Security-Constrained Unit Commitment with Optimal Robust Confidence Levels

Changsen Feng, Linna Ni, Fushuan Wen
College of Electrical Engineering
Zhejiang University
Hangzhou 310027, China
fengchangsen@126.com

Zhiyi Li, Mohammad Shahidehpour
ECE department
Illinois Institute of Technology
Chicago IL 60616, USA
ms@iit.edu

Yusheng Xue
State Grid Electric Power Research Institute
Nanjing 210003, China
xueyusheng@sgepri.sgcc.com.cn

***Abstract*—Due to the increasing penetration of wind power, the fluctuation and forecasting error have posed significant challenges to dispatchers for secure and economic operation of the power system concerned. This paper proposes a model for attaining a robust solution to the security-constrained unit commitment (SCUC) problems based on scenarios. Different from most robust optimization models, the model in this paper guarantees a robust solution with the optimal confidence level, and some measures such as wind power curtailment and load shed are considered. The proposed model provides theoretical basis to help operators strike a balance between economic performance and robustness. The proposed model is solved by Benders decomposition. The effectiveness of the proposed model is verified by results of numerical cases on the modified IEEE 39, 118-bus system.**

***Index Terms*—Benders decomposition, robustness, robust confidence level, unit commitment, wind power.**

I. Introduction

With the increasing depletion of fossil energy and degradation of the environment, renewable-based generation resources such as photovoltaic panel and wind power are rapidly deployed. However, owing to the inherent intermittence, fluctuation, and low predictability, they have posed significant challenges to the system operation. One of the key issue is how to model the uncertainties and How to get the optimal strategy at minimum cost when renewable generations output seriously deviates from the prediction.

In existing literatures, there are mainly two distinct methods to model the uncertainties, e.g. probabilistic method and the interval-number method. The probabilistic method generates scenarios via probability distribution functions and the scenario can be generated by Monte Carlo Simulation (MCS) or Latin Hypercube Sampling (LHS)[1]. The interval optimization uses uncertain intervals in terms of upper and lower bounds for uncertainties of certain parameters, and finds the worst and the optimal solution respecting system security constraints (see, e.g. [2], [2]).

The robust optimization (RO) has been broadly applied to economic dispatch (ED) (e.g. [4]-[7]) and unit commitment (UC) (e.g. [8]-[10]) consider uncertainty parameter when large-scale wind farms are integrated into the power system. When focusing too much on operation security, the strategies of RO model is conservative, not economical [6]. Thus, to strike a balance between economic performance and conservatism is the key point of RO. In the existing frameworks of RO, the objective function is usually to find the optimal solution for the worst-case, which can be transformed into the "min-max problem" However, in practice, the worst-case is a low probability event (e.g. [7]-[9]). Further, the optimal solution to RO model is usually somewhat conservative when the RO model solved by interval optimization method this is because it emits the correlation of uncertainties [11].

Based on two points above, we extended the conventional SCUC model and proposed a new robust SCUC (RSCUC) model which guarantees a robust solution with optimal confidence level. We use the confidence level as an index to quantitatively evaluate the strategy's robustness. The strategy with a high level of confidence means that it has good robustness and meanwhile is somewhat conservative. In addition, the proposed robust model based on scenario can get a more economical solution without loss of security while the interval-number in the conventional SCUC may drive a very conservative solution due primarily to lack of considering correlations of uncertainties. At last, our model also considers some flexible countermeasures such as load shed or wind curtailment which inevitably brings the compensation expense to consumers and wind farm owners (e.g. [9], [12], [13]). The solution obtained is a trade-off between economic performance and robustness.

The proposed RSCUC model is solved in an iteration process. In every iteration, the robust confidence set would be determined and then Benders decomposition [14] is applied to get a robust solution with a certain level of confidence. At last, the solution with minimal total cost is selected as optimum and its confidence level can also be obtained. For convenience, we call the scenario set which the solution is robust against as

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the robust confidence set (RCS), and the probability of RCS as robust confidence level (RCL). In addition, the scenario set is generated by LHS and reduced by Fast Forward Selection (FFS) (e.g. [15]).

The paper is organized as follows. Section II describes the two-stage RSCUC formulation. Section III provides the solution methodologies, including the method of scenario generation and scenario reduction. Section IV presents numerical case study results, and conclusions are drawn in Section V.

II. Problem Formulation

A. Objective Function and Constraints

We extend the conventional model to takes load shedding or wind curtailment into consideration. The energy production cost is described by a piecewise linear function. Let F_1denote the operation cost and F_2 denote the compensate expense resulting from load shed and wind curtailment. Thus, the objective function can be described as follows:

$$\min F = F_1 + F_2 = \sum_{t=1}^{T}\sum_{i}^{N_g}[\sum_{k} l_{i,k}\cdot p_{i,k}^{t} + x_i^t c_i^t + u_i^t e_i^t] + \sum_{s\in S-S_R}\rho_s\sum_{t=1}^{T}F_{ld}(P_{l,shed}^{s,t} + P_{w,curt}^{s,t}) \quad (1)$$

where, N_g and T are the number of generations and time periods (in hours), respectively. $l_{i,k}$ is the incremental cost of segment k of unit i. For each unit i, $l_{i,k}$ is increasing for larger k for ensuring that the cost function is convex. x_i^t is commitment of unit i at time t. u_i^t is startup/shutdown state of unit i at time t. p_{ik}^t is the production of generator i at time t at segment k. F_{ld} [\$/MWh] is the price of load shedding or wind abandoning. ρ_s is the probability of the scenario s. S is the scenario set and S_R is the RCS. $P_{l,shed}^{s,t} / P_{w,curt}^{s,t}$ is the total load shed power /wind curtailment at time t in scenario s.

B. Constraints

1) Deterministic SCUC constraints

The deterministic SCUC constraints include system power balance,

$$\sum_{i}^{N_g} p_i^t + \sum_{j}^{N_w}\overline{p}_{wj}^t = \sum_{k}^{N_d} p_{dk}^t \quad (2)$$

where p_i^t, $\overline{p}_{wj}^t$, and p_{dk}^t are generation power of unit i, the forecast value of the wind farm j, and the load demand k at time t , respectively. Generation capacity limits of units,

$$p_i^{\min} x_i^t \le p_i^t \le p_i^{\max} x_i^t \qquad \forall i, \forall t \quad (3)$$

where $p_i^{\max}$ and $p_i^{\min}$ are the upper limit and lower limit of real power generation of unit i, respectively. Minimum ON/OFF time limits and startup constraints,

$$\begin{cases} -x_i^{t-1} + x_i^t - x_i^k \le 0 & t \le k \le T_{on}^i + t - 1 \\ x_i^{t-1} - x_i^t + x_i^k \le 1 & t \le k \le T_{off}^i + t - 1 \\ -x_i^{t-1} + x_i^t - u_i^t \le 0 & \end{cases} \quad (4)$$

Ramping up/down limits,

$$\begin{cases} p_i^{t+1} - p_i^t \le x_i^t R_i^+ + (1 - x_i^t) p_i^{\max} \\ p_i^t - p_i^{t+1} \le x_i^{t+1} R_i^- + (1 - x_i^{t+1}) p_i^{\max} \end{cases} \quad (5)$$

where R_i^+ and R_i^- are the ramp-up and ramp-down rate limit of unit i. System spinning reserve limits

$$\sum_{i}^{N_g} x_i^t p_{\max}^i + \sum_{j}^{N_w}\overline{p}_{wj}^t \ge (1 + r)\sum_{k}^{N_d} p_{dk}^t \quad (6)$$

where r is the spinning reserve rate. DC transmission network security constraints,

$$-F_l^{\max} \le \sum_{i}^{N_g}\pi_i^l p_i^t + \sum_{j}^{N_w}\pi_j^l\overline{p}_{wj}^t - \sum_{k}^{N_d}\pi_k^l p_{dk}^t \le F_l^{\max} \quad (7)$$

where π^l is shift factor of line l.

2) Description of SCUC Robustness

How to control the robust performance of the solution is the key issue in the robust optimization. The existing literatures (e.g. [3], [4], [7], [16]) usually introduce the concept "price of robustness". The level of conservatism of the robust solutions is flexibly adjusted in terms of probabilistic bounds of constraint violations. Conventionally, the robust optimization problem can be described as :

$$\begin{cases} \min c^T x \\ s.t.\ Ax + Cw \le b \quad \forall w \in W(\Gamma) \end{cases} \quad (8)$$

where Γ is the price of robustness. The robustness of x can be given as follows.

$$0 \le b - Ax - Cw, \forall w \in W(\Gamma) \quad (9)$$

However, the price of robustness is usually empirically determined and lacks the clear physical meaning. Here, we introduce RCS and RCL to quantify robustness. Specifically, the strategy with high RCL means that it has a good robust performance. RCL is also the probability of RCS. More importantly, through constructing S_R in accordance with some rules as described in Section III, our method guarantees a robust solution with the optimal RCL.

We define the robustness of the SCUC strategy in our model as follows:

$$\Omega(p^s) = \{p^s \mid A(\hat{x}, p_w^s, p^s) \le 0, \forall s \in S_R\} \ne \varnothing \quad (10)$$

Specifically, for any $i \in N_g, t \in T, s \in S_R$

$$\begin{aligned} \Omega(p^s) = \{ & \sum_{i}^{N_g} p_i^{s,t} + \sum_{j}^{N_w} p_{wj}^{s,t} = \sum_{k}^{N_d} p_{dk}^t \\ & p_i^{\min}\hat{x}_i^t \le p_i^{s,t} \le p_i^{\max}\hat{x}_i^t \\ & p_i^{s,t+1} - p_i^{s,t} \le \hat{x}_i^t R_i^+ + (1 - \hat{x}_i^t) p_i^{\max} \\ & p_i^{s,t} - p_i^{s,t+1} \le \hat{x}_i^{t+1} R_i^- + (1 - \hat{x}_i^{t+1}) p_i^{\max} \\ & -F_l^{\max} \le \sum_{i}^{N_g}\pi_i^l p_i^{s,t} + \sum_{j}^{N_w}\pi_j^l p_{wj}^{s,t} - \sum_{k}^{N_d}\pi_k^l p_{dk}^t \le F_l^{\max}\} \end{aligned} \quad (11)$$

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III. SLOUTION METHODOLOGY

A. Solution Framework

An iteration process is applied in the solution framework and there are mainly three steps in every iteration. At first, we determine the S_R and then the RSCUC model is solved through benders decomposition. Thirdly, the expected compensate expense from load shed and wind curtailment is computed. At last, the optimal solution with minimal total cost is selected and the corresponding RCL is also determined.

1) First-step:S_R construction

The S_R construction need to be determined before solving the proposed model in every iteration. Assuming the wind power output scenario S is obtained through LHS and FFS method, we sort scenarios according to the probability. Then we select one scenario with maximal probability in (S-S_R) and add it to the S_R in every iteration.

2) Second-step:Benders decomposition

Benders decomposition decomposes the original problem into a master deterministic SCUC problem with forecast values of uncertain parameters, and then the UC strategy is introduced to the feasibility check subproblem for each scenario in S_R.

a) Master problem

The master problem is composed by the objective function F_1, constraints (2)-(7) and infeasible cut generated by feasible check.

$$\min F_1 = \sum_{t=1}^{T}\sum_{i}^{N_g}[\sum_{k} l_{i,k}\cdot p_{i,k}^t + x_i^t c_i^t + u_i^t e_i^t]$$

$$s.t.\begin{cases}(2)-(7)\\ \text{infeasible cut set}\end{cases}$$

b) Subproblem

Through introducing non-negative slack variables v_1,v_2,and v_3, equ(11) can be transformed into a linear program problem as follows:

$$\Omega(p^s)=\{p^s \mid A(x,p_w^s,p^s)\le 0,\forall s\in S_R\}\ne\varnothing \tag{12}$$

$$\Rightarrow\begin{cases}R_1^s(v)=\min\limits_{p^s,v_1^s,v_2^s,v_3^s}(1^T v_1^s+1^T v_2^s+v_3^s)\\ \sum_{i}^{N_g} p_i^{s,t}+\sum_{j}^{N_w} p_{wj}^{s,t}+v_1^{s,t}-v_{2,s}^{s,t}=\sum_{k}^{N_d} p_{dk}^t\\ \sum_{i}^{N_g}\pi_i^l p_i^{s,t}+\sum_{j}^{N_w}\pi_j^l p_{wj}^{s,t}-\sum_{k}^{N_d}\pi_k^l p_{dk}^{s,t}-v_3^s\le F_l^{\max}\\ -\sum_{i}^{N_g}\pi_i^l p_i^{s,t}-\sum_{j}^{N_w}\pi_j^l p_{wj}^{s,t}+\sum_{k}^{N_d}\pi_k^l p_{dk}^{s,t}-v_3^s\le F_l^{\max}\\ p_i^{s,t}\le p_i^{\max}\hat{x}_i^t \quad \to\theta_{1i}^{s,t}\\ p_i^{s,t}\ge p_i^{\min}\hat{x}_i^t \quad \to\theta_{2i}^{s,t}\\ p_i^{s,t+1}-p_i^{s,t}\le\hat{x}_i^t R_i^+ +(1-\hat{x}_i^t)p_i^{\max} \quad \to\theta_{3i}^{s,t}\\ p_i^{s,t}-p_i^{s,t+1}\le\hat{x}_i^{t+1} R_i^- +(1-\hat{x}_i^{t+1})p_i^{\max} \to\theta_{4i}^{s,t}\end{cases} \tag{13}$$

If $R_1^s(v)>0$, it means $\Omega(p^s)=\varnothing$. Then the infeasibility Benders cut will be generated and fed back to the master problem,

$$R_1^s(v)+(x-\hat{x})*E^T*\boldsymbol{\theta}^s\le 0 \tag{14}$$

where E is the coefficient matrix of variables $\hat{x}$. $\boldsymbol{\theta}^s$ is the dual multiplier vector.

3) Third-step:computation of compensate expense

$$\text{Min } F_2=\sum_{s\in S-S_R}\rho_s\sum_{t=1}^{T}F_{ld}(P_{l,shed}^{s,t}+P_{w,curt}^{s,t})$$

For any $s\in S-S_R$,

$$\begin{cases}R_1^s(v)=\min\limits_{p^s,v_1^s,v_2^s}(1^T v_1^s+1^T v_2^s)\\ \sum_{i}^{N_g} p_i^{s,t}+\sum_{j}^{N_w} p_{wj}^{s,t}+v_1^{s,t}-v_2^{s,t}=\sum_{k}^{N_d} p_{dk}^t\\ -F_l^{\max}\le\sum_{i}^{N_g}\pi_i^l p_i^{s,t}+\sum_{j}^{N_w}\pi_j^l p_{wj}^{s,t}-\sum_{k}^{N_d}\pi_k^l p_{dk}^{s,t}\le F_l^{\max}\\ p_i^{\min}\hat{x}_i^t\le p_i^{s,t}\le p_i^{\max}\hat{x}_i^t\\ p_i^{s,t+1}-p_i^{s,t}\le\hat{x}_i^t R_i^+ +(1-\hat{x}_i^t)p_i^{\max}\\ p_i^{s,t}-p_i^{s,t+1}\le\hat{x}_i^{t+1}R_i^- +(1-\hat{x}_i^{t+1})p_i^{\max}\end{cases} \tag{15}$$

Note that there is only the v_1 and v_2 are introduced. This is because we acquire the load shed or wind curtailment strategy which must respect transmission line thermal limits. $P_{l,shed}$ and $P_{w,curt}$ can be computed as:

$$P_{l,shed}^s=v_1^s\ ,\ P_{w,curt}^s=v_2^s \tag{16}$$

The complete process is shown as the below flow chart.

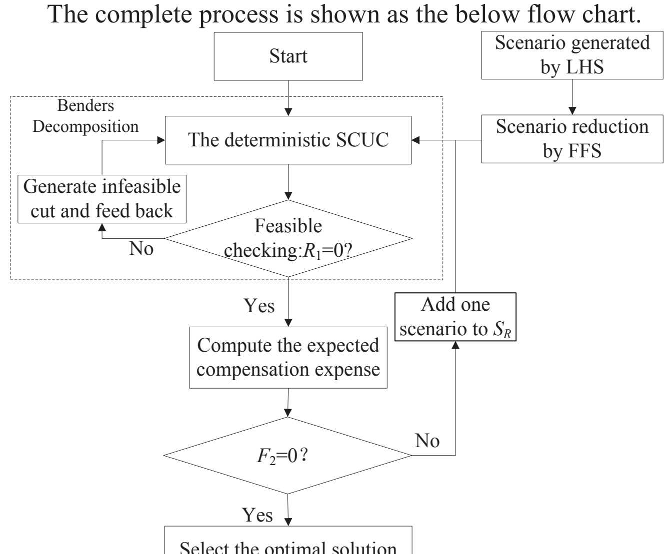

Fig. 1. Flowchart of the proposed solution methodology

B. Scenario Generation and Scenario Reduction

The scenarios is generated by LHS and Cholesky decomposition. The scenario reduction determine a reduced scenario set Q which is the closest to the original scenario set P in terms of a certain probability distance between P and Q. The minimal distance can be described as:

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$$\min_J \left(\sum_{i\in J} prob_i \sum_{j\notin J} c_T(\xi_i,\xi_j)\right) \tag{17}$$

where $c_t(\xi_i,\xi_j)=\sum_{\tau}^{t}|\xi_i-\xi_j|$,t=1,...,T. J denotes the index set of deleted scenarios. $prob_i$ is the probability of scenario ξ_i . The probability q_j of the preserved scenarios ξ_j $j\notin J$ is given by rule:

$$q_j = p_j + \sum_{i\in J(j)} prob_i \tag{18}$$

$$J(j):=\{i\in J: j=j(i)\}\ ,\ j(i)\in \arg\min_{j\notin J} c_T(\xi_i,\xi_j), \forall i\in J$$

Obviously, the scenario reduction is a set covering problem. The FFS is shown as follows:

Step 0: Compute the distance of scenario pairs

$$c_{ku}^{[1]} := c_T(\xi^k,\xi^u)\ ,\ k,u=1\cdots,S$$

Step 1: Compute the probability distance

$$z_u^{[1]} := \sum_{\substack{k=1\\k\neq u}} p_k c_{ku}^{[1]}\ ,\ u=1\cdots S$$

Choose $u_1 \in \arg\min_{u\in\{1\cdots S\}} z_u^{[1]}$, set $J^{[1]} := \{1\cdots S\}\setminus\{u_1\}$

Step i: Compute $c_{ku}^{[i]} := \min\{c_{ku}^{[i]}, c_{ku_{i-1}}^{[i-1]}\}$

$k,u\in J^{[i-1]}$ and $u\in J^{[i-1]}$

Choose $u_i \in \arg\min_{u\in J^{[i-1]}} z_u^{[i]}$, set $J^{[i]} = J^{[i-1]}\setminus\{u_i\}$

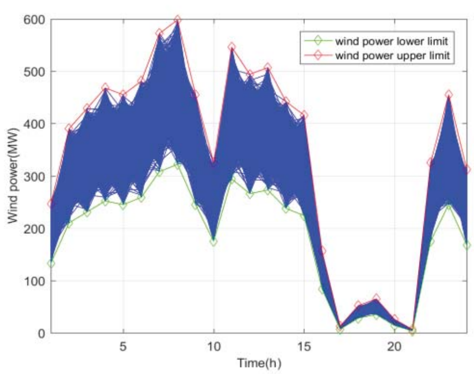
Step s+1: Compute probabilities for the preserved scenarios from (18)

IV. Case Studies

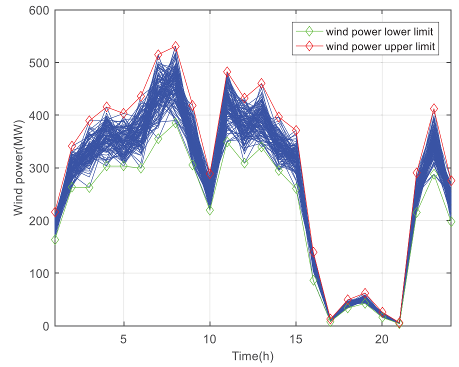
The modified IEEE 39, 118-bus testing systems are employed to demonstrate the performance of the proposed RSCUC model. All case studies utilize CPLEX 12.5.1 on personal computer with an Intel Core i5 3.20-GHz and 4GB memory. Different wind power volatilities and robust confident levels are taken into consideration in case studies.

A. Data Process

The 24-h wind power generation and load demand profiles can be found in [4]. We assume the forecast error of wind farm j output power are normally distributed. According to Section III.B, the original scenario set and the reduced scenario set can be obtained and the result is shown in fig. 2.



(a) original scenarios



(b) reduced scenarios

Fig. 2 Production and reduction of wind power scenarios

B. IEEE 39-Bus system

A modified IEEE 39-bus testing system is employed which includes 10 thermal units, 1 wind farms, and 46 branches. A wind farm is connected to the main grid at bus 29. The characteristics of generators and other system data can be found in [18].

1) Optimization Results for Base Condition

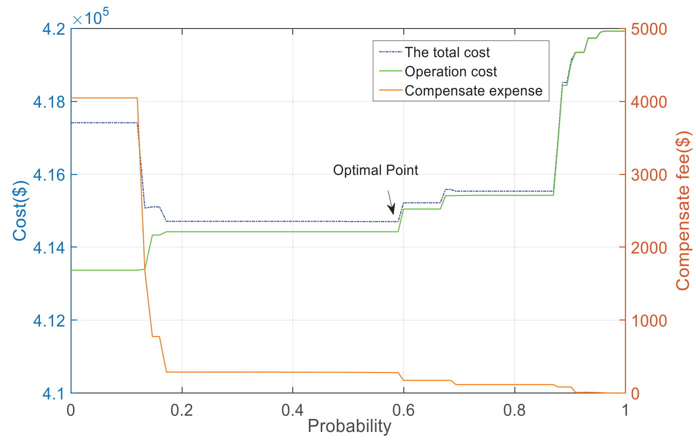


Fig. 3. Cost curve of base condition for IEEE 39-bus system

When σ / μ is 1/10, we call this condition as base condition. As displayed in the Fig. 3, the operation cost increases with the higher confidence level and shoots up when the confidence level reaches 85%. As the confidence level increases, the strategy will cover more uncertain scenarios, which in turn induces higher the operation cost as well as lower compensate expense. The optimal strategy with the operation cost 414422.3$ is achieved when the confidence level reaches 59%. As for the optimal strategy, the expected quantities of load shedding or wind curtailment is about 0.35MWh during the whole scheduling horizon and the compensate expense is 280.32$. When the confidence level reaches 100%, the operation cost is 419923.9$, which is 5221.3$ higher than that of the optimal strategy. Moreover, the operation cost is 417412.9$ when the confidence level is 0, which is also higher than optimal strategy.

2) Analysis of Forecast Error

The efficiency of the proposed model is compared with the conventional RO model.

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1) Mode A (extreme case) RCL is set as 100% without considering the load shed or wind curtailment.
2) Mode B (common case) The model in this paper.

TABLE I

IMPACT OF PREDICTION ERROR ON THE OVERALL OPERATION COST

σ / μ	Mode A	Mode B		
	Total cost ($)	Total cost ($)	$P_{l,shed} / P_{w,\mathrm{curt}}$ (MWh)	RCL (%)
0	413367.0	413367.0	—	—
1/30	413395.7	413371.5	0.15	94.4
1/15	414422.3	413699.5	0.32	74.9
1/10	419923.9	414702.6	0.35	59.0
2/15	422390.3	416797.8	2.97	27.5
1/6	424839.7	422399.0	8.83	20.6

As shown in the Table I, the total cost in the mode A is always higher than that in mode B. This is because in mode B some measures such as load shedding or wind curtailment are considered to keep system power balance. In addition, in model B, the RCL decreases and the total cost increases with the higher forecast error and the optimal strategy is usually achieved at the low confidence level. This is because that covering more uncertain scenarios induces the higher compensate expense. When σ / μ is 1/6, the total cost is 9032$ higher than that with σ / μ being 0. Hence, to improve forecasting accuracy of the wind power is of great importance to reducing the operation cost.

C. IEEE 118-Bus System

We also test our model on a modified IEEE 118-bus testing system and the detailed 118-bus system data and load demand profiles can be found in [8] [9]. First, the SCUC solution with daily total cost of $3015430 is achieved for the system operation with the forecast value of wind power and the expected compensate expense is summed up to $62313. In the base condition, the optimal strategy with the operation cost $2424592 is obtained when the RCL is 100%, in which case the optimal strategy is robust against all the values in the uncertainty sets.

It should be pointed that when applying a higher wind power volatility (σ / μ=1/6), the optimal solution obtained is still same as above. This is because the committed units at low load level provide the sufficient ramping capabilities and reserve capacity. Thus, it makes the 118-bus system more robust when compared to the 39-bus system.

V. CONCLUSION

The robust optimization has been widely applied in power system unit commitment and economic dispatch problems. A robust strategy with optimal RCL can be obtained from the RSCUC model proposed in this paper which takes the massive penetration of wind power into consideration. More importantly, a new index called RCL is proposed to quantitatively evaluate the robustness of the strategy. As a result, the proposed model provides a basis for system operators to strike a balance between robustness and economic performance. The results for the 39-bus system and 118-bus system show that the model in this paper derives more economical, less conservative solutions. Thus, it is an alternative for solving the day-ahead operation planning problem as well as long term of power systems with massive penetration of wind power.

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