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Unit Commitment Dispatch Problem with Wind Energy Resources Using Mixed-Integer Linear Programming Method †

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Abstract

This paper presents a two-stage stochastic unit commitment model to mitigate the costs and reliability effects of high wind energy penetration into the power system. Wind energy variability/uncertainty is explored through this system. Mixed-integer linear programming (MILP) is used to solve the model and find optimal unit commitment and dispatch variables under uncertainty in wind conditions. The model champions reduced reliance on deterministic approaches, lowered costs, increased wind utilization, and provides reliable systems that can sustain 24 h. Wind energy is expected to constitute a significant share of future electricity generation portfolios; however, its inherent intermittency and variability often lead to mismatches between energy supply and demand. This uncertainty complicates generation scheduling decisions, particularly in determining which power plants to commit, their operating durations, and the optimal dispatch timing. Consequently, advanced optimization strategies are required to ensure efficient and reliable system operation. The proposed approach provides a structured, robust framework for optimal generation scheduling and resource allocation, even under limited wind availability. By enhancing the integration of wind energy into the power system, the method minimizes operational costs, improves resource utilization, and maintains system reliability and stability.

Keywords: unit commitment; wind energy; MILP; optimization method; renewable integration

1. Introduction

The expectations that the world will head in a sustainable and clean energy direction, that renewables such as wind are viable energy options, and that wind energy is becoming more significant in today's energy systems [1,2] are valid. Wind energy boasts numerous environmental benefits and helps to prevent reliance on traditional fossil fuels. Unfortunately, the inconsistent and unpredictable nature of wind energy complicates life for system operators and managers, making it more challenging to maintain consistent, low-cost energy operations [3,4]. Yet one concern remains constant. The unit commitment problem in power system operations seeks to determine how much load must be met at any given time to turn on generators [5,6]. This is not such a complicated model when it comes to the realm of traditional generation—coal, natural gas, or nuclear—As traditional resource operators can employ deterministic models. Deterministic models assume accurate forecasting for demand/needs and generation. Yet as conventional resources, such as wind power [7,8],

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become a more significant player, these models become less useful. Nevertheless, the uncertainties have been solved through innovative and academic solutions, and more stochastic optimization methodologies [9] can be used [5]. These methodologies account for uncertainty in wind generation across various scenarios, increasing the flexibility and resilience of resource scheduling [10,11]. Thus, stochastic unit commitment models are desirable. Wind constantly changes in real-time, affecting the accessibility and operational cost of the systems. In addition, regarding stability and sustainability, stochastic unit commitment provides cost savings in operations, providing sustainable system stability [5,9,12,13].

The review findings indicate that stochastic MILP provides the optimal trade-off in system modeling, particularly in systems with renewable uncertainty [14,15]. Therefore, this research project aims to advance these efforts by developing a two-stage stochastic unit commitment model that explicitly accounts for wind energy uncertainty. The goal is to improve generator scheduling and dispatch decisions, supporting more efficient and dependable power system operations as renewable energy sources become more prominent. The rise of wind energy in modern power systems poses a significant challenge to system operation, as wind is inherently variable and uncertain. Conventional unit commitment (UC) models have mostly been deterministic, treating generation and demand as known quantities. Nonetheless, these methods are ineffective in highly wind-integrated systems because they do not adequately account for the stochastic nature of renewable energy generation. This restriction can lead to suboptimal scheduling choices, higher operating expenses, excessive reserve allocation, and possible reliability issues.

Even though stochastic UC models have been studied in literature, most studies either oversimplify the characterization of wind uncertainty or fail to integrate commitment and dispatch decisions within a formal two-stage framework. Additionally, it is computationally efficient. Mixed-integer linear programming (MILP) formulations that can handle wind uncertainty over a 24 h scheduling horizon while maintaining tractability are still needed. This paper covers the introduction in Section 1, detailed mathematical modeling of the two-stage unit commitment problem formulation in Section 2, use-case studies and the data used to solve the unit commitment problem in Section 3, unit commitment simulation results and analysis based on the linear programming method in Section 4, and the conclusions and future recommendations in Section 5.

2. A Mixed-Integer Linear Programming Method for the Unit Commitment Problem

The unit commitment problem is formulated as a mixed-integer linear programming (MILP) problem, allowing for the joint optimization of binary commitment and continuous dispatch decisions while explicitly accounting for the stochastic nature of wind generation. This reduces the total operating expenses, which are constrained by the system and the generators, thereby enhancing wind use and the system's reliability.

2.1. Decision Variables

ui(t) $\in$ {0, 1}: U variables, count n_U = G $\times$ T;
Pi(t, s) $\geq$ 0: Count np = G $\times$ T $\times$ S;
Wcurt(t, s) $\geq$ 0: Cou$n_P$nt n_{WC} = T $\times$ S;
Total variables: $n_{vars} = n_U + n_P + n_{WC}$.

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2.2. Objective Function

$$\boldsymbol{min}\sum_{\boldsymbol{t=1}}^{\boldsymbol{T}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{G}}\boldsymbol{c_i^{fixed}U_i(t)}+\sum_{\boldsymbol{s=1}}^{\boldsymbol{S}}\boldsymbol{p_s}\sum_{\boldsymbol{t=1}}^{\boldsymbol{T}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{G}}\boldsymbol{C_i^{prod}P_i(t,s)}+\sum_{\boldsymbol{t=1}}^{\boldsymbol{T}}\boldsymbol{C^{wc}W_{curt}(t,s)} \quad (1)$$

where

- c_i^{fixed}: No load cost for generator I (R/h);
- $U_i(t)$: Binary (0/1) variable that shows if the generator is ON(1)/OFF(0);
- p_s: Probability of scenario s;
- C_i^{prod}: Production cost coefficient of generator i (R/MWh);
- $P_i(t,s)$: Power output of generator i at time t under scenario s;
- C^{wc}: Cost penalty for each MWh of curtailed wind;
- $W_{curt}(t,s)$: Amount of curtailed wind at time $\boldsymbol{t}$, scenario $\boldsymbol{s}$.

2.3. Constraints

Power balance

$$\sum_{\boldsymbol{i}}\boldsymbol{P_i(t,s)}+\boldsymbol{W(t,s)}=\boldsymbol{D(t)}+\boldsymbol{W_{curt}(t,s)} \quad (2)$$

where

Pi(t, s): Output power of generator i at time t in scenario s;
W(t, s): Available wind generation (uncertain);
D(t, s): Electricity demand.
Generation Limit constraints

$$\boldsymbol{P_i^{min}u_i(t)}\leq\boldsymbol{P_i(t,s)}\leq\boldsymbol{P_i^{max}u_i(t)} \quad (3)$$

where

$P_i^{\min}$: Minimum power output;
$P_i^{\max}$: Maximum power output.
Ramp Rate Limits

$$|\,P_i(t,s)-P_i(t-1,s)\,|\leq R_i \quad (4)$$

Reserve Margin constraints

$$\sum_{\boldsymbol{i}}\boldsymbol{R_i^{up}(t)}\geq\boldsymbol{R_{req}(t)} \quad (5)$$

2.4. Matrix Formulation

$(\boldsymbol{A_{eq}, b_{eq}, A_{ineq}, b_{ineq}})$ bounds $(\boldsymbol{lb, ub})$.

2.5. Solve MILP: Using the MILP Solver in MATLAB R2025a

The MILP flowchart is shown in Figure 1.

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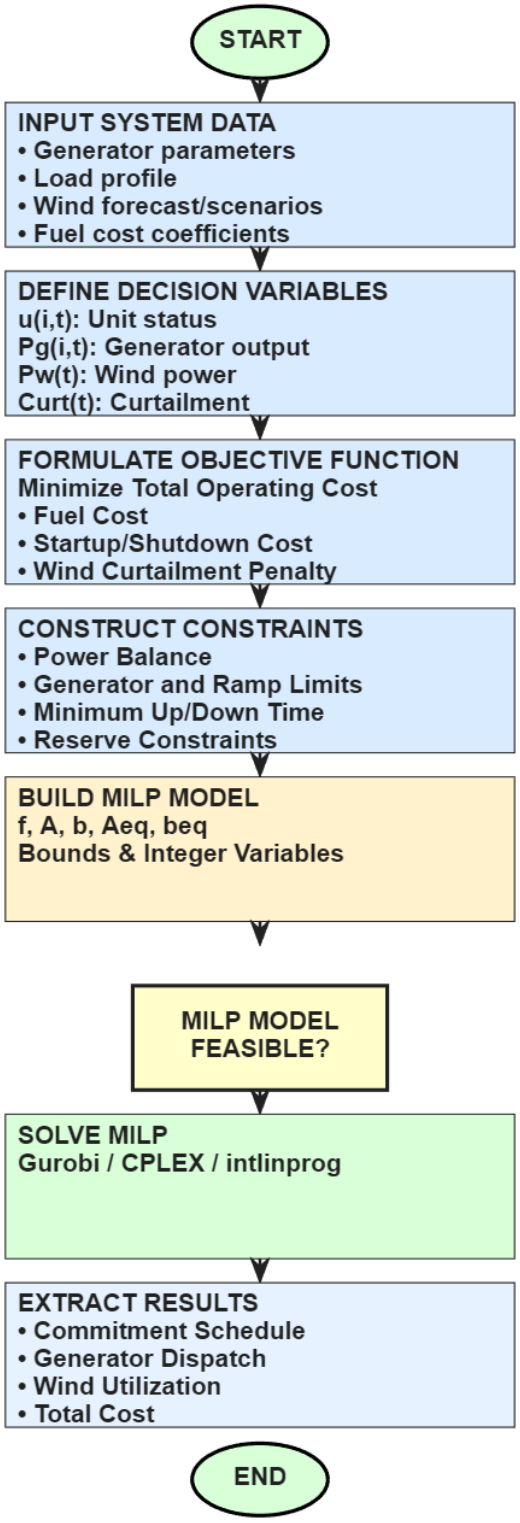


Figure 1. Mixed-integer programming method for unit commitment.

3. Unit Commitment Use-Case Study and Data Analysis

The electrical layout of the wind-integrated power system adopted in this study is shown in Figure 2. The single-line diagram provides a simplified view of the system's significant components, showing the relationships among the wind farm, conventional generating units, transformers, transmission lines, buses, and loads.

The windfarm is connected via a step-up transformer that raises the voltage from the wind turbines to the transmission voltage. Conventional generators also interconnect to

the same bus using transformers and circuit breakers. A high-voltage bus connects all the generation units and sends power through a tie line to the main grid and load buses. This configuration allows us to continuously add renewable and conventional generation units, with all flows, unit commitments, dispatch, and stability studies being based on the single-line diagram.

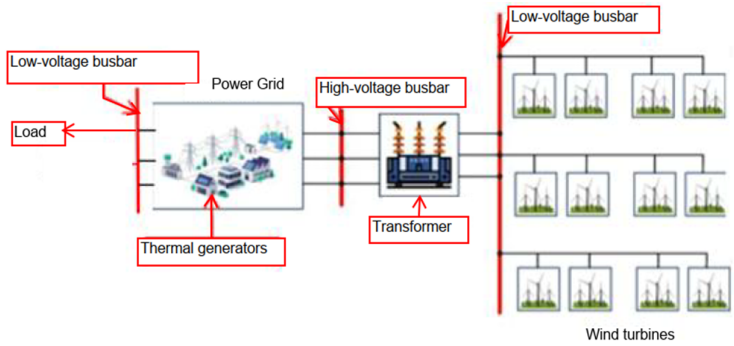


Figure 2. Wind farm power system single-line diagram.

The standard UC literature [16] was used to obtain thermal generator data, including maximum/minimum limits, start-up costs, fuel coefficients, and ramp constraints. The wind conditions were simulated using the popular stochastic wind uncertainty processes described in [17]. The demand was typical of a 24 h load curve, as determined in [3].

The MILP unit commitment code takes the generator, load, and wind data and solves for the minimum operating cost, including generator on/off and dispatch decisions. It applies system constraints, including the balance, limits, reserves, and wind uncertainty. It checks for feasibility and returns the optimal wind dispatch commitment.

The simulation uses a 24 h load profile, as given in Table 1. Its load ranges between 950 MW (minimum) and 3400 MW (maximum). The minimum demand is in the early morning, and the maximum is during evening peak hours. This modification allows assessment of the UC model under different load structures to support realistic commitment and dispatch decisions.

Table 1. Generation profile.

Units	P(min) MW	P(max) MW	A (Coefficient Cost)	Start-Up Cost
1	190	600	450	10,000
2	80	300	380	8000
3	100	400	420	9000
4	70	280	395	8500
5	150	500	480	11,000
6	20	100	320	6000
7	120	450	460	10,500
8	60	200	370	7000
9	180	550	510	12,000
10	30	120	340	6500

Table 2 shows the minimum and maximum outputs for each unit, which determine the units' operating window. For instance, Unit 1 can provide 600 MW, while Unit 6 operates between 20 MW and 100 MW. The coefficient a is the marginal cost of fuel (R/MWh); units with lower marginal costs are dispatched first, while higher-cost units are considered mid-merit or peaking. Fixed start-up costs reflect the cost of starting a unit and the wear and tear. Units with high start-up costs, e.g., Unit 9 (R12,000), are only dispatched in high-demand situations.

The system includes a wind farm of rated capacity of 350 MW. It is observed that 40 equally likely wind scenarios are generated to model wind uncertainty. Those scenarios are based on realistic hourly wind changes and are applied in the second step of the stochastic UC formulation.

Table 2. Wind farm capacity and scenarios.

Parameter	Value
Wind farm capacity	350 MW
Wind scenario	40

4. Unit Commitment Simulation Results and Analysis Based on the Linear Programming Method

The mathematical formulation is implemented in MATLAB R2025a using the intlinprog MILP solver and tested on a 10-unit thermal system with operational (generation) constraints (generation limits, cost coefficients, minimum up and down times, and start-up cost) and a 24-h load profile. Wind generation comprises four equally likely scenarios. A two-stage stochastic unit commitment model with wind curtailment is solved across 40 scenarios, with solution results on unit commitment, dispatch amounts, wind use, start-ups, and total system cost [18].

4.1. Unit Commitment Schedule

Lower-cost units are dispatched, followed by higher-cost units with full commitments during peak periods, yielding exact SUC results. The 24 h commitment schedule in Figure 3 shows ON/OFF for all ten units and confirms that the model can smartly optimize available generation, wind, and online generation capacity, customized to needs.

During the early hours (1–5), when demand was low, only the base-load units were scheduled to operate as essential reserves. As system demand increased, as shown in Figure 4, additional generators were progressively committed, with all ten units operating during the peak period (10–18) to ensure system reliability. The flexible weighting factor incorporated in the model enables cost-effective operation by minimizing unnecessary fixed and start-up costs during off-peak periods while maintaining adequate reserve margins. This operational strategy is consistent with findings reported in the literature [3,7].

4.2. Wind Curtailment

Variations in wind generation were observed throughout the day, consistent with predictions from stochastic wind models. Wind curtailment was negligible, indicating effective integration of wind power into the system and successful utilization of the available renewable energy resources (See Table 3).

Table 3. Total system cost.

Reference	Method	Total_Expected_Cost	FirstStage_Fixed	SecondStage_Exp
From MATLAB results	MILP	R 843,510,440,816	R 5,743,200.00	R 843,504,697,616

The second-stage cost of R843,504,697,616.02 reflects the advantages of the two-stage stochastic unit commitment model. By incorporating wind uncertainty, the model avoids over-committing thermal resources and effectively utilizes wind power, thereby avoiding unnecessary start-up and fuel costs. The cost saving between the first and second stages provides a quantitative measure of this value of stochasticity, reinforcing the finding that the model is the least cost and most applicable to renewable-energy-dominated systems.

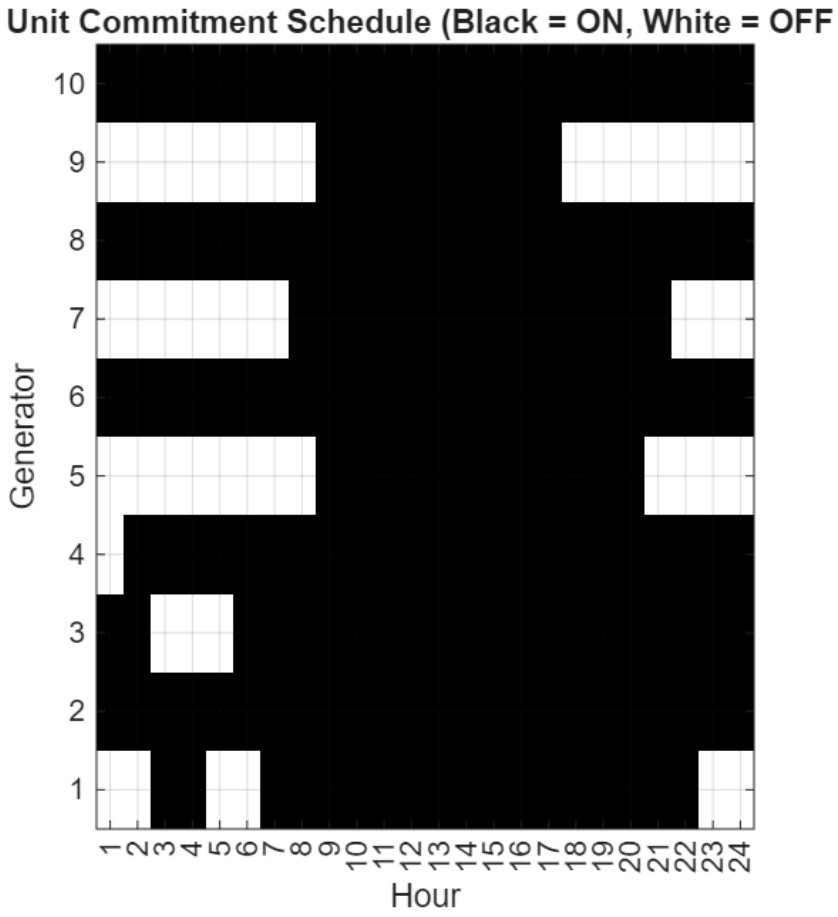


Figure 3. Chart visualizing the generator's ON/OFF status.

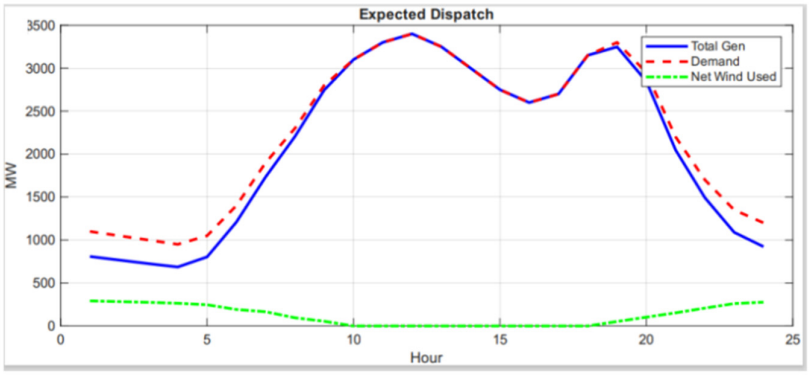


Figure 4. Unit commitment dispatch schedule, including wind-energy resources.

5. Conclusions

Overall, the two-stage stochastic unit commitment model in this study is a viable option for the optimal operation of renewable energy power systems. The MATLAB implementation shows substantial reductions in total operating costs, while demand, system reliability, and wind applications all suggest more effective solutions. Ultimately, through stochastic (versus deterministic) optimization, modeled solutions more appropriately respond to wind uncertainty and ultimately provide reliable, economically feasible, and technically sound solutions. Additionally, the model could serve as a precedent for expansion to larger regional or even national grids, incorporating various other renewable resources and additional transmission constraints. Future work could involve comparing

the MILP solution with other metaheuristic solutions, such as GA or PSO, to determine performance and trade-offs for similarly situated challenges.

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