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Optimal Power Flow using Glowworm Swarm Optimization

Salkuti Surender Reddy *, Ch Srinivasa Rathnam

Department of Railroad and Electrical Engineering, Woosong University, South Korea

A R T I C L E I N F O

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A B S T R A C T

An important objective of the Optimal Power Flow (OPF) problem is to minimize the generation cost and keep the power outputs of generators, bus voltages, bus shunt reactors/capacitors and transformer tap settings in their secure limits. Solving this OPF problem using classical methods suffer from the disadvantages of highly limited capability to solve the practical large scale power system problems. To overcome the inherent limitations of conventional optimization techniques, Swarm Intelligence (SI) methods have been developed. However, the environmental concern, dictate the minimization of emissions of the thermal plants. Individually, if one objective is optimized, other objective is compromised. Hence, Multi-Objective Optimal Power Flow (MO-OPF) problem has been formulated in this paper. Swarm Intelligence methods, such as Particle Swarm Optimization (PSO) and Glowworm Swarm Optimization (GSO) have been used to solve the OPF problem with generation cost and emission minimizations as objective functions. The effectiveness of the proposed algorithms are tested on IEEE 30 bus and practical Indian 75 bus systems for cost minimization as objective function, and IEEE 30 bus test system for minimization of cost and emission as objectives. The results obtained from both the networks, the PSO and GSO are compared with each other based on different parameters.

Introduction

The Optimal Power Flow (OPF) is a highly non-linear and constrained power system optimization problem. The ordinary power flow problem is defined by specifying the real and reactive load demands in megawatts (MWs) and megavars (MVARs) to be supplied at certain bus bars/nodes of a transmission system and by using generated powers and voltage magnitudes at the remaining nodes of this system together with a complete topological description of the system involving its impedances. The objective is to find the complex nodal voltages from which all other quantities like currents, line flows and transmission losses can be calculated. The model of transmission system is given in complex quantities, since an AC system is assumed to generate and supply the powers and loads in MWs and MVARs.

Mathematically, the OPF problem can be reduced to a set of non-linear equations, where the real and imaginary components of nodal voltages are variables. The number of equations are equal to twice the number of nodes. The non-linearities can roughly be classified being of a quadratic nature. Gradient and relaxation approaches are the only methods for the solution of these systems. The output of a power flow problem tells the system operator or system planner of a system in which way the lines in the system are loaded, what the voltages at different buses are, how much of the generated power is lost and where limits are exceeded. The power flow problem is one of the basic problems in which both load and generator powers are given or fixed. The Optimal Power Flow has a long history in its development, and it was first presented by Carpentier in 1962 [1] and the subsequent surveys on OPF in [2–7]. However, it took a long time to become a successful algorithm that could be applied in everyday use. Current interest in the OPF centers on its ability to solve for the optimal solution that takes account of the security of the system.

Optimal Power Flow has been applied to regulate the generator active power outputs and voltages, transformer tap settings, shunt reactors/capacitors and other controllable variables to minimize the generator fuel cost, network active power loss, voltage stability index, while keeping all the load bus voltages, generator reactive power outputs, network power flows and all other state variable in the power system in their secure and operational limits. In its most common problem formulation, the OPF is a non-linear, non-convex, static, large-scale optimization problem with both the continuous and discrete control variables. Even in the absence of non-convex generator operating cost functions, prohibited operating zones (POZs) of generating units, and discrete control variables, the OPF problem is a non-convex due to the existence of the non-linear AC power flow equality constraints. The presence

* Corresponding author. Tel.: +82 426296737.
E-mail address: salkuti.surenderreddy@gmail.com (S. Surender Reddy).

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Nomenclature

P_{gi}	active power generation of ith bus
V_{gi}	voltage of ith bus
a_i, b_i and c_i	cost coefficients of ith generator
n	total number of buses in the system
N_L	number of load buses
N_{trans}	transformer taps
N_{cap}	compensation capacitors
N_{obj}	number of objective functions
N_{gen}	number of thermal generators
$\alpha_i, \beta_i, \gamma_i, \eta_i$ and δ_i	emission coefficients of ith generator
P_{gi} and Q_{gi}	active and reactive power generations of ith generator
P_{loadi} and Q_{loadi}	active and reactive load demands
ω	inertia weight
V_{ij}^{t+1}	velocity vector of ith particle in dimension j at time 't'
X_{ij}^{t}	position vector of ith particle in dimension j at time 't'
$P_{best,I}^{t}$	personal best position of ith particle in dimension j found from the initialization through time 't'
G_{best}	global best position of ith particle in dimension found from the initialization through time 't'
c_1 and c_2	positive acceleration constants, and these are used to level the contribution of cognitive and social components, respectively
r_{1j}^{t} and r_{2j}^{t}	random numbers from uniform distribution at time 't'
t_{max}	maximum number of iterations
t	current iteration number
$F(G_{best}^{k})$	fitness of global optimum solution
V_{Li}^{min}	minimum voltage limit of load demand buses
V_{Li}^{max}	maximum voltage limit of load demand buses
$C\omega^{K}$	chaotic inertia weight factor at iteration k
ω^{K}	inertia weight factor at iteration k
D_k	chaotic parameter at iteration k
ρ	luciferin decay constant ($0 < \rho < 1$)
γ	luciferin enhancement constant
μ	control parameters
F_i^{min} and F_i^{max}	minimum and maximum bounds of ith objective function
β_k	weight factor for kth objective function
m	number of non-dominated solutions
$J_j(t)$	value of objective function at agent j's location at time t
n_t	threshold parameter to control number of neighbors
t	time/step index
$di, j(t)$	Euclidian distance between glowworms i and j at time t
$r_d^i(t)$	variable local decision range associated with the glowworm i at time t
$\ell j(t)$	luciferin level associated with the glowworm j at time t
rs	radial range of luciferin sensor
β	constant parameter

of discrete control variables, such as transformer tap positions, switchable shunt devices, phase shifters, further complicates the problem formulation and solution.

The conventional optimization approaches that make use of derivatives and gradients are in general not able to locate or identify the global optimum. Many mathematical assumptions such as convex, analytic and differential objective functions have to be made to simplify the problem. However, the OPF problem is an optimization problem with in general non-convex, non-differentiable and non-smooth objective functions. Hence, it becomes important to develop the optimization techniques that are efficient to overcome these drawbacks and to handle such difficulties efficiently. Therefore, in this paper heuristic algorithms such as Particle Swarm Optimization (PSO), Glowworm Swarm Optimization (GSO) have been used for solving the OPF problem with different objective functions. The OPF can also solve for an optimal solution with multiple objectives such as minimization of generation cost, emission, and transmission loss minimization, etc. Whenever, we deals with such sort of problems i.e. optimization problem with more than one constraint and objective functions, Swarm Intelligent methods are one of the best method available in the literature.

OPF solution approaches are broadly categorized as conventional and intelligent. The conventional approaches include well known methods like Gradient Method, Newton Method, Linear Programming (LP) Method, Quadratic Programming (QP) Method, and Interior Point Method (IPM). The mathematical programming methods, like Non-Linear Programming (NLP) [8,9], QP [10,11] and LP [12,13] have been used for the solution of OPF problem. Many different mathematical methods have been employed for its solution such as Lamda-Iteration, Gradient Method, Newton's Method and IPM. However, they are not guaranteed to converge to the global optimum of general non-convex problem.

Intelligent methodologies include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and recently developed Glowworm Swarm Optimization (GSO), etc. Ref. [14] combines a decoupled quadratic load flow solution with Enhanced Genetic Algorithm (EGA) to solve the OPF problem. A Strength Pareto Evolutionary Algorithm based approach with strongly dominated set of solutions is used to form the Pareto optimal set. In [15], non-dominated sorting multi objective opposition based gravitational search algorithm has been proposed to solve different single and multi objective OPF problems. An adaptive real coded biogeography-based optimization approach to solve different objective functions of OPF problems with various physical and operating constraints is proposed in [16]. Ref. [17] investigates the possibility of using recently emerged evolutionary-based approach as a solution for the OPF problems which is based on a teaching learning based optimization algorithm using Lévy mutation strategy for optimal settings of OPF problem control variables. A hybrid algorithm consisting of biogeography based optimization with an adaptive mutation scheme and the concept of predator–prey optimization technique for solving the multi-objective OPF problems is proposed in [18]. Ref. [19] presents the application of non-dominated sorting multi objective based gravitational search algorithm for the solution of different OPF problems. In Genetic Algorithm, the execution time and quality of solution deteriorates as the size of the system increases [20]. Hence, to overcome the above limitations, in this paper an attempt has been made to solve the OPF problem with PSO and GSO techniques.

Several approaches have been developed to solve the Multi-Objective Optimization (MOO) problems such as, the penalty function method [21], weighted sum method [22], ϵ-constrained method [23], non-dominated sorting genetic algorithm (NSGA) based approach [24], strength Pareto evolutionary algorithm (SPEA) [25] etc. have been used for solving different MOO problems. But, these techniques have difficulties. For instance, in penalty function approach, choosing proper penalty factors is a difficult task [26], Weighted sum method combines all the objectives to a single objective by using the weight factors. This formulation may lose the significance of the objective function and, moreover, there is no rational basis for finding the weight factors