.52

5. CONCLUSION

Design and performance analysis of a hybrid self-adaptive Spider Monkey Optimization (SaSMO) for AGC of interconnected power systems is presented in this paper. The proposed SaSMO technique has an improved balance between the algorithm stages and also gives more importance to the fittest search monkey to find the new position of spider monkey during the iterations. The superiority of SaMO has been illustrated. For the proposed method the results clearly shows that the proposed SaSMO optimized controller gives good dynamic performances for the same power system than some recently reported AGC methods such as Differential Evolution (DE), and spider monkey algortihm.

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