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Optimal PID Tuning for Load Frequency Control Using Lévy-Flight Firefly Algorithm

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Abstract—**Nature-inspired algorithms are among the most powerful algorithms for optimization. In this paper, a load frequency control (LFC) in two-area power systems using the lévy-flight firefly optimization algorithm (LFOA) is presented. The system simulation is realized by using MatLab/Simulink. The proposed LFOA-based PID controller has been compared with the firefly optimization algorithm (FOA)-based and particle swarm optimization (PSO) algorithm-based PID controllers. Simulations and results indicate that the proposed LFOA is superior to other ones for the LFC in two-area power systems.**

Keywords- Firefly optimization algorithm; lévy-flight firefly optimization algorithm; particle swarm optimization; load frequency control; two-area power system

I. INTRODUCTION

This Large scale power systems are normally composed of control areas or regions representing coherent groups of generators. Various areas are interconnected through tie lines. The tie lines are utilized for contractual energy exchange between areas and provide inter-area support in case of abnormal conditions. Area load changes and abnormal conditions lead to mismatches in frequency and scheduled power interchanges between areas. These mismatches have to be corrected by load frequency control (LFC), which is defined as the regulation of the power output of generators within a prescribed area [1]. The regulation is performed so as to maintain the scheduled system frequency and/or established interchange with other areas within predetermined limits in response to changes in system frequency and tie line loading [2].

Several strategies for the LFC of power systems have been proposed by researchers over the past decades. A robust decentralized power system LFC controller design approach using structure singular value has been designed in [3]. Two robust decentralized LFC controllers are introduced in [4]. The first one is based on $H\infty$ theory, and results in a high order controller. The second controller is a PI controller tuned by genetic algorithm (GA) to achieve the same robust performance as the first one. A decentralized adaptive control scheme for LFC of multi-area power systems to deal with variations of system parameters is introduced in [5]. An approach based on the tabu search (TS) algorithm for optimal design of a fuzzy logic based Proportional Integral (FLPI) LFC in a two-area interconnected power system is presented in [6]. The PI and I control parameters are tuned based on hybrid particle swarm optimization (HPSO) algorithm method for LFC control in a two-area power system in [7]. PSO based multi-stage fuzzy controller is proposed for solution of LFC problem in power system in [8]. Designing of PID controller for LFC in interconnected power system using PSO has been discussed in [9]. Hybrid neuro-fuzzy (HNF) approach is employed in [10] for an automatic generation control (AGC) of interconnected power system with and without generation rate constraint (GRC). Application of real coded GA for optimizing the gains of a PI controller for two-area thermal reheat power system has been discussed in [11]. Fuzzy logic controller is designed for automatic LFC of two-area interconnected power system in [12].

Nature-inspired metaheuristic algorithms are becoming powerful in solving modern global optimization problems [13-14]. For example, PSO was developed by Kennedy and Eberhart in 1995 [13], based on the swarm behavior such as fish and bird schooling in nature. It has now been applied to find solutions for many optimization applications. Another example is the firefly optimization algorithm (FOA) developed by Yang [14] which has demonstrated promising superiority over many other algorithms.

The search strategies in these multi-agent algorithms are controlled randomization, efficient local search and selection of the best solutions. However, the randomization typically uses uniform distribution or Gaussian distribution.

On the other hand, various studies have shown that flight behavior of many animals and insects has demonstrated the typical characteristics of lévy flights [15]. A recent study by Reynolds and Frye shows that fruit flies or Drosophila melanogaster, explore their landscape using a series of straight flight paths punctuated by a sudden 90ø turn, leading to a lévy-flight-style intermittent scale free search pattern. Even light can be related to lévy flights [16]. Subsequently, such behavior has been applied to optimization and optimal search, and preliminary results show its promising capability [15].

This paper aims to implement a lévy-flight firefly optimization algorithm (LFOA) and to provide the comparison study of the LFOA with FOA and PSO algorithms in LFC of two-area power systems. We will first outline the firefly algorithms, then formulate the LFOA and finally give the comparison about the performance of these algorithms. The LFOA optimization seems more promising than PSO and FOA in the sense that LFOA has a less fitness function value and converges quickly and deals with global optimization more naturally. In addition, PSO is just a special class of the LFOA as it is demonstrated in [17].

II. FIREFLY ALGORITHM

A. Behavior of Fireflies

The flashing light of fireflies is an amazing sight in the summer sky in the tropical and temperate regions. There are about two thousand firefly species, and most fireflies produce short and rhythmic flashes. The pattern of flashes is often unique for a particular species. The flashing light is produced by a process of bioluminescence, and the true functions of such signaling systems are still debating. However, two fundamental functions of such flashes are to attract mating partners (communication), and to attract potential prey. In addition, flashing may also serve as a protective warning mechanism. The rhythmic flash, the rate of flashing and the amount of time form part of the signal system that brings both sexes together. Females respond to a male's unique pattern of flashing in the same species, while in some species such as photuris, female fireflies can mimic the mating flashing pattern of other species so as to lure and eat the male fireflies who may mistake the flashes as a potential suitable mate.

The flashing light can be formulated in such a way that it is associated with the objective function to be optimized, which makes it possible to formulate new optimization algorithms.

B. Firefly Algorithm

Now we can idealize some of the flashing characteristics of fireflies so as to develop firefly-inspired algorithms. For simplicity in describing our FOA, we now use the following three idealized rules: 1) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex; 2) Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly; 3) The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms or the bacterial foraging optimization algorithm (BFOA) [18].

In the FOA, there are two important issues: the variation of light intensity and formulation of the attractiveness. For simplicity, we can always assume that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function.

In the simplest case for maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x) \propto f(x)$. However, the attractiveness β is relative, it should be seen in the eyes of the beholder or judged by the other fireflies. Thus, it will vary with the distance r_{ij} between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity $I(r)$ varies according to the inverse square law $I(r) = I_s/r^2$.

where I_s is the intensity at the source. For a given medium with a fixed light absorption coefficient γ, the light intensity I varies with the distance r. That is

$$I = I_0 e^{-\gamma r} \tag{1}$$

where I_0 is the original light intensity.

As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly by

$$\beta = \beta_0 e^{-\gamma r^2} \tag{2}$$

C. Lévy-Flight Firefly Algorithm

If we combine the three idealized rules with the characteristics of lévy flights, we can formulate a new LFOA which can be summarized as the pseudo code shown in [17].

In the implementation, the actual form of attractiveness function β(r) can be any monotonically decreasing functions such as the following generalized form

$$\beta(r) = \beta_0 e^{-\gamma r^m} \qquad (m \ge 1) \tag{3}$$

For a fixed γ, the characteristic length becomes $\Gamma = \gamma^{-1/m} \rightarrow 1$ as $m \rightarrow \infty$. Conversely, for a given length scale Γ in an optimization problem, the parameter γ can be used as a typical initial value. That is $\gamma = 1/\Gamma^m$.

The distance between any two fireflies i and j at x_i and x_j, respectively, is the Cartesian distance

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k} \right)^2} \tag{4}$$

where $x_{i,k}$ is the kth component of the spatial coordinate x_i of ith firefly. The movement of a firefly i is attracted to another more attractive (brighter) firefly j is determined by

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha\, sign\left[rand - \frac{1}{2}\right] \oplus \text{Lévy} \quad (5)$$

where the second term is due to the attraction while the third term is randomization via lévy flights with α being the randomization parameter. The product ⊕ means entry wise multiplications. The $sign[rand\text{-}\frac{1}{2}]$ where rand ∈ [0,1] essentially provides a random sign or direction while the random step length is drawn from a lévy distribution

$$\text{Lévy} \cong u = t^{-\lambda} \qquad (1 < \lambda \le 3) \quad (6)$$

which has an infinite variance with an infinite mean. Here the steps of firefly motion is essentially a random walk process with a power-law step-length distribution with a heavy tail.

In this study, we took $\beta_0 = 1$, $\alpha = 0.7$, $\gamma = 1$, and $\lambda = 1.5$. The parameter γ now characterizes the variation of the attractiveness, and its value is crucially important in determining the speed of the convergence and how the FOA algorithm behaves.

III. Two-Area Power System

A two-area interconnected power system consists of two single areas connected through a power line called the tie line. Each area feeds its user pool, and the tie line allows electric power to flow between areas.

Since two areas are tied together, a load perturbation in one area affects the output frequencies of all two areas as well as the power flow on the tie line. The control system of each area needs information about the transient situation of two areas in order to bring the local frequency back to its steady state value. Information about the other areas is found in the output frequency fluctuation and in the tie line power fluctuation of that area. Therefore, the tie line power is sensed, and the resulting signal is fed back into related areas. A block diagram related to the two-area interconnected power system is given in Fig. 1. The two-area power system parameters are available in appendix.

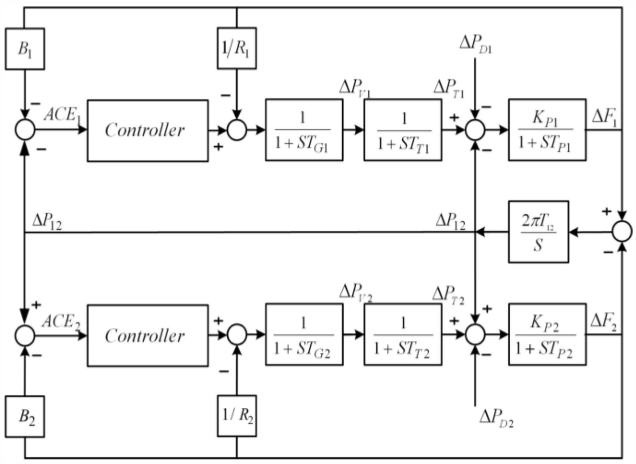

Figure 1. Block diagram of two-area power system

IV. Simulations and Results

The study system is simulated in MatLab/Simulink. Each of three algorithms (PSO, FOA and LFOA) is implemented to optimize the PID controller parameters of two areas. PID controllers are similar and simultaneously having the same parameters along with optimization process. The fitness function for the search algorithms is chosen as the integral of the time multiplied absolute value of the error (*ITAE*) index. *ITAE* penalizes long duration transients, and it is much more selective than other indices. A system designed using this criterion exhibits small overshoots and well damped oscillations. *ITAE* is defined

$$f_{ITAE} = \int_0^\infty t\left|e(t)\right|dt \quad (7)$$

where, *e(t)* is defined as the sum of *ACE1* and *ACE2* shown in Fig. 1, and *t* is also the simulation time. The system is stable, and the control task is to minimize the system frequency deviation δF_1 in *area1*, δF_2 in *area2* and the deviation in the tie line power flow δP_{tie} between the two areas under the load disturbances δP_{D1} and δP_{D2} in the two areas. Since the system parameters for the two areas are identical and δP_{tie} is caused by (δF_1 - δF_2) the system performance can be mainly tested by applying a disturbance δP_{D1} to the system and observing the time response of δF_1 [19]. System frequency deviation δF_1 in area1 under 0%, 15% and 30% disturbance δP_{D1} is demonstrated in Figs. 2, 3 and 4, respectively, using the optimization algorithms. Since the power flow oscillation of the tie line is exactly zero under PID controllers optimized by three aforementioned algorithms, so it is not demonstrated in this paper. Furthermore, ITAE value is calculated to compare the performance of these three optimization algorithms tabulated in Table 1. The obtained results show better performance of LFOA than the other ones.

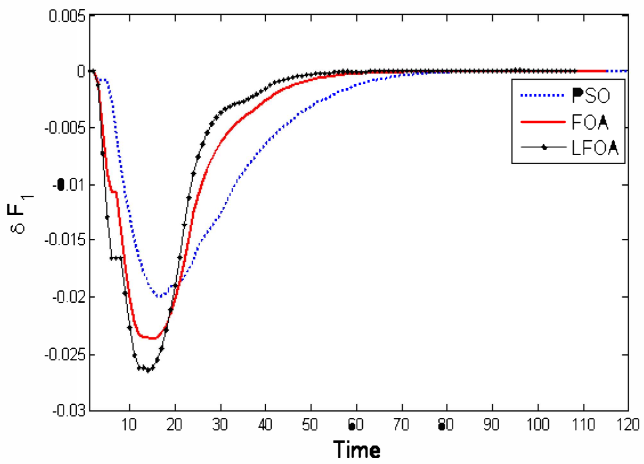

Figure 2. The frequency variation of two areas when PID controllers are optimized by PSO, FOA and LFOA under 0% load disturbance δPD1

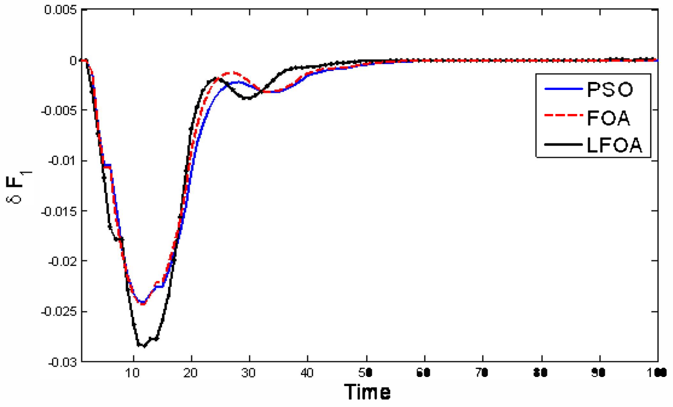

Figure 3. The frequency variation of two areas when PID controllers are optimized by PSO, FOA and LFOA under 15% load disturbance δPD1

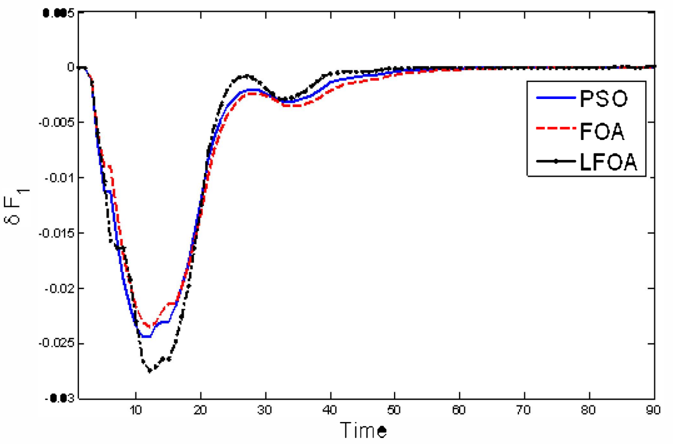

Figure 4. The frequency variation of two areas when PID controllers are optimized by PSO, FOA and LFOA under 30% load disturbance δPD1

TABLE I. ITAE VALUE FOR OPTIMIZATION ALGORITHMS UNDER DIFFERENT LOAD DISTURBANCES ΔPD1

Optimization Method	0% load disturbance	15% load disturbance	30% load disturbance
PSO	0.8693	0.0499	0.0560
FOA	0.0620	0.0438	0.0544
LFOA	0.0349	0.0404	0.0530

V. CONCLUSION

Nature-inspired metaheuristic algorithms are becoming powerful in solving modern global optimization problems. Therefore, in this paper, PID controllers are optimized by PSO, FOA and LFOA for the LFC of two-area interconnected power systems. It is seen LFOA-optimized controllers have the better performances than two other algorithms-optimized controllers for the LFC in two-area power systems.

APPENDIX

Two-area power system parameters:
$T_{T1}=T_{T2}=0.3$s, $T_{G1}=T_{G2}=0.08$s, $T_{P1}=T_{P2}=20$s,
$T_{12}=0.0866$ p.u., $B_1=B_2=0.425$ p.u. MW/Hz
$R_1=R_2=2.4$ Hz/p.u. MW, $KP_1=KP_2=120$ Hz/p.u. MW.

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