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# Proper Security Criteria Determination in a Power System with High Penetration of Renewable Resources

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## SUMMARY

The primary objective of a power system is to reliably provide a continuous supply of electricity. Power system is a complex structure and is exposed to various sources of uncertainties including the variations of demand and unexpected equipment failures. The increasing integration of large-scale semi-dispatchable, variable and uncertain renewable resources further challenges the ability to provide a reliable supply of electricity. In order to operate the system in a secure manner, the operator should provide sufficient reserve to overcome the sudden failures of facilities as well as the uncertainties caused by errors in load forecast or unexpected deviations of generating units from their production schedules. Many probabilistic approaches have been applied in power system security assessment. The traditional reserve commitment approach is, however, based on a deterministic approach. Most utilities use the deterministic criterion known as the N-1 security criterion. The N-1 criterion states that the system could lose any single one of its N components and still be able to continue operating in a secure manner. There is a growing interest in combining deterministic criteria with probabilistic methods to obtain integrated approaches to evaluate the security and determine the required reserve level of the system. In this paper, the inherent distinction between the uncertainty in wind farm generation and that of other generating units has been clarified, indicating the challenges of dealing with uncertainties in the presence of large-scale wind generations. This paper reviews the assumptions that the N-1 criterion is based upon and argues that this security criterion, by itself, is insufficient at addressing the challenges imposed by renewables. As a result, a robust unit commitment schedule, which minimizes the total cost under the worst-case disturbance the uncertain parameters can cause, is proposed. The uncertain parameters are modeled using an uncertainty set. The unit commitment decisions are robust against all parameters ranging in the defined uncertainty set. The problem is formulated as a two-stage optimization problem. The first stage finds a minimum cost unit commitment schedule and the second stage find the worst-case load shedding cost that may occur under a fixed unit commitment solution. A Benders' decomposition algorithm has been applied to solve the obtained optimization problem. Numerical studies performed on a modified IEEE-118 test case demonstrate the significant effectiveness of the proposed approach in dealing with the system uncertainties.

## KEYWORDS

Power system security, N-1 criterion, Renewable energy, Reserve requirement, Robust optimization

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## 1. Introduction

A power system is subject to various inevitable uncertainties such as load forecast errors and unscheduled outage of the generators. The increasing integration of large-scale renewable energy resources introduces more uncertainty within power systems operations. In order to operate the system in a secure manner, the operator should schedule sufficient reserve to overcome the uncertainties. This has raised an interest in applicable approaches for determining the amount of required reserve for secure operation of the system in an uncertain environment. The challenge of committing reserves lies in the trade-off between system security and operation of the system at least cost. The committed reserve should be able to mitigate both continuous and discrete sources of uncertainties. Fluctuations in demand and renewable supply are examples of continuous uncertainty whereas the failures of the network elements are discrete uncertainty events.

Large-scale integration of wind farm generation in power system calls for scheduling more reserve due to the inherent variability and uncertainty of the wind power. A simple idea may be to consider the wind farm as yet another generating unit and generalize the N-1 criterion to count for the capacity of the wind farm as well. Previous works that have studied the impact of wind power on each reserve category separately have concluded that wind power does not impact the contingency reserve requirement [1]-[5]. This is because wind power plants that could trip off instantaneously have smaller capacity than the largest single contingency. The increase in the penetration of intermittent renewable generation makes it crucial for the power system operators to have effective methodologies to produce unit commitment decisions that are robust against these uncertainties.

Prior studies in this area fall into two general categories. The first group analyzes the required reserve in the presence of uncertainty and tries to derive deterministic rules for adjusting the levels of reserve requirements [6]-[7]. Such rules are easy to implement. However, committing extra reserve is not always economically efficient. The second group uses a stochastic optimization approach to consider different possible scenarios. In this approach, it is usually assumed that the continuous uncertainty follows a certain probability distribution function and sampling techniques are used to represent various uncertainty scenarios [8]-[11]. The two-stage scenario-based stochastic approach suffers from two main drawbacks. First, it is not easy to find an accurate distribution function that represents the continuous uncertainty. Second, in order to get a good performance guarantee, a large number of scenarios need to be modeled, which results in a computationally intensive problem.

In this paper, a robust optimization model is proposed for the unit commitment problem. Robust optimization has been recently used as a modeling structure to address parameter uncertainty in various optimization problems. In robust optimization, instead of making assumptions on probability distributions, the uncertain parameters are defined to lay in a deterministic uncertainty set. The way of defining the uncertainty is flexible enough to incorporate probabilistic information into the model. The uncertainty set can be created using the historical data or considered with a confidence interval. The optimal solution should be robust against all realizations of the uncertain data within the uncertainty set. Reference [13] uses robust optimization to obtain security constrained unit commitment decisions that are robust against load uncertainties. In [14] robust optimization is applied to ensure system robustness under large deviation of wind farm output from its forecasted level. The authors of [15] have applied the robust framework to solve contingency constrained unit commitment. In the present study, the robust optimization approach is employed to hedge against both continuous and discrete uncertainties. The proposed structure aims to obtain a robust unit commitment schedule that minimizes the total cost under the worst disturbance the uncertain parameters can cause.

The rest of the paper is organized as follows: In section 2 the definition of the N-1 security criteria is revisited. The assumptions behind using such criteria are described. Section 3 introduces the two types of uncertainty that can impact the operation of the power system. The wind uncertainty model used for the simulation studies is described in section 4. In section 5 the mathematical model of the two-stage robust optimization is presented. Section 6 describes the solution approach. Simulation studies and their results are discussed in section 7. Section 8 concludes the paper.

## 2. N-1 criterion

The fundamental principle of power system security is that a system should always be operated in such a way that no contingency could trigger cascading outages or other forms of instability [12]. The power system is subject to a variety of failures and faults caused by events such as lightning strikes on transmission lines or failures in power plants as well as failures caused due to maintenance actions. Since these events are unpredictable and unavoidable, the system should be operated within a proper security margin so as to prevent consumer disconnection. In order to determine the proper reserve capacity, one has to come up with a list of possible contingencies and their impact on the system. Since securing the system against all possible contingencies is clearly impossible, the fundamental principle only calls for securing against the contingencies that are likely to happen. It is typically assumed that the probability of two or more independent faults or failures taking place simultaneously is too low to be considered. Most security rules call for the system to be able to withstand the loss of any single component. When a power system satisfies this criterion, it is said to be "N-1 secure".

## 3. Discrete vs. continuous uncertainty

The uncertainty faced by a power system can be classified into two categories. The first category relates to low probability discrete events, called contingencies. This type of the uncertainty has a discrete nature. An online conventional generator, for instance, is assumed to be in either an operating or a contingency state. Such contingencies are usually represented as a discrete event with an associated probability. The second category deals with model parameters that can vary within a range and are, thus, known to be continuous. The uncertainty of the future demand or that of the available generation from a wind farm, for example, falls into this category. Continuous uncertainties can usually be described as a set of probability distributions for the uncertain parameters. This probability distribution may vary across the time if the variable has a non-stationary nature.

## 4. Wind uncertainty in robust formulation framework

In the proposed robust framework, the random wind power output is modeled with the uncertainty set *W*. In order for the system to operate reliably in the presence of wind, it should be able to sustain wind power ramp events, which can be viewed as the counterparts of contingency for conventional generators. Note that the N-1 reliability criterion is based upon the fact that independent discrete events are not likely to happen simultaneously, i.e., it is rather unlikely for two generators to fail simultaneously. In contrast, it is quite common for nearby wind farms to experience a ramp event at the same time since they are exposed to similar weather variation patterns. The power outputs of different wind farms in a system are, therefore, both temporally and spatially correlated. The correlation of the output of two wind farms is a measure of the synchronism in their output variations. The uncertainty set considered for wind generation should, therefore, be constructed in a way that takes the impact of correlation of multiple wind farms into consideration. If two wind farms have the same exact output over the time they will have a maximum possible correlation measure, which is equal to 1. Inspired with that, we assume a maximum aggregate deviation for two wind farms to be proportional to their correlation coefficient. In the present study, the following uncertainty set has been considered for the wind generation:

$$W := \{P_{wt} \in \mathbb{R}^{N_w \times T}: \widehat{W}_{it} - dw_{it} \leq P_{wt} \leq \widehat{W}_{it} + dw_{it}, \sum_{i \in N_w} \frac{dw_{it}}{\widehat{W}_{it}} \leq \Delta^t,$$

$$\left| \frac{dw_{it}}{\widehat{W}_{it}} + \frac{dw_{jt}}{\widehat{W}_{jt}} \right| \leq \frac{\Delta^t}{2} + \frac{\Delta^t}{2} cor_{i,j}, \forall\, i, \forall j \in N_w \,\} \quad (1)$$

where $\widehat{W}_{it}$ is the forecasted wind farm output and $\Delta^{\mathrm{t}}$ is the budget of uncertainty. It is assumed that the output of any single wind generator cannot exceed half of the total uncertainty budget. As $\Delta^{\mathrm{t}}$ increases, larger aggregate deviation from the forecasted wind generation is considered leading to a more conservative unit commitment solution that is robust against a larger set of possible uncertainties.

For the conventional generators, the binary decision variable $z_{cg}$ is introduced, which takes a value of 0 if generator g is under contingency, and a value of 1 otherwise. In this study, we try to hedge against single generator contingencies, i.e., $Z := \{z_{cg} \in \{0,1\}^{N_g}: \sum_g z_{cg} \geq N_g - 1\}$. (2)

The above set allows at most one generator to be under contingency in the model. Considering sets (1) and (2) together, enables us to find a unit commitment solution that is robust against the worst-case disturbance.

## 5. Model description

The day-ahead SCUC model used here is a multi-period unit commitment model with a DCOPF formulation. The proposed robust SCUC model is described below. The objective function has two parts, representing the two stages of the problem. The first part is the unit commitment cost (including start-up, no-load, and operating costs). The second part is the worst-case second stage load shedding penalty cost. The mathematical formulation is given as follows:

$$min_{u,v,p}\left(\sum_t \sum_g c_g^{SU} v_{gt} + c_g^{NL} u_{gt} + c_g P_{gt} + max\ min \sum_n c_c^n (LS_{nt}^+ + LS_{nt}^-)\right) \quad (3)$$

*s.t.*:

**Base case constraints:**

$$P_{gt} \geq P_g^{min} u_{gt} \qquad \forall\, g,t \quad (4)$$
$$P_{gt} + r_{gt} \leq P_g^{max} u_{gt} \qquad \forall\, g,t \quad (5)$$
$$\sum_{s=t-UT_g-1}^{t} v_{gs} \leq u_{gt} \qquad \forall\, g,t \geq 1 + UT_g \quad (6)$$
$$\sum_{s=t-DT_g-1}^{t} w_{gs} \leq 1 - u_{gt} \qquad \forall\, g,t \geq 1 + DT_g \quad (7)$$
$$v_{gt} - w_{gt} = u_{gt} - u_{g,t-1} \qquad \forall\, g,t \quad (8)$$
$$P_{kt} - B_k(\theta_{nt} - \theta_{mt}) = 0 \qquad \forall\, k,t \quad (9)$$
$$-P_k^{max} \leq P_{kt} \leq P_k^{max} \qquad \forall\, k,t \quad (10)$$
$$\sum_{k\in\delta^+(n)} P_{kt} - \sum_{k\in\delta^-(n)} P_{kt} + \sum_{w\in w(n)} P_{wt} + \sum_{g\in g(n)} P_{gt} = d_{nt} \qquad \forall\, n,t \quad (11)$$
$$P_{gt} - P_{g,t-1} \leq R_g^{HR} u_{g,t-1} + R_g^{SU} v_{gt} \qquad \forall\, g,t \quad (12)$$
$$P_{g,t-1} - P_{gt} \leq R_g^{HR} u_{gt} + R_g^{SD} w_{gt} \qquad \forall\, g,t \quad (13)$$
$$r_t^{max} \leq \sum_g r_{gt} \qquad \forall\, t \quad (14)$$
$$r_t^{max} \geq P_{gt} + r_{gt} \qquad \forall\, g,t \quad (15)$$
$$0 \leq r_{gt} \leq R_g^{10} u_{gt} \qquad \forall\, g,t \quad (16)$$
$$u_{gt} \in \{0,1\}; 0 \leq v_{gt}, w_{gt} \leq 1 \qquad \forall\, g,t \quad (17)$$

**Second stage constraints:**

$$z_{cg} P_{gt} - P_{gct} \leq R_g^{10} \mathrm{u_{gt}} \qquad [\delta_{gt}] \quad \forall\, g,t \quad (18)$$
$$P_{gct} - z_{cg} P_{gt} \leq R_g^{10} u_{gt} \qquad [\gamma_{gt}] \quad \forall\, g,t \quad (19)$$
$$P_{gct} \geq P_g^{min} u_{gt} z_{cg} \qquad [\eta_{gt}] \quad \forall\, g,t \quad (20)$$
$$P_{gct} \leq P_g^{max} u_{gt} z_{cg} \qquad [k_{gt}] \quad \forall\, g,t \quad (21)$$
$$-P_k^{max} \leq P_{kct} \leq P_k^{max} \qquad [\varphi_{kt}, \tau_{kt}] \quad \forall\, k,t \quad (24)$$
$$\sum_{g\in g(n)} P_{gct} + \sum_{k\in\delta^+(n)} P_{kst} - \sum_{k\in\delta^-(n)} P_{kst} + \sum_{w\in w(n)} P_{wct}$$
$$+ LS_{nt}^+ - LS_{nt}^- = d_{nt} \qquad [\varsigma_{nt}] \quad \forall\, n,t \quad (22)$$
$$P_{kct} - B_k(\theta_{nct} - \theta_{mct}) = 0 \qquad [\pi_{kt}] \quad \forall\, k,t \quad (23)$$
$$P_{wct} \in W \qquad \forall\, w,t \quad (25)$$
$$z_{cg} \in Z = \{\sum_g z_{cg} \geq N-1\} \qquad \forall\, g,t \quad (26)$$

The second stage objective function is defined to minimize the penalty cost for the worst case deviation that may occur under the unit commitment schedule obtained in the first stage. The second stage problem can be expressed as problem $R$ below:

$$R = max_{z,w}\, Q(z, p_w, u, v, p_g) \quad (27)$$

*s.t.*: constraints (25)-(26)

where $Q(z, p_w, u, v, p_g)$ is equal to:

$$min \sum_n c_c^n (LS_{nt}^+ + LS_{nt}^-) \quad (28)$$

*s.t.*: constraints (18)-(24)

We can transfer this max-min problem into an MILP by constructing the dual formulation of the inner minimization problem as follows:

$Q'(z, p_w, u, v, p_g) : max\ \sum_t \sum_g \delta_{gt}\,(z_{cg}P_{gt} + R_g^{10}u_{gt}) - \sum_t \sum_g \gamma_{gt}\,(z_{cg}P_{gt} - R_g^{10}u_{gt}) -$
$\sum_t \sum_g \eta_{gt}\,P_g^{min}u_{gt}z_{cg} + \sum_t \sum_g k_{gt}\,P_g^{max}u_{gt}z_{cg} + \sum_t \sum_k \varphi_{kt}\,P_k^{max} + \sum_t \sum_k \tau_{kt}\,P_k^{max} -$
$\sum_t \sum_n \varsigma_{nt}\,(\sum_{w\in w(n)} P_{wct} - d_{nt})$ (29)

*s.t.*:

$-\gamma_{gt} + \delta_{gt} - \eta_{gt} + k_{gt} + \varsigma_{nt} \leq 0$ $\forall\ g, t$ (30)

$\varsigma_{it} - \varsigma_{jt} + \pi_{kt} - \varphi_{kt} + \tau_{kt} = 0$ $\forall\ k, t$ (31)

$-\sum_{k\in\delta^+(n)} B_k\pi_{kt} + \sum_{k\in\delta^-(n)} B_k\pi_{kt} = 0$ $\forall\ n$ (32)

$\varsigma_{nt} - c_c^n \leq 0$ $\forall\ n$ (33)

$-\varsigma_{nt} - c_c^n \leq 0$ $\forall\ n$ (34)

where $\delta, \gamma, \eta, k, \varphi, \tau, \varsigma, \pi$ are the dual variables for constraints (18)-(24) respectively.

Now, if we substitute the inner problem with this equivalent dual and combine the two maximization problems, the second stage problem will be equivalent to a bilinear optimization problem. There are two types of nonlinear terms in the above objective function. The bilinear terms including the product of a binary and a continuous variable, e.g., $\delta_{gt}z_{cg}$, can be linearized using a big M reformulation. The bilinear term including the product of $\varsigma_{nt}$ and $P_{wct}$, however, consists of two continuous variables and cannot be linearized in the same way. To deal with this nonlinear format, an outer approximation algorithm, similar to the one used in [13], is employed where the bilinear term is linearized around intermediate solution points. The solution procedure for obtaining the optimal solution is described in the following section.

## 6. Solution method

As explained earlier, the proposed robust formulation is a two-stage problem. The first stage finds a minimum cost unit commitment schedule and the second stage finds the worst-case penalty cost under a fixed unit commitment solution. The problem is solved using a two-stage algorithm. A Benders' decomposition method is employed to add new constraints to the master problem using the information obtained from the inner subproblem. The algorithm is described below.

Initialization: Start from a feasible first stage solution. Initialize the outer level lower bound, $L^O = -\infty$ and upper bound $U^O = +\infty$. For iteration $l \geq 1$:

Step 1) Solve the master problem, expressed as:

$$\min_{u,v,p} \sum_t \sum_g c_g P_{gt} + c_g^{NL}u_{gt} + c_g^{SU}v_{gt} + \alpha$$

*s.t.*: constraints (4)-(17)

$\alpha \geq \sum_t \sum_g \delta_{gt}^i(z_{cg}^i P_{gt} + R_g^{10}u_{gt}) - \sum_t \sum_g \gamma_{gt}^i(z_{cg}^i P_{gt} - R_g^{10}u_{gt}) - \sum_t \sum_g \eta_{gt}^i P_g^{min}u_{gt}z_{cg}^i +$
$\sum_t \sum_g k_{gt}^i\,P_g^{max}u_{gt}z_{cg}^i + \sum_t \sum_k \varphi_{kt}^i P_k^{max} + \sum_t \sum_k \tau_{kt}^i P_k^{max} - \sum_t \sum_n \varsigma_{nt}^i\,(\sum_{w\in w(n)} P_{wct}^i - d_{nt})$
$\forall\ i \leq l$

Let $(P_{gt}^l, u_{gt}^l, v_{gt}^l, \alpha_l)$ be the optimal solution.

Step 2) Solve the subproblem using the outer approximation algorithm as follows:

Initialization: Fix the decision variables passed from the master problem. Start from an initial $P_{wt}^1 \in W$. Set the inner level lower bound, $L^i = -\infty$ and upper bound $U^i = +\infty$. For iteration $j \geq 1$:

1- Solve the dual subproblem $Q'$ for $(P_{gt}^l, u_{gt}^l, v_{gt}^l, P_{wt}^j)$. Let $(\delta_{gt}^j, \gamma_{gt}^j, \eta_{gt}^j, k_{gt}^j, \varphi_{kt}^j, \tau_{kt}^j, \varsigma_{nt}^j, z_{cg}^i)$ be the optimal solution. Update the lower bound $L^i = Q'(P_{gt}^l, u_{gt}^l, v_{gt}^l, P_{wct}^j)$. Linearize the bilinear term $\varsigma_{nt}\sum_{w\in w(n)} P_{wct}$ around $\varsigma_{nt}^j$ and $P_{wct}^j$:
   $L_j(\varsigma_{nt}^j, P_{wct}^j) = \varsigma_{nt}^j \sum_{w\in w(n)} P_{wct}^j + (\varsigma_{nt} - \varsigma_{nt}^j)\sum_{w\in w(n)} P_{wct} + \varsigma_{nt}^j \sum_{w\in w(n)}(P_{wct} - P_{wct}^j)$
2- Check the inner level convergence. If converged, stop and report the inner level solution. Otherwise set *j=j+1*.
3- Solve the linearized version of the subproblem:
   $\backslash max \sum_t \sum_g \delta_{gt}\,(z_{cg}P_{gt} + R_g^{10}u_{gt}) - \sum_t \sum_g \gamma_{gt}\,(z_{cg}P_{gt} - R_g^{10}u_{gt}) -$
   $\sum_t \sum_g \eta_{gt}\,P_g^{min}u_{gt}z_{cg} + \sum_t \sum_g k_{gt}\,P_g^{max}u_{gt}z_{cg} + \sum_t \sum_k \varphi_{kt}\,P_k^{max} + \sum_t \sum_k \tau_{kt}\,P_k^{max} -$
   $\sum_t \sum_n \varsigma_{nt}\,(-d_{nt}) + \beta$

s.t. $\beta \geq L_k(\varsigma_{nt}^j, P_{wt}^j) \quad \forall\, k \leq j$
constraints (25)-(26)
constraints (28)-(32)

4- Set the upper bound $U^i$ to be equal to the optimal solution.

Step 3) Let $(\delta_{gt}^{i+1}, \gamma_{gt}^{i+1}, \eta_{gt}^{i+1}, k_{gt}^{i+1}, \varphi_{kt}^{i+1}, \tau_{kt}^{i+1}, \varsigma_{nt}^{i+1}, z_{cg}^{i+1}, P_{wt}^{i+1})$ be the optimal solution of the inner problem. Update the upper bound $U^O = \sum_t \sum_g c_g P_{gt}^l + c_g^{NL} u_{gt}^l + c_g^{SU} v_{gt}^l + Q'\,(P_{gt}^l, u_{gt}^l, v_{gt}^l)$

Step 4) check the outer level convergence. If converged, stop and report the solution. Otherwise set $i=i+1$, and go to step 1.

## 7. Simulation results and analysis

The proposed structure has been applied to the IEEE-118 bus test case [23]. The test system is modified by integrating three 250 MW wind farms at buses 4, 27, and 59. This additional capacity accounts for roughly 15% of the total system-wide generation capacity. It is assumed that the wind generators at bus 4 and 27 have a highly correlated output, whereas the wind generator at bus 59 is located far from the other two generators and has a smaller value of correlation with them. Table 1 shows the presumed values for correlation coefficients of the wind generators.

Table I
Correlation coefficients between wind generators

| | W2(bus 27) | W3(bus 59) |
|---|---|---|
| W1(bus 4) | 0.51 | 0.15 |
| W2(bus 27) | | 0.17 |

To model the wind uncertainty, the budgeted uncertainty set defined in (1) is used. The proposed robust unit commitment has been performed for different values of $\Delta^t$. The convergence tolerance for both the outer and inner level algorithm is set to be $10^{-3}$. In order to assess the security of the unit commitment decisions made using this approach, the performance have been tested against a set of 100 generated wind farm outputs. The load shedding penalty cost is set to $10000/MWh. The performance is compared to that of a deterministic reserve adjustment approach. For this deterministic approach the level of required reserve is adjusted by adding the amount of total allowed deviation, $\Delta^t$. The unit commitment is then solved for this new required reserve level. Table II summarizes the results. As suggested by the results, if the budget level of the uncertainty set is adjusted properly, the adaptive robust solution has lower average commitment and penalty costs. It is worth noting that the commitment cost, penalty cost and total cost when implementing an N-1 reliability criteria for this system is equal to 2.693, 0.466 and 3.159 M$ respectively.

Table II
Average costs for the robust formulation and the reserve adjustment approach

| | Robust formulation | | | Reserve adjustment approach | | |
|---|---|---|---|---|---|---|
| $\Delta^t$ | Commitment cost (M$) | Penalty cost (M$) | Total cost (M$) | Commitment cost (M$) | Penalty cost (M$) | Total cost (M$) |
| 0 | 2.805 | 0.285 | 3.090 | 2.805 | 0.285 | 3.090 |
| 0.1 | 2.841 | 0.245 | 3.086 | 2.851 | 0.251 | 3.102 |
| 0.2 | 2.859 | 0.024 | 2.883 | 2.860 | 0.041 | 2.901 |
| 0.3 | 2.818 | 0.011 | 2.829 | 2.862 | 0.041 | 2.903 |
| 0.4 | 2.833 | 0.099 | 2.932 | 2.865 | 0.067 | 2.932 |
| 0.5 | 2.853 | 0.073 | 2.926 | 2.867 | 0.214 | 3.081 |
| 0.6 | 2.780 | 0.275 | 3.055 | 2.872 | 0.21 | 3.082 |
| 0.7 | 2.867 | 0.390 | 3.257 | 2.881 | 0.202 | 3.083 |
| 0.8 | 2.853 | 0.039 | 2.892 | 2.887 | 0.201 | 3.088 |
| 0.9 | 2.917 | 0.012 | 2.929 | 2.921 | 0.168 | 3.089 |

To come up with a proper value for the budget level, both commitment costs and penalty costs associated with the extreme events should be considered. Although the probabilistic information is not directly taken into consideration in the robust optimization for defining the uncertainty set, the historical data related to the extreme ramping events can be utilized to address the penalty costs. A set of extreme events along with their probabilities, for instance, can be employed in offline simulation studies to test the output of the robust unit commitment and adjust the uncertainty budget level.

## 8. Conclusions

Integration of large scale wind generation in the power system increases the uncertainty that the operator has to deal with due to the variability of the wind energy. This paper revisits the common N-1 criterion for allocating capacity reserve in the presence of wind farm generation. The basic assumption behind the N-1 criterion is described using the fundamental distinction of two different types of uncertainty. A robust optimization framework is proposed alternatively to account for both discrete and continuous uncertainties. Numerical studies, via the IEEE-118 test case, demonstrate the effectiveness of this methodology when a high amount of continuous uncertainty is introduced into the system by integrating wind farm generation.

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# APPENDIX 1
# NOMENCLATURE

**Indices and Sets**

| | |
|---|---|
| $g$ | Index of generators, $g \in G$ |
| $k$ | Index of transmission lines, $k \in K$ |
| $n$ | Index of buses, $n \in N$ |
| $t$ | Index of time periods, $t \in T$ |
| $w$ | Index of wind generators, $w \in W$ |
| $\delta^{+}(n)$ | Set of lines specified as to node *n* |
| $\delta^{-}(n)$ | Set of lines specified as from node *n* |

**Parameters**

| | |
|---|---|
| $\widehat{W}_{it}$ | Point forecast of the output of wind unit *i* for period *t* |
| $cor_{i,j}$ | Correlation coefficient of the output of wind units *i* and *j* |
| $B_k$ | Electrical susceptance of line *k* |
| $c_g$ | Operation cost ($/MWh) |
| $c_g^{NL}$ | No-load cost of unit $g$ |
| $c_g^{SD}, c_g^{SU}$ | Shutdown and startup cost of unit $g$ |
| $c_c^n$ | Load shedding penalty cost |
| $P_g^{max}, P_g^{min}$ | Max output and min output of unit $g$ |
| $P_k^{max}$ | Thermal rating of transmission line *k* |
| $R_g^{HR}$, $R_g^{10}$ | Max hourly and 10-min ramp rates of unit $g$ |
| $R_g^{SD}$, $R_g^{SU}$ | Max shutdown and startup ramp rates of unit $g$ |
| $UT_g, DT_g$ | Minimum up time and down time of unit $g$ |
| $r_t^{max}$ | Required level of reserve in period *t* |

**Variables**

| | |
|---|---|
| $P_{gt}$ | Scheduled real power output of conventional unit $g$ in period $t$ |
| $u_{gt}$ | Unit commitment binary variable for generation unit $g$ in period $t$ |
| $v_{gt}$, $\mathrm{w}_{\mathrm{gt}}$ | Start-up and shut-down variables for generation unit $g$ in period *t* respectively |
| $P_{wt}$ | Scheduled real power output of wind unit *w* in period *t* |
| $r_{gt}$ | Scheduled spinning reserve from conventional unit $g$ in period *t* |
| $d_{nt}$ | Demand at bus n in period *t* |
| $LS_{nt}^{+}, LS_{nt}^{-}$ | Violations in node power balance equation (load shedding). |
| $P_{kt}$ | Real power flow of line *k* in period *t* |
| $\theta_{nt}$ | Voltage angle at bus *n* in period *t* |
| $dw_{it}$ | Deviation from the forecasted output of wind unit *i* for period *t* |
| $\Delta^t$ | Budget of uncertainty |
| $z_{gc}$ | Binary decision variable: “0” if generator $g$ is under contingency; “1” otherwise |
| $\delta_{gt}, y_{gt}, \eta_{gt}, k_{gt}, \varphi_{kt}, \tau_{kt}, \varsigma_{nt}, \pi_{kt}$ | Dual variables corresponding to the second stage constraints |