



# A genetic evolving ant direction DE for OPF with non-smooth cost functions and statistical analysis

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## ABSTRACT

This paper proposes an evolving ant direction differential evolution (EADDE) algorithm for solving the optimal power flow problem with non-smooth and non-convex generator fuel cost characteristics. The EADDE employs ant colony search to find a suitable mutation operator for differential evolution (DE) whereas the ant colony parameters are evolved using genetic algorithm approach. The Newton–Raphson method solves the power flow problem. The feasibility of the proposed approach was tested on IEEE 30-bus system with three different cost characteristics. Several cases were investigated to test and validate the robustness of the proposed method in finding the optimal solution. Simulation results demonstrate that the EADDE provides superior results compared to a classical DE and other methods recently reported in the literature. An innovative statistical analysis based on central tendency measures and dispersion measures was carried out on the bus voltage profiles and voltage stability indices.

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## 1. Introduction

In the present day power systems, optimal power flow (OPF) is an important tool for power system operators both in planning and operating stages. The main purpose of an OPF is to determine the optimal operating state of a power system and the corresponding settings of control variables for economic operation, while at the same time satisfying various equality and inequality constraints. The OPF problem, in general, is a large-scale highly constrained nonlinear non-convex optimization problem. Many mathematical programming techniques [1] such as linear programming [LP] [2,3], nonlinear programming (NLP) [4], quadratic programming (QP) [5], Newton method [6], and interior point methods (IPM) [7] have been applied to solve the OPF problem successfully. Usually, these methods rely on the assumption that the fuel cost characteristic of a generating unit is a smooth, convex function. However, there are situations where it is not possible, or even appropriate, to represent the unit's fuel cost characteristics as a convex function. This situation arises

when valve-points, units' prohibited operating zones, and piecewise quadratic cost characteristics are present [8].

In recent years, many heuristic algorithms, such as genetic algorithms (GA) [9], evolutionary programming [10], simulated annealing [11], tabu search [12], and particle swarm optimization [13] have been proposed for solving the OPF problem, without any restrictions on the shape of the cost curves. The results reported were promising and encouraging for further research in this direction. Moreover, many hybrid algorithms have been introduced to enhance the search efficiency. For instance, a hybrid tabu search and simulated annealing (TS/TA) [14] was applied to solve the OPF problem with flexible alternating current transmission systems (FACTS) device; a hybrid evolutionary programming and tabu search or improved tabu search (ITS) [15] was used to solve the economic dispatch problem with non-smooth cost functions. Meanwhile, an improved evolutionary programming (IEP) [16] was successfully used to solve combinatorial optimization problems.

In the recent past, Storn and Price introduced a powerful evolutionary algorithm called differential evolution (DE) to solve the OPF problems [17]. DE is a numerical optimization approach that is simple, easy to implement, significantly faster than other algorithms, and robust. DE combines simple arithmetic operators with the classical operators of crossover, mutation and selection to evolve from

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a randomly generated starting population to a final solution. The fittest of an offspring competes one-to-one with the corresponding parent, which is different from the other evolutionary algorithms. This one-to-one competition gives rise to a faster convergence rate.

The DE has been successfully applied to various power system optimization problems such as generation expansion planning [18], hydrothermal scheduling [19]. Figueroa and Cederio [20] applied DE for power system state estimation. Coelho and Mariani [21] used this algorithm for economic dispatch with valve-point effect. M. Basu [22] applied DE for solving the OPF problem incorporating FACTS devices. The hybrid differential evolution (HDE) has been employed for the solution of a large capacitor placement problem [23]. The mixed integer hybrid differential evolution (MIHDE) has been employed for hydrothermal coordination [24], hydrothermal optimal power flow [25], and network reconfiguration problem [26].

Colorni [27] proposed the concept of ant system (AS) and applied to the traveling salesman problem (TSP) [28]. The Ant algorithm has been inspired by the behavior of real ant colonies, in particular, by their foraging behavior. Recently, the ant algorithm has been applied to various optimization problems, such as the short-term generation scheduling problem [29], unit commitment [30], and hydro-electric generation scheduling [31].

In this paper, an efficient evolving ant direction DE based approach is proposed to solve the OPF problem with non-smooth cost functions. Evolving ant direction mutation operator selection is suggested to the original DE algorithm. Though there are five mutation operations stated in this paper, the EADDE uses only one mutation operator during the solution process. The proposed EADDE method embedded with the ant colony search is able to constantly choose different but most appropriate mutation operators during the solution process to accelerate the search for the global optimum solution. The proposed approach has been examined and tested on IEEE 30-bus standard test system with three different types of generator cost curves. Simulation results demonstrate that the EADDE algorithm is superior to the original DE algorithm and provides significantly better results compared to those reported in the literature.

The remainder of the paper is organized as follows: Section 2 describes the formulation of an optimal power flow problem, while section 3 explains the standard DE approach. Section 4 then details the procedure of proposed evolving ant direction DE. Section 5 presents the statistical analysis and Section 6 presents the results of the optimization and compares methods to solve the case studies of optimal power flow problems with IEEE 30-bus system. Lastly section 7 provides the conclusion.

## 2. Problem formulation

The main goal of the OPF is to optimize a certain objective subject to several equality and inequality constraints. The problem can be mathematically modeled as follows:

$$\text{Min } OF(x, u) \quad (1)$$

subject to

$$g(x, u) = 0 \quad (2)$$

$$h_{\min} \leq h(x, u) \leq h_{\max} \quad (3)$$

where vector  $x$  denotes the state variables of a power system network that contains the slack bus real power output ( $P_{G1}$ ), voltage magnitudes and phase angles of the load buses ( $V_i, \delta_i$ ), and generator reactive power outputs ( $Q_G$ ). Vector  $u$  represents control variables that consist of real power generation levels ( $P_{Gi}$ ) and

generator voltages magnitudes ( $|V_{Gi}|$ ), transformer tap setting ( $T_K$ ), and reactive power injections ( $Q_{CK}$ ) due to volt-amperes reactive (VAR) compensations; i.e.,

$$u = [P_{G2} \dots P_{GN}, V_{G1} \dots V_{GN}, T_1 \dots T_{NT}, Q_{C1} \dots Q_{CS}] \quad (4)$$

where  $N$  = number of generator buses,

$NT$  = number of tap changing transformers

$CS$  = number of shunt reactive power injections.

The OPF problem has two categories of constraints:

### 2.1. Equality constraints

These are the sets of nonlinear power flow equations that govern the power system, i.e.,

$$P_{Gi} - P_{Di} - \sum_{j=1}^n |V_i| |V_j| |Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (5)$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^n |V_i| |V_j| |Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad (6)$$

where  $P_{Gi}$  and  $Q_{Gi}$  are the real and reactive power outputs injected at bus  $i$  respectively, the load demand at the same bus is represented by  $P_{Di}$  and  $Q_{Di}$ , and elements of the bus admittance matrix are represented by  $|Y_{ij}|$  and  $\theta_{ij}$ .

### 2.2. Inequality constraints

These are the set of constraints that represent the system operational and security limits like the bounds on the following:

- 1) generators real and reactive power outputs

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max}, i = 1, \dots, N \quad (7)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, i = 1, \dots, N \quad (8)$$

- 2) voltage magnitudes at each bus in the network

$$V_i^{\min} \leq V_i \leq V_i^{\max}, i = 1, \dots, NL \quad (9)$$

where  $NL$  = number of load buses.

- 3) transformer tap settings

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i = 1, \dots, NT \quad (10)$$

- 4) reactive power injections due to capacitor banks

$$Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max}, i = 1, \dots, CS \quad (11)$$

- 5) transmission lines loading

$$S_i \leq S_i^{\max}, i = 1, \dots, nl \quad (12)$$

where  $nl$  = number of transmission lines.

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