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Probabilistic Resource Planning With Explicit Reliability Considerations

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***Abstract-* The main objective of power system planning is maintaining an adequate level of reliability. The reliability concept has two characteristics: resource adequacy and operational reliability. Traditionally these two characteristics are addressed separately through a sequence of probabilistic and deterministic analyses without a systematic view. This paper presents a resource planning problem that explicitly models the system reliability requirement as chance constraints. Using this formulation, we examine the existing resource planning process to reveal its underlying assumptions. Solution methodology for the problem is also explored. The proposed formulation provides an analytic foundation for designing new planning procedures in a competitive environment and paves the way to a fully probabilistic planning paradigm.**

I. INTRODUCTION

A main objective of power system planning is to maintain an adequate level of reliability. According to North American Electric Reliability Corporate (NERC), power system reliability is evaluated in two aspects of the system: *resource adequacy* and *operational reliability* [1]. In a vertically integrated environment, these two aspects are addressed by two distinct but coordinated processes: the resource planning without considering transmission constraints; and the transmission planning considering operational issues. While these two planning processes together achieve a certain level of system reliability, such level is not explicit in the absence of a *composite* reliability index that captures both resource adequacy and operational reliability. This absence makes it difficult to control the actual reliability level of the planned system or to compare the reliability levels of different systems. As a result, a clearly defined composite reliability index is desired.

The power industry restructuring brings major changes to the conventional planning paradigm. While transmission remains a regulated business, the generation sector becomes competitive, and resource expansion decisions are made by individual resource owners instead of a central planner under the vertically integrated structure. Nevertheless, an Independent System Operator (ISO) or Regional Transmission Organization (RTO) who bears the responsibility to ensure system reliability needs to perform the resource planning function in some form. In contrast to the conventional resource planning that addresses principally adequacy, the resource "planning" in the restructured environment must consider both resource adequacy and transmission reliability since one cannot ignore the issues like deliverability that were traditionally handled by the transmission planning [2]-[3].

While the industry restructuring has mostly changed the resource "planning" paradigm, the implementation is often performed by using the conventional planning procedures without major modifications. While this eases the implementation, the aforementioned issue of the conventional planning process persists, i.e., there is no composite system reliability metric. In addition, the planning process involves various assumptions and engineering judgment, which are often ambiguous and poorly understood. These issues raise transparency concerns and place the ISO/RTO in a fishbowl under the close scrutiny of the various stakeholders. Furthermore, the conventional planning procedures, e.g., the calculation of capacity requirements and the selection of credible scenarios, become even more difficult to justify in an environment of deepening penetration by variable resources with their significant uncertainty. In view of the above, a clear foundation for resource planning in the restructured environment is desired.

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In this paper, we first define a composite reliability index by extending the Loss of Load Probability (LOLP) measure to include transmission and other considerations[2]. Since the resource planning needs to consider the overall system reliability, i.e., both resource adequacy and transmission reliability, a formulation with *explicit reliability constraint* is introduced. Using the composite LOLP as reliability index, the reliability requirement is modeled as a joint chance constraint [7]. The model serves as an analytic foundation for analyzing the current planning procedures and revealing their underlying assumptions. Solution methodology of the chance constrained problem is also investigated.

The remainder of this paper is organized as follows: Section II presents the chance-constrained model; Section III uses the model to analyze some conventional planning procedures; Section IV discusses the solution methodology; and Section V concludes the paper.

II. A RESOURCE PLANNING FORMULATION

In this section, we formulate a resource planning problem with explicit reliability constraint. The reliability constraint is modeled as the probabilistic LOLP limit in subsection II.A; and the cost objective is presented in subsection II.B.

A. Reliability Constraint

A composite reliability index needs to cover both the resource adequacy and the transmission reliability of the power system. The well known Loss of Load Probability (LOLP) in general denotes only the probability of generation capacity shortage [4]. From another perspective, it represents the probability of violating the power balance constraint under the uncertain load and generator outages. It is therefore natural to extend such metric to include transmission and other operational constraints, i.e., the composite LOLP is defined as the probability of violating *any* of the system constraints under consideration. As a result, the composite LOLP captures the loss of load caused not only by the shortage of generation but the violation of operational constraints as well.

Consider a system with I buses. Each bus $i \in \{1, 2,\ldots, I\}$ has an aggregated uncertain load $\underline{d}_i$ with a known probability distribution, and a set of exisiting or new generators with capacities $\{\underline{p}_{i,n}^{\max}: n=1, 2,\ldots, N_i\}$ and known outage rates. We introduce the binary planning decision variable associated with resource n at bus i as $y_{i,n}$, with a value of 1 for "adding the new capacity or keeping the existing one" and a value of 0. For simplicity, we represent the network in terms of DC power flow relations. Under contingency $k \in \{0,1,2,\ldots, K\}$ with k=0 be the base case, the limit of line $l \in \{0,1,2,\ldots, L\}$ is $f_l^{\max(k)}$, and the shift factor of the line with respect to bus i is denoted by $SF_{l,i}^{(k)}$. The composite LOLP index is then measured on following system constraints:

$$\sum_i \left[\sum_n p_{i,n} - \underline{d_i} \right] = 0, \qquad (1)$$

$$\sum_i \left[SF_{l,i}^{(k)} \left(\sum_n p_{i,n} - \underline{d_i} \right) \right] \le f_l^{\max(k)}, \ \forall l, \forall k, \qquad (2)$$

$$p_{i,n} \le y_{i,n} \cdot \underline{p_{i,n}^{\max}}, \ \forall i, \forall n. \qquad (3)$$

where (1) is the power balance constraint, (2) represents base flow and contingency flow constraints, and (3) reflects the generation capacity limits. The uncertainty inload $\underline{d}_i$ and generation capacity $\underline{p}_{i,n}^{\max}$ are marked by the underscores.

For given probability distributions of these uncertain parameters, the probability of (1)-(3) not holding *jointly* defines the composite LOLP of the system, i.e.,

$$LOLP(Y) \equiv 1 - Pr\{(1)-(3) \ hold \ jointly\}. \qquad (4)$$

where we indicate that the composite LOLP is a function of the planning decision vector Y. The definition in (4) is general, so additional constraints could be included. For instance, voltage limits may be included together with the nonlinear power flow equations for a more detailed representation of the power network.

With the above composite the reliability index (4), the reliability constraint is modeled as

$$Pr\{(1)-(3) \ hold \ jointly\} \ge 1 - \alpha, \qquad (5)$$

where α is the maximum allowed probability of violation. Such a constraint is also known as a joint chance constraint since it models the chance of (1)-(3) being simultaneously satisfied [6].

B. Objective Function

Our planning objective is to select Y that minimize the total "costs," i.e.,

$$\underset{Y}{Min} \ C(Y), \qquad (6)$$

subject to the reliability constraint (5). $C(Y)$ represents

[2] The assessment of LOLP considering transmission constraints has been investigated in the earlier literature [16]-[17]. However, to the best of our knowledge, explicit formulation of such composite LOLP index and its consideration in the planning optimization problem has not been found in the literature.

the costs associated with the planning decision vector Y. Depending on the problem context, the cost can take different meanings. In a vertically integrated industry for instance, the cost is typically the sum of capital investments. In a restructured industry, capacity expansion or retirement plans are driven by individual investors based on their private information. These plans may compete for approval by the ISO under a centralized capacity market form. In this case, the cost would be the total bid-in cost. Under both types of industry structure, the operational costs may also be considered in the objective to weigh in the operational efficiency.

III. ANALYSIS OF EXISTING PROCEDURES

Despite of the different industry structures, similar planning procedures have been used by a utility or an ISO in their planning practice, e.g., defining zones and producing zonal requirements. Various assumptions are involved in these procedures, and are often implicit and poorly understood. This poses difficulty for a planner to fully understand and justify the planning outcomes of these procedures. In this section, the planning model (5)-(6) is used as an analytic foundation for analyzing existing planning procedures. By applying a sequence of simplifying conditions to the model, we show how this model evolves into some existing planning procedures. The underlying assumptions are therefore clarified along this process.

A. From buses to zones

In some ISOs' practice, the resource planning process is built on the concept of zones instead of buses. This greatly reduces the problem dimensionality at the cost of the network granularity. In essence, a zone is a group of buses. Below we discuss one way of clustering the buses into zones, and compare it to the current practice.

According to (5)-(6), it is intuitively clear that if buses have the same impact on reliability, i.e., the composite LOLP in (5), then they can be grouped into a zone. In particular under DC power flow, such reliability impacts can be expressed in terms of shift factors, i.e.,

Proposition 1: Resources located in buses with the same set of shift factors impact the system reliability uniformly, and can be grouped into a "reliability" zone.

Consider two buses 1 and 2 having the same set of shift factors[3], i.e., $SF_{l,1}^{(k)} = SF_{l,2}^{(k)}$, $\forall\, l$, $\forall\, k$. To prove these two buses can be grouped into a zone A, we assign zone A resources to be $p_{A,n} = p_{1,n}$ (n=1,…, N_1) and $p_{A,\, N1+n} = p_{2,n}$ (n=1,…, N_2). Also let $SF_{l,A}^{(k)} = SF_{l,1}^{(k)}$ and $\underline{d}_A = \underline{d}_1 + \underline{d}_2$. The reliability constraint (5) becomes

$$\Pr\left[\begin{array}{l} \sum\limits_{i=A,i\geq 3}\left[\sum\limits_{n} p_{i,n} - \underline{d_i}\right] = 0, \\ \sum\limits_{i=A,i\geq 3}\left[SF_{l,i}^{(k)}\left(\sum\limits_{n} p_{i,n} - \underline{d_i}\right)\right] \leq f_l^{\max(k)}, \forall l,k \\ p_{i,n} \leq y_{i,n}\cdot \underline{p_{i,n}^{\max}},\ \forall i = A\ or\ i\geq 3,\ \forall n. \end{array}\right] \geq 1-\alpha \tag{7}$$

Zone A acts as a single bus with N_1+N_2 resources. Therefore, buses 1 and 2 can be grouped into a zone.

The above proposition indicates that zones can be defined based on each bus's reliability impact, which is characterized by the shift factors under the reliability index (4). In reality, however, it is unlikely that two buses will have the exact same set of shift factors, i.e., the above clustering principle may result in each bus defining a zone. As a solution to reduce the number of zones, one may group the buses with a *similar* set of shift factors into a zone. Depending on how "similarity" is measured, different clustering methods can be applied, e.g., [5]. Furthermore, one may consider only a few line or interface constraints in (5) to reduce the number of zones by deploying the appropriate clustering methods. These approximations allow tradeoffs between simplicity and accuracy of the model.

One important feature of the above zone definition is that within the zone, a resource's location does not affect the system reliability. This allows moving or trading capacity freely inside a zone without causing reliability problems that often concern system planners and in a market environment reduce the concerns of market power. However, in practice, zones are often defined based on geographic or jurisdictional borders instead of electric properties. Consequently, capacity located in different buses within such a zone may have major reliability implications. This explains the occurrence of local reliability issues inside the zone and the need for reliability reviews in some capacity markets.

B. From the meshed network to a radial network

Even with buses being grouped into fewer zones, the

[3] The shift factors are reference-bus dependent. With DC power flow, a different selection of reference bus will only cause the deviation of shift factors by a constant number, and thus the proposition still holds.

resulting system topology is still likely to be a meshed network, which involves complex loop flows. One simplification is to replace the transmission constraints (2) by predefined interface constraints. These interfaces must be closed ones (i.e., each interface splits the system into two islands) to result in a radial network, i.e.,

Proposition 2: In a network of zones and interfaces, if every interface is closed, then the network is radial.

To prove the proposition, assume that a meshed network with closed interfaces only exists. The meshed network has at least one loop path. Then each interface on that path is not closed, contradicting the assumption.

The radial network is a transportation network, which can be handled by many existing planning software, e.g., GE MARS. The reliability constraint (5) for the radial network may then be simplified to:

$$\Pr\begin{bmatrix} \sum_n p_{i,n} - \underline{d_i} = \sum_{j\in NB_i} I_{ij}, \\ I_{ij} \le I_{ij}^{\max}, \ \forall (i,j) \\ p_{i,n} \le y_{i,n}\cdot \underline{p_{i,n}^{\max}}, \ \forall i, \forall n. \end{bmatrix} \ge 1-\alpha \tag{8}$$

where I_{ij} is the flow on the interface between zones i and j, and NB_i is the set of neighboring zones connected to zone i. The interface constraints are assumed to reflect the major bottlenecks of power transfer in the system. However, interface limits are only an approximation to the transfer capability constraints. As a result, individual lines that are ignored in the simplified radial network model could violate their limits, causing reliability concerns.

C. From reliability constraint to capacity requirement

The reliability index (4) for a radial network is probabilistic. In practice, planners often represent the probabilistic assessment by deterministic capacity requirements. For instance, one way is to define capacity requirements for every zone, i.e.,

$$\sum_n \left(y_{i,n} \cdot \underline{p_{i,n}^{\max}} \right) - \underline{d_i} \ge R_i, \ \forall i. \tag{9}$$

where R_i is the deterministic requirement for zone i. Such representation involves assumptions. To identify these assumptions, we first clarify the underlying principle for the deterministic representation, i.e., the capacity constraint (9) should be sufficient to ensure the reliability constraint (8). Obviously, the deterministic requirements R_i's depend on the capacity mix, which is unknown before the planning decision. Therefore, one assumption has to be made on the characteristics of the capacity change, e.g., ΔC. Usually, planners assume the characteristic of aggregated existing capacities or the forecast load for ΔC. These assumptions bear a risk of violating the principle especially when the major technology transition such as the implementation of renewable energy is underway.

With the above assumption on ΔC, any feasible $\{y_{i,n}^*\}$ of (8) can be used to determine R_i's, i.e., $R_i = \Sigma_n(y_{i,n}^* \cdot p_{i,n}^{\max})$. To demonstrate that (9) implies (8) under these R_i's, consider first the following proposition.

Proposition 3: The addition of new capacity reduces the composite LOLP and therefore improves reliability of the system.

This is intuitive since one can choose to use the additional capacity only when the system has capacity shortage or transmission violation. As a result of the proposition, a plan Y satisfying (9) has a lower LOLP than $LOLP(Y^*)$. Since $LOLP(Y^*) \le \alpha$, we have $LOLP(Y) \le \alpha$, or (8) holds.

Based on the above discussion, there are many R_i's for (9) to imply (8). Additional condition is then needed to choose the requirements. One intuitive condition is minimizing the requirements. In practice, this minimization scheme is often implemented by using an alternative form of capacity requirements to (9), i.e., a requirement is imposed on each group of zones separated by an interface from the network. Take for example an interface that divides the network into two zones, A and B. There is an interface limit from B to A. Two capacity requirements may be defined, i.e., the total requirement R_{AB} and the local requirement R_A. To determine the minimal R_{AB}, consider first the LOLP as a function of R_{AB} assuming infinite interface limit. According to Proposition 3, $LOLP(R_{AB})$ is a non-increasing function as shown in Fig. 1. The minimal R_{AB} is then obtained at $LOLP(R_{AB}^{\min}) = \alpha$. Now consider the interface limit and consider the LOLP as a function of R_A with the total requirement R_{AB} fixed at $R_{AB}^{\min}$. It can be shown that $LOLP(R_A)$ is also a non-increasing function. Therefore the minimal R_A is obtained at $LOLP(R_A^{\min}) = \alpha$. Following the above steps, we can determine capacity requirements associated with each interface.

IV. DISCUSSION OF SOLUTION METHOD

While Section III uses the formulation (5)-(6) as an analytic basis for the analysis of some existing procedures, our ultimate goal is to solve the chance-constrained planning problem efficiently. The chance constraint, however, poses major challenges because its feasibility region is non-convex the evaluation of the constraint is complicated [6].

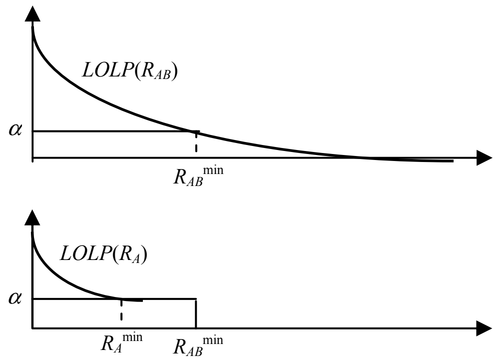

Fig.1. Determination of total and local capacity requirements.

One intuitive simplification therefore is to replace the probabilistic chance constraints by equivalent deterministic constraints. However, the approach is restricted to a small set of specific problems with strong conditions on the form of equations defining the chance constraint and the distribution of random parameters [7]-[8]. Another approach based on a branch-reduce-cut algorithm is developed for linear chance constrained programs in [9]. Limitations include: uncertain parameters and decision variables are separable in constraints, and the uncertain parameters have a small number of realizations. Recent efforts have also focused on approximations of the chance constraint, e.g., convex approximation of the non-convex chance constraints in [10]. The convex constraint is designed to be sufficient for the original chance constraint. As a result, the approach may be quite conservative and the closeness of the approximation may be difficult to measure.

The chance constraint (5) in our model is particularly complex since a set of equations is involved and there are multiple sources of uncertainty. Moreover, the problem is of integer type and involves various types of randomness, e.g., load, wind generation output and thermal generator outage rate. As a result, it is difficult to directly apply the above approaches to our problem. A generic approach based on simulation and evolutionary algorithm is then adopted. The simulation process is used to assess the feasibility of chance constraint for a given plan decision. The decision then is optimized by using a genetic algorithm. Similar approach has recently been applied to planning problems, and tested on small scale examples [11]-[15]. We are currently testing the computational tractability of this approach and exploring other potentially efficient approaches.

V. CONCLUDING REMARKS

Power industry is undergoing structural changes and technological transformations. The ongoing deregulation trend and looming smart technologies bring major challenges to the power system planning and operation. The existing planning procedures, however, have largely remained the same as decades ago. Those procedures involve many assumptions that are often implicit and not well understood in the lack of a clear foundation, causing difficulties of addressing the challenges. As the first step to build such a foundation, this paper presents a resource planning model with explicit consideration of the system reliability requirement. By defining a composite LOLP reliability index that captures both resource adequacy and operational reliability, the reliability requirement is modeled as the probabilistic LOLP constraint, resulting in a chance constrained program. We use the model as an analytic foundation to examine some existing planning procedures and shed light into the underlying assumptions. We finally describe the main challenges and potential solutions for the proposed formulation. Our future research will focus on the computational tractability of different approaches to solve the joint chance-constrained planning problem.

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