# Stochastic Optimization for Unit Commitment—A Review

Qipeng P. Zheng, *Member, IEEE*, Jianhui Wang, *Senior Member, IEEE*, and Andrew L. Liu, *Member, IEEE*

***Abstract*—Optimization models have been widely used in the power industry to aid the decision-making process of scheduling and dispatching electric power generation resources, a process known as unit commitment (UC). Since UC's birth, there have been two major waves of revolution on UC research and real life practice. The first wave has made mixed integer programming stand out from the early solution and modeling approaches for deterministic UC, such as priority list, dynamic programming, and Lagrangian relaxation. With the high penetration of renewable energy, increasing deregulation of the electricity industry, and growing demands on system reliability, the next wave is focused on transitioning from traditional deterministic approaches to stochastic optimization for unit commitment. Since the literature has grown rapidly in the past several years, this paper is to review the works that have contributed to the modeling and computational aspects of stochastic optimization (SO) based UC. Relevant lines of future research are also discussed to help transform research advances into real-world applications.**

***Index Terms*—Electricity market operations, mixed integer programming, pricing, risk constraints, robust optimization, stochastic programming, uncertainty, unit commitment.**

## I. INTRODUCTION

UNIT commitment (UC) is one of the key applications in power system operations [1]. In a deregulated electricity market, UC is often used by the independent system operators (ISOs) for day-ahead market clearing, reliability assessment, and intra-day operations. Generation companies (GENCOs) have also used UC to construct optimal bidding strategies [2]. In contrast to its usage in the markets, UC is solely used for cost minimization in an integrated utility operation environment. The output of UC is the commitment status and generation dispatch of various generating units satisfying system-wide constraints such as load balance and specific unit constraints such as capacity and ramping limits. To ensure UC solutions can meet security and reliability requirements, constraints associated with N-1 security are also added to the UC formulation and some form of reserve requirements is often enforced. Due to the use of binary variables to represent the commitment (ON/OFF) of generating units, coupled with many other constraints, UC is proven to be NP-hard [3] and difficult to solve when the size of the problem becomes large. Many different formulations have been proposed to model UC and many solution methodologies have been developed [4]. Those formulation and solution methodologies have evolved and advanced over the years from early ones based on priority list and dynamic programming to the current most commonly used ones based on mixed integer programming. Although the UC problem has been well researched in the literature, recent challenges caused by the increasing penetration of renewable generation have drawn a tremendous amount of interest worldwide in improving UC models and algorithms. Due to the significant uncertainty and variability from renewable generation, high levels of renewable generation increase the flexibility requirements of the system in response to fast and large variations in load and renewable energy output. Since many conventional generators such as coal-fired and nuclear units have limited flexibilities (e.g., ramping and minimum on/off times), novel power system operational methods are required to schedule the generating units more efficiently in order to accommodate the large fluctuations in renewable generation outputs while maintaining power system reliability. A number of measures have been proposed to improve grid operation and planning with renewables, including balancing area consolidation, increasing flexibility in the resource portfolio, demand-side management, and use of storage devices [5]. In addition to the physical means, updating current systems' planning and operation with stochastic and probabilistic methods has been particularly recommended as a promising solution to help maintain and improve system reliability with increasing penetration of variable energy resources [6]. Although stochastic methods including stochastic optimization (SO) have advantages in accounting for uncertainty and risks in many other fields [7], questions and barriers for their application to UC remain. System operators and other interested parties are concerned with the complexity and transparency of the SO-based methods as the efficacy and high computational requirements still need to be further addressed before their full practical implementation. Based on the vast amount of relevant research available, the motivation and purpose of this paper is to review and survey state-of-the-art applications of SO to UC by analyzing various formulations and solution methodologies used, investigating the barriers of applying SO-based methods in practice, and identifying future

Manuscript received February 20, 2014; revised June 26, 2014, August 26, 2014; accepted August 29, 2014. Date of publication September 26, 2014; date of current version June 16, 2015. The work of Q. P. Zheng was supported in part by the National Science Foundation under Grant CMMI-1355939. The work of J. Wang was supported by the U.S. Department of Energy Office of Electricity Delivery and Energy Reliability. The work of A. L. Liu was supported in part by the National Science Foundation under Grant CMMI-1234057. Paper no. TPWRS-00243-2014.

Q. P. Zheng is with the Department of Industrial Engineering and Management Systems, University of Central Florida, Orlando, FL 32816 USA (e-mail: qipeng.zheng@ucf.edu).

J. Wang is with the Decision and Information Sciences Division, Argonne National Laboratory, Argonne, IL 60439 USA (e-mail: jianhui.wang@anl.gov).

A. L. Liu is with the School of Industrial Engineering, Purdue University, West Lafayette, IN 47907 USA (e-mail: andrewliu@purdue.edu).

Digital Object Identifier 10.1109/TPWRS.2014.2355204

research directions to facilitate employment of such methods in UC applications. Due to the large number of papers related to this subject, and to focus on addressing the short-term variability and uncertainties of renewables, we particularly limit our discussions to the following areas:

1) short-term unit commitment (hours-ahead to day-ahead) rather than longer-term unit commitment (weekly, seasonal, and yearly);
2) SO techniques in the formulation and solution of UC, instead of deterministic UC problems with additional constraints incorporating inputs derived from statistical methods (e.g., reserve requirements calculated based on probabilistic forecasts);
3) optimization algorithms that have explicit formulations and can lead to exact solutions rather than metaheuristic methods such as genetic algorithms, simulated annealing, or swarm-based approaches.

The remainder of this paper is organized as follows. We first review the basic uncertainty modeling approaches for UC in Section II. Section III introduces various formulations and solution techniques that have been applied to UC. In Section IV, we discuss other related aspects such as market clearing and pricing. Section V concludes the paper and discusses the future research directions.

## II. Uncertainty Modeling as an Input to UC

Representation of uncertainty is critical in SO. Depending on the specific SO techniques used, the representation and modeling of uncertainty can be quite different. Overall, uncertainty modeling can be divided into three types: scenarios, uncertainty sets, and probabilistic constraints. We will focus on scenarios and uncertainty sets here, leaving the discussion of probabilistic constraints for the next section. Scenario representation of uncertainty is one of the most commonly used techniques in SO. The basic idea of the scenario representation is to generate a large number of scenarios where each scenario represents a possible realization of the underlying uncertain factors. This kind of simulation method is an approximation of the true distribution of the uncertainties. Depending on the number of stages in the problem, the structure of scenarios can be a number of parallel scenarios in a two-stage SO problem or a scenario tree in a multistage SO problem. For the former, Monte Carlo simulation is often used to populate the scenarios based on certain (pre-defined) probability distribution functions learned from historical data; for the latter, a scenario tree composed of random paths is generated based on the underlying stochastic process(es). Scenario generation is also tightly coupled with forecasting [8]. For instance, a number of scenario generation techniques have been proposed for generating wind power scenarios, where the spatial and temporal effects of wind power must be considered. Some representative references include [9]–[11], where modeling of forecasting errors and validation of the quality of scenarios are discussed in detail. Many research efforts have been done on uncertainty modeling as an input to UC. For example, [12] and [13] use the normal distribution to model wind speed forecasting errors and apply Monte-Carlo simulation to generate scenarios for UC. The impact of uncertain forecasting errors on UC is evaluated in [14]. Instead of focusing on forecasting errors, wind speed is directly modeled through the Weibull distribution [15] or the normal distribution [16], [17]. Wind power output can then be directly derived from the wind speed. Besides continuous distributions, discrete probability distributions are also used to represent wind power output for UC [18].

Intuitively, the quality of solutions increases with a larger number of scenarios, since a more comprehensive picture about the future can be presented. However, increasing the number of scenarios beyond a certain threshold may lead to only a marginal improvement in the quality of the solution and the objective function. To this end, sample average approximation (SAA) [19] and multiple replications procedure (MRP) [20] can be used to test the convergence of the solution and objective function, respectively. Since the computational requirements also increase with the number of scenarios, a tradeoff usually needs to be made between the desired accuracy and the computational performance of the algorithm. Correspondingly, scenario reduction techniques have been proposed in the literature to bundle similar scenarios based on certain probabilistic metrics [21]–[23]. The goal is to reduce the number of scenarios without sacrificing their accuracy to a large extent.

Probabilistic forecasting is another alternative to model uncertainties, especially in robust optimization-based algorithms where a range/band needs to be defined to represent the upper and lower bounds of the uncertainty. The most common output from probabilistic forecasts is a set of quantiles, which can be computed through probability density functions (pdfs) or cumulative distribution functions (cdfs). Quantiles represent the probabilistic levels of the forecasts for a certain look-ahead time period. Probabilistic forecasting is a natural fit in such problems, because it can predict the level of a forecast output at a certain probability, and using two probabilistic forecasts can conveniently model the confidence intervals required in uncertainty set definitions. Much research has been done in probabilistic forecasting. For example, quantile regression for probabilistic wind power forecasts is carried out in [24]. Kernel density estimator-based forecasts for wind power are investigated in [25]. A time-adaptive method is proposed in [26], where a novel quantile-Copula estimator for kernel density forecasts is proposed and shown to outperform the traditional quantile regression approaches.

The most straightforward and basic uncertainty sets used in robust-optimization-based UC models are the *box* intervals, $[\max\{0, \bar{d} + z_\alpha\sigma\}, \bar{d} + z_\beta\sigma]$, where $\bar{d}$ is the expected value and $\sigma$ is the variance of a random variable, respectively; $z_\alpha$ and $z_\beta$ are the $\alpha$- and $\beta$-quantile of the probability distribution (with $\alpha < \beta$). The random variable can be wind power outputs and nodal loads, for example, as in [27]. Because robust UC may yield overconservative solutions, polyhedral constraints on budget of uncertainty are also utilized to yield smaller (but not necessarily less confident) uncertainty sets, e.g., [28], [29]. Other than the polyhedral form, ellipsoidal uncertainty sets can also be considered by utilizing the expectations and covariance matrices [27], [30], [31]. In addition to the continuous and convex uncertainty sets, nonconvex and discrete sets are also extensively used in robust UC models. For example, robust UC models with $N-k$ contingencies used a knapsack constraint to define the scope of uncertainty [32]–[34]. For tri-level models, the inner problem could be a bilinear problem, which can be avoided if the uncertainty sets of the random variables are modeled only allowing special extreme points, e.g., [28], [35]. Instead of directly using the box intervals, uncertainty sets can also be derived based on risk measures (such as Value-at-Risk) as in [36] and [37]. Particularly notable is that constraints on coherent risk measures (such as Conditional-Value-at-Risk) can be translated to polyhedral uncertainty sets for some types of distributions [38]. This fact actually links stochastic and robust UC models together.

## III. UC Models Under Uncertainty and Solution Algorithms

Deterministic UC problems address the short-term (e.g., day-ahead) scheduling of generators (e.g., [39] and [40]), where the next day situation is assumed to be fixed. Stochastic models also have the same time frame but include the uncertainties for the next day or the next several hours. Most of the uncertainties modeled in the literature result from the high penetration of renewable energy (e.g., wind and solar), deregulated energy markets, failures of power system components, and demand variations. Three main types of modeling and solution approaches have been proposed to handle UC under various uncertainties: stochastic programming, robust optimization, and stochastic dynamic programming.

### A. Stochastic Programming

Stochastic unit commitment (SUC) has been introduced as a promising tool to deal with power generation problems involving uncertainties e.g., [16], [40]–[52]. The idea of SUC is to utilize scenario-based uncertainty representation in the UC formulation. Compared to simply using reserve constraints, stochastic models have certain advantages, such as cost saving and reliability improvement, as shown in [53] and [54].

*1) Two-Stage Models and Algorithms:* The benefits of using stochastic programming versus deterministic models can be evaluated by two measures in terms of the total expected cost: the expected value of perfect information and the value of stochastic solution. In theory [7], both measures are in favor of stochastic models. In a two-stage SUC model, decisions are divided into two categories: day-ahead versus real-time decisions. This is shown in the following model:

$$\min_{\mathbf{u}\in\mathbb{U}} \mathbf{c}^{\mathsf{T}}\mathbf{u} + E_{\xi}[F(\mathbf{u},\xi)]. \tag{1}$$

In the day-ahead category (first stage), commitment decisions of traditional units (e.g., coal and nuclear generators), $\mathbf{u}$, are made ahead of time because they can not be turned on or off quickly in real time. $\mathbb{U}$ represents the set of feasible commitment decisions (constraints only on commitments, such as minimum up/down time requirements) [55]. Various startup and shutdown costs are captured in the vector $\mathbf{c}$. The second term in the objective function of (1) is the expected cost of real-time operations, where $\xi$ is the uncertain vector with a known joint probability distribution. For each realization, $s$, of the random vector $\xi$, the second-stage problem can be formulated as follows:

$$F(\mathbf{u},s) = \min_{\mathbf{p}_s,\mathbf{f}_s} \quad f(\mathbf{p}_s) \tag{2a}$$

$$\text{s.t.} \quad A_s\mathbf{u} + B_s\mathbf{p}_s + H_s\mathbf{f}_s \geq \mathbf{d}_s, \tag{2b}$$

where $\mathbf{p}_s$ includes both dispatches and reserves of multiple periods, and $\mathbf{f}_s$ is the vector of other second-stage decisions (such as power flows in [16], [56], and pump-storage hydro unit decisions in [47]–[49], [57]). The function $f(\cdot)$ represents the fuel cost, which is typically quadratic and convex, but can be approximated by piecewise linear functions [58]. According to different modeling perspectives, different sets of parameters in (2) are treated as uncertain. For example, the uncertain left-hand-side matrices $(A_s, B_s, H_s)$ are usually used to model contingencies (e.g., power system equipment outage) as in [42]; uncertain right-hand-side vectors $(\mathbf{d}_s)$ usually model the uncertain demand and renewable energy outputs as in [16], [41], [56], [59], and [60]. Although $\xi$ might follow a continuous probability distribution, for computational purposes, discrete simulated scenarios are often used.

Because of the large number of scenarios simulated, the resulting deterministic problem could be quite large. However, in the second stage, different scenarios are not directly linked to each other. Because of this, decomposition has been used as an efficient tool for stochastic unit commitment problems. In the two-stage model (1), once the first-stage decision $\mathbf{u}$ is made, the second stage (2) of different scenarios can be treated independently, resulting in a group of much smaller individual optimization problems. Benders Decomposition or the L-shaped algorithm [7] is usually applied when (2) is a linear program (e.g., [16]). However, the value function $F(\mathbf{u},s)$ is not necessarily convex or even continuous when integer decision variables are included in (2). In this case, other methods such as the integer L-shaped method, disjunctive cuts, convexification of the second stage or a combination of such methods are needed (for example, [55], [61]). As is well known, cutting plane methods may need to include a large number of cuts in the restricted master problem. To resolve this difficulty, both regularized methods and trust region methods have been used to restrict step length and hence stabilize the convergence (see [62] and [63]). Lagrangian relaxation is another method to break the original problem into smaller pieces by dualizing the coupling constraints between scenarios (see [47], [56], and [57]). Bundle method has shown fast convergence in solving the dual problems, and branch-and-bound-based method is used to solve the decoupled single-scenario/deterministic unit commitment problem, such as in [47] and [57]. Another Lagrangian relaxation approach is to decouple the generation units by dualizing/relaxing the demand and reserve constraints [48], which is also used for multistage problems and will be discussed in the next subsection.

*2) Multistage Models and Algorithms:* In contrast to two-stage models, which treat uncertainty statically (only once), multistage models attempt to capture the dynamics of unfolding uncertainties over time and adjust decisions dynamically. To facilitate the formulation of multistage models, scenario trees

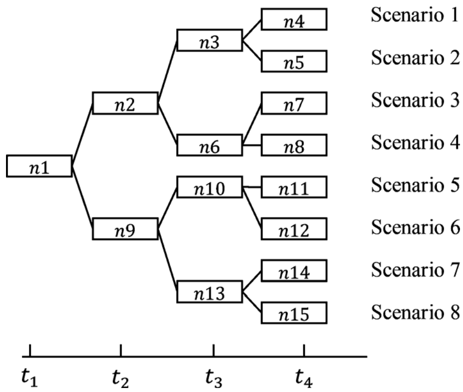



Fig. 1. Scenario tree with four stages, eight scenarios, and 15 nodes.

are often used, as illustrated in Fig. 1. When information is updated hourly (or multihourly or subhourly), decision-makers can adjust their unit commitment, dispatch, and reserve decisions based on the current states of the system and future uncertainties. The main benefit of using multistage models is that the interaction between decision making and uncertainty unfolding is represented more accurately and realistically.

As in Fig. 1, a scenario is equivalent to a unique path from the root node $n1$ to a leaf node (e.g., $n5$, $n7$, and $n15$), where each node along a path denotes a time epoch at which decisions are made. For each scenario, the corresponding problem is the same as a deterministic UC problem. The added difficulty of multistage models comes from the nonanticipative constraints, which state that only one set of decision variables are allowed at each node. A multistage stochastic unit commitment model with nonanticipative constraints is as follows:

$$\min \quad \sum_{s\in S} \mathrm{Prob}_s f(\mathbf{u}_s, \mathbf{p}_s, \mathbf{r}_s, \mathbf{x}_s) \tag{3a}$$

$$\text{s.t.} \quad (\mathbf{u}_s, \mathbf{p}_s, \mathbf{r}_s, \mathbf{x}_s) \in \mathcal{U}_s, \quad \forall s \in S \tag{3b}$$

$$(u_{s,t}, p_{s,t}, r_{s,t}, x_{s,t}) = (u_n, p_n, r_n, x_n), \quad \forall (s,t) \in S_n, n \in N \tag{3c}$$

where the objective function is the expected cost. $\mathbf{u}_s, \mathbf{p}_s, \mathbf{r}_s, \mathbf{x}_s$ are, respectively, the unit commitment, dispatch, reserve, and other decision vectors corresponding to scenario $s$. These vectors are composed of subvectors $u_{s,t}$, $p_{s,t}$, $r_{s,t}$, and $x_{s,t}$, denoting the decisions under scenario $s$ at time $t$ correspondingly. $f(\cdot)$ is the cost function. $\mathcal{U}_s$ is the set of feasible solutions under a scenario $s$. Constraint (3c) enforces the non-anticipative requirement, where all scenarios going through a node $n \in N$ (denoted by set $S_n$) should have the same decision.

Similar to the two-stage models, uncertainties in the multistage cases come from various sources. Carpentier *et al.* [45] address the demand and unit failure uncertainties. Takriti *et al.* [44] take into account demand uncertainty in multistage stochastic unit commitment. Among the efforts addressing stochastic demand/load dynamics, there are also models considering combined hydro-and-thermal systems, such as [48], [50], [64]. Takriti *et al.* [43] add fuel and electricity price uncertainty and fuel constraints to their original model. Shiina and Birge [65] include both demand uncertainty and unit outage randomness in their model. Li *et al.* [66] address uncertainties on the prices of both electricity and reserves. Sen *et al.* [67] deal with a power portfolio/contract problem while including uncertainties in demand and prices. The multistage, multiscale model in [67] has a longer portfolio decision period and short-term unit commitment problems. All models have reported cost/profit reduction/gain as a result of using multistage stochastic models.

The benefits of multistage models also come with computational difficulties. The number of scenarios grows exponentially as the number of outcomes of each stage and the number of stages increases. As a result, multistage models are much harder problems than two-stage models. Advanced decomposition algorithms, especially multilayered or nested decomposition techniques, are often used in these cases. In terms of decomposition targets, there are unit-based decomposition and scenario-based decomposition. In unit-based decomposition, the demand-satisfaction-constraints

$$\sum_i p^i_{s,t} \geq d_{s,t} \quad \forall s \in S, t \in T \tag{4}$$

where $p^i_{s,t}$ is the dispatch of unit $i$ and $d_{s,t}$ is the demand, are dualized. The reminder of the problem becomes many separate subproblems each involving only one generator. Augmented Lagrangian relaxation is preferred in this case over classical Lagrangian relaxation as in [45]. However, even the single generator problem might not be easy if there are many decision stages. Stochastic dynamic programming is used to solve the single unit problem in [64]. In the Lagrangian dual cutting plane methods, the Bundle method has been used to speed up convergence for solving the dual problem (e.g., [48] and [64]). Preconditioning using the scenarios' probability information for the Bundle method can help decrease the number of iterations, as reported in [50]. Scenario-based decomposition tries to dualize constraint (3c) in Lagrangian relaxation (e.g., [42]) and keep only the original constraint (3c) in the relaxed master problem in Dantzig–Wolfe decomposition (column generation). In [44], progressive hedging (see [68]) is used, and, for the subproblem corresponding to each scenario, unit-based decomposition is used to result in multiple single-unit problems. Benders decomposition is embedded within the progressive hedging algorithms to approximate the fuel-allocation problem in [43]. A column generation approach is used to decompose the original problem by unit, and the single-unit multistage SUC is solved by dynamic programming as in [65]. In the power portfolio problem of [67], nested column generation is used, where the first layer obtains contracting columns of the longer time scale and the second layer finds the columns of unit commitments.

*3) Risk Consideration in Stochastic Models:* Most of the stochastic models minimize the total expected cost while satisfying all technical operating constraints under any possible scenario, which may include extremely rare events (and lead to very costly solutions). This concern then leads to the notion of risk-averse UC decisions. In risk-averse UC models, additional constraints are added to restrict risk exposures of a particular set of UC decisions. Several different risk measures have been used in the literature, such as Expected Load Not Served (ELNS) in [69]–[71], Variance of the total profit in [72], Loss of Load Probability (LOLP) in [69]–[71], [73]–[76], and Conditional Value at Risk (CVaR) in [13], [77], and [78].

ELNS is also referred to as Expected Energy Not Supplied or Expected Loss of Loads (Load Shedding). It is evaluated at each time period by taking the expectation of total net load minus the total dispatch including both scheduled generation and spinning reserves. Uncertainties may arise from, for example, the net load, the random outage of equipments, or demand response. It can be either integrated in the objective function or embedded in risk constraints. The main advantage of ELNS is its easiness to calculate and hence it can be included in the objective function as a penalty term or in a bounding constraint. However, since ELNS is based on expected values, it cannot tell how risky a certain decision may be.

A natural idea to overcome the limitation of the ELNS approach is to consider both the expected value and variance of a certain quantity associated with a set of UC decisions. Such an approach has been used in several works focusing on self-scheduling UC problems [72], [79], [80]. In such problems, generation companies (GenCos) try to find optimal bidding strategies to an organized wholesale power market. To ensure that their bids would be accepted by the system operator, which have to be feasible with respect to the market's physical constraints, the GenCos also need to solve UC problems. Since GenCos' profits are directly affected by the market-clearing electricity prices, which often exhibit extreme volatilities, the variance of a GenCo's profit is often used to quantify the riskiness of its bidding decisions. It can be added into the objective function to help balance the total expected profit and risk exposure. In addition to the simple mean-variance approach, the well-developed risk-aversion models in the economics and decision science literature, such as those using different utility functions to represent decision-makers' risk aversion, can also be applied here. Since we are more focused on UC problems from a system operator's perspective than from a GenCo's perspective, we do not attempt to provide a detailed account on individual's risk-aversion models.

For a system-wide risk measure, arguably the most widely used metric is the LOLP, defined as follows:

$$\mathrm{LOLP}_t = \mathrm{Prob}\left(\mathbf{1}^{\mathsf{T}}\mathbf{p}_t^{\xi} \geq d_t^{\xi}\right) \tag{5}$$

where $\mathbf{1}^{\mathsf{T}}\mathbf{p}_t(\xi)$ is the total dispatch subject to random outages, and $d_t^{\xi}$ is the random net load/demand at time period $t$. To ensure system reliability, constraints restricting LOLP at all time periods $t$ can be added to a UC problem, such as $\mathrm{LOLP}_t \geq 1-\varepsilon$, where $1-\varepsilon$ is the confidence level with $\varepsilon$ being a very small number. A variant of LOLP constraints could include the loss of load (load not served or interrupted load) as follows:

$$\mathrm{Prob}\left(\mathbf{1}^{\mathsf{T}}\mathbf{p}_t^{\xi} + l_t^{\xi} \geq d_t^{\xi}\right) \geq 1-\varepsilon, \forall t \tag{6}$$

where $l_t^{\xi}$ is the load shedding required to meet the power balance subject to uncertainties. The probabilistic constraints can be used to limit the total load loss [69], [70], [73], [75], [76] or load losses at different zones [71]. The main advantage of using LOLP is the use of the explicit reliability measure (exact probabilities) to balance total cost and reliability, compared to using either expected value or variance. However, it also comes with significant computational challenges. For example, uncertain outages of equipments could mean a large number of scenarios, for each of which a binary variable needs to be introduced, with 0 and 1 representing if a scenario will be selected or not. Hence approximations using a limited number of outages (e.g., [70]), exponential functions (e.g., [81]), Sample Average Approximation (e.g., [75] and [76]) have been used. Because the explicit constraints to formulate (6) (e.g., [75]) also involves binary variables, the models are computationally demanding even with a fair number of scenarios.

The probabilistic constraints restricting LOLP are sometimes referred to as chance constraints (e.g., [73]–[76]), and they are equivalent to restricting the $\varepsilon$-Value-at-Risk of the random loss of load, which is defined as follows:

$$\mathrm{VaR}_{\varepsilon}\left(l_t^{\xi}\right) = \inf\left\{l \,\middle|\, \mathrm{Prob}\left(l \geq l_t^{\xi}\right) \geq 1-\varepsilon\right\} \tag{7}$$

where the $\varepsilon$ is the small upper tail probability. However, VaR is not a coherent risk measure as it does not satisfy subadditivity property (for general probability distributions). Instead, a coherent and more conservative risk measure, Conditional Value at Risk (CVaR) is also used to fend off risk in stochastic UC models in [13], [77], and [78]. CVaR, also referred to as Expected Shortfall (ES) or Expected Tail Loss (ETL), is the conditional expectation of load loss given that loss of load is beyond $\mathrm{VaR}_{\varepsilon}(l_t^{\xi})$, that is,

$$\mathrm{CVaR}_{\varepsilon}\left(l_t^{\xi}\right) = \mathbb{E}\left(l_t^{\xi} \,\middle|\, \mathrm{VaR}_{\varepsilon}(l_t^{\xi}) \geq \eta\right) \tag{8}$$

where $\eta$ is a prespecified maximum allowed load loss/shedding. Constraints restricting $\mathrm{CVaR}_{\varepsilon}(l_t^{\xi})$ can be formulated by using only continuous variables with linear functions [78], [82], [83]. As a result, CVaR-based models are computationally tractable even with a large number of scenarios. In addition, its solutions also provide information of the related VaR and LOLP because of the CVaR is defined upon VaR (8) [82].

While the above discussions are centered around VaR and CVaR as risk measures, any other coherent or convex risk measures [84], [85] can be used to represent the overall system's risk exposure. In particular, the worst-case regret is shown to be a coherent risk measure [86], and minimizing regret is closely related to the subject of robust optimization, which is the main topic of the next section.

### B. Robust Optimization

In contrast to stochastic programming models, robust unit commitment (RUC) models try to incorporate uncertainty without the information of underlying probability distributions, and instead with only the range of the uncertainty. In place of minimizing the total expected cost as in SUC, RUC minimizes the worst-case cost regarding all possible outcomes of the uncertain parameters. Certainly this type of models produce very conservative solutions, but computationally it can avoid incorporating a large number of scenarios.

In the power system literature, RUC models have been used to address uncertainties mainly from nodal net electricity injection [29], wind power availability [28], [35], power systems component contingencies [32]–[34], and demand-side management [87]. The RUC literature mostly features two-stage robust unit commitment models, which generally appear in the following form:

$$\min_{\mathbf{u}\in\mathbb{U}}\{\mathbf{c}^{\mathsf{T}}\mathbf{u}+\max_{\mathbf{v}\in\mathbb{V}}[F(\mathbf{u},\mathbf{v})]\} \tag{9}$$

where $\mathbf{u}$ and $\mathbb{U}$ are the same as defined in SUC models, $\mathbf{v}$ is the uncertainty parameter, and $\mathbb{V}$ is the deterministic uncertainty set (a range or region). $F(\mathbf{u},\mathbf{v})$ is the real-time dispatch cost function given UC decisions $\mathbf{u}$ and the uncertain variable $\mathbf{v}$. Note that $\mathbf{v}$ is not a parameter vector but a variable vector as (9) aims to minimize the total cost of the worse-case scenario. $F(\mathbf{u},\mathbf{v})$ is defined as the optimal objective value of the following minimization problem:

$$\begin{aligned} F(\mathbf{u},\mathbf{v}) = & \min_{\mathbf{p},\mathbf{f}} \quad \mathbf{q}^{\mathsf{T}}\mathbf{p} && \text{(10a)}\\ & \text{s.t.} \quad A_{\mathbf{v}}\mathbf{u}+B_{\mathbf{v}}\mathbf{p}+H_{\mathbf{v}}\mathbf{f}\geq\mathbf{d}_{\mathbf{v}}. && \text{(10b)}\end{aligned}$$

The formulation of this problem is the same as the SUC second-stage problem, except that the left-hand-side coefficient matrices and the right-hand-side vectors are functions of the uncertain parameters. The objective function uses a piecewise linear approximation ($\mathbf{q}$ is the coefficient vector) of the original quadratic cost function. The deterministic uncertainty set $\mathbb{V}$ highly depends on the sources of uncertainties. For $N-k$ contingency models [32]–[34], knapsack constraints are used to define $\mathbb{V}$. For wind output uncertainty, polyhedral or ellipsoidal constraints can be used instead [29]. Discrete sets are also used to model possible wind outputs [28], [35]. Other RUC models include single-stage models (the worst case is incorporated in constraints, e.g., [32]), three-stage models (e.g., [87]), and combined worst-case and average real-time dispatch costs (e.g., [88]).

The computational tractability of RUC models highly depends on the definition of the uncertainty set $\mathbb{V}$, because the innermost problem (10) needs to be dualized to transform the maximization problem (given $\mathbf{u}$) in the objective function of (9) into a single-level problem as follows:

$$\begin{aligned} \max_{\mathbf{v},\pi} \quad & (\mathbf{d}_{\mathbf{v}}-A_{\mathbf{v}}\mathbf{u})^{\mathsf{T}}\pi && \text{(11a)}\\ \text{s.t.} \quad & H_{\mathbf{v}}\pi\leq 0 && \text{(11b)}\\ & B_{\mathbf{v}}\pi\leq\mathbf{q} && \text{(11c)}\\ & \mathbf{v}\in\mathbb{V} && \text{(11d)}\end{aligned}$$

where $\pi$ is the dual variable corresponding to constraint (10b), and we assume all nonnegative variables in (10). With the reformulated (11), the original problem can be solved via Benders decomposition because the optimal solution (denoted with superscript $*$) of (11) is also an extreme point of its feasible region. The Benders cut is formulated as follows:

$$z\geq(\mathbf{d}_{\mathbf{v}^*}-A_{\mathbf{v}^*}\mathbf{u})^{\mathsf{T}}\pi^* \tag{12}$$

where $z$ is an upper-bound variable of the second-stage cost. However, it can be difficult to solve (11) because of the bilinear terms between $\mathbf{v}$ and $\pi$. Outer approximation algorithms have been used to solve this bilinear program when $d_{\mathbf{v}}$ is assumed to be uncertain within a polyhedral set [29]. However, if $\mathbb{V}$ is a discrete set defined by explicit constraints, the problem can be easily solved as a mixed integer linear program, such as in $N-k$ contingency models [32]–[34] and in models with discrete worst-case wind output scenarios [28], [35], [89]. Another method [28] to approximate the master problem is to use the column-and-constraint generation by adding new primal variables $(\mathbf{p}^i,\mathbf{f}^i)$ from the innermost problem

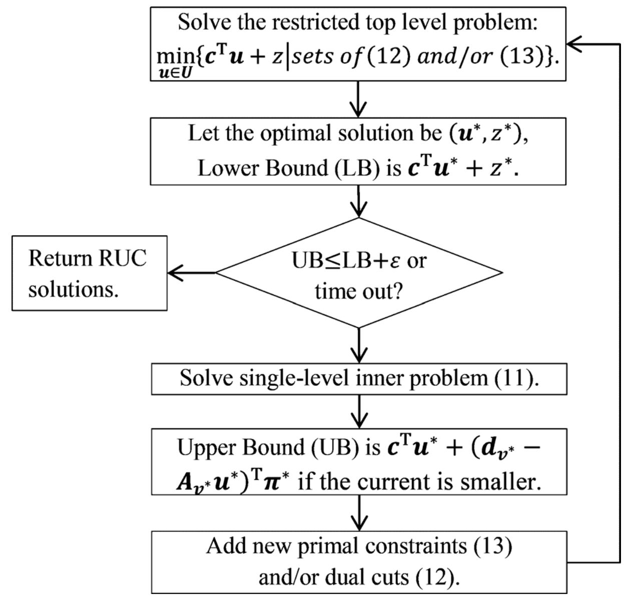



Fig. 2. RUC solution process.

$$\begin{aligned} & z\geq\mathbf{q}^{\mathsf{T}}\mathbf{p}^i && \text{(13a)}\\ & A_{\mathbf{v}^*}\mathbf{u}+B_{\mathbf{v}^*}\mathbf{p}^i+H_{\mathbf{v}^*}\mathbf{f}^i\geq\mathbf{d}_{\mathbf{v}^*}. && \text{(13b)}\end{aligned}$$

The process of solving the problems, as is shown in Fig. 2, is very similar to the standard Benders decomposition (in many references it is considered equivalent to Benders Decomposition) except that the subproblems [i.e., the single-level inner problem (10)] could be different and primal cuts are also available in RUC.

As mentioned, RUC models may produce very conservative solutions, which translate to higher expected costs. On the other hand, RUC-based solutions provide security against worst-case scenarios. The conservativeness of an optimal solution depends on how the uncertainty set $\mathbb{V}$ is defined. The larger the set, the more conservative the optimal solution. In this respect, the notion of a budget of uncertainty is used to help balance between cost and reliability by adding different kinds of constraints to $\mathbb{V}$. For example, the maximum allowed number of equipment failures can be varied to adjust the budget of uncertainty in $N-k$ contingency models [32], [33]; the total allowed number of wind output cases can be varied [35]; the linear coefficients of the polyhedral sets also can be varied, such as in [28] and [29].

### C. Stochastic Dynamic Programming

Dynamic programming (DP) is a class of optimization problems designed to aid decision-making in multiple stages. In such situations, decisions made in the current stage to lower one-stage cost may (inadvertently) raise future stages' costs, and DP captures such trade-offs. Due to its multiperiod setting and its amenability to model stochastic input data, it is a natural idea to use DP to model UC under uncertainty.

Similar to the setting of multistage stochastic programming, a finite-horizon, discrete-time UC problem can be formulated in a stochastic dynamics programming (SDP) framework as follows:

$$\inf_{\pi \in \Pi} V_\pi(s_0) := \mathbb{E}\left[\sum_{t=0}^{T-1} C_t(s_t, \mu_t(s_t), \xi_t) + C_T(u_T)\right] \tag{14}$$

where the expectation is taken over the random variables $\xi_t$. $C_t(\cdot)$ represents the system cost at time periods $t = 0, 1, \ldots, T$, and the function $V_\pi$ is referred to as the value function. $s_t$ in (14) represents the state of a system at $t$. In a power system, the state variables may include electricity demand, UC status, water availability of hydro power plants, stored energy in electricity storage units, and so on. The commitment and dispatch decisions $(u_t)$ at each time epoch are made according to a policy function $\mu_t(\cdot)$, which maps from a system state at $t$ to an action; that is, $u_t = \mu_t(s_t)$. The set $\Pi$ in (14) represents the collection of all feasible policies in the form of $\pi := \{\mu_0, \mu_1, \ldots, \mu_{T-1}\}$.

Transitioning of a power system from the current state to the state in the next period can be characterized by a specific transition mechanism (denoted as $g_t(\cdot)$) as follows:

$$s_{t+1} = g_t(s_t, \mu_t(s_t), \xi_t), \qquad t = 0, 1, \ldots, T-1. \tag{15}$$

The uncertainties affecting a power system's transition may include, for instance, demand fluctuation, variability of intermittent renewable resources, and power plants' or transmission lines' availability.

Use of DP to model and solve deterministic UC problems can be dated back to the late 1970s (e.g., [90]). However, since the classic approach for solving DPs is the backward induction approach, based on Bellman's Principle of Optimality [91], all the earlier works of DP-based problems suffer the curse of dimensionality; that is, the solution time increases exponentially as the number of states or variables increases. A commonly used approach in overcoming the computational difficulty is to use a predetermined priority list to enumerate policies for UC decisions, based on the units' marginal costs. While this approach can significantly reduce computational complexity, it is not well-suited for models with uncertainty because the merit order of generation dispatching may change endogenously, for reasons including requirements for ramping capability and reserve quantities. To overcome computational difficulties, various methods have been developed to obtain an approximate solution of a DP, giving rise to the broad class of algorithms referred to as approximate dynamic programming (ADP). Generally speaking, ADP methods can be classified as value function approximation, policy function approximation, and state-space approximation [92], [93]. All three approaches have been applied to solve stochastic UC problems. State-space approximation is utilized in [94], in which the large state space representing UC states is reduced to a set of representative states. The approach is tested on a 40-unit, 168-h UC problem. Policy function approximation in the form of model predictive control (MPC) has been applied in [95], [96]. MPC, also referred to as the receding horizon control approach, finds policy approximations through repeatedly solving an (finite-horizon) optimal control problem with a rolling horizon. A simplified 12-bus representation of NYISO is used in [95], [96] for testing the MPC algorithm, with 1500 5-min intervals in the UC problem. Recently, a value function approximation approach based on separating uncertainties realized before and after a decision being made is proposed in [93]. Such an approach is utilized in [97] to incorporate price-responsive demand response in a stochastic economic dispatch model.

While ADP approaches have seen promising applications in stochastic UC, two major issues remain. First, solutions obtained from an ADP approach are only approximate to the true optimal solutions of the original DP problem. How to gauge the solution quality is a challenging question and is under active research. Second, ADP approaches share the feature of DP models, which endogenously consider the feedback effects of a decision in a multistage problem. How electricity should be efficiently priced in such a dynamic market mechanism is still an unanswered question.

### D. Comparisons of Models and Algorithms

As surveyed in this paper, there has been a rich literature on using SO methods to improve decision-making in the UC process. To provide a quick overview of the literature, with a general comparison among the three major SO methods, we provide a summary table (Table I). In the table, we also list the common algorithms used to solve various SUC models. Following the listed algorithm are the corresponding references.[1] There also exist other works that focus on the modeling aspects of SUC and only use an existing software, such as CPLEX, to solve the resulting SUC models by the default branch-and-bound-and-cut method. Such pieces of works are not included in the table. Note that Table I only qualitatively compares the advantage and disadvantage among stochastic programming, robust optimization and stochastic dynamic programming. Quantitative comparisons are outside the scope of this paper, and can be found in [35], [89], [98]. It is noted that even within the same category of algorithms, different models and corresponding algorithms may differ significantly. For two-stage stochastic programming models, Benders decomposition guarantees exact optimal solution but may experience slow convergence; accelerated Bender decomposition could speed up convergence [99]; Lagrangian relaxation (LR) using the bundle method is reported to converge faster [47], [57]; sample average approximation is mainly used to solve chance-constrained stochastic UC models. For multistage stochastic programming models, the progressive hedging (PH) method, which is an augmented Lagrangian relaxation method, has been shown to have good computational performance for large-scale stochastic mixed integer problems (MIPs). However, even though PH is a convergent algorithm for convex problems, it is only a heuristic algorithm for nonconvex cases, such as for MIPs; column generation (CG) is an exact method

[1]Note that, due to the vastness and complexity of the literature, any omissions or inaccurate characterization of the works cited here is strictly due to the limitation of the authors' knowledge.

TABLE I
COMPARISON OF SUC METHODS

| Stochastic Optimization UC methods | Structures | Algorithms and Literature | Advantages | Disadvantages |
|---|---|---|---|---|
| Stochastic Programming | Two-stage models | ▪ Benders Decomposition (BD) [16][55][78]<br>▪ Accelerated BD [99]<br>▪ Lagrangian Relaxation (LR) [56][73]<br>▪ Stabilized LR (using Bundle methods) [47-49][57]<br>▪ Sample Average Approximation [74-76] | ▪ Minimize total expected cost; easier to understand (and compute) than minimizing regret or minimizing the worst-case cost.<br>▪ Various decomposition and sampling-based algorithms already existed with convergence and performance guarantees.<br>▪ Can address robustness issues using risk measures.<br>▪ Can provide expected value of perfect information (EVPI) and value of stochastic solution (VSS). | ▪ Need to assign probabilities for scenarios.<br>▪ Computationally demanding for large numbers of scenarios.<br>▪ Difficulties in dealing with integer variables in the second stage (e.g., unit rescheduling in real-time).<br>▪ Static assumption of the uncertainties. |
| | Multi-stage models | ▪ Lagrangian Relaxation (LR) [42-43]<br>▪ Augmented LR [45]<br>▪ Column Generation (CG) [65]<br>▪ Progressive Hedging [44]<br>▪ Stabilized LR or CG (using Bundle methods) [48][50][64]<br>▪ Nested CG [67] | ▪ Truly a decision-making model (as opposed to "what-if" analysis) over multiple time periods under uncertainty.<br>▪ Ability to model the dynamic process of uncertainties and decisions.<br>▪ Useful for systems with generators that can reschedule quickly.<br>▪ Can provide EVPI and VSS. | ▪ Curse of dimensionality, and hence computationally very expensive.<br>▪ Need explicit scenario trees and random paths' probabilities.<br>▪ Even more difficult with integer variables present in all stages. |
| Robust Optimization | Bi-level and tri-level models | ▪ Benders Cutting Plane method (dual) [27][29][32-35][87-89]<br>▪ Column-Constraint Generation method (primal) [28][34] | ▪ Do not need probability distribution.<br>▪ Solutions can provide decision-makers guarantee towards the worst-case.<br>▪ Computationally not as demanding as stochastic programming models with large numbers of scenarios. | ▪ May yield over-conservative solutions.<br>▪ Need expertise and rationale on uncertainty set construction.<br>▪ Need to use different algorithms for different types of uncertainty sets.<br>▪ Difficult to incorporate the uncertainty dynamics (e.g., multi-level/stage models). |
| (Approx.) Stochastic Dynamic Programming | multi-stage, discrete time models | ▪ Value-function approximation [97]<br>▪ Policy iteration/Model predictive control [95, 96]<br>▪ State-space approximation [94] | ▪ ADP can handle multi-stage stochastic problems with relatively low computational burden.<br>▪ Can model closed-loop systems (such as real-time pricing). | ▪ For ADP, convergence to optimal solutions may be difficult to establish.<br>▪ Integer variables may present difficulties in general. |

but could have slow and unstable convergence issues. It may be accelerated and stabilized using bundle-type methods; nested CG can help solve large-scale problems with multilevel decisions. For robust optimization UC models, methods based on primal cuts (although including more variables) have been shown to have faster convergence over the ones using dual cuts, especially when applied in contingency-based robust UC models [34]. Within the category of stochastic dynamic programming, what accounts for an efficient algorithm often depends on the specific problems at hand. While value function approximation may be intuitive to apprehend and implement, policy-iteration based approximation methods may produce more efficient algorithms. (See [93] for more detailed discussion and numerical comparisons.)

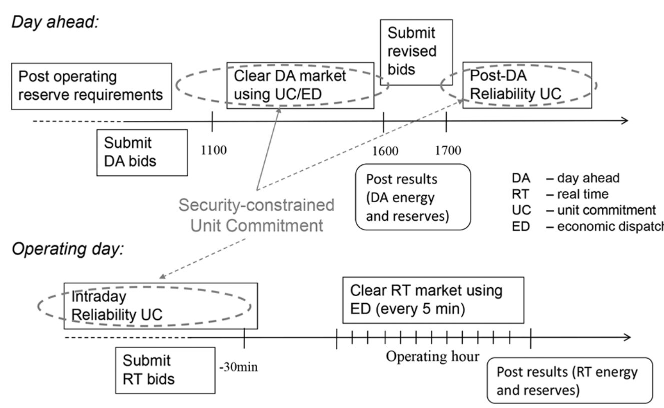



Fig. 3. Role of UC in electricity market operations.

## IV. MARKET OPERATIONS

UC has multiple applications in electricity market operations. Fig. 3 shows a typical U.S. electricity market operation timeline. As can be seen, UC can be used to aid day-ahead market clearing, and to improve post-day- ahead and intraday reliability. These applications serve as potential candidates for SO-based UC in the market procedure. If SO is mainly used in reliability UC procedures, common issues such as computational requirements would emerge. When it comes to the application of SO in day-ahead market clearing, additional issues exist.

First and foremost, stochastic market clearing needs to ensure revenue adequacy, which means the payment based on the proposed model must be lower than the revenue received. Due to the variety of SO methods used in the literature, revenue adequacy is not guaranteed and has been largely ignored. Stochastic market clearing considering contingencies is discussed in a series of early papers in [100]–[102]. The most salient feature of the model is that the reserve requirements are not predetermined; instead, they are calculated by simulating probabilistic contingencies. In [103], a single-settlement energy-only market is proposed to consider unpredictable and intermittent participants such as wind power producers. A stochastic-programming-based model is used and shown to be revenue adequate in expectation. However, the model does not consider other market products such as ancillary services in the formulation. The impact of co-optimization of energy and ancillary services, which is the current practice in the industry, needs further investigation. An energy and reserve cooptimization model using SO is studied in [104]. The model is mainly focused on $N-1$ contingency scenarios without addressing the extra uncertainty from renewable generation. A stochastic market clearing model with wind producers is introduced in [105]. The model can maintain revenue adequacy and generate prices that are suitable for both wind producers and conventional units. However, non-convexities such as start-up costs or minimum power output limits are not included.

Among various stochastic optimization methods, robust optimization has been increasingly favored by the system operators [98], [106]. Compared with the other methods such as stochastic UC where issues regarding the number of scenarios and computational complexity exist, robust UC is less computation-intensive and more acceptable to the system operators as their top operation priority is to ensure the system reliability even in the worst-case scenario, which is guaranteed by robust UC. Robust UC can have multiple applications in the market operation process including the reliability UC runs and real-time look-ahead UC as discussed in [98], [106].

In summary, market clearing with stochastic formulations is a complex issue. Revenue adequacy and associated issues such as pricing, settlement, market power, and uplift charges all need to be addressed before any model can be put into use in practice. Furthermore, the model should be transparent, fair, and comprehensible for all the market participants involved to reach consensus. It is expected that issues such as the definition of scenarios, number of scenarios and definition of uncertainty sets related to SO will be highly contentious among the various stakeholders/regulators and remain a barrier to implementing SO in the market clearing process.

## V. Conclusion and Future Research

There is an increasing demand to equip UC with better uncertainty handling to integrate increasing renewable penetration. A large body of research effort has been devoted to apply SO-techniques in UC applications. This paper reviews three main issues associated with modeling the UC problems under uncertainty: uncertainty modeling, model and solution algorithms, and market operations. Based on the analysis and discussion of the existing research literature on SO for UC, we point out various possibilities to extend relevant research as follows.

### A. Uncertainty Modeling

While the forecasting methods for renewable generation such as wind and solar have made significant progress in recent years, the errors of such forecasts are still an order of magnitude larger than load forecasting in general. Besides the need for further research on forecasting, how to incorporate forecasting errors is critical for all the SO methods discussed above. The modeling and inclusion of forecast errors strongly depends on the quality of forecasts and directly leads to the choice of a specific SO framework (e.g., scenario-based stochastic programming or uncertainty-set-based robust optimization [27]). The selection of a certain SO method is also case dependent and highly influenced by the risk preference of the system operator. A delicate balance needs to be achieved between economics and reliability (e.g., reducing the over-conservativeness of robust optimization). New research topics in this area include the following.

1) Better weather forecasting. As the objective of weather forecasting is driven by how it is used in system operations, renewable generation forecasting and how to incorporate it in system operations are closely coupled and should be analyzed in an integrated fashion.
2) Improvement of existing SO approaches. For instance, many questions such as the number of scenarios, scenario reduction, and the evaluation of the quality of scenarios in stochastic programming still need further research. It is also worth investigating how to integrate the advantages of each individual stochastic techniques into system operations [88].
3) Novel uncertainty modeling concepts. A significant amount of research is being carried out in the operations research field that can be leveraged to address power system problems. For example, newer topics such as data-driven robust optimization, distributionally robust optimization, and the recently-revived decision-rule approximation method [107] all hold promise in overcoming some challenging data issues for power grid applications. Distributionally robust optimization assumes that the probability distribution of the uncertainty is not well known, and seeks to find a set of cost-effective solutions that for all possible probability distributions, are either always feasible or at least feasible in the worst case [108], [109]. This is a contrast to the stochastic models with risk measures, which usually assume the complete knowledge of probability distributions of the underlying uncertainty.
4) Multiscale modeling. The multiple sources of uncertainties in system operations usually exhibit various temporal resolutions, ranging from instantaneous contingencies, to constant demand and renewable output fluctuations, to daily fuel supply variations. More detailed modeling of different decisions that correspond to the unfolding of the multiscale uncertainties will improve model fidelity, and hence help bring academic models closer to real-world implementation.

### B. Computational Challenges and Approaches

Advances in modeling also bring new challenges to computational algorithms. In stochastic-programming-based models, real operational practices and modeling requirements introduce discrete decisions in the second stage, such as quick-start generator rescheduling and chance constraints. Efficient and effective convexification methods [61] can be applied to the discrete second stage to help apply decomposition algorithms. For general SUC problems, acceleration techniques with more effective cuts [99] can be integrated in decomposition algorithms to speed up the algorithm convergence rate. When considering a very large number of scenarios, efficient scenario selection and reduction methods should be sought and integrated with corresponding decomposition algorithms. In robust-optimization-based models, advanced algorithms for bilinear, or even trilinear programs, should be developed to efficiently solve RUC problem with more general uncertainty sets. Novel reformulations and algorithms based on nested decomposition [87] could be used to handle adaptive RUC models with multiple stages and distributionally robust models. In SDP-based models, approximation algorithms are unavoidable to overcome the curse of dimensionality. Value function approximation approaches using post-state decision variables [93], [97] and those using linear programming [110] all show promising computational performance, while having solution quality guarantees under certain conditions. Applications of MPC methods to UC also deserve more investigation [95].

### C. Market Design

The current market design needs to be revised to accommodate the employment of SO techniques. Compared to the uncertainty modeling and computational approaches, there is less research on market design issues for SO. A great deal of research needs to be carried out on such sensitive issues as settlement rules and pricing in order for them to be acceptable to all market participants before SO is fully implemented in practice. How forecasting errors would affect market prices, and how to calculate requirements and fair compensations for reserves, also deserve further study in SO-based market operations. In addition, sustainability and environmental impacts have received more attentions in power systems operations (e.g., [111]).

## Acknowledgment

The authors would like to thank Dr. F. Qiu for discussions and the reviewers for suggestions.

## References

[1] A. Wood and B. Wollenberg, *Power Generation Operation and Control*. New York, NY, USA: Wiley, 1996.

[2] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*. New York, NY, USA: Wiley, 2002.

[3] C.-L. Tseng, "On Power System Generation Unit Commitment Problems," Ph.D. dissertation, Dept. Ind. Eng. Oper. Res., Univ. California, Berkeley, CA, USA, Dec. 1996.

[4] N. P. Padhy, "Unit commitment—A bibliographical survey," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1196–1205, May 2004.

[5] U.S. Dept. Energy, "20% Wind Energy by 2030: Increasing Wind Energy's Contribution to U.S. Electricity Supply," Jul. 2008 [Online]. Available: http://www1.eere.energy.gov/wind/pdfs/41869.pdf

[6] "Accommodating High Levels of Variable Generation," NERC, , Tech. Rep., Apr. 2009 [Online]. Available: http://www.nerc.com/files/IVGTF_Report_041609.pdf

[7] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*. New York, NY, USA: Springer Verlag, 1997.

[8] C. Monteiro, R. Bessa, V. Miranda, A. Botterud, J. Wang, and G. Conzelmann, "A Quick Guide to Wind Power Forecasting: State-of-the-Art," Argonne Nat. Lab., , Tech. Rep. ANL/DIS-10-2, Nov. 2009 [Online]. Available: http://www.dis.anl.gov/pubs/65614.pdf

[9] P. Pinson, G. Papaefthymiou, B. Klockl, H. Nielsen, and H. Madsen, "From probabilistic forecasts to statistical scenarios of short-term wind power production," *Wind Energy*, vol. 12, no. 1, pp. 51–62, 2009.

[10] J. M. Morales, R. Mínguez, and A. J. Conejo, "A methodology to generate statistically dependent wind speed scenarios," *Appl. Energy*, vol. 87, no. 3, pp. 843–855, Mar. 2010.

[11] P. Pinson and R. Girard, "Evaluating the quality of scenarios of short-term wind power generation," *Appl. Energy*, vol. 96, pp. 12–20, Aug. 2012.

[12] M. Ortega-Vazquez and D. Kirschen, "Estimating the spinning reserve requirements in systems with significant wind power generation penetration," *IEEE Trans. Power Syst.*, vol. 24, no. 1, pp. 114–124, Feb. 2009.

[13] D. Pozo and J. Contreras, "A chance-constrained unit commitment with an n-k security criterion and significant wind generation," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2842–2851, Aug. 2013.

[14] C. Lowery and M. O'Malley, "Impact of wind forecast error statistics upon unit commitment," *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 760–768, Oct. 2012.

[15] B. Venkatesh, P. Yu, H. Gooi, and D. Choling, "Fuzzy MILP unit commitment incorporating wind generators," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1738–1746, Nov. 2008.

[16] J. Wang, M. Shahidehpour, and Z. Li, "Security-constrained unit commitment with volatile wind power generation," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1319–1327, Aug. 2008.

[17] R. Billinton, B. Karki, R. Karki, and G. Ramakrishna, "Unit commitment risk analysis of wind integrated power systems," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 930–939, May 2009.

[18] J. Restrepo and F. Galiana, "Assessing the yearly impact of wind power through a new hybrid deterministic/stochastic unit commitment," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 401–410, Feb. 2011.

[19] S. Ahmed and A. Shapiro, "Solving chance-constrained stochastic programs via sampling and integer programming," *Tuts. Oper. Res.*, vol. 27, no. 3, pp. 261–269, 2008.

[20] W. K. Mak, D. P. Morton, and R. K. Wood, "Monte carlo bounding techniques for determining solution quality in stochastic programs," *Oper. Res. Lett.*, vol. 24, pp. 47–56, 1999.

[21] J. Sumaili, H. Keko, V. Miranda, A. Botterud, and J. Wang, "Clustering-based wind power scenario reduction technique," in *Proc. 17th Power Syst. Computation Conf.*, Stockholm, Sweden, Aug. 2011, pp. 391–397.

[22] J. Dupacová, N. Gröwe-Kuska, and W. Römisch, "Scenario reduction in stochastic programming: An approach using probability metrics," *Math. Programming A*, vol. 3, pp. 493–511, 2003.

[23] N. Gröwe-Kuska, H. Heitsch, and W. Römisch, "Scenario reduction and scenario tree construction for power management problems," in *Proc. IEEE Power Tech. Conf.*, Bologna, Italy, Jun. 2003, pp. 1–7.

[24] J. B. Bremnes, "Probabilistic wind power forecasts using local quantile regression," *Wind Energy*, vol. 7, no. 1, pp. 47–54, 2004.

[25] J. Juban, L. Fugon, and G. Kariniotakis, "Probabilistic short-term wind power forecasting based on kernel density estimators," in *Proc. Eur. Wind Energy Conf.*, Milan, Italy, 2007, pp. 1–11.

[26] R. Bessa, V. Miranda, A. Botterud, Z. Zhou, and J. Wang, "Time-adaptive quantile-copula for wind power probabilistic forecasting," *Renewable Energy*, vol. 40, no. 1, pp. 29–39, 2012.

[27] Y. Guan and J. Wang, "Uncertainty sets for robust unit commitment," *IEEE Trans. Power Syst.*, vol. 29, no. 3, pp. 1439–1440, Aug. 2014.

[28] L. Zhao and B. Zeng, "Robust unit commitment problem with demand response and wind energy," in *Proc. IEEE Power and Energy Soc. Gen. Meeting*, 2012, pp. 1–8.

[29] D. Bertsimas, E. Litvinov, X. Sun, J. Zhao, and T. Zheng, "Adaptive robust optimization for the security constrained unit commitment problem," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 52–63, Feb. 2013.

[30] A. Ben-Tal, L. E. Ghaoui, and A. Nemirovski, *Robust Optimization*, ser. Princeton Series in Appl. Math.. Princeton, NJ, USA: Princeton Univ., 2009.

[31] D. Bertsimas, D. Brown, and C. Caramanis, "Theory and applications of robust optimization," *SIAM Rev.*, vol. 53, no. 3, pp. 464–501, 2011.

[32] A. Street, F. Oliveira, and J. Arroyo, "Contingency-constrained unit commitment with N-k security criterion: A robust optimization approach," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1581–1590, Aug. 2011.

[33] P. Xiong and P. Jirutitijaroen, "An adjustable robust optimization approach for unit commitment under outage contingencies," in *Proc. IEEE Power and Energy Soc. Gen. Meeting*, 2012, pp. 1–8.

[34] Q. Wang, J.-P. Watson, and Y. Guan, "Two-stage robust optimization for N - k contingency-constrained unit commitment," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2366–2375, Aug. 2013.

[35] R. Jiang, J. Wang, and Y. Guan, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 800–810, May 2012.

[36] A. Nemirovski and A. Shapiro, "Convex approximations of chance constrained programs," *SIAM J. Optim.*, vol. 17, no. 4, pp. 969–996, 2007.

[37] W. Chen, M. Sim, J. Sun, and C.-P. Teo, "From CVaR to uncertainty set: Implications in joint chance-constrained optimization," *Oper. Res.*, vol. 58, no. 2, pp. 470–485, 2010.

[38] D. Bertsimas and D. B. Brown, "Constructing uncertainty sets for robust linear optimization," *Oper. Res.*, vol. 57, no. 6, pp. 1483–1495, 2009.

[39] G. B. Sheble and G. Fahd, "Unit commitment literature synopsis," *IEEE Trans. Power Syst.*, vol. 9, no. 1, pp. 128–135, Feb. 1994.

[40] R. Baldick, "The generalized unit commitment problem," *IEEE Trans. Power Syst.*, vol. 10, no. 1, pp. 465–475, Feb. 1995.

[41] J. Wang, A. Botterud, V. Miranda, C. Monteiro, and G. Sheble, "Impact of wind power forecasting on unit commitment and dispatch," in *Proc. 8th Int. Wind Integration Workshop*, Bremen, Germany, Oct. 2009, pp. 1–8.

[42] L. Wu, M. Shahidehpour, and T. Li, "Stochastic security-constrained unit commitment," *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 800–811, May 2007.

[43] S. Takriti, B. Krasenbrink, and L. S.-Y. Wu, "Incorporating fuel constraints and electricity spot prices into the stochastic unit commitment problem," *Oper. Res.*, vol. 48, no. 2, pp. 268–280, 2000.

[44] S. Takriti, J. R. Birge, and E. Long, "A stochastic model for the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 11, no. 3, pp. 1497–1508, Aug. 1996.

[45] P. Carpentier, G. Gohen, J.-C. Culioli, and A. Renaud, "Stochastic optimization of unit commitment: A new decomposition framework," *IEEE Trans. Power Syst.*, vol. 11, no. 2, pp. 1067–1073, May 1996.

[46] N. Gröwe, W. Römisch, and R. Schultz, "A simple recourse model for power dispatch under uncertain demand," *Ann. Oper. Res.*, vol. 59, no. 1, pp. 135–164, 1995.

[47] C. C. Carøe, A. Ruszczyński, and R. Schultz, "Unit Commitment Under Uncertainty Via Two-Stage Stochastic Programming," Dept. Comput. Sci., Univ. Copenhagen, Copenhagen, Denmark, Tech. Rep. DIKU-TR-97/23, 1997.

[48] D. Dentcheva and W. Römisch, , K. Marti and P. Kall, Eds., "Optimal power generation under uncertainty via stochastic programming," in *Stochastic Programming Methods and Technical Applications*, ser. Lecture Notes in Economics and Math. Syst.. Berlin, Germany: Springer, 1998, vol. 458, pp. 22–56.

[49] C. C. Carøe and R. Schultz, "A two-stage stochastic program for unit commitment under uncertainty in a hydro-thermal power system," Preprint SC 98-11, Konrad-Zuse-Zentrum Fur Informationstechnik 1998, pp. 1–17.

[50] L. Bacaud, C. Lemaréchal, A. Renaud, and C. Sagastizábal, "Bundle methods in stochastic optimal power management: A disaggregated approach using preconditioners," *Computational Optim. Applications*, vol. 20, no. 3, pp. 227–244, 2001.

[51] S. W. Wallace and S.-E. Fleten, , A. Ruszczyński and A. Shapiro, Eds., "Stochastic programming models in energy," in *Stochastic Programming*, ser. Handbooks in Oper. Res. Manag. Sci.. Dordrecht, The Netherlands: Elsevier, 2003, vol. 10, pp. 637–677.

[52] ABC Corp. REs., "Uncertainty of Renewable Power, Stochastic Unit Commitment, and Implication on DA Market," 2012 [Online]. Available: http://www.ferc.gov/CalendarFiles/20120627090051-Wednesday SessionB Feng.pdf

[53] P. Ruiz, C. Philbrick, E. Zak, K. Cheung, and P. Sauer, "Uncertainty management in the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 642–651, May 2009.

[54] P. Ruiz, C. Philbrick, and P. Sauer, "Modeling approaches for computational cost reduction in stochastic unit commitment formulations," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 588–589, 2010.

[55] Q. P. Zheng, J. Wang, P. M. Pardalos, and Y. Guan, "A decomposition approach to the two-stage stochastic unit commitment problem," *Ann. Oper. Res.*, vol. 210, no. 4, pp. 387–410, 2013.

[56] A. Papavasiliou and S. S. Oren, "Multiarea stochastic unit commitment for high wind penetration in a transmission constrained network," *Oper. Res.*, vol. 61, no. 3, pp. 578–592, 2013.

[57] M. P. Nowak, R. Schultz, and M. Westphalen, "A stochastic integer programming model for incorporating day-ahead trading of electricity into hydro-thermal unit commitment," *Optim. Eng.*, vol. 6, no. 2, pp. 163–176, 2005.

[58] B. F. Hobbs, M. H. Rothkopf, R. P. O'Neil, and H. Chao, *The Next Generation of Electric Power Unit Commitment Models*. Norwell, MA, USA: Kluwer Academic, 2001.

[59] J. Morales, A. Conejo, and J. Perez-Ruiz, "Economic valuation of reserves in power systems with high penetration of wind power," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 900–910, May 2009.

[60] A. Tuohy, P. Meibom, E. Denny, and M. O'Malley, "Unit commitment for systems with significant wind penetration," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 592–601, May 2009.

[61] R. Jabr, "Tight polyhedral approximation for mixed-integer linear programming unit commitment formulations," *IET Gener., Transm. Distrib.*, vol. 6, pp. 1104–1111(7), Nov. 2012.

[62] A. Ruszczyński, , A. Ruszczyński and A. Shapiro, Eds., "Decomposition methods," in *Stochastic Programming*, ser. Handbooks Oper. Res. Manag. Sci.. Dordrecht, The Netherlands: Elsevier, 2003, vol. 10, pp. 637–677.

[63] A. Ruszczyński and A. Shapiro, *Stochastic Programming*, ser. Handbooks Oper. Res. Manag. Sci.. Dordrecht, The Netherlands: Elsevier, 2003.

[64] M. P. Nowak and W. Römisch, "Stochastic Lagrangian relaxation applied to power scheduling in a hydro-thermal system under uncertainty," *Ann. Oper. Res.*, vol. 100, pp. 251–272, 2000.

[65] T. Shiina and J. R. Birge, "Stochastic unit commitment problem," *Int. Trans. Oper. Res.*, vol. 11, pp. 19–32, 2004.

[66] T. Li, M. Shahidehpour, and Z. Li, "Risk-constrained bidding strategy with stochastic unit commitment," *IEEE Trans. Power Syst.*, vol. 22, no. 1, pp. 449–458, Feb. 2007.

[67] S. Sen, L. Yu, and T. Genc, "A stochastic programming approach to power portfolio optimization," *Oper. Res.*, vol. 54, no. 1, pp. 55–72, 2006.

[68] R. T. Rockafellar and J.-B. Wets, "Scenario and policy aggregation in optimization under uncertainty," *Math. Oper. Res.*, vol. 16, no. 1, pp. 119–147, 1991.

[69] H. Gooi, D. Mendes, K. R. W. Bell, and D. Kirschen, "Optimal scheduling of spinning reserve," *IEEE Trans. Power Syst.*, vol. 14, no. 4, pp. 1485–1492, Nov. 1999.

[70] F. Bouffard and F. Galiana, "An electricity market with a probabilistic spinning reserve criterion," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 300–307, Feb. 2004.

[71] A. Ahmadi-Khatir, M. Bozorg, and R. Cherkaoui, "Probabilistic spinning reserve provision model in multi-control zone power system," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2819–2829, Aug. 2013.

[72] A. Conejo, F. Nogales, J. Arroyo, and R. Garcia-Bertrand, "Risk-constrained self-scheduling of a thermal power producer," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1569–1574, Aug. 2004.

[73] U. Ozturk, M. Mazumdar, and B. Norman, "A solution to the stochastic unit commitment problem using chance constrained programming," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1589–1598, Aug. 2004.

[74] Q. Wang, J. Wang, and Y. Guan, "Wind power bidding based on chance-constrained optimization," in *Proc. IEEE Power and Energy Soc. Gen. Meeting*, 2011, pp. 1–2.

[75] Q. Wang, Y. Guan, and J. Wang, "A chance-constrained two-stage stochastic program for unit commitment with uncertain wind power output," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 206–215, Feb. 2012.

[76] Q. Wang, J. Wang, and Y. Guan, "Stochastic unit commitment with uncertain demand response," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 562–563, Feb. 2013.

[77] R. Jabr, "Robust self-scheduling under price uncertainty using conditional value-at-risk," *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1852–1858, Nov. 2005.

[78] Y. Huang, Q. P. Zheng, and J. Wang, "Two-stage stochastic unit commitment model including non-generation resources with conditional value-at-risk constraints," *Electr. Power Syst. Res.*, vol. 116, pp. 427–438, Nov. 2014.

[79] H. Y. Yamin and M. S. Shahidehpour, "Risk and profit in self-scheduling for GENCOS," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2104–2106, 2004.

[80] A. Philpott and R. Schultz, "Unit commitment in electricity pool markets," *Math. Programming*, vol. 108, no. 2–3, pp. 313–337, 2006.

[81] D. Chattopadhyay and R. Baldick, "Unit commitment with probabilistic reserve," in *Proc. IEEE Power Eng. Soc. Winter Meeting*, 2002, vol. 1, pp. 280–285, vol. 1.

[82] R. T. Rockafellar and S. Uryasev, "Optimization of conditional value-at-risk," *J. Risk*, vol. 2, pp. 21–42, 2000.

[83] Q. P. Zheng and P. M. Pardalos, "Stochastic and risk management models and solution algorithm for natural gas transmission network expansion and lng terminal location planning," *J. Optim. Theory Applic.*, vol. 147, pp. 337–357, 2010.

[84] P. Artzner, F. Delbaen, J.-M. Eber, and D. Heath, "Coherent measures of risk," *Math. Finance*, vol. 9, no. 3, pp. 203–228, 1999.

[85] A. Ben-Tal and M. Teboulle, “An old-new concept of convex risk measures: The optimized certainty equivalent,” *Math. Finance*, vol. 17, no. 3, pp. 449–476, 2007.

[86] A. Shapiro, “Minimax and risk averse multistage stochastic programming,” *Eur. J. Oper. Res.*, vol. 219, no. 3, pp. 719–726, 2012.

[87] C. Zhao, J. Wang, J.-P. Watson, and Y. Guan, “Multi-stage robust unit commitment considering wind and demand response uncertainties,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2708–2717, Aug. 2013.

[88] C. Zhao and Y. Guan, “Unified stochastic and robust unit commitment,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 3353–3361, Aug. 2013.

[89] R. Jiang, J. Wang, M. Zhang, and Y. Guan, “Two-stage minimax regret robust unit commitment,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2271–2282, Aug. 2013.

[90] C. K. Pang and H. C. Chen, “Optimal short-term thermal unit commitment,” *IEEE Trans. Power App. Syst.*, vol. 95, no. 4, pp. 1336–1346, 1976.

[91] R. Bellman, “On the theory of dynamic programming,” *Proc. Nat. Acad. Sci. USA*, vol. 38, no. 8, pp. 716–719, 1952.

[92] D. P. Bertsekas*, Dynamic Programming and Optimal Control*. Belmont: Athena Scientific, 2007, vol. 1, no. 2.

[93] W. B. Powell*, Approximate Dynamic Programming: Solving the Curses of Dimensionality*, 2nd ed. Hoboken, NJ, USA: Wiley, 2011.

[94] W. Zhang and D. Nikovski, “State-space approximate dynamic programming for stochastic unit commitment,” in *Proc. North Amer. Power Symp.*, 2011, pp. 1–7.

[95] L. Xie and M. D. Ilic, “Model predictive dispatch in electric energy systems with intermittent resources,” in *Proc. IEEE Int. Conf. Syst., Man Cybern.*, 2008, pp. 42–47.

[96] L. Xie and M. D. Ilic, “Model predictive economic/environmental dispatch of power systems with intermittent resources,” in *Proc. IEEE Power Energy Soc. Gen. Meeting*, 2009, pp. 1–6.

[97] J. Xiao, “Grid integration and smart grid implementation of emerging technologies in electric power systems through approximate dynamic programming,” Ph.D. dissertation, Sch. Electr. Eng., Purdue Univ., West Lafayette, IN, USA, 2013.

[98] Y. Chen, X. Wang, and Y. Guan, “Applying Robust Optimization to MISO Look-Ahead Unit Commitment,” [Online]. Available: http://www.ferc.gov/CalendarFiles/20140411125134-M1

[99] L. Wu and M. Shahidehpour, “Accelerating the benders decomposition for network-constrained unit commitment problems,” *Energy Syst.*, vol. 1, no. 3, pp. 339–376, 2010.

[100] F. Bouffard, F. D. Galiana, and A. J. Conejo, “Market-clearing with stochastic security—Part I: Formulation,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1818–1826, Nov. 2005.

[101] F. Bouffard, F. D. Galiana, and A. J. Conejo, “Market-clearing with stochastic security—Part II: Case studies,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1827–1835, Nov., 2005.

[102] F. D. Galiana, F. Bouffard, J. M. Arroyo, and J. F. Restrepo, “Scheduling and pricing of coupled energy and primary, secondary and tertiary reserves,” *Proc. IEEE*, vol. 93, no. 11, pp. 1970–1983, Nov. 2005.

[103] G. Pritchard, G. Zakeri, and A. Philpott, “A single-settlement, energy-only electric power market for unpredictable and intermittent participants,” *Oper. Res.*, vol. 58, no. 4, Pt. 2, pp. 1210–1219, 2010.

[104] S. Wong and D. J. Fuller, “Pricing energy and reserves using stochastic optimization in an alternative electricity market,” *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 631–638, May 2007.

[105] J. Morales, A. Conejo, K. Liu, and J. Zhong, “Pricing electricity in pools with wind producers,” *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1366–1376, Aug. 2012.

[106] E. Litvinov, J. Zhao, T. Zheng, F. Zhao, D. Bertsimas, and A. Sun, “Study of Two-Stage Robust Unit Commitment,” 2011 [Online]. Available: http://www.ferc.gov/CalendarFiles/20110628072925-Jun28-SesA3-Zhao-ISONE.pdf

[107] J. Warrington, P. Goulart, S. Mariethoz, and M. Morari, “Policy-based reserves for power systems,” *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4427–4437, Nov. 2013.

[108] E. Delage and Y. Ye, “Distributionally robust optimization under moment uncertainty with application to data-driven problems,” *Oper. Res.*, vol. 58, no. 3, pp. 595–612, 2010.

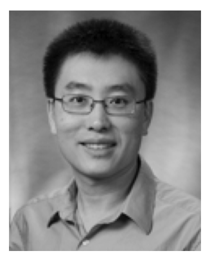
[109] A. Ben-Tal, D. Bertsimas, and D. B. Brown, “A soft robust model for optimization under ambiguity,” *Oper. Res.*, vol. 58, no. 4-Part-2, pp. 1220–1234, 2010.

[110] D. P. de Farias and B. Van Roy, “The linear programming approach to approximate dynamic programming,” *Oper. Res.*, vol. 51, no. 6, pp. 850–865, 2003.

[111] , Q. P. Zheng, S. Rebennack, P. M. Pardalos, M. V. F. Pereira, and N. A. Iliadis, Eds.*, Handbook of $CO_2$ in Power Systems*, ser. Energy Syst.. Berlin, Germany: Springer, 2012.


**Qipeng P. Zheng** (M’10) received the B.S. degree in automation from North China University of Technology, Beijing, China, in 2001, the M.S. degree in automation from Tsinghua University, Beijing, China, in 2005, and the Ph.D. degree in industrial and systems engineering from the University of Florida, Gainesville, FL, USA, in 2010.

He is an Assistant Professor with the Department of Industrial Engineering and Management Systems, University of Central Florida, Orlando, FL, USA. His research area is optimization and applications, especially in energy and power systems and transportation planning under uncertainty. He is an associate editor of the journal Energy Systems.



**Jianhui Wang** (M’07–SM’12) received the Ph.D. degree in electrical engineering from Illinois Institute of Technology, Chicago, IL, USA, in 2007.

Presently, he is a Computational Engineer with the Decision and Information Sciences Division at Argonne National Laboratory, Argonne, IL, USA. He is also an Affiliate Professor with Auburn University and an Adjunct Professor with the University of Notre Dame.

Dr. Wang is the secretary of the IEEE Power & Energy Society (PES) Power System Operations Committee. Before being promoted and elected to this position, he was the chair of the IEEE PES Power System Operation Methods Subcommittee for six years. He is an editor of the IEEE TRANSACTIONS ON POWER SYSTEMS, the IEEE TRANSACTIONS ON SMART GRID, an associate editor of the *Journal of Energy Engineering*, an editor of the IEEE PES LETTERS, and an associate editor of *Applied Energy*. He is an IEEE PES Distinguished Lecturer.

**Andrew L. Liu** (M’10) received the B.S. degree in applied mathematics from Beijing Institute of Technology, Beijing, China, in 2000, and the Ph.D. degree in applied mathematics and statistics from the Johns Hopkins University, Baltimore, MD, USA, in 2009.

He is currently an Assistant Professor with the School of Industrial Engineering, Purdue University, West Lafayette, IN, USA. Before joining Purdue, he was a Senior Associate with the Wholesale Power Group at ICF International, Fairfax, VA, USA. His research interests include optimization, game theory and their applications in power systems, smart grid, and environmental policy analysis.