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Optimal power flow using moth swarm algorithm

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ABSTRACT

This work presents a novel Moth Swarm Algorithm (MSA), inspired by the orientation of moths towards moonlight to solve constrained Optimal Power Flow (OPF) problem. The associative learning mechanism with immediate memory and population diversity crossover for Lévy-mutation have been proposed to improve exploitation and exploration ability, respectively, in addition to adaptive Gaussian walks and spiral motion. The MSA and four heuristic search algorithms are carried out on the IEEE 30-bus, 57-bus and IEEE 118-bus power systems. These approaches are applied to optimize the control variables such as real power generations, load tap changer ratios, bus voltages and shunt capacitance values under several power system constraints. Fourteen different cases are executed on different curves of fuel cost (e.g., quadratic, valve-loading effects, multi-fuels options), environmental pollution emission, active power loss, voltage profile and voltage stability for contingency and normal conditions, in single and multi objective optimization space. Furthermore, the impacts of the updating mechanism of optimizers on those objective functions are investigated. The effectiveness and superiority of the MSA have been demonstrated in comparison with many recently published OPF solution

1. Introduction

In deregulated power system, OPF is the main tool used to offere the electrical energy at minimum cost with high quality, which is a large-scale, multi-dimensional, non-convex, non-linear, and constrained optimization problem. In this study, the main objectives of OPF problem have been achieved in single/multi-optimization space under different operating conditions.

In recent years, metaheuristic optimization algorithms have been developed for simulating some of chemical, physical and biological phenomena [1]. Several nature-inspired optimization methods have been used to determine the optimized parameters of the power systems for the OPF problem. These algorithms include Adaptive Real Coded Biogeography-Based Optimization (ARCBBO) [2], Grey Wolf Optimizer (GWO) [3], Modified Gaussian Bare-bones Imperialist Competitive algorithm (MGBICA) [4], Artificial Bee Colony (ABC) algorithm[5], Differential Search Algorithm (DSA) [6], Efficient Evolutionary Algorithm (EEA) [7], Particle Swarm Optimization with an Aging Leader and Challengers (ALC-PSO) algorithm [8], Lévy mutation Teaching–Learning-Based Optimization (LTLBO) algorithm [9], Krill Herd Algorithm (KHA) [10], Teaching-Learning-Based Optimization (TLBO) technique [11], Improved Electromagnetism-like Mechanism (IEM) Method [12], Multi-Objective forced initialized Differential Evolution Algorithm (MO-DEA) [13], Fuzzy Harmony Search Algorithm (FHSA) [14], Improved Colliding Bodies Optimization (ICBO) algorithm [15], Hybrid Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA) [16], Hybrid Modified Particle Swarm Optimization and the Shuffle Frog Leaping algorithms (HMPSO-SFLA) [17], Gravitational Search Algorithm (GSA) [18], Hybrid Shuffle Frog Leaping Algorithm and Simulated Annealing (HSFLA-SA) [19], Gbest guided Artificial Bee Colony (GABC) optimization algorithm [20], and hybrid of Imperialist Competitive Algorithm and Teaching Learning Algorithm (MICA–TLA) [21]. In this paper, the potential and performance capabilities of the proposed MSA are presented in a comparison with all above-mentioned methods.

In the 90's of last century, the most popular nature inspired algorithms have been originated such as Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Ant Colony Optimisation (ACO) and Differential Evolution (DE). The strategies, operators and coding of those algorithms have been modified to be applied in different science fields [22]. The velocity reflection and Set-On-

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Boundary strategies, have been applied on Modified Particle Swarm Optimisation (MPSO) [23], whereas the random uniform distribution has been used to tune mutation and crossover of the Modified Differential Evolution (MDE) [24]. In the proposed algorithm a set of different optimization strategies are hybridized to simulate some of behavioral patterns of the moth swarm.

The development of new algorithms is encouraged by the "No Free Lunch" theorem [25], which states that no single method is best in solving all optimization problems. Therefore, recently there is a dramatic increase in the number of novel algorithms. Those algorithms were proposed inspired by different behavioral rules and key features of the bacterias [26], the cuckoos [27], the frogs [28], etc. The transverse orientation of moths toward artificial lights has been formulated in Moth-Flame Optimization (MFO) algorithm [29], while the pollination process of flowers has been modelled in Flower Pollination Algorithm (FPA) [30]. The two previous algorithms are joined recently to the family of nature-inspired algorithms in the bio-inspired category, and will be tested and compared through this study.

Metaheuristics aim to establish a trade off between the exploitation and exploration, by starting with a high population diversity (high exploration) and decreasing it during the search process. It is noted that, the increase of diversity supports exploration, whereas the decrease of diversity does not necessarily imply a good exploitation or a fast convergence. Therefore, the population diversity is still a stuck problem, and needs a smart treatment [31,32]. In this regard, the hybridization with the mutation originated from GA or DE is one of the most applicable operators to spread the search agents over a wide scope. In the other hand, almost all local search operators (e.g, path finding operator in ACO [33], learning operators in PSO [34] and immune clone and vaccination operators in GA [35]) can be employed for exploiting the solution space in a narrow scope. For that purpose, the DE-mutation and the PSO-learning operators have been included in the MSA method in line with the natural characteristics of the moths.

In the proposed approach, pathfinders in a pure exploration phase use a new adaptive crossover with mutation scaled by Lévy flights for more solutions diversity. Meanwhile, prospectors with logarithmic spiral motion is used to balance exploration–exploitation dilemma. The convergence speed of the MSA is hyperbolic increased by converting the navigation from transverse orientation to celestial navigation adaptively towards the promising areas in the solution space. Hence, onlookers are forced to update its positions with wide (by adaptive Gaussian walks) and narrow (by associative learning mechanism) scope exploitation methods. In addition, most of the control parameters have been adaptively performed to increase the celestial navigation and decrease the transverse orientation during the optimization process.

2. Optimal power flow formulation

Generally, an OPF is a non-convex and nonlinear optimization problem to reduce certain power system objectives subjected to several inequality and equality constraints by determines the best control variables for a given settings of load. The general form of OPF problem can be obtained as follows:

$$\text{Minimize} : f(x,u) \tag{1}$$

$$\text{Subject to} : g(x,u) = 0 \tag{2}$$

$$h(x,u) \le 0 \tag{3}$$

Where, x is vector of system state/dependent variables, u is vector of control/independent variables, $f(x,u)$ is the objective function to be minimized, $g(x,u)$ is the equality constraints and $h(x,u)$ is the inequality constraints. The control and the state variables of the OPF problem are stated as follows:

2.1. State variables

The set of variables, which describe the state of the power system, can be defined as follows:

$$x = \left[P_{G_1}, V_{L_1}, \ldots, V_{L_{NL}}, Q_{G_1}, \ldots, Q_{G_{NG}}, S_{l_1}, \ldots, S_{l_{nl}}\right] \tag{4}$$

Where, P_{G1},Q_G,V_L and S_l are the active power generation at slack bus, reactive power outputs of the generators, the voltage magnitude at load bus and apparent power flow, respectively.*NL*, *NG* and *nl* are the number of load buses (P-Q buses), generators buses (P-V buses) and the transmission lines, respectively.

2.2. Control variables

The set of parameters, which can be control the power flow equations, are represented in terms of the decision vector as follows:

$$u = \left[P_{G_2}, \ldots, P_{G_{NG}}, V_{G_1}, \ldots, V_{G_{NG}}, T_1, \ldots, T_{NT}, Q_{C_1}, \ldots, Q_{C_{NC}}\right] \tag{5}$$

Where, P_G is the generator active power, V_G is the generators voltage magnitude, T is the transformer tap, Q_c is the reactive power of shunt VAR compensators, *NT* and *NC* are the number of regulating transformers and shunt VAR compensators units, respectively.

2.3. Constraints

The problem of OPF has to fulfill both inequality and equality constraints. The power balance constraints are considered as equality constraint. The operating limits of power system components are considered as inequality constraints.

2.3.1. Equality constraints

These constraints represent the typical load flow equations using the balance of the active and reactive power, as follows:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j [G_{ij} cos(\delta_i - \delta_j) + B_{ij} sin(\delta_i - \delta_j)] = 0 \,\forall\, i\varepsilon nb \tag{6}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j [G_{ij} sin(\delta_i - \delta_j) - B_{ij} cos(\delta_i - \delta_j)] = 0 \,\forall\, i\varepsilon nb \tag{7}$$

Where, *nb* is the total number of buses, Q_G is the generator reactive power, P_D is the active load demand, Q_D is the reactive load demand, G_{ij} and B_{ij} are the transfer conductance and susceptance between bus *i* and bus *j*, respectively. These constraints are strictly enforced during the load flow procedure, which guarantees that the searched optimal solution is feasible.

2.3.2. Inequality constraints

These constraints represent the power system operating limits as follows:

Generation constraints: For stable operation, the voltages, real power, and reactive power of the generators are restricted by the lower and upper limits as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \,\forall\, i\varepsilon NG \tag{8}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \,\forall\, i\varepsilon NG \tag{9}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \,\forall\, i\varepsilon NG \tag{10}$$