Electrical Power and Energy Systems 54 (2014) 198–210

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Faster evolutionary algorithm based optimal power flow using incremental variables

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ARTICLE INFO

Article history:
Received 19 February 2013
Received in revised form 22 June 2013
Accepted 13 July 2013

Keywords:
Enhanced genetic algorithm
Evolutionary algorithms
Linear programming
Multi-objective optimization
Optimal power flow

ABSTRACT

This paper proposes an efficient approach for evolutionary algorithm based Optimal Power Flow (OPF). The main drawback of evolutionary based OPF is the excessive execution time due to large number of power flows required in the solution process. The proposed Efficient Evolutionary Algorithm (EEA) uses the concept of incremental power flow model, based on sensitivities. With this, the number of power flows are reduced substantially, resulting in solution speed up. The original advantages of the evolutionary algorithms, like: the ability to handle discontinuities, complex non-linearities in the objective function, discrete variables, and multi-objective optimization, are still available in the proposed approach. The OPF solution is obtained with single objectives (fuel cost, loss, voltage stability index) and multiple objective (fuel cost and voltage stability index). The potential of the proposed approach is tested on IEEE 30, 118 and 300 bus systems, and the results obtained with proposed EEA are compared with other evolutionary algorithms. The proposed approach is generic one and can be used with any evolutionary algorithm based OPF.

1. Introduction

The Optimal Power Flow (OPF) has been commonly used as an important tool in the power system planning and operation for many years. It is also an important tool in modern Energy Management System (EMS). It plays an important role in maintaining the security and economy of the power system. The OPF optimizes the power system operating objective function, while satisfying a set of equality and inequality constraints. The equality constraints are power flow equations, and inequality constraints are the limits on power system variables/functions (control variables and functional operating constraints). The problem of OPF was originally formulated in 1962 by Carpentier [1]. The OPF problem in [2] is a highly nonlinear, non-convex, large scale, static optimization problem with both continuous (generator voltage magnitudes and active powers) and discrete (transformer taps and switchable shunt devices) control variables.

The OPF solution based on mathematical programming approaches are not guaranteed to converge to the global optimum of the general non-convex OPF problem, and discrete variables. Recent attempts to overcome the limitations of mathematical programming approaches include the application of Genetic Algorithms (GA), Enhanced Genetic Algorithms (EGA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Bacterial Foraging and Simulated Annealing (SA) methods, etc. GA, EGA, Improved GA have been successfully applied for solution of OPF problem [3–5]. In [6], PSO was used to solve the OPF problem. PSO has a flexible and well-balanced mechanism to enhance and adapt the global and local exploration abilities. Different types of PSOs' are proposed in [6–11]. Ref. [12] presents an improved PSO for the multi-objective optimization problem. In [13], an effective and reliable algorithm, based on Shuffle Frog Leaping Algorithm (SFLA) and SA is proposed for solving OPF problem with non-smooth and non-convex generator fuel cost characteristics.

Evolutionary Algorithms (EAs) differ from classical search and optimization algorithm [14] in many ways. Classical search techniques use a single solution updates in every iteration, and mainly use some deterministic transition rules for approaching the optimum solution. Such algorithms start from a random guess solution, and based on some pre-specified transition rule, the algorithm suggests a search direction which is arrived at by considering local information. A unidirectional search is performed along the search direction, to find a best solution. The best solution becomes the new solution, and the search is continued for a number of times.

Classical optimization methods can be direct methods and gradient based methods. In direct search methods, only the objective function and the constraint values are used to guide the search process, whereas gradient based methods use first order or second order derivative of objectives and constraints to guide the search process. Direct search methods are usually very slow requiring

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http://dx.doi.org/10.1016/j.ijepes.2013.07.019

many function evolutions for convergence. Without major change in the algorithm, they can be applied to solve many problems. Gradient based methods quickly converge to an optimal solution, but are not efficient for non-differentiable or discontinuous problems [14].

All meta-heuristic/ evolutionary algorithms perform a separate power flow for each chromosome. This may be used for objective function evaluation and/or constraint feasibility check. Penalties are added as per the extent of infeasibility. This exercise is repeated for every chromosome. Hence, the number of power flows to be run is enormous. This is the main reason for excessive computational burden in these algorithms. Other parts of the algorithm require comparatively insignificant time.

It has been recognized that EAs perform much better, if we can make use of domain specific knowledge of the problem at hand in the computational process. In view of this, the present paper explores a possibility of reducing computational burden by performing much lesser power flows. This is possible because the effects of the control changes on the network are not likely to be too large. In that case, it should be possible to use one power flow for a chromosome and evaluate the changes due to chromosome differences, by using incremental power flow model and sensitivities, using a non-linear approximation. Objective functions with discontinuities, complex non-linearities and discrete variables can be handled as easily as in the original evolutionary algorithms. The main aim of the proposed approach is to reduce the time of execution, and is suitable for any type of complex problem involving any objective.

It may be noted that sensitivities of control variables have also been used extensively in Linear Programming (LP), Quadratic Programming (QP) and other gradient based approaches. However, it is well known that all these lead to a local optima. The proposed EEA uses sensitivity information in an approach which has near global optimization capability. Most of the real world problems involve simultaneous optimization of several, often mutually concurrent objectives. Multi-objective evolutionary algorithms are used to find the optimal trade-off solution. In multi-objective optimization, gradient based methods are often impossible to apply. However, the proposed EEA approach can easily be applied to any multi-objective based OPF.

The present work chooses EGA [4] for implementing the proposed Efficient Evolutionary Algorithm (EEA), but the modeling methodology can be easily extended to include any type of evolutionary algorithms such as PSO, DE, Bacterial Foraging, and SA. In this paper, some case studies are also performed by applying the proposed EEA approach to the PSO.

The rest of the paper is organized as follows: Section 2 presents incremental variable modeling for OPF, real power generation cost, real power loss and system voltage stability index minimizations using proposed EEA. Section 3 presents brief description of multi-objective optimization. Section 4 presents results and discussion. Finally, Section 5 brings out contributions with concluding remarks.

2. OPF problem formulation

The OPF problem optimizes the steady state performance of the power system in terms of the objective function while satisfying a set of equality and inequality constraints. OPF is a highly non-linear, non-convex, large scale static optimization problem due to large number of variables and constraints. In general, OPF is formulated as a constrained optimization problem, and can be mathematically stated as follows:

$$\begin{aligned}&\textit{minimize } F(x,u)\\&\textit{Subject to } g(x,u)=0\\&h(x,u)\leqslant 0\end{aligned} \tag{1}$$

where the minimization function 'F' (objective function) can take different forms.

g is the equality constraints, represent the non-linear power flow equations.

h is the system operating constraints that include functional operating constraints and limits on control variables.'x' is the vector of dependent variables consisting of load bus voltage magnitude limits, reactive capabilities of generators, slack bus active power and branch flow limits.

$$x^T=[V_{L_1},\ldots,V_{L_{NL}},Q_{G_1},\ldots,Q_{G_{NG}},P_{GSlack},S_{L_1},\ldots,S_{L_{nl}}] \tag{2}$$

where NL, N_G and nl are number of load buses, number of generator buses and number of transmission lines, respectively.'u' Is the vector of control or independent variables consisting of generator bus voltage magnitudes, active power generations, transformer tap settings and reactive shunt compensators.

$$u^T=[P_{G_2},\ldots,P_{G_{NG}},V_{G_1},\ldots,V_{N_G},T_1,\ldots,T_{NT},Q_{C_1},\ldots,Q_{C_{NC}}] \tag{3}$$

where NT and NC are number of transfer taps and number of switchable VAR sources, respectively.

In this paper, three objectives: (i) real power generation cost, (ii) system transmission loss, and (iii) voltage stability index of the system are considered. First, these three objectives are optimized independently, and then the best combination of objectives are optimized simultaneously using Strength Pareto Evolutionary Algorithm 2+ (SPEA 2+).

The proposed Efficient Evolutionary Algorithm (EEA) is the hybrid approach considering Enhanced Genetic Algorithm (EGA) and some concepts borrowed from the Successive Approximation using Linear Programming (SALP) or Quadratic Programming (SAQP). Many of these models use incremental variable modeling approach. Moreover, the popular compact model does not use original equality constraints as part of main OPF. Power flow is solved outside the main OPF iteration. It also generates sensitivity relations for expressing dependent variable changes in terms of control variable changes.

Usual meta-heuristic OPF algorithms performs a separate load flow for every chromosome, in every iteration. Hence, the number of load flows required is equal to *number of chromosomes* $\times$ *number of iterations*. Whereas, proposed EEA approach, performs only one load flow for best-fit chromosome, and evaluates load flow information for other chromosomes using sensitivities from this load flow, in a non-linear approximation of functions/variables, in every iteration. Therefore, the number of load flows required is equal to *number of iterations/generations*.

2.1. Real and reactive power OPF for real power generation cost minimization using EEA

In this OPF formulation, generator fuel cost minimization is considered as an objective function and it is formulated as follows,

$$\textit{minimize}\quad F_T=\sum_{i=1}^{N_G}F_i(P_{Gi}) \tag{4}$$

The proposed approach can be applicable for any type of objective function like discontinuous (prohibited operating zones), discrete, valve point loading, etc. The control variables considered in this optimization problem are changes in active power generations (ΔP_G), generator bus voltage magnitudes (ΔV_G), transformer tap settings (Δt) and bus shunt admittances (ΔB_{sh}), from the base case. All other variable changes are also with respect to the base case load flow.

The quadratic fuel cost function of ith generator is given by [15,16],

$$F_i(P_{Gi})=a_i+b_iP_{Gi}+c_iP_{Gi}^2 \tag{5}$$