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Optimal power flow under both normal and contingent operation conditions using the hybrid fuzzy particle swarm optimisation and Nelder–Mead algorithm (HFPSO–NM)

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ABSTRACT

In this paper, we solve the optimal power flow problem using by the new hybrid fuzzy particle swarm optimisation and Nelder–Mead (NM) algorithm (HFPSO–NM). The goal of combining the NM simplex method and the particle swarm optimisation (PSO) method is to integrate their advantages and avoid their disadvantages. The NM simplex method is a very efficient local search procedure, but its convergence is extremely sensitive to the selected starting point. In addition, PSO belongs to the class of global search procedures, but it requires significant computational effort. In the other side, in the PSO algorithm, two variables (Φ_1, Φ_2) are traditionally constant; in this case, due to the importance of these two factors, we decided to obtain these two as fuzzy parameters. The proposed method is firstly examined on some benchmark mathematical functions. Then, it is tested an IEEE 30-bus standard test system by considering different objective functions for normal and contingency conditions to solve optimal power flow. The simulation results indicate that the FPSO–NM algorithm is effective in solving the mathematical functions and the OPF problem.

1. Introduction

Economic operation is one of the serious problems for all power systems. Optimal power flow (OPF) is a powerful tool for the strategic planning and operation of power systems. The solution of the OPF problem leads to the selection of an objective function in networks and generator operation constraints for economic and safe operation [1,2].

Many optimisation techniques have been developed to solve the OPF problem, which is a non-linear optimisation problem with static constraints. In addition, the OPF problem has been considered in power system research because of the enhancement of classical mathematics methods. The classical mathematics-based programming methods, such as linear programming, non-linear programming, quadratic programming (QP), the interior point methods (IPMs) and the Newton-based method, have been completely investigated in the literature [3–5]. The OPF problem has more than one local optimum because it is an extremely non-linear and multi-modal optimisation problem. In addition, there are no criteria to select a local optimum as the global optimum. Hence, local optimisation techniques are not suitable for such optimisation problems. Therefore, conventional optimisation methods, which are based on gradients and derivatives, are not able to determine the global optimum.

Generally, the OPF problem is an optimisation problem with a non-convex, non-smooth and non-differentiable objective function. Many intelligent optimisation methods have been developed to overcome the above mentioned issues and limitations of the classical methods for solving the OPF problem. A wide range of evolutionary optimisation algorithms, such as the evolutionary programming algorithm (EP) [6], improved evolutionary programming (IEP) [7], the improved genetic algorithm (IGA) [8], simulated annealing (SA) [9], Tabu search (TS) [10], differential evaluation (DE) [11–14], modified differential evaluation (MDE) [15] and biogeography-based optimisation (BBO) [16] have been used to solve the OPF problem.

Recently, a novel optimisation algorithm called particle swarm optimisation (PSO) has been presented to solve many optimisation problems of power systems [17–19], PSO belongs to the class of global search procedures but requires significant computational effort. The PSO algorithm is a population-based approach that utilises a set of candidate solutions, called particles, that move along the search space. The trajectory followed by each particle is guided by the particle's own memory and its interaction with other particles. The specific method of adjusting the trajectory of each particle is modelled after the means by which a flock of birds or a school of fish interact with each other. This interaction is used

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in guiding the particles towards good minima in the search space of the problem. At the end of the algorithm's execution, a few of the particles have converged to the optimal solutions. In addition, the PSO algorithm has been applied to determine optimal power flow [17,20]. Traditionally, in the PSO algorithm, two acceleration variables (Φ_1, Φ_2) are constant; in this case, due to the importance of these two accelerations, we decided to obtain these two as fuzzy parameters [21].

It is an indubitable fact that for several problems a simple Evolutionary algorithm might be good enough to find the desired solution. As reported in the literature, there are several types of problems where a direct evolutionary algorithm could fail to obtain a convenient (optimal) solution [22]. This clearly paves way to the need for hybridisation of evolutionary algorithms with other optimisation algorithms, machine learning techniques, heuristics etc. Some of the possible reasons for hybridisation are as follows [23]:

1. To improve the performance of the evolutionary algorithm (example: speed of convergence).
2. To improve the quality of the solutions obtained by the evolutionary algorithm.
3. To incorporate the evolutionary algorithm as part of a larger system.

Accordingly, all algorithms that search for an extremum of a cost function perform exactly the same, when averaged over all possible cost functions [24]. According to the Wolpert and Macready [24], if algorithm A outperforms algorithm B on some cost functions, then loosely speaking there must exist exactly as many other functions where B outperforms A. Hence, from a problem solving perspective it is difficult to formulate a universal optimisation algorithm that could solve all the problems. Hybridisation may be the key to solve practical problems.

In recent years, BF–NM method has been used to solve engineering optimisation problems [32]. Nelder and Mead proposed the Nelder–Mead (NM) simplex and local search method, which was designed to solve the constrained optimisation problem without using gradient information. The NM simplex method is a very efficient local search procedure, but its convergence is extremely sensitive to the selected starting point. In this paper, the goal of combining the PSO and NM methods is to integrate their advantages and avoid their disadvantages [25]. The NM algorithm exploits local information and converges to the nearest optimal point [26], while the PSO algorithm belongs to the class of global search procedures.

This paper introduces the application of the combination of the fuzzy PSO and NM (HFPSO–NM) algorithms to solve the OPF problem, which has not been previously applied to solve the OPF problem in the literature. The remainder of the paper is organised as follows. Section 2 describes the formulation of the OPF problem. In Section 3, the constraints and control and state variables limits are presented, while Section 4 describes the fuzzy logic, PSO method and NM approach followed by the details of the proposed algorithm. Simulation results are presented in Section 5, and these results are compared to other methods, that were used for solving the OPF problem. Finally, the conclusion is presented in Section 6.

2. The OPF formulation and cost function

The OPF problem solution determines a certain objective function subject to various equality and inequality constraints [27]. Mathematically, the OPF problem can be presented as follows:

$$\min F(x,u) \quad \text{subject to}: \begin{cases} g(x,u)=0 \\ h^{\min} \le h(x,u) \le h^{\max} \end{cases} \tag{1}$$

where $F(x, u)$, $g(x, u)$ and $h(x, u)$ are a cost function and the equality (power flow equations) and inequality (practical limit of control and state variables) constraints, respectively. In addition, u and x are control (independent variables) and state (dependent variables) variables, respectively. Generally, the control variables of power systems are the output active power of generators except the slack bus, the voltage of the generator bus, transformer taps, phase shifters and the reactive compensator. In addition, the state variables are the voltage magnitude of the load buses, the angle magnitude of the buses, transmission line loading, the output reactive power of generators and the active power of the slack bus.

3. Constraints of the OPF problem

Equality and inequality constraints have been considered for solving the proposed OPF problem.

3.1. Equality constraints

Active and reactive power balance constraints are considered as follows:

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} \left|V_i\right| \left|V_j\right| \left|Y_{ij}\right| \mathrm{Cos}(\theta_{ij} - \delta_i + \delta_j) = 0 \tag{2}$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n} \left|V_i\right| \left|V_j\right| \left|Y_{ij}\right| \mathrm{Sin}(\theta_{ij} - \delta_i + \delta_j) = 0 \tag{3}$$

where P_{Gi}, Q_{Gi} are the active and reactive output powers of the generator at the ith bus. In addition, P_{Di}, Q_{Di} are the active and reactive output powers of the load at the ith bus, and $\left|Y_{ij}\right.$ and θ_{ij} are the elements $i-j$ of the admittance matrix.

3.2. Inequality constraints

These constraints satisfy the security and operational limits of the power system; these constraints are expressed as follows:

3.2.1. Control variables limit

(1) Active power limits

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \quad i = 1, \ldots, G_N \tag{4}$$

where $P_{Gi}^{\max}$, $P_{Gi}^{\min}$ are the maximum and minimum limits of the active power for each generator, respectively. The number of generators except at the slack bus is G_N.

(2) Voltage magnitude limits

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad i = 1, \ldots, G_N \tag{5}$$

where $V_i{}^{\max}$ and $V_i{}^{\min}$ are the maximum and minimum voltage of the generators, respectively.

(3) Tap changing transformers

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1, \ldots, T_N \tag{6}$$

where $T_i{}^{\max}$ and $T_i{}^{\min}$ are the maximum and minimum of the tap changing transformers, respectively. The number of tap changing transformers is T_N.

(4) Reactive power injection sources

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, \quad i = 1, \ldots, C_N \tag{7}$$

where $Q_i{}^{\min}$ and $Q_i{}^{\max}$ are the minimum and maximum of the reactive power injection sources, respectively. The number of reactive power injection sources is C_N.