Comparison of Scenario-Based and Interval Optimization Approaches to Stochastic SCUC

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***Abstract*—This paper compares applications of scenario-based and interval optimization approaches to stochastic security-constrained unit commitment (Stochastic SCUC). The uncertainty of wind power generation is considered in this study to compare the two approaches, while other types of uncertainty can be addressed similarly. For the simulation of uncertainty, the scenario-based approach considers the Monte Carlo (MC) method, while lower and upper bounds are adopted in the interval optimization. The Stochastic SCUC problem is formulated as a mixed-integer linear programming (MIP) problem and solved using the two approaches. The scenario-based solutions are insensitive to the number of scenarios, but present additional computation burdens. The interval optimization solution requires less computation and automatically generates lower and upper bounds for the operation cost and generation dispatch, but its optimal solution is very sensitive to the uncertainty interval. The numerical results on a six-bus system and the modified IEEE 118-bus system show the attributes of the two approaches for solving the Stochastic SCUC problem. Several convergence acceleration options are also discussed for overcoming the computation obstacles in the scenario-based approach.**

***Index Terms*—Interval optimization, scenario-based approach, stochastic SCUC.**

NOMENCLATURE

Variables:

i	Index of thermal units.
I_{it}	Commitment of unit i at time t.
k	Index of curve segments.
P_{ikt}	Dispatch of unit i at time t at segment k.
ΔP_{ikt}^s	Corrective dispatch capability of unit i at time t at segment k in scenario s.
P_{it}	Power dispatch of unit i at time t.
P_{wt}	Power dispatch of wind unit w at time t.
s	Index of scenarios.
$s_{(\cdot)}^{(\cdot)}$	Slack variable.
SU_{it}, SD_{it}	Startup/shutdown cost of unit i at time t.
t	Index of hours.
w	Index of wind generation units.
θ_t^s	Production cost of scenario s at time t.
λ, μ	Dual variables.
$\hat{\cdot}$	Solution to variable.
$(\cdot)^s$	Variable related to scenario s.
$(\cdot)^{\pm}$	Interval variable.

Constants:

c_{ik}	Incremental cost for segment k of unit i.
N_i	No load cost of unit i.
p^s	Probability of scenario s.
P_{Dt}	System load at time t.
$P_{f,wt}^-$	Interval numbers for the pessimistic wind scenario.
$P_{f,wt}^+$	Interval numbers for the optimistic wind scenario.
P_i^{min}	Minimum capacity of unit i.
P_i^{max}	Maximum capacity of unit i.
$P_{ik}^{\max}$	Power capacity of segment k of unit i.
$P_{f,wt}$	Generation forecast for wind unit w at time t.
R_i^{up}, R_i^{dn}	Up/down limits for corrective dispatch of unit i.

Matrices and Vectors:

$\mathbf{K_P}, \mathbf{K_D}$	Bus-generator/bus-load incidence matrix.
$\mathbf{PL^{max}}$	Vector of upper limit for power flow.
SF	Shift factor matrix.

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I. Introduction

THE wind generation uncertainty and price-sensitive demand response (DR) introduce new challenges for managing the operational security of electric power systems. Operational data from wind power plants in Denmark [1], Finland [2], and Germany [3] show that the hourly wind energy may often swing by about 20% of its installed capacity within a short span of time. Such fluctuations make it a challenging task to accurately forecast the short-term wind power generation. State-of-the-art forecasting techniques can predict the wind farm aggregated power generation for the next several hours with a forecast error of 5%–20% of the installed capacity [4], [5]. With DR, the price-sensitive load forecasting would require additional price-related inputs. However, price forecast errors of 5%–20% are not uncommon [6]–[8], which will further deteriorate the accuracy of price-sensitive load forecasts.

The modern power systems would have to plan for alternate backup generation in case the day-ahead wind power generation forecast does not materialize or the real-time consumption deviates a lot from the DR-based load forecasts. When the wind power penetration reaches a critical level, the dependency of power systems to wind power generation could inevitably result in additional supply risks associated with the variability of wind speed. Furthermore, when DR reaches a critical market level, the inaccuracy of price-sensitive load forecast could inevitably pose real-time electricity balance risks.

The impact of uncertainty on the operational security of power systems is of fundamental importance when multiple uncertain factors are integrated into power systems. The operational security of power systems can be addressed via Stochastic SCUC. In this paper, the uncertainty of wind power generation is considered in Stochastic SCUC and two distinct solution approaches are compared for maintaining the operational security of power systems.

The first one is the scenario-based approach, in which multiple scenarios are generated to simulate the possible realization of uncertainties. With presumed probability distribution functions, scenarios are generated by the sampling method or the direct discretization of uncertain parameters. Reference [9] presented an effective AC corrective/preventive contingency dispatch for the SCUC model to minimize the system operation cost while maintaining the system security. Reference [10] explored a decentralized solution to the security-constrained optimal power flow problem for large interconnected multi-area power systems. Reference [11] proposed an analytically-sufficient condition for system demand and network parameters to manage security constraints in SCUC. Reference [12] used the N-K contingency criterion to study the impact of random generator outages on power system security. With the assumption that the load forecast uncertainty follows a normal distribution, [13] discretized the normal distribution into intervals and used mid-points as well as probabilities of individual intervals to represent load point uncertainties. References [14]–[16] studied the impact of random generator outages and load forecast errors on unit commitment (UC) via sample scenario trees. References [17] and [18] studied the impact of the high penetration wind power generation on UC, in which the wind forecast uncertainty was simulated via scenarios sampled from certain probability distributions.

A key issue in the scenario-based approach is to generate scenarios that would truly reflect the probabilistic characteristics of system uncertainties. Scenario-generation methods include MC sampling, moment matching principles, and methods motivated by stability analysis. A general survey of scenario tree algorithms is provided in [19]. The scenario-based approach acknowledges a given probability distribution for simulating uncertainties. A large number of scenarios are usually generated in order to achieve an acceptable solution accuracy, which could increase the scale and the computation burden significantly.

The second approach to Stochastic SCUC is the interval optimization. Instead of sampling scenarios, the interval optimization uses confidence intervals in terms of upper and lower bounds to represent the uncertainty spectrum, and derives optimistic and pessimistic solutions for satisfying the system security requirements. The interval optimization does not require a presumed probability distribution for uncertainties, since interval numbers are acceptable for uncertain inputs [20]–[22]. Reference [23] used the interval optimization to study the impact of bus load uncertainty on system security. The solution was obtained by transforming the problem into two extreme deterministic subproblems corresponding to upper and lower bounds of desired objective function values. Decision alternatives were derived by adjusting decision variables within their solution intervals. Although explicit probability distributions are not required in the interval optimization, the uncertainty intervals would need to be carefully selected. A narrow confidence interval may not cover the entire uncertainty spectrum and, in turn, lead to a UC solution that would not correspond to all possible uncertain situations. On the other hand, a wide interval could lead to pessimistic solutions which would not utilize system resources efficiently and be of limited use to system operators.

The chance-constrained UC was used in [24] to study the load uncertainty by specifying a probability at which stochastic constraints would hold. Usually, such chance constraints are nonconvex and generally intractable. The solution to the chance-constrained UC problem could be obtained by sampling scenarios to approximate the true distribution of random variables, or converting it to a sequence of deterministic UC problems which converge to the solution of the chance-constrained UC. The problem scale and the computation burden of the two options would be comparable to those of scenario-based and interval optimization approaches, respectively.

An efficient solution of Stochastic SCUC problem may often lack a rigorous representation of uncertainty when considering complex operating details of generating units and large-scale transmission networks. In this paper, the Stochastic SCUC problem is studied and the wind power generation uncertainty is considered by applying scenario-based and interval optimization approaches. The scenario-based approach generates multiple scenarios by the MC method to simulate the wind power generation uncertainty. In addition to the base case operation cost, the scenario-based approach minimizes expected costs of corrective actions. The interval optimization uses interval numbers, in terms of lower and upper bounds, to represent the wind power generation uncertainty. The major contribution of this paper is to compare the two approaches to the solution of Stochastic SCUC to address the power system security.

The rest of the paper is organized as follows. Sections II and III present the scenario-based and interval optimization approaches. Section IV applies a six-bus system and the modified IEEE 118-bus system to compare the two approaches. Several convergence acceleration options are discussed in Section V, and the conclusion is drawn in Section VI.

II. Scenario-Based Stochastic SCUC

A. Scenario-Based Stochastic SCUC Formulation

A large number of scenarios are generated to simulate wind speed uncertainty, which would follow the Weibull probability distribution function with the autocorrelation factor and diurnal pattern [25]. The hourly wind energy is procured according to the power curve of wind turbines and hourly wind speed. Other statistical distributions can be similarly considered. The low-discrepancy Latin Hypercube Sampling (LHS) technique is adopted for decreasing the variance of simple MC simulation. Each scenario is assigned a probability that is one divided by the number of scenarios. The scenario reduction technique is adopted to aggregate close scenarios by measuring the distance between scenarios based on the probability metrics and eliminate scenarios with very low probabilities for reducing the scale of the stochastic model and the computation effort [26], [27]. Other scenario reduction techniques may also be adopted including measuring the impact of each scenario on the objective by pre-solving single scenario problems [28], the target/moment matching which matches specified statistical properties [29], and the worst-case scenario probability study which assigns different sets of probabilities by experts and considers the worse scenario [30].

The objective (1) is to minimize the cost of supplying the hourly load in the base case (which includes the no-load cost, startup cost, shutdown cost, and the energy production cost) plus the expected corrective dispatch cost of scenarios, while satisfying various system and unit constraints. The sum of probabilities for all scenarios is equal to one. That is, $\sum_s p^s = 1$. Startup and shutdown costs are considered as time varying variables, which are functions of the number of hours a generating unit has been off and on, respectively [36]. In this paper, only non-quick start generating units are considered in order to facilitate the comparison of the two optimization approaches. That is, in each time interval of the base case and in all scenarios, each generating unit would have the same UC decisions. The formulation for quick-start units can also be included in the formulation [35]. By defining P_{ikt}^s as the power generation of unit i at time t, segment k, and scenario s, which satisfies $P_{ikt}^s = P_{ikt} + \Delta P_{ikt}^s$, (1) is equivalently converted to (2):

$$\begin{aligned} Min \quad & \sum_t \sum_i \left[N_i \cdot I_{it} + SU_{it} + SD_{it} + \sum_k c_{ik} \cdot P_{ikt} \right] \\ & + \sum_s p^s \cdot \sum_t \sum_i \left[\sum_k c_{ik} \cdot \Delta P_{ikt}^s \right] \end{aligned} \tag{1}$$

$$\begin{aligned} Min \quad & \sum_t \sum_i [N_i \cdot I_{it} + SU_{it} + SD_{it}] \\ & + \sum_s p^s \cdot \sum_t \sum_i \left[\sum_k c_{ik} \cdot P_{ikt}^s \right] \end{aligned} \tag{2}$$

subject to the following constraints.

Constraints for the Base Case: Base case constraints include the system load balance (3). In addition, system reserve requirements are implicitly represented by deviations in the dispatch solutions of the base case and scenarios, and will be optimally determined via preventive and corrective actions. Generating unit constraints include capacity limits of thermal units (4) and power generation limits of wind power generation units (5):

$$\sum_i P_{it} + \sum_w P_{wt} = P_{Dt} \tag{3}$$

$$\begin{aligned} & P_i^{\min} \cdot I_{it} \le P_{it} \le P_i^{\max} \cdot I_{it} \\ & P_{it} = \sum_k P_{ikt} \qquad 0 \le P_{ikt} \le P_{ik}^{\max} \cdot I_{it} \end{aligned} \tag{4}$$

$$0 \le P_{wt} \le P_{f,wt}. \tag{5}$$

Other unit constraints include minimum on/off time, ramping up/down rate, reserve capacity, and fuel and/or emission limitations [31], [32]. Other types of units, such as combined-cycle gas turbine, cascaded hydro, and pumped-storage units, can also be considered. Transmission network constraints include branch flow limits (6), which is enforced in the base case to guarantee the network security of power systems operation:

$$-\mathbf{PL^{max}} \le \mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{P_t} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) \le \mathbf{PL^{max}}. \tag{6}$$

Constraints for Each Scenario: Constraints for each scenario include the system load balance (7), generation limits of thermal and wind power units (8), and dispatch adjustment capabilities of generating units (9), which are restricted by the dispatch in the base case by ramping up/down rate limits. Transmission network constraints (10) are enforced in each scenario to guarantee the network security:

$$\sum_i P_{it}^s + \sum_w P_{wt}^s = P_{Dt} \tag{7}$$

$$\begin{aligned} & P_i^{\min} \cdot I_{it} \le P_{it}^s \le P_i^{\max} \cdot I_{it} \\ & P_{it}^s = \sum_k P_{ikt}^s \qquad 0 \le P_{ikt}^s \le P_{ik}^{\max} \cdot I_{it} \\ & P_{wt}^s \le P_{f,wt}^s \end{aligned} \tag{8}$$

$$\begin{aligned} & P_{it}^s - P_{it} \le R_i^{up} \cdot I_{it} \\ & P_{it} - P_{it}^s \le R_i^{dn} \cdot I_{it} \end{aligned} \tag{9}$$

$$-\mathbf{PL^{max}} \le \mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{P_t^s} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) \le \mathbf{PL^{max}}. \tag{10}$$

Other unit constraints include minimum on/off time, ramping up/down rate, reserve capacity, and fuel and/or emission limitations. The detailed formulation is not included in the paper, which can be obtained in the authors' previous work [31], [32]. However, ramping limits between two successive time intervals in each scenario is not considered because it is assumed that the scenarios at successive time intervals are independent. That is, the scenario s at hour t is not necessarily a consequence of the scenario s at hour $(t-1)$. In addition, the proposed Stochastic SCUC is an hourly based model; thus, it is reasonable to assume that there is enough time to adjust the system back to the base case operation status at hour t. Thus, ramping constraints are used to guarantee the secure and economic transfer of system operation status between two successive time intervals in the base, and from the base case to all scenarios at each hour, but not between two successive time intervals in each scenario. In the proposed decomposition framework, the ramping constraints between two successive time intervals in the base is considered in the master UC problem (11), and the ramping constraints between the base case and each hourly scenario is considered in the hourly scenario feasibility and optimality check subproblems (14) and (16).

B. Solution Methodology

The scenario-based Stochastic SCUC model in (2)–(10) is a large-scale, non-convex, non-deterministic polynomial-time hard (NP-hard) problem. The corresponding solution for large-scale systems would be an intractable task without decomposition. The Benders decomposition (BD) is adopted to decompose the Stochastic SCUC problem into one master problem and several tractable subproblems for each scenario.

1) Master Unit Commitment Problem: The master UC problem (11) is to minimize the operation cost of the base case with respect to constraints (3)–(5) and other unit constraints mentioned above:

$$Min \quad \sum_t \sum_i [N_i \cdot I_{it} + SU_{it} + SD_{it}] + \sum_s p^s \cdot \sum_t \theta_t^s. \quad (11)$$

2) Hourly Network Evaluation for the Base Case: The hourly network evaluation subproblem (12) checks possible network violations of the master UC solution for the base case. If the objective value $\hat{s}_t$ of (12) is larger than the predefined threshold, a feasibility cut (13) will be utilized:

$$\begin{aligned} & Min\ s_t \\ & S.t. -1 \cdot s_t \le \mathbf{PL^{max}} - \mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{\hat{P}_t} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) \quad \boldsymbol{\lambda}_{\mathbf{1,t}} \\ & \qquad -1 \cdot s_t \le \mathbf{PL^{max}} + \mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{\hat{P}_t} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) \quad \boldsymbol{\lambda}_{\mathbf{2,t}} \\ & \quad 0 \le s_t \qquad (12) \end{aligned}$$

$$-(\boldsymbol{\lambda}_{\mathbf{1,t}} - \boldsymbol{\lambda}_{\mathbf{2,t}})^T \cdot \mathbf{K_P} \cdot (\mathbf{P_t} - \mathbf{\hat{P}_t}) + \hat{s}_t \le 0. \quad (13)$$

3) Hourly Feasibility Check for Each Scenario: The hourly feasibility check subproblem (14) checks possible violations of the master UC solution in each scenario. If the objective value $\hat{S}_t^s$ in (14) is larger than the predefined threshold, a feasibility cut (15) will be utilized:

$$\begin{aligned} & Min\ S_t^s = s_t^s + s_{1t}^s + s_{2t}^s \\ & S.t. \mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{P_t^s} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) - 1 \cdot s_t^s \le \mathbf{PL^{max}} \\ & \quad -\mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{P_t^s} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) - 1 \cdot s_t^s \le \mathbf{PL^{max}} \\ & \quad \sum_i P_{it}^s + \sum_w P_{wt}^s + s_{1t}^s - s_{2t}^s = P_{Dt} \\ & \quad P_{it}^s \le R_i^{up} \cdot \hat{I}_{it} + \hat{P}_{it} \qquad \lambda_{1,it}^s \\ & \quad -P_{it}^s \le R_i^{dn} \cdot \hat{I}_{it} - \hat{P}_{it} \qquad \lambda_{2,it}^s \\ & \quad P_{it}^s \le P_i^{\max} \cdot \hat{I}_{it} \qquad \mu_{1,it}^s \\ & \quad -P_{it}^s \le -P_i^{\min} \cdot \hat{I}_{it} \qquad \mu_{2,it}^s \\ & \quad P_{wt}^s \le P_{f,wt}^s \\ & \quad 0 \le s_t^s, s_{1t}^s, s_{2t}^s \qquad (14) \end{aligned}$$

$$\begin{aligned} & \sum_i \Big[\left(\hat{\lambda}_{1,it}^s - \hat{\lambda}_{2,it}^s \right) \cdot (P_{it} - \hat{P}_{it}) \\ & \quad + \left(\hat{\lambda}_{1,it}^s \cdot R_i^{up} + \hat{\lambda}_{2,it}^s \cdot R_i^{dn} + \hat{\mu}_{1,it}^s \cdot P_i^{\max} \right. \\ & \qquad \left. - \hat{\mu}_{2,it}^s \cdot P_i^{\min} \right) \cdot (I_{it} - \hat{I}_{it}) \Big] + \hat{S}_t^s \le 0. \quad (15) \end{aligned}$$

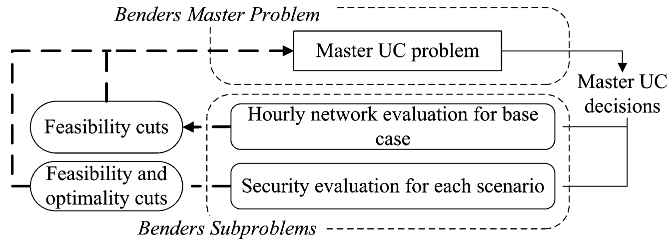

Fig. 1. Scenario-based approach.

4) Optimality Check for Each Scenario: The optimality check subproblem (16) checks the optimality of master UC solution in each scenario. If the objective value $\hat{W}_t^s$ in (16) is larger than the corrective dispatch cost $\hat{\theta}_t^s$ obtained from the master problem, the optimality cut (17) will be utilized:

$$\begin{aligned} & Min \quad W_t^s = \sum_i \left[\sum_k c_{ik} \cdot P_{ikt}^s \right] \\ & S.t. -\mathbf{PL^{max}} \le \mathbf{SF} \cdot (\mathbf{K_P} \cdot \mathbf{\hat{P}_t} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}) \le \mathbf{PL^{max}} \\ & \quad P_{it}^s \le R_i^{up} \cdot \hat{I}_{it} + \hat{P}_{it} \qquad \lambda_{1,it}^s \\ & \quad -P_{it}^s \le R_i^{dn} \cdot \hat{I}_{it} - \hat{P}_{it} \qquad \lambda_{2,it}^s \\ & \quad P_{it}^s \le P_i^{\max} \cdot \hat{I}_{it} \qquad \mu_{1,it}^s \\ & \quad -P_{it}^s \le -P_i^{\min} \cdot \hat{I}_{it} \qquad \mu_{2,it}^s \\ & \quad P_{it}^s - \sum_k P_{ikt}^s = 0 \\ & \quad P_{wt}^s \le P_{f,wt}^s \qquad (16) \end{aligned}$$

$$\begin{aligned} \theta_t^s \ge \hat{W}_t^s + \sum_i \Big[& \left(\hat{\lambda}_{1,it}^s \cdot R_i^{up} + \hat{\lambda}_{2,it}^s \cdot R_i^{dn} \right. \\ & \left. + \hat{\mu}_{1,it}^s \cdot P_i^{\max} - \hat{\mu}_{2,it}^s \cdot P_i^{\min} \right) \cdot (I_{it} - \hat{I}_{it}) \\ & + \left(\hat{\lambda}_{1,it}^s - \hat{\lambda}_{2,it}^s \right) \cdot (P_{it} - \hat{P}_{it}) \Big]. \quad (17) \end{aligned}$$

Fig. 1 shows the flowchart of the scenario-based Stochastic SCUC solution. The master UC problem (11) is solved first. The hourly UC and dispatch solutions are then passed on to the hourly network evaluation subproblems (12). The subproblems will examine the feasibility of the master solution. If a subproblem is infeasible which violates the remaining constraints, a corresponding feasibility cut (13) will be generated and added to the next calculation of master problem. The hourly UC and dispatch solutions are also passed on to the hourly security evaluation subproblem (14) and the optimality evaluation subproblem (16) in each scenario. If a scenario subproblem is infeasible, a corresponding feasibility cut (15) will be generated. If the optimal objective $\hat{W}_t^s$ is larger than the corrective dispatch cost

$\hat{\theta}_t^s$, an optimality cut (17) will be generated and added to the next iteration of the master problem. The iterative process will stop when the master solution satisfies feasibility and optimality checks.

III. Interval Optimization for Stochastic SCUC

The scenario-based approach in Section II holds a presumption that the wind speed uncertainty follows a certain probability distribution. However, the wind speed distribution is often more complex. In addition, a huge number of scenarios are needed in order to achieve an acceptable solution accuracy, which could increase the scale and the computation burden of the stochastic problem. In this section, the interval optimization is adopted as an alternative for the Stochastic SCUC solution with the consideration of wind power generation uncertainty.

The objective of the interval optimization approach is to minimize the cost of supplying the hourly load in the base case (18). Different from the scenario-based approach, the interval optimization approach does not hold any presumptions on probability distributions. The expected corrective dispatch costs are not explicitly included in the objective function. Instead, the impact of uncertainty on operation costs is reflected via the operation cost interval:

$$Min \quad \sum_t \sum_i \left[\sum_k c_{ik} \cdot P_{ikt} + N_i \cdot I_{it} + SU_{it} + SD_{it} \right]. \tag{18}$$

The base case constraints are (3)–(6) and constraints describing the wind power generation uncertainty are given in (19)–(21) with interval variables $P_{it}^{\pm}$ and $P_{wt}^{\pm}$. In (20), the uncertainty interval is derived from a forecasting model [34]. If the forecasting model does not provide such functionality, the uncertainty interval can be formulated using a percentage of the forecast value around such forecast value, i.e., $(1 \pm \alpha)$. The value of α ranges from 0 to 1, for controlling the level of uncertainty under consideration:

$$\sum_i P_{it}^{\pm} + \sum_w P_{wt}^{\pm} = P_{Dt} \tag{19}$$

$$\begin{aligned} &P_{it} - R_i^{up} \cdot I_{it} \le P_{it}^{\pm} \le P_{it} + R_i^{up} \cdot I_{it} \\ &P_i^{\min} \cdot I_{it} \le P_{it}^{\pm} \le P_i^{\max} \cdot I_{it} \\ &P_{wt}^{\pm} \le \left[P_{wt}^{-}, P_{wt}^{+}\right] \end{aligned} \tag{20}$$

$$-\mathbf{PL^{max}} \le \mathbf{SF} \cdot \left(\mathbf{K_P} \cdot \mathbf{P_t^{\pm}} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}\right) \le \mathbf{PL^{max}}. \tag{21}$$

A. Feasibility Check for the Interval Optimization Subproblem

In (22), the largest violation would occur when the available wind power generation is at its minimum $P_{f,wt}^{-}$. Thus, by checking the worst case (23), if the objective value S_t^{-} is larger than the predefined threshold, a feasibility cut (24) will be utilized. Otherwise, if S_t^{-} is smaller than the predefined threshold, the worst case is feasible. Thus, all other cases will be feasible:

$$\begin{aligned} &Min \quad s_t^{\pm} + s_{1t}^{\pm} + s_{2t}^{\pm} \\ &S.t. \mathbf{SF} \cdot \left(\mathbf{K_P} \cdot \mathbf{P_t^{\pm}} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}\right) - 1 \cdot s_t^{\pm} \le \mathbf{PL^{max}} \\ &\quad -\mathbf{SF} \cdot \left(\mathbf{K_P} \cdot \mathbf{P_t^{\pm}} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}\right) - 1 \cdot s_t^{\pm} \le \mathbf{PL^{max}} \\ &\quad \sum_i P_{it}^{\pm} + \sum_w P_{wt}^{\pm} + s_{1t}^{\pm} - s_{2t}^{\pm} = P_{Dt} \\ &\quad \hat{P}_{it} - R_i^{up} \cdot \hat{I}_{it} \le P_{it}^{\pm} \le \hat{P}_{it} + R_i^{up} \cdot \hat{I}_{it} \\ &\quad P_i^{\min} \cdot \hat{I}_{it} \le P_{it}^{\pm} \le P_i^{\max} \cdot \hat{I}_{it} \\ &\quad P_{wt}^{\pm} \le \left[P_{f,wt}^{-}, P_{f,wt}^{+}\right] \\ &\quad 0 \le s_t^{\pm}, s_{1t}^{\pm}, s_{2t}^{\pm}. \end{aligned} \tag{22}$$

B. Confidence Intervals

The interval optimization derives the power generation confidence interval $[\hat{P}_{it}^{-}, \hat{P}_{it}^{+}]$ for each unit i at each hour t, and the confidence interval $[\sum_t \sum_i (\sum_k c_{ik} \cdot \hat{P}_{ikt}^{-} + N_i \cdot \hat{I}_{it} + \hat{SU}_{it} + \hat{SD}_{it}), \sum_t \sum_i (\sum_k c_{ik} \cdot \hat{P}_{ikt}^{+} + N_i \cdot \hat{I}_{it} + \hat{SU}_{it} + \hat{SD}_{it})]$ of the total operation cost, in response to wind power generation uncertainty. The unique feature of the interval optimization is that it uses confidence interval numbers to simulate uncertainty, without considering any assumptions on probability distributions, and derives optimistic and pessimistic solutions for satisfying the security and economic requirements of power systems:

$$\begin{aligned} &Min \quad S_t^{-} = s_t^{-} + s_{1t}^{-} + s_{2t}^{-} \\ &S.t. \mathbf{SF} \cdot \left(\mathbf{K_P} \cdot \mathbf{P_t^{-}} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}\right) - 1 \cdot s_t^{-} \le \mathbf{PL^{max}} \\ &\quad -\mathbf{SF} \cdot \left(\mathbf{K_P} \cdot \mathbf{P_t^{-}} - \mathbf{K_D} \cdot \mathbf{P_{Dt}}\right) - 1 \cdot s_t^{-} \le \mathbf{PL^{max}} \\ &\quad \sum_i P_{it}^{-} + \sum_w P_{wt}^{-} + s_{1t}^{-} - s_{2t}^{-} = P_{Dt} \\ &\quad P_{it}^{-} \le R_i^{up} \cdot \hat{I}_{it} + \hat{P}_{it} \qquad \lambda_{1,it}^{-} \\ &\quad -P_{it}^{-} \le R_i^{dn} \cdot \hat{I}_{it} - \hat{P}_{it} \qquad \lambda_{2,it}^{-} \\ &\quad P_{it}^{-} \le P_i^{\max} \cdot \hat{I}_{it} \qquad \mu_{1,it}^{-} \\ &\quad -P_{it}^{-} \le -P_i^{\min} \cdot \hat{I}_{it} \qquad \mu_{2,it}^{-} \\ &\quad P_{wt}^{-} \le P_{f,wt}^{-} \\ &\quad 0 \le s_t^{-}, s_{1t}^{-}, s_{2t}^{-} \end{aligned} \tag{23}$$

$$\begin{aligned} \sum_i \Big[&\left(\hat{\lambda}_{1,it}^{-} - \hat{\lambda}_{2,it}^{-}\right) \cdot \left(P_{it} - \hat{P}_{it}\right) \\ &+ \left(\hat{\lambda}_{1,it}^{-} \cdot R_i^{up} + \hat{\lambda}_{2,it}^{-} \cdot R_i^{dn} + \hat{\mu}_{1,it}^{-} \cdot P_i^{\max} \right. \\ &\left. - \hat{\mu}_{2,it}^{-} \cdot P_i^{\min}\right) \cdot \left(I_{it} - \hat{I}_{it}\right) \Big] + \hat{S}_t^{-} \le 0. \end{aligned} \tag{24}$$

IV. Case Studies

A six-bus system and the modified IEEE 118-bus system are used to analyze scenario-based and interval optimization approaches to Stochastic SCUC. The case studies utilize CPLEX 12.1.0 on an Intel Core i7 2.67-GHz personal computer.

A. Six-Bus System

The six-bus system shown in Fig. 2 is used to illustrate the proposed study, which has three regular thermal generators and one wind farm [31]. Corrective dispatch capabilities of the three

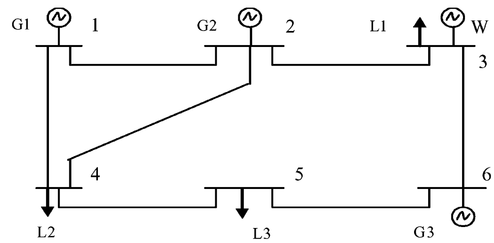

Fig. 2. One-line diagram of the six-bus system.

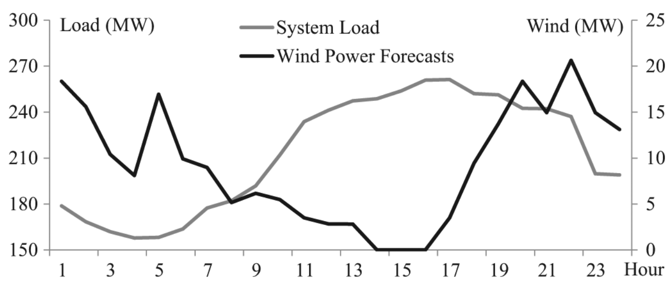

Fig. 3. 24-h load profile and wind power generation forecasts.

TABLE I
INTERVAL OPTIMIZATION RESULTS IN CASE 1

	Cost ($)	G1 (MW)	G2 (MW)	G3 (MW)	Wind (MW)
Base case	3,305.38	163.24	0	0	15.52
Pessimistic	3,496.68	172.40	0	0	6.36
Optimistic	3,114.34	154.08	0	0	24.68

TABLE II
SCENARIO-BASED RESULTS IN CASE 1 (REDUCED 100 SCENARIOS)

	Cost ($)	G1 (MW)	G2 (MW)	G3 (MW)	Wind (MW)
Base case	3437.19	169.60	0	0	9.16
Corrective action	-75.12	160.43-178.76	0	0	0-18.33

TABLE III
INTERVAL OPTIMIZATION RESULTS FOR 40% WIND VOLATILITY IN CASE 1

	Cost ($)	G1 (MW)	G2 (MW)	G3 (MW)	Wind (MW)
Base case	3,437.84	169.60	0	0	9.16
Pessimistic	3,632.93	178.76	0	0	0
Optimistic	3,246.79	160.44	0	0	18.32

thermal units are 9.16 MW, 8.33 MW, and 3.33 MW, respectively. The system load profile and wind power generation forecasts for the 24 h are shown in Fig. 3. The wind power generation is calculated based on wind speed forecasts and wind turbine power curves, where the cut-in, rated, and cut-out wind speeds are 5 m/s, 14 m/s, and 24 m/s, respectively. The total installed wind power generation capacity is 60 MW, which represents 14.63% of the total system generation capacity. Two cases are studied here:

Case 1) Stochastic SCUC study at hour 1.
Case 2) The 24-h Stochastic SCUC study.

Case 1: The Stochastic SCUC is studied at hour 1, which is a high wind and low load hour. The wind speed forecast is 9.44 m/s, which corresponds to the wind power generation of 18.39 MW. The system load is 178.76 MW.

First, the interval optimization approach for the Stochastic SCUC problem is studied, in which the wind power generation uncertainty is considered as 20% of its installed capacity, i.e., $60 * 20\% = 12$ MW. That is, the available wind power generation in the pessimistic case is $(18.39 - 12)$ MW, and $(18.39 + 12)$ MW in the optimistic case. The Stochastic SCUC solution with the interval optimization approach is shown in Table I. The economic operation strategy while satisfying the operational security under both pessimistic and optimistic cases is to switch on the G1 unit only and adopt wind power generation of 15.52 MW, 6.36 MW, and 24.68 MW in the base case, pessimistic case, and optimistic case, respectively. In this case, the corrective dispatch capability of G1 can balance the wind power generation uncertainty and securely transfer the system operation status from the base case to both pessimistic and optimistic cases. The interval optimization method also provides an operation cost interval of [$3114.34, $3496.68].

Second, the scenario-based approach is used to study the Stochastic SCUC. The wind speed is assumed to follow the Weibull distribution and its uncertainty is simulated via 10 000 scenarios. The scenario reduction is used to reduce the scale and the computation time of the stochastic model. Table II shows the results with the reduced 100 scenarios. The expected operation cost is $3362.07, which includes the base case cost of $3437.19 and the expected corrective dispatch cost of $−75.12.

In the interval optimization approach with 20% wind power generation uncertainty, 6.36 MW wind power generation is available in the pessimistic case. This makes it possible to adopt 15.52 MW wind power generation in the base case, with a corrective dispatch of 9.16 MW provided by G1. In comparison, the scenario-based approach includes scenarios with wind speeds lower than the cut-in value, which derives 0 MW wind power output. In order to securely transfer the system operation status from the base case to scenarios, the base case would dispatch 9.16 MW of wind power generation, which leads to a higher base case cost than that of the interval optimization.

The sensitivity analysis is performed for the two approaches. Table III shows the interval optimization results when the wind power generation uncertainty is assumed to be 40% of the installed wind power generation capacity, i.e., $40\% * 60 = 24$ MW. In this situation, the pessimistic case will have 0 MW wind power output, which adopts 9.16 MW wind power generation in the base case and derives the same base case result as that of the scenario-based approach in Table II. This study shows that the interval optimization solution is very sensitive to the presumed wind uncertainty interval. Fig. 4 shows the operation cost for all 100 scenarios and the operation cost intervals for the interval optimization approach. All scenario costs fall within the lower and upper bounds derived from the interval optimization, which indicates that when the wind uncertainty interval is properly set, the interval optimization could provide accurate operation cost boundaries to cover possible scenarios in the scenario-based approach.

Table IV shows the expected corrective dispatch costs of different tests in the scenario-based approach. For all tests, the base case UC results are the same as those in Table II. In Table IV, the tests with different number of original scenarios and the

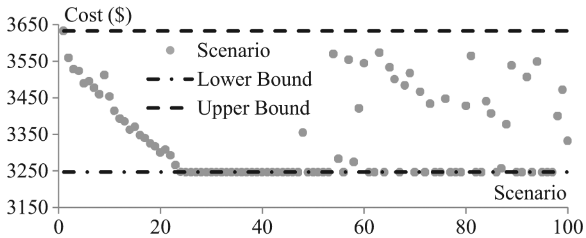

Fig. 4. Scenario operation costs and the operation cost interval.

TABLE IV
EXPECTED CORRECTIVE DISPATCH COSTS IN CASE 1 ($)

	# of scenarios after scenario reduction		
# of original scenarios	5	10	100
1,000	-70.47	-74.91	-74.92
10,000	-70.78	-75.15	-75.12
10,000 (Another sample)	-70.75	-75.10	-75.12

TABLE V
RESULTS FOR EACH SCENARIO IN CASE 1 (REDUCED FIVE SCENARIOS)

	S1	S2	S3	S4	S5
Probability	0.171	0.211	0.346	0.113	0.159
Available wind power (MW)	0	29.76	59.82	3.44	12.72
Adopted wind power (MW)	0	18.33	18.33	3.44	12.72
Scenario cost ($)	3,632.93	3,246.79	3,246.79	3,559.20	3,363.75
Corrective cost ($)	195.43	-190.40	-190.40	122.01	-73.44

same number of reduced scenarios have close expected corrective dispatch costs. In addition, ten appears to be an appropriate number of scenarios since their expected corrective dispatch costs are quite close to those of 100 scenarios; though the cost of five scenarios deviates a lot. Furthermore, the last two rows of Table IV show that the expected corrective dispatch costs of another 10 000 sample test are quite close to those of the first 10 000 scenario sample test, which shows that the expected corrective dispatch costs are stable for different scenario samples. Table IV shows that, in this case, the expected corrective dispatch costs are all negative for different tests. This is because in most scenarios, the amount of wind power generation adopted is higher than that of the base case. Thus, less generation from regular thermal units is needed and the scenario operation cost is lower than that of the base case. Table V shows the test results with reduced five scenarios. In this study, scenarios 2, 3, and 5 would adopt more wind power generation and correspondingly have lower scenario operation costs than the base case. The total probability of scenarios 2, 3, and 5 is $0.211 + 0.346 + 0.159 = 0.716$, which brings out the negative expected corrective dispatch cost of $\$-70.47$.

Case 2: The 24-h Stochastic SCUC is studied in this case. Tables VI and VII show the 24-h Stochastic SCUC results with the interval optimization and the scenario-based approaches, respectively. Table VI show that the expected operation costs of test cases, given in Table VII, fall in the operation cost interval of [$100 048.78, $109 294.13]. Table VII again shows that ten would be an appropriate number of scenarios in this case since

TABLE VI
INTERVAL OPTIMIZATION RESULTS IN CASE 2

	Base case	Pessimistic	Optimistic
Cost ($)	105,595.50	109,294.13	100,048.78

TABLE VII
SCENARIO-BASED RESULTS IN CASE 2 ($)

# of scenarios after reduction	5	10	100
Expected cost for the first run	102,270.05	103,887.93	104,295.86
Expected cost for the second run	102,294.87	103,835.80	104,273.27

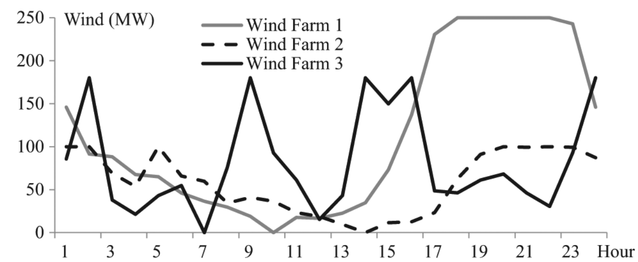

Fig. 5. Wind power generation forecasts for the three wind farms.

TABLE VIII
INTERVAL OPTIMIZATION RESULTS FOR 24 H ($)

Wind Uncertainty	Base case	Pessimistic	Optimistic
15%	2,006,689.78	2,032,250.47	1,968,175.55
25%	2,006,844.22	2,042,033.43	1,944,019.38

TABLE IX
SCENARIO-BASED RESULTS FOR 24 H ($)

# of scenarios after reduction	5	10	100
Expected cost for the first run	1,969,428.82	1,970,747.87	1,969,768.34
Expected cost for the second run	1,971,080.53	1,970,771.70	1,969,547.27

their costs are close to those of 100 scenarios (i.e., the differences are $(104\,295.86 - 103\,887.93)/104\,295.86 = 0.39\%$ and $(104\,273.27 - 103\,835.80)/104\,273.27 = 0.42\%$). In addition, the expected costs are stable with different replications (i.e., the differences are $(102\,270.05 - 102\,294.87)/102\,270.05 = -0.024\%$, $(103\,887.93 - 103\,835.80)/103\,887.93 = 0.05\%$, and $(104\,295.86 - 104\,273.27)/104\,295.86 = 0.022\%$).

B. IEEE 118-Bus System

The modified IEEE 118-bus system with 54 thermal units, three wind farms, and 186 branches is studied. The peak load is 7200 MW with detailed generator and transmission network data given in [31]. The 24-h wind power generation forecasts for the three geographically dispersed wind farms are shown in Fig. 5.

Table VIII shows operation costs of the base case, the pessimistic case, and the optimistic case for the entire 24 h, when the wind power uncertainty is considered to be 15% and 25% of the total installed wind power generation capacity, respectively. Table IX shows operation costs of test cases with 10 000 original scenarios for the scenario-based approach. In comparison, the scenario-based solutions are more rigid, i.e., the optimal objectives values are approximately the same in test cases. However, the objective intervals in the interval optimization deviate a lot as the wind power uncertainty interval is changed. When the wind power uncertainty is increased from 15% to 25%, the costs of pessimistic and optimistic cases would change by $(2\,042\,033.43 - 2\,032\,250.74)/2\,032\,250.74 = 0.48\%$ and $(1\,944\,019.38 - 1\,968\,175.55)/1\,968\,175.55 = -1.23\%$ although the base case costs are close. In comparison, changes in the expected operation costs of test cases are within 0.084% in the scenario-based approach.

The interval optimization approach takes five iterations with a computation time of 73 s to reach the optimal solution. For the scenario-based approach, with the reduced ten scenarios, it takes seven iterations with a computation time of 178 s. For reduced 100 scenarios, it needs 20 iterations with the total computation time of 2108 s. Since the Stochastic SCUC is an NP-hard problem, the increase in the number of scenarios will dramatically increase the computation burden. In comparison, the computation time for the interval optimization is equivalent to that of a scenario-based approach with the consideration of only two scenarios.

V. Acceleration Strategy

The computation burden of the scenario-based approach for the Stochastic SCUC problem may be improved by applying the following options:

1) Tighten the master UC problem formulation (11). It is conceivable that the inclusion of system reserve requirement and/or a few scenarios in the first iteration of the master UC problem would result in a better initial UC solution.
2) Make use of the specific structure of Stochastic SCUC problem in certain cases for eliminating optimality cuts. An alternative partition strategy enabled by the combination of (11) and (16) as the master problem may eliminate the need for optimality cuts and require fewer iterations, when a combined optimization of the MIP problem (11) and (16) is possible.
3) Adopt acceleration strategies proposed for the deterministic SCUC [11], [32]. Reference [11] proposed a necessary and sufficient condition to identify and eliminate inactive security constraints in the SCUC problem, for reducing the problem scale and the computation burden. Reference [32] explored a reasonable operational strategy for fixing and unlocking generating units at each SCUC iteration, to control the iterative SCUC solution efficiently and accelerate the execution.
4) Generate multiple strong cuts to accelerate the convergence of the Benders decomposition approach [33]. Multiple strong cuts would restrict the feasible region of the master UC problem at each iteration and, in turn, result in a significant reduction in the number of iterations and the necessary CPU time for computation. Subproblems for generating additional cuts can be executed in parallel, which would not introduce any extra computation time.

VI. Conclusions

The impact of various uncertainties on the operational security of power systems is becoming more important, as more uncertainty factors are integrated into power systems. This paper evaluates the scenario-based approach and the interval optimization approach for the Stochastic SCUC solution with the consideration of uncertain wind power generation. A six-bus system and the modified IEEE 118-bus system are studied to evaluate the two approaches. The scenario-based approach provides more stable solutions. However, the scenario-based approach may come with larger problem scales and higher computation burdens. A few convergence acceleration options are referred to in the paper for overcoming the computation obstacles of the scenario-based approach. More research on this issue will be required in the future. The interval optimization approach requires less computation time to generate lower and upper bounds automatically for the objective value. However, its optimal solution is very sensitive to the uncertainty interval. In addition, the interval optimization may not be suitable for simulating discrete uncertain variables such as random outages of generators and transmission lines in power systems.

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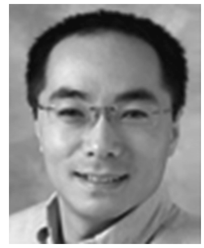

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