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Sensitivity-based chance-constrained Generation Expansion Planning

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ABSTRACT

A Generation Expansion Planning problem with load uncertainty is formulated based on joint chance-constrained programming (CCP) and is solved by incorporating sensitivity into iterative algorithms. These algorithms exploit the characteristics of the system and its response to load variations. Sensitivities help to classify buses according to stress level, and sensitivity-based iterative algorithms distinguish each bus based on its contribution to the overall system reliability. The use of sensitivity overcomes some of the mathematical obstacles to solving joint CCP problems and, in addition, leads to optimal expansion solutions because uncertain loads are correctly estimated. The IEEE 30- and 118-bus test systems are used to demonstrate the proposed algorithms, and the results of these algorithms are compared with those of other algorithms for solving the joint CCP problem.

1. Introduction

Today's power systems, be they regulated or deregulated, are exposed to ever more sources of uncertainty, such as the integration of renewable sources, demand participation, and generation and transmission availability. This uncertainty and the increasing demand for power raise new challenges for utility planners, whose goal is to provide reliable power to consumers at the lowest possible cost.

Generation Expansion Planning (GEP) models are used to determine the size, type, and location of the additional units required to satisfy the forecasted demand. GEP models are often sensitive to uncertainty, so neglecting uncertainty may lead to unrealistic solutions. Thus, stochastic-optimization approaches are used to incorporate uncertainty into GEP models. A deterministic multi-period and multi-objective GEP is solved in [18]. In [20], a GEP model with uncertain demand is formulated and solved by using stochastic dynamic programming. Different applications have led to different types of stochastic-optimization models. One such model is the recourse-based model [8] in which, in a first step, optimal decisions are taken and, after some of the uncertainty is resolved, a recourse is available to re-optimize. Another model is the expected-value model, which minimizes the expected value of the cost subject to the expected values of constraints [8,14]. Yet another way to handle uncertainty in probabilistic terms is chance-constrained programming (CCP).

The contribution of this paper is to incorporate sensitivity into the iterative algorithms used to solve the GEP problem with load uncertainty for a vertically integrated power system modeled by using joint CCP. The proposed iterative algorithm distinguishes between stressed and nonstressed buses in the system, and the iterative updates for each bus are different. Although joint CCP has several advantages, it is not widely used because of the mathematical challenges involved. This work addresses several of those challenges and differs from other similar algorithms [27,19] in the way that different chance constraints are treated differently as appropriate. The present study builds on [21], which only separated stressed buses: herein we consider information from both stressed and nonstressed buses.

The rest of the paper is structured as follows: Section 2 briefly describes expansion planning models and the optimization approaches that they use, with an emphasis on the CCP approach. Section 3 uses CCP to formulate the GEP problem with load uncertainty. Section 4 discusses previous iterative procedures to solve the CCP formulation, and Section 5 explains the improved algorithms proposed herein that incorporate sensitivities. Section 6 reports and analyzes the computational results of applying the algorithms to two standard test systems. Section 7 concludes the paper.

2. Background

Power system planning has become an intensive process and the investment in utility planning is significant [22]. A survey of

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the optimization techniques used in utility planning is given in [12], and of the several stochastic optimization techniques used to model uncertainty, only robust optimization [6,7] and CCP explicitly aim to achieve a prescribed reliability level. When the probability distribution of the uncertain random variable is known, CCP is a particularly suitable optimization technique for including uncertainty in the solution. Although the GEP problem contains several sources of uncertainty, we concentrate in this work on demand uncertainty, which is the main source of uncertainty. For power-system demand, the probability distribution can be obtained by using historic data.

Unlike in deterministic optimization where all the constraints have to be satisfied, CCP allows some or all of the constraints to be satisfied only with a given probability. It was first introduced in [1] and has been applied extensively to a wide range of engineering, financial, and management applications. Originally, CCP was used as an analytical tool for planning problems because it explicitly incorporates risk.

Since then, CCP has been applied to power-system planning and operation problems. A generation-planning model was introduced in [11], where a probabilistic reliability criterion was considered for both discrete and continuous random generation. In [28], a CCP-based formulation of transmission expansion planning was solved by using a genetic algorithm. The effect of wind uncertainty in transmission expansion planning was discussed in [30], in which the authors modeled wind uncertainty with a probability density function and the resulting CCP-based problem was solved by using a genetic algorithm. In [13], a generation and transmission expansion problem was modeled by using two-stage stochastic programming, in which a risk factor is introduced into the objective function. The solution algorithm was based on the minimum-variance approach [16], which minimizes the risk in an investment project. A market-based generation and transmission expansion planning model was solved in [25] by using scenario-based formulation and Monte Carlo simulation (MCS). In that work, a reduction technique was applied to reduce the number of scenarios considered. A GEP problem for vertically integrated systems with load uncertainty was modeled by using CCP and solved with a modified iterative algorithm in [19]; this approach proved to have fewer iterations. CCP has also been applied to operation and stability problems; for example, a unit-commitment problem was modeled by using CCP in [3] and was solved iteratively.

These previous applications of CCP to power system problems present two drawbacks: separate chance constraints are used [11,29] where only one probabilistic constraint is relevant, and the solution approach for joint CCP is computationally costly. Problems based on joint CCP are difficult to solve and therefore are usually transformed into equivalent deterministic approximations, as proposed in [2]. In the present work, these approximations and thus the resulting iterative algorithms are improved by including sensitivities, which leads to better solutions.

3. Generation Expansion Planning under uncertainty

The main objective in GEP is to minimize cost subject to the operational constraints of the system. Mathematically, this can be expressed by using a modified version of the following formulation [11]:

$$\min \sum_{i=1}^{n_{\mathrm{bus}}} w_i C^{\mathrm{n}}_{b,i} p^{\mathrm{n,max}}_{g,i} + \sum_{i=1}^{n_{\mathrm{bus}}} C^{\mathrm{n}}_{p,i} p^{\mathrm{n}}_{g,i} + \sum_{i=1}^{n_{\mathrm{bus}}} C^{\mathrm{e}}_{p,i} p^{\mathrm{e}}_{g,i}, \tag{1a}$$

s.t.

$$p^{\mathrm{n}}_{g,i} + p^{\mathrm{e}}_{g,i} - p_{s,i} = p^{\mathrm{L}}_i,\ i = 1, \ldots, n_{\mathrm{bus}}, \tag{1b}$$

$$p_{s,i} = \sum_j -b_{i,j}(\delta_i - \delta_j),\ i = 1, \ldots, n_{\mathrm{bus}}, \tag{1c}$$

$$p^{\min}_{s,i} \le p_{s,i} \le p^{\max}_{s,i},\ i = 1, \ldots, n_{\mathrm{bus}}, \tag{1d}$$

$$p^{\mathrm{e,min}}_{g,i} \le p^{\mathrm{e}}_{g,i} \le p^{\mathrm{e,max}}_{g,i},\ i = 1, \ldots, n_{\mathrm{bus}}, \tag{1e}$$

$$w_i p^{\mathrm{n,min}}_{g,i} \le p^{\mathrm{n}}_{g,i} \le w_i p^{\mathrm{n,max}}_{g,i},\ i = 1, \ldots, n_{\mathrm{bus}}, \tag{1f}$$

$$w_i \in \{0, 1\}, \tag{1g}$$

where $C^{\mathrm{n}}_{b,i}$, $C^{\mathrm{n}}_{p,i}$ are the investment and production cost of a new unit at bus i; $C^{\mathrm{e}}_{p,i}$ is the production cost of an existing unit at bus i; $p^{\mathrm{n}}_{g,i}$, $p^{\mathrm{e}}_{g,i}$ are the active power levels of respectively new and existing units g at bus i; $p^{\mathrm{n,min}}_{g,i}$ and $p^{\mathrm{n,max}}_{g,i}$ are the minimum and maximum active power levels of a new unit g at bus i; $p^{\mathrm{e,min}}_{g,i}$ and $p^{\mathrm{e,max}}_{g,i}$ are the minimum and maximum active power levels of existing units g at bus i; p^{L}_i is the load connected to bus i; $p_{s,i}$ is the net power flow in all the lines connected to bus i; $p^{\min}_{s,i}$ and $p^{\max}_{s,i}$ are the minimum and maximum net power flow in lines connected to bus i; δ_i is the voltage phase angle at bus i $b_{i,j}$ is the susceptance of the line between buses i and j; n_{bus} is the number of buses in the system; w_i is the binary decision variable for new generation at bus i.

The objective function (1a) is the total of investment and operation costs, the constraint (1b) is the real-power balance equation, and Eq. (1c) is the sum of the line flows over all lines connected to bus i. Constraints (1d)–(1f) give the operational limits for the transmission lines and generating units. Finally, constraint (1g) expresses the binary nature of the decision variable w_i.

The constraints (1b) and (1c) are the DC power flow equations. Although there are models for transmission network expansion planning that enable the use of AC power flow equations [31,24] and could arguably be used here, we chose to use the DC formulation because our algorithms are for the initial stages of planning that are carried out several years before the actual situation, and the DC approximation suffices for this purpose. If desired, an AC power flow can be computed afterwards to confirm feasibility.

Note that the above formulation ignores load uncertainty. The load represented here is the average forecasted load. The loading level appears in Eq. (1b), so to include uncertainty in probabilistic terms, we change constraint (1b) to

$$\mathrm{Prob}\left(\bigcap_{i=1}^{n_{\mathrm{bus}}} (p^{\mathrm{n}}_{g,i} + p^{\mathrm{e}}_{g,i} - p_{s,i} \ge p^{\mathrm{L}}_i)\right) \ge \alpha, \tag{2}$$

where α is a user-defined probability threshold that represents the confidence level (or reliability level). Traditional GEP usually uses the loss of load expectation or the installed reserve margin as the reliability criterion. However, it was shown in [11] that modeling transmission-line constraints in terms of reliability criteria is advantageous in GEP. If the optimization becomes infeasible with this type of modeling and load curtailment is not allowed, a transmission upgrade is needed in the first stage of planning. This helps to identify the equilibrium conditions whereby the demand is matched with installed generation and does not account for any contingency studies. The left-hand side of Eq. (2) is a joint probability, i.e., it is the probability of n_{bus} events occurring simultaneously; thus constraint (2) is a joint chance constraint [23]. This probability can be calculated by numerical integration, but this technique is limited by dimensionality [23] and is only possible in practice for small problems.

A practical means to address this difficulty is to convert the joint chance constraint (2) into a set of individual constraints. First, observe that Eq. (2) can be reformulated as

$$\mathrm{Prob}\left\{\bigcup_{i=1}^{n_{\mathrm{bus}}} (p^{\mathrm{n}}_{g,i} + p^{\mathrm{e}}_{g,i} - p_{s,i} \ge p^{\mathrm{L}}_i)^c\right\} \le 1 - \alpha \tag{3}$$