Electrical Power and Energy Systems 64 (2015) 947–955

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Efficient sensitivity based assessment of impact of uncertainties in multi-objective framework

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A R T I C L E I N F O

Article history:
Received 6 December 2013
Received in revised form 28 July 2014
Accepted 19 August 2014
Available online 18 September 2014

Keywords:
Interior point method
Sensitivity
Pareto optimal
Multi-objective optimization
Uncertainty
Fuzzy variables

A B S T R A C T

This paper presents a novel Primal–Dual Interior Point Method (PDIPM) based sensitivity approach for efficient assessment of the impact of uncertainties in Multi-objective Optimization (MO). This shall aid in robust decision making. The MO problem considered, in this paper, is the Environmental–Economic dispatch (EED) problem. The two objectives, i.e. the emission and economic cost, are continuous convex functions. The uncertainties in the system parameters such as loads (or injections) and limits on line flows and voltage magnitudes, are assumed to be of fuzzy type, more specifically in an interval. Results for the IEEE 30 bus system have been obtained using the proposed approach and compared with those obtained by Monte Carlo Simulations (MCS) and Particle Swarm Optimization (PSO) based on Harmony Search (HSPSO). The results obtained provide interesting insights on how uncertainties in input data can affect decision making in MO.

Introduction

Multi-objective Optimization (MO) has been an area of research for over two decades now. It serves as an important decision making tool when two or more conflicting objectives are optimized in a feasible solution space, formed by certain equality and inequality constraints [1]. Ever since, MO has had myriad of applications in many fields. A few to mention are aerospace engineering [2], communications [3], production research [4], finance [5], supply chain management [6], water demand assessment [7,8] and power systems [9]. A good review on applications of MO can be seen in [10–13].

Pioneering work in MO applications to power systems can be seen in [9,14–16] with the most notable contributions being in [17–19]. Among the various MO applications to power systems, most of the literature consists of solving the two objective EED problem. A few recent contributions in EED problem have been in [20–23]. The EED problem solves for the minimization of the economic generation costs and the resultant emissions while subject to the satisfaction of the power balance equations and a set of certain operational and physical constraints [22].

Most of the methods in literature for solving the EED problem make use of the meta-heuristic algorithms and their variants [9]. A few notable methods are the Genetic Algorithms (GA) and it's variants [17–19], PSO and it's variants (such as HSPSO [24]) and Differential Evolution Algorithm [25] with it's variants [26]. Through these methods, a set of non-dominated pareto optimal solutions (otherwise, more commonly known as pareto optimal front) is generated in a single run [23]. From this set of solution, the decision maker then chooses a best compromised solution [19] for actual system operation or planning. Albeit their popularity, these algorithms, being stochastic in nature [23], are computationally burdensome and do not guarantee the same pareto optimal front and consequently, same best compromised solution in each run.

There also exist techniques in which the EED problem has been solved as a single objective optimization problem such as [15,23,27,28]. In [15], the EED problem has been solved with the total generation cost as the single objective while the total emission is a constraint. In [27], both cost and emission objectives have been coupled into a single objective through the use of weights. [23] also uses a similar formulation but is modeled as a semidefinite programming problem. In [28], one of the objectives is minimized while the other objective is a constraint bounded within an allowable tolerance ϵ and thus, the name of this approach is the epsilon (ϵ) constraint method. These proposed approaches can be easily solved by classical techniques such as PDIPM [29], provided the objective functions and other constraints are continuous and convex. In order to obtain the entire set of desired number of non-dominated pareto optimal solutions, multiple runs of PDIPM are required (one run each for each of the pareto solution) in each of these approaches. However, the total computational

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http://dx.doi.org/10.1016/j.ijepes.2014.08.023
0142-0615/

time involved in multiple PDIPM runs is expected to be considerably less than that of an evolutionary algorithm such as HSPSO.

Further, any optimization problem requires a set of known input data. For the EED problem, this set of input data constitutes the nodal demand forecasts, non controllable renewable generations, load models, network parameters, cost and emission characteristics and limits on line flows, voltages and generations [30]. Generally, this data set is not known with complete certainty. Consequently, several approaches [30–33] for modeling uncertain data in single objective optimization problem have been proposed. To represent uncertain data which is repetitive in nature, probability density functions [31] are generally used. Another common way of representing the uncertainty in system data is through the use of fuzzy membership functions [32]. Boundary representation [30] is a very special case of fuzzy membership functions in which the uncertain data varies in an interval or a range with crisp 0 and 1 possibilities.

Attempts for robust MO applications in power systems are very few in literature [34–37]. Also, most of these robust MO applications make use of meta-heuristic algorithms to obtain the best compromised robust solution. The computational burden of these applications is thus expected to be huge as optimization with uncertainties further leads to enhanced computational effort, apart from what is already because of use of meta-heuristic algorithms. Further, a detailed assessment on how the pareto optimal front gets affected because of the uncertainties in the input data has not been studied yet.

This paper here, thus, attempts to develop a simple yet efficient approach for assessing the impact of input data uncertainties on the pareto optimal front in an EED problem. This is expected to aid in robust decision making. The input data, i.e. nodal loads, limits of inequality constraints, network parameters, etc., are assumed to be uncertain within given specified intervals or bounds. The approach shall provide possible pareto optimal fronts in the presence of these uncertainties. The proposed approach is a sensitivity based approach, wherein the sensitivities are obtained from the Lagrange multipliers of PDIPM. These sensitivities indicate possible objective functions' minimum or maximum values for a given set of uncertain interval input data. The EED problem considered here has continuous convex objectives and constraints and is modeled as a single objective optimization problem with the other objective considered as a constraint. PDIPM [29] is used to solve this. The use of PDIPM leads to the efficiency of this approach (even though multiple PDIPM runs are required) when compared to using HSPSO for this uncertain EED problem. Thus, in a nutshell, the main contributions of this paper are as follows.

- ★ To efficiently assess the impact of uncertain input data on the pareto optimal front of the EED problem by solving it with PDIPM [29].
- ★ To show how the best compromised solution shall possibly change in presence of these uncertainties.

The paper is organized as follows: Section 'Deterministic EED problem' describes the general deterministic EED problem and its model which is to be solved by PDIPM. The sensitivity analysis of the objectives in this problem with respect to system changes is given in Section 'Sensitivity analysis'. Section 'Proposed approach' presents the proposed approach for assessing the impact of uncertain input data on the pareto optimal front of the EED problem. Results for the IEEE 30 bus system are given in Section 'Results'. The paper summarizes in Section 'Conclusion'.

Deterministic EED problem

The EED problem is discussed in this section. A general deterministic EED problem solves for the minimization of two conflicting objectives, i.e. economic fuel cost and emission, subject to the set of power balance equations and a set of inequality constraints such as bus voltage magnitude limits, line flows and real and reactive generation limits. It can be stated as follows

$$\begin{aligned} \text{Min.} \quad & [f_1(\mathbf{x}), f_2(\mathbf{x})] \\ \text{s.t.} \quad & \mathbf{g}(\mathbf{x}) = 0 \\ & \underline{\mathbf{h}} \leqslant \mathbf{h}(\mathbf{x}) \leqslant \overline{\mathbf{h}} \end{aligned} \tag{1}$$

where $\mathbf{x}$ is the variable vector which includes generations and bus voltages. f_1 and f_2 are the total fuel cost and total emission functions, respectively, which can be stated as

$$f_1 = \sum_{i=1}^{N_g} a_i P_{gi}^2 + b_i P_{gi} + c_i \tag{2}$$

$$f_2 = \sum_{i=1}^{N_g} \gamma_i P_{gi}^2 + \beta_i P_{gi} + \alpha_i \tag{3}$$

where N_g is the number of generators. P_{gi} is the ith generator active power. $\gamma_i,\ \beta_i,\ \alpha_i$ and $a_i,\ b_i,\ c_i$ are the respective emission and cost characteristics coefficients of the ith generator.

Equality constraints $\mathbf{g}$ are the power flow equations while inequality constraints $\mathbf{h}$ include limits on active power flows, generations and bus voltage magnitudes at all buses. $\underline{\mathbf{h}}$ and $\overline{\mathbf{h}}$ are the respective lower and upper limits on $\mathbf{h}$. The line active power flow constraint is of the form

$$-P_l \leqslant P_{ij} \leqslant P_l \tag{4}$$

where P_l is the upper limit of line active flow P_{ij} between buses $i-j$.

The best form of solution for a MO is in the form of pareto optimal front which shows different compromise solutions. This is generally solved by meta-heuristic algorithms like HSPSO [24]. Although for convex problems, classical PDIPM type solution is possible using ϵ constraint approach [28], the quality of the pareto optimal front is better in the former over the latter. However, the computational efficiency of latter is far better than the former. In view of this, a simple technique is proposed (along with the use of PDIPM) to obtain a pareto front which is a best compromise between these two requirements.

In this technique, the first half of the specified number of pareto solutions are obtained by considering cost as objective and emission as constraint while the second half is obtained in a vice versa manner. Thus in the first variant, economic cost f_1 is considered the objective while emission f_2 is a constraint, which can be stated as

$$\begin{aligned} \text{Min.} \quad & f_1(\mathbf{x}) \\ \text{s.t.} \quad & f_2(\mathbf{x}) \leqslant f_2^{sp} \\ & \mathbf{g}(\mathbf{x}) = 0 \\ & \underline{\mathbf{h}} \leqslant \mathbf{h}(\mathbf{x}) \leqslant \overline{\mathbf{h}} \end{aligned} \tag{5}$$

where f_2^{sp} is some specified emission value. In the second variant, emission f_2 is considered as objective while cost f_1 is a constraint. This can be stated as

$$\begin{aligned} \text{Min.} \quad & f_2(\mathbf{x}) \\ \text{s.t.} \quad & f_1(\mathbf{x}) \leqslant f_1^{sp} \\ & \mathbf{g}(\mathbf{x}) = 0 \\ & \underline{\mathbf{h}} \leqslant \mathbf{h}(\mathbf{x}) \leqslant \overline{\mathbf{h}} \end{aligned} \tag{6}$$

where f_1^{sp} is some specified cost value.

Let the number of desired non-dominated pareto optimal solutions be $2N$ where N is a natural number. In effect, $2N$ PDIPM runs are required to obtain these distinct solutions. The 1st and $2N$th solution points are the two extremes on the pareto front. These