Security-Constrained Unit Commitment With Volatile Wind Power Generation

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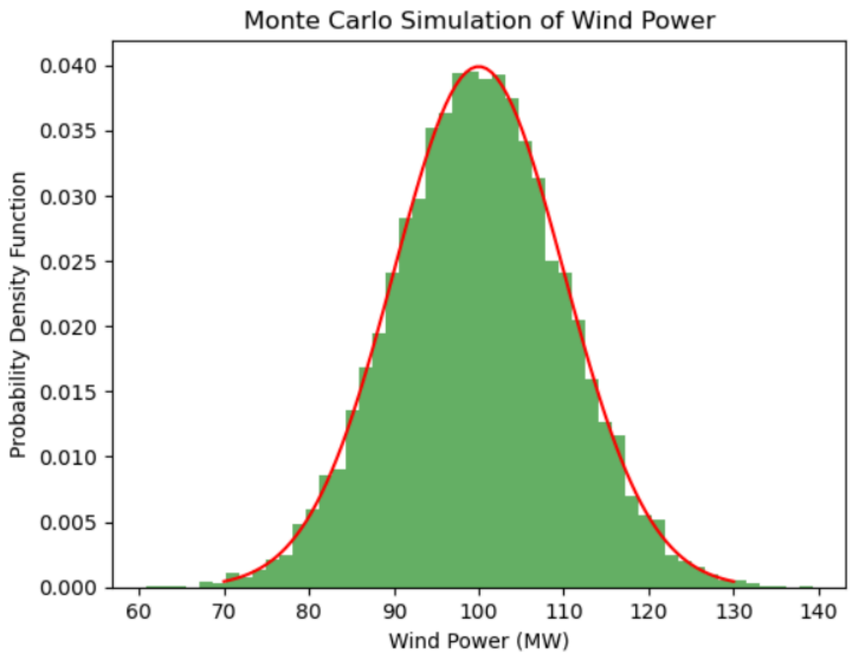
Introduction:

The paper talks about and addresses the challenges posed by the volatile nature of wind power generation on power systems. There are two main factors in the SCUC Algorithm which are to be made feasible using numerical simulations - Intermittency and Volatility of wind power generation.

Scenario Generation and Reduction:

The authors assume that wind power follows a normal distribution with forecasted wind power as mean. Monte Carlo simulation is used to generate wind power scenarios, each assigned a probability. To better this, LHS(Latin Hypercube Sampling) is applied to improve randomness and minimize runs & decrease variance of the Monte Carlo Simulation. Scenario reduction is used to decrease computational demands by eliminating low probability scenarios and grouping similar ones

```
import numpy as np
import matplotlib.pyplot as plt

# Parameters
forecasted_wind_power = 100  # Example: Forecasted wind power in MW
volatility_percentage = 10  # Example: Volatility as a percentage

# Monte Carlo simulation parameters
num_scenarios = 10000

# Generate scenarios
np.random.seed(42)  # Set seed for reproducibility
scenarios = np.random.normal(loc=forecasted_wind_power, scale=(forecasted_wind_power * volatility_percentage / 100), size=num_sce

# Plot the histogram of the scenarios
plt.hist(scenarios, bins=50, density=True, alpha=0.6, color='g')

# Plot the theoretical normal distribution
mean = forecasted_wind_power
std_dev = forecasted_wind_power * (volatility_percentage / 100)
x = np.linspace(mean - 3 * std_dev, mean + 3 * std_dev, 100)
y = (1 / (std_dev * np.sqrt(2 * np.pi))) * np.exp(-(x - mean)**2 / (2 * std_dev**2))
plt.plot(x, y, color='r')

plt.title('Monte Carlo Simulation of Wind Power')
plt.xlabel('Wind Power (MW)')
plt.ylabel('Probability Density Function')
plt.show()
```



The above histogram resembles a normal distribution and the red curve represents the theoretical normal distribution based on specified mean and standard deviation.

Problem Formulation and Solution:

After the Scenario Simulation using Monte Carlo simulation Method, we get a basic optimization problem which can be solved by either the Lagrangian relaxation method or the mixed integer programming method.

Now the aim is to make the solution feasible in large scale applications and avoid computational intractability.

$$\sum_{i=1}^{NG} P_{it}^{s} * I_{it} + \sum_{i=1}^{NW} P_{W,it}^{s} = P_{D,t} + P_{L,t} \qquad (t = 1, \ldots, NT)$$

$$\sum_{i=1}^{NG} R_{S,it}^{s} * I_{it} \geq R_{S,t} \quad (t = 1, \ldots, NT)$$

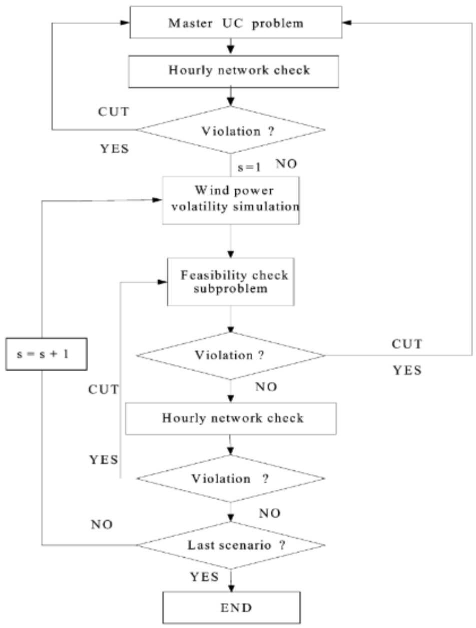
$$\sum_{i=1}^{NG} R_{O,it}^{s} * I_{it} \geq R_{O,t} \quad (t = 1, \ldots, NT)$$

$$|P_{it}^{s} - P_{it}| \leq \Delta_i \qquad (i = 1, \ldots, NG; t = 1, \ldots, NT)$$

$$P_{i,\min} * I_{it} \leq P_{it}^{s} \leq P_{i,\max} * I_{it} \qquad (i = 1, \ldots, NG; t = 1, \ldots, NT)$$

$$\mathbf{G}(P_{it}^{s}, P_{W,it}^{s}) \leq 0.$$

The flowchart below shows the master UC problem and method proposed by the writer to solve the problem keeping the feasibility constraints kept in check. The process is iterative and is to be repeatedly solved until the feasibility constraints are satisfied.



Bender’s decomposition process:

The problem-solving methodology involves decomposing the challenge into three sequential subproblems: Master Unit Commitment, Feasibility Check, and Network Security Check.

The initial step, Master Unit Commitment, focuses on optimizing unit commitment decisions based on economic goals and global constraints. It encompasses the operational aspects of starting up, shutting down, and managing generation units.

Following this, the Feasibility Check scrutinizes the proposed solution's practicality, ensuring alignment with project goals and constraints. This step identifies and addresses potential obstacles, contributing to a more robust solution.

The final phase, Network Security Check, concentrates on fortifying the power grid against risks. It examines security constraints like transmission line limits and contingency analysis, ensuring the proposed solution's resilience to unexpected events.

This structured approach ensures a systematic and effective problem-solving strategy, optimizing unit commitment decisions, validating solution practicality, and enhancing power grid security.

In instances where the proposed solution is deemed infeasible, a responsive mechanism is activated. Adjustments are systematically made to the master problem, initiating an iterative process. This iterative approach continues until a feasible and secure solution is successfully attained. The adaptability of the methodology to refine and modify the master problem ensures that the optimization process is dynamic and responsive to changing conditions.

The utilization of the Benders decomposition technique further enhances the efficiency and scalability of the optimization process. By decomposing the Security-Constrained Unit Commitment (SCUC) problem into its constituent components—Master Unit Commitment, Feasibility Check, and Network Security Check—the Benders decomposition technique allows for a more streamlined and scalable optimization process. This systematic breakdown of the problem facilitates parallel processing of subproblems, thereby improving computational efficiency and enabling the solution to be obtained in a more resource-efficient manner.

In summary, the integration of iterative adjustments in response to infeasibility, coupled with the application of the Benders decomposition technique, contributes to the overall effectiveness, adaptability, and scalability of the problem-solving methodology employed in addressing the SCUC challenge.

Example of Bender's decomposition(with one generator):

Master Problem:

Objective Function:

$$\text{Minimize} \quad c \cdot P + c_{\text{wind}} \cdot W + My$$

Subject to:

- Power balance constraint: $P + W = D$ (where D is the electricity demand).
- Unit commitment constraint: $P \leq P_{\max} \cdot UC$ (where $P_{\max}$ is the maximum output of the generator, and UC is a binary variable indicating commitment).

Subproblem (Feasibility Check):

Objective Function:

$$\text{Maximize} \quad \pi \cdot (D - P) + \pi_{\text{wind}} \cdot (W_{\max} - W)$$

Subject to:

- Dual feasibility conditions: $\pi \geq 0, \pi_{\text{wind}} \geq 0$

Subproblem (Optimality Check):

Objective Function:

$$\text{Maximize} \quad \lambda \cdot (P - P_{\max} \cdot UC) + \lambda_{\text{wind}} \cdot (W - W_{\max})$$

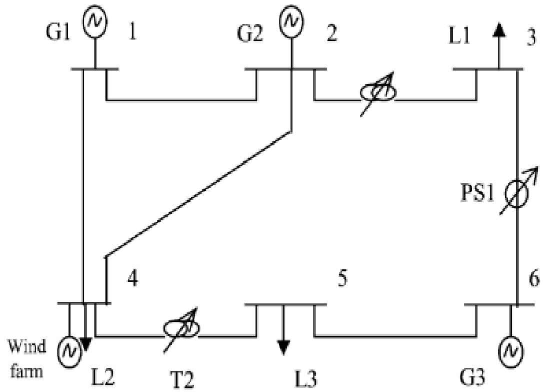
Subject to:

- Dual feasibility conditions: $\lambda \geq 0, \lambda_{\text{wind}} \geq 0$

- c is the cost per unit of power for the conventional generator.
- c_{wind} is the cost per unit of power for wind.
- P is the power output of the conventional generator.
- W is the power output from wind.
- D is the electricity demand.
- $P_{\max}$ is the maximum output of the generator.
- UC is a binary variable indicating commitment of the generator.
- $W_{\max}$ is the maximum potential power output from wind.
- M is a large positive constant.
- y is a binary variable associated with the master problem.

Testing feasibility- six bus system:

In the context of a six-bus system for unit commitment checking, it means that there are six locations in the power grid where generators can be connected or disconnected based on the system's requirements. The goal is to determine the optimal scheduling of these generators to meet the load demand while considering factors such as generation costs, unit constraints, and system reliability.



Case I - Dispatch with forecasted wind power:

We solve the SCUC using the forecasted data given beside and determine the dispatch of non-wind units.

To observe the impact of wind power scenarios, we execute 10 SCUC scenarios and display some of them.

HOURLY LOAD AND FORECASTED WIND POWER

Hr	Pd	Qd	Pwind	Hr	Pd	Qd	Pwind
1	219.19	50.4	44	13	326.18	69.6	84
2	235.35	47.4	70.2	14	323.60	70.0	80
3	234.67	45.6	76	15	326.86	71.6	78
4	236.73	44.5	82	16	287.79	73.5	32
5	239.06	44.6	84	17	260.00	73.6	4
6	244.48	46.1	84	18	246.74	70.9	8
7	273.39	49.9	100	19	255.97	70.7	10
8	290.40	51.1	100	20	237.35	68.2	5
9	283.56	53.7	78	21	243.31	68.2	6
10	281.20	59.5	64	22	283.14	66.9	56
11	328.61	65.7	100	23	283.05	56.3	82
12	328.10	67.9	92	24	248.75	56.2	52

Observing the results and tabulating them, we infer that :

- The cheapest Unit 1 is always committed.

- The more expensive unit 2 is committed between Hours 12 and 22.

- Unit 3 is committed between Hours 10 and 22.

The system operation cost is $100 890.97.

GENERATION DISPATCH (MW) WITH FORECASTED WIND POWER

Hour	U1	U2	U3
1	178.69	0	0
2	168.45	0	0
3	161.84	0	0
4	157.83	0	0
5	158.16	0	0
6	163.69	0	0
7	176.86	0	0
8	194.21	0	0
9	209.67	0	0
10	211.54	0	10
11	220	0	13.18
12	220	10	10.82
13	220	10	17.03
14	220	10	18.47
15	220	13.83	20
16	220	20.9	20
17	220	21.12	20
18	220	10	13.68
19	220	10.89	20
20	217.1	10	10
21	220	10	12.05
22	211.68	10	10
23	205.07	0	0
24	200.69	0	0

Case II - Dispatch with volatile wind power

If any violation of the master solution occurs, corrective actions will be considered by redispatching the committed non-wind units. If the redispatch fails to mitigate the violations, a Benders cut will be calculated as a preventive action and returned to the master unit commitment problem. The flowchart seen before comes into use in this case.

If there is difference between the forecasted wind power and scenario defined wind power (volatile wind power), redispatch takes place with consideration of cost and feasibility constraints.

Case III : Ramping Capabilities of Non-Wind Units and Volatility of Wind Power:
During problem formulation, our initial constraints also included ramping limits of non-wind units. We have to keep in mind that the ability of a system to accommodate wind power volatility is strongly correlated with the real power ramping capabilities of non-wind units.

Also, higher volatility means lesser chance of transfer of power without violations, and higher ramping capability will help accommodate greater ranges of volatility.

Our contribution:

Real-time pricing based on wind forecasting involves setting electricity prices dynamically according to the forecasted availability of wind power. The goal is to incentivize consumers to shift their electricity consumption to periods with higher wind generation, thereby promoting a more efficient use of renewable energy. To model this, we can formulate a simple optimization problem.

Objective Function:

$$\text{Minimize} \quad \sum_{t=1}^{T} \left(\lambda_t \cdot P_t + C_t \cdot |P_t - P_{\text{wind},t}| \right)$$

Constraints:

1. **Power Balance:**

   $$P_t = P_{\text{demand},t}$$

   (Where $P_{\text{demand},t}$ is the total electricity demand at time t).
2. **Non-Negativity:**

   $$P_t \geq 0$$

λ_t is set based on forecasted wind power availability. So higher wind power forecasts means lower electricity price

$C_t \cdot |P_t - P_{\text{wind},t}|$ penalizes significant changes in electricity consumption

- P_t: Power consumed at time t.
- $P_{\text{wind},t}$: Wind power generation forecast at time t.
- λ_t: Electricity price at time t.
- C_t: Cost of ramping (penalty for changing consumption) at time t.

Conclusion:

This paper introduces a SCUC algorithm addressing wind power volatility. Iterations between master unit commitment and wind scenarios reveal a robust solution, emphasizing the significance of unit limitations like ramping in accommodating wind power fluctuations.

Demonstrated on six-bus and IEEE 118-bus systems, the algorithm proves valuable for day-ahead operational planning and long-term considerations in constrained thermal power systems.

This can contribute to the efficient and reliable integration of wind power into power systems, ultimately facilitating the transition towards a cleaner and more sustainable energy future