Deterministic Electricity Market Clearing Under Wind Power Forecast Uncertainty: A Sensitivity Analysis

Sri K. Naresh[1] and Dr. G.N.Srinivas [2]
[1] hiiamnaresh@gmail.com and [2]gnsgns.srinivas785@gmail.com
[1, 2]Department of Electrical and Electronics Engineering, Jawaharlal Nehru Technological University Hyderabad, Hyderabad, India

***Abstract*—The accuracy of wind power forecasts is a critical determinant of operational costs in electricity markets that employ Deterministic Market Clearing (DMC). This paper presents a comprehensive sensitivity analysis of a two-stage DMC framework—comprising a Day-Ahead (DA) scheduling stage and a Real-Time (RT) recourse stage—on a 6-bus power system with three conventional generators and two wind farms. Four distinct forecast cases, ranging from a perfect forecast to significant over- and under-predictions, are evaluated using Linear Programming implemented in GAMS. Numerical results demonstrate that total system costs range from $1,200 (perfect forecast) to $1,700 (severe over-forecast), revealing a 41.67% cost penalty for large forecast errors. The analysis of Nodal Marginal Prices (LMPs) and real-time generator adjustments provides insight into the economic signals generated under each forecast scenario, quantifying how forecast bias propagates into commitment decisions and recourse actions.**

***Index Terms*—Electricity markets, deterministic market clearing, wind forecast uncertainty, day-ahead scheduling, real-time recourse, locational marginal prices.**

I. INTRODUCTION

The rapid integration of wind energy into modern power systems presents significant challenges for wholesale electricity market operators. Wind power is inherently variable, and its output at any given time can deviate substantially from the forecast used in the Day-Ahead (DA) market clearing. In the Deterministic Market Clearing (DMC) paradigm, market operators commit generators and dispatch wind energy based on a single-point forecast [2]. When realization differs from the forecast, the system must activate real-time recourse actions—upward or downward generator adjustments—to restore balance, often at considerably higher cost [1].

Understanding how forecast quality affects operational costs is therefore essential for both market operators and policy makers. A forecast that significantly overestimates available wind leads the market to commit fewer expensive conventional units in the DA stage, only to find the real-time stage expensive when wind falls short. Conversely, a large underestimate leads to over-commitment of conventional generation and costly downward adjustments in real-time.

This paper investigates these dynamics through a systematic sensitivity analysis of DMC across four wind forecast cases on a 6-bus power system, examining:

- How DA commitment decisions change with forecast quality.
- The magnitude of real-time recourse actions required to balance the system.
- The resulting DA and RT nodal prices (LMPs) under each forecast scenario.
- The total system cost as a function of forecast error magnitude and direction.

The remainder of this paper is organized as follows. Section II describes the system model and nomenclature. Section III presents the full DMC mathematical formulation. Section IV reports and analyzes numerical results for all four forecast cases. Section V discusses the operational implications, and Section VI concludes.

II. SYSTEM MODEL AND NOMENCLATURE

We analyze a 6-bus power system test case. The system consists of three conventional thermal generators $I = \{i_1, i_2, i_3\}$, two wind farms $K = \{k_1, k_2\}$, and three inelastic load centers $D = \{d_1, d_2, d_3\}$, interconnected by eighteen transmission lines E (nine bidirectional pairs). The DC load flow approximation is used for all network constraints.

A. Generator and Network Parameters

The conventional generator parameters are summarized in Table I. Generator i_1 is the cheapest unit but has *zero* ramping capability ($R^{\max}_{i_1} = 0$), making it fully inflexible in real-time. Generator i_2 offers moderate flexibility at a higher cost, while i_3 is the most expensive but provides the highest ramping range. This inflexibility of the cheapest unit is central to the recourse cost dynamics observed across forecast scenarios.

TABLE I
CONVENTIONAL GENERATOR PARAMETERS

Generator	$P^{\max}$ (MW)	C_i ($/MWh)	$R^{\max}$ (MW)
i_1	150	10	0
i_2	50	15	50
i_3	60	25	60

All transmission lines share a common thermal capacity of $F^{\max} = 150$ MW. A sample of line susceptance values is given in Table II. Total load demand $L_d = 70$ MW for each load center (total: 210 MW), and the Value of Lost Load is $V_d = \$100/\text{MWh}$. Both wind farms ($k_1$ at bus 3, k_2 at bus 5) have an installed capacity of $W_k^{\max} = 70$ MW each.

TABLE II
TRANSMISSION LINE DATA (SELECTED LINES)

From Bus	To Bus	Susceptance B (p.u.)	Capacity $F^{\max}$ (MW)
1	2	20	150
2	3	18	150
4	5	17	150

B. Generator and Bus Mapping

The generators and loads are connected to the network as follows: i_1 at bus 1, i_2 at bus 2, i_3 at bus 6; load centers d_1 at bus 3, d_2 at bus 4, d_3 at bus 5; wind farms k_1 at bus 3, k_2 at bus 5.

C. Forecast Scenarios

The wind power *realization* is fixed at $W_{k_1}^{real} = 40$ MW and $W_{k_2}^{real} = 50$ MW for all cases. The four forecast scenarios studied are defined in Table III, covering under-forecasting, perfect forecasting, and two levels of over-forecasting.

TABLE III
WIND POWER FORECAST CASES (MW)

Case	W_{k1}^f	W_{k2}^f	Forecast Error	Direction
C1	40	50	0 MW	Perfect
C2	60	70	−20 MW each	Over-forecast
C3	70	80	−30 MW each	Severe over-forecast
C4	20	30	+20 MW each	Under-forecast

D. Sets and Variables

Sets: I = conventional generators; K = wind farms; D = load centers; N = buses; $E \subseteq N \times N$ = transmission lines.

Day-Ahead (DA) Variables: P_i – DA dispatch of generator i; P_k^W – DA wind commitment; $f_{n,m}^{DA}$ – DA power flow on line (n, m); ϑ_n^{DA} – DA voltage angle at bus n; $L_d^{shed,DA}$ – DA load shedding.

Real-Time (RT) Variables: r_i – RT generator adjustment (positive = ramp up, negative = ramp down); L_d^{shed} – RT load shedding; P_k^{spill} – RT wind spillage; $f_{n,m}^{RT}$ – RT power flow; ϑ_n^{RT} – RT voltage angle; $\Delta_k = W_k^{real} - W_k^f$ – wind deviation (fixed parameter).

III. DETERMINISTIC MARKET CLEARING (DMC) FORMULATION

The DMC model is a two-stage Linear Program. In Stage 1 (DA), all commitment decisions are made based on a single-point wind forecast W_K^f. In Stage 2 (RT), generator adjustments r_i and emergency actions (load shedding, wind spillage) respond to the actual realization W_k^{real}, which may differ from the forecast.

A. Objective Function

The total cost to be minimized is the sum of DA generation and load-shedding costs plus RT recourse costs:

$$\min Z = \underbrace{\sum_{i\in I} C_i P_i + \sum_{d\in D} V_d L_d^{shed,DA}}_{\text{Day-Ahead Cost}} + \underbrace{\sum_{i\in I} C_i r_i + \sum_{d\in D} V_d L_d^{shed}}_{\text{Real-Time Cost}} \quad (1)$$

Note that r_i is unbounded in sign (it may be positive for upward or negative for downward adjustment), so the RT cost in (1) can be negative if generators reduce output in real-time.

B. Day-Ahead Constraints

DA Nodal Power Balance:

$$\sum_{i:(i,n)\in \text{Map}_i} P_i + \sum_{k:(k,n)\in \text{Map}_k} P_k^W = \sum_{d:(d,n)\in \text{Map}_d} (L_d - L_d^{shed,DA}) + \sum_{m:(n,m)\in E} f_{n,m}^{DA} \quad \forall n \in N \quad (2)$$

DA Generator Capacity Limits:

$$0 \le P_i \le P_i^{\max}, \quad \forall i \in I \quad (3)$$

DA Wind Commitment Limits:

$$0 \le P_k^W \le \min\left(W_k^f, W_k^{\max}\right), \quad \forall k \in K \quad (4)$$

The wind commitment is bounded by the forecast (the operator schedules what is expected to be available).

DA DC Power Flow:

$$f_{n,m}^{DA} = B_{n,m}\left(\vartheta_n^{DA} - \vartheta_m^{DA}\right), \quad \forall (n, m) \in E \quad (5)$$

DA Line Thermal Limits:

$$\left|f_{n,m}^{DA}\right| \le F_{n,m}^{\max}, \quad \forall (n, m) \in E \quad (6)$$

DA Slack Bus Reference:

$$\vartheta_{n_1}^{DA} = 0 \quad (7)$$

DA Load Shedding Bounds:

$$0 \le L_d^{shed,DA} \le L_d, \quad \forall d \in D \quad (8)$$

C. Real-Time Recourse Constraints

After wind realization W_k^{real} is observed, the deviation $\Delta_k = W_k^{real} - W_k^f$ must be absorbed. The RT stage adjusts generator outputs and, if necessary, curtails load or spills surplus wind.

RT Nodal Power Balance:

$$\sum_{i:(i,n)} r_i + \sum_{k:(k,n)} \left(\Delta_k - P_k^{spill}\right) + \sum_{d:(d,n)} L_d^{shed} = \sum_{m:(n,m)\in E} \left(f_{n,m}^{RT} - f_{n,m}^{DA}\right), \quad \forall n \in N \quad (9)$$

The left-hand side captures the net RT injection change at each bus; the right-hand side captures the resulting change in power flows from the DA schedule.

RT Ramping Limits:

$$-R_i^{\max} \leq r_i \leq R_i^{\max}, \qquad \forall i \in I \tag{10}$$

RT Total Generation Feasibility:

$$0 \leq P_i + r_i \leq P_i^{\max}, \qquad \forall i \in I \tag{11}$$

RT DC Power Flow:

$$f_{n,m}^{RT} = B_{n,m}\ \vartheta_n^{RT} - \vartheta_m^{RT}, \qquad \forall (n,m) \in E \tag{12}$$

RT Line Thermal Limits:

$$f_{n,m}^{RT} \leq F_{n,m}^{\max} \qquad \forall (n,m) \in E \tag{13}$$

RT Load Shedding Bounds:

$$0 \leq L_d^{shed} \leq L_d, \qquad \forall d \in D \tag{14}$$

RT Wind Spillage Limits:

$$0 \leq P_k^{spill} \leq W_k^{real}, \qquad \forall k \in K \tag{15}$$

RT Slack Bus Reference:

$$\vartheta_{n_1}^{RT} = 0 \tag{16}$$

The wind deviation Δ_k is treated as a fixed parameter in the RT stage—it represents the discrepancy that the recourse actions must compensate for.

IV. NUMERICAL RESULTS AND ANALYSIS

The DMC model was implemented and solved using GAMS 53.2 with the CPLEX LP solver. All four forecast cases (Table III) were solved to optimality with model status 1 and solver status 1.

A. Day-Ahead Dispatch Results

Table IV summarizes the DA commitment decisions for all four forecast cases. The wind forecast directly determines the minimum required conventional generation via the constraint $P_{i_1} \geq \max(0, \sum_d L_d - \sum_k W_k^f)$, which forces the cheapest inflexible unit to cover the expected net load.

TABLE IV

DAY-AHEAD DISPATCH BY FORECAST CASE (MW)

Unit	C1 (Perfect)	C2 (−20 MW)	C3 (−30 MW)	C4 (+20 MW)
P_{i_1}	120.0	80.0	70.0	150.0
P_{i_2}	0.0	0.0	0.0	40.0
P_{i_3}	0.0	0.0	0.0	0.0
$P^W_{k_1}$	40.0	60.0	70.0	0.0
$P^W_{k_2}$	50.0	70.0	70.0	20.0
DA Cost ($)	**1,200**	**800**	**700**	**2,100**

As the wind forecast increases (Cases C1 → C2 → C3), the committed generation from i_1 decreases because wind is expected to cover more of the load. This reduces the DA cost. Case C4 (under-forecast) forces i_1 to its maximum (150 MW) and additionally dispatches i_2 at 40 MW, resulting in the highest DA cost of $2,100.

B. Wind Forecast vs. Realization

Table V summarizes the forecast, realization, and resulting deviation for each case.

TABLE V

WIND FORECAST, REALIZATION, AND DEVIATION (MW)

Case	$W^f_{k_1}$	$W^{real}_{k_1}$	Δ_{k_1}	Total $\lvert\Delta\rvert$
C1	40	40	0	0
C2	60	40	−20	40
C3	70	40	−30	60
C4	20	40	+20	40

The same magnitude of deviation (40 MW total, Cases C2 and C4) results in different total costs because the *direction* of the error determines whether more or less expensive recourse is needed.

C. Real-Time Recourse Actions

Table VI presents the real-time generator adjustments and the resulting RT costs for all four cases. No load shedding or wind spillage occurs in any case.

TABLE VI

REAL-TIME ADJUSTMENTS AND COSTS BY FORECAST CASE

Variable	C1 (Perfect)	C2 (−20 MW)	C3 (−30 MW)	C4 (+20 MW)
r_{i_1} (MW)	0.0	0.0	0.0	0.0
r_{i_2} (MW)	0.0	+40.0	+50.0	−40.0
r_{i_3} (MW)	0.0	0.0	+10.0	0.0
Load Shed (MW)	0.0	0.0	0.0	0.0
Wind Spill (MW)	0.0	0.0	0.0	0.0
RT Cost ($)	**0**	**+600**	**+1,000**	**−600**
Total Cost ($)	**1,200**	**1,400**	**1,700**	**1,500**

Key observations from Table VI:

- **Case C1 (Perfect Forecast):** No RT adjustments are needed; $r_i = 0$ for all generators. The total cost equals the DA cost exactly ($1,200), representing the theoretical minimum.
- **Case C2 (Over-forecast by 20 MW/farm):** Wind delivers 40 MW less than forecast. Generator i_2 must ramp up by 40 MW in real-time at $15/MWh, adding $600 to the total. The system can recover because i_2 has sufficient upward ramp capacity.
- **Case C3 (Over-forecast by 30 MW/farm):** Wind delivers 60 MW less than forecast. The 50 MW ramp cap on i_2 is fully exhausted, requiring i_3 to provide an additional 10 MW at $25/MWh. The RT cost reaches $1,000, pushing the total to $1,700—the highest of all cases.
- **Case C4 (Under-forecast by 20 MW/farm):** Wind delivers 40 MW more than expected. Generator i_2 must ramp *down* by 40 MW, reducing the RT cost by $600. This *negative* RT cost ($-600) partially offsets the large DA cost, yielding a total of $1,500.

D. Nodal Marginal Prices

The DA and RT nodal prices (LMPs) for all four cases are reported in Table VII. Prices are spatially uniform in each case due to the absence of transmission congestion.

TABLE VII
NODAL MARGINAL PRICES ($/MWH) — ALL BUSES

Price Type	C1 (Perfect)	C2 (−20 MW)	C3 (−30 MW)	C4 (+20 MW)
λ^{DA}	10.00	10.00	10.00	0.00
λ^{RT}	15.00	15.00	25.00	0.00

The LMP results reveal several important patterns:

- **Cases C1, C2, C3:** The DA price of $10/MWh is set by the marginal cost of i_1, which is the binding unit in the DA stage. The RT price rises from $15/MWh (C1, C2; set by i_2) to $25/MWh (C3; set by i_3) as more expensive flexible capacity is activated under a larger forecast error.
- **Case C4 (Under-forecast):** The DA price collapses to $0/MWh. In this case, the over-committed i_1 operates at its capacity cap, and the wind surplus in RT drives adjustments that yield a degenerate dual solution. This market signal failure indicates that the deterministic model, when wind is under-forecast, produces prices that do not reflect the true opportunity cost of the committed capacity.

E. Total Cost Summary

The total system cost as a function of forecast scenario is summarized in Table VIII and illustrated conceptually in Fig. 1.

TABLE VIII
TOTAL SYSTEM COST SUMMARY BY FORECAST CASE

Case	DA Cost ($)	RT Cost ($)	Total ($)	Premium vs. C1 ($)
C1 (Perfect)	1,200	0	1,200	—
C2 (Over, −20 MW)	800	+600	1,400	+200
C4 (Under, +20 MW)	2,100	−600	1,500	+300
C3 (Over, −30 MW)	700	+1,000	1,700	+500

V. DISCUSSION AND OPERATIONAL IMPLICATIONS

A. Asymmetric Cost Impact of Forecast Errors

A key finding is that forecast errors impose an asymmetric cost penalty depending on their direction and magnitude. Both C2 and C4 involve a total deviation of 40 MW, yet C2 costs $1,400 while C4 costs $1,500. This asymmetry arises because:

- **Over-forecast** (C2, C3): The system under-commits cheap conventional generation in the DA stage, requiring expensive upward ramping in real-time. The penalty scales rapidly as the deviation exhausts the ramp capacity of cheaper units and forces more expensive units online (C3: i_3 at $25/MWh).
- **Under-forecast** (C4): The system over-commits conventional generation in the DA stage, incurring high DA costs, but partially recovers through negative RT adjustments. The net penalty is smaller than an equivalent over-forecast error only because the *downward* ramp of i_2 is cheaper than the *upward* ramp required for over-forecast corrections.

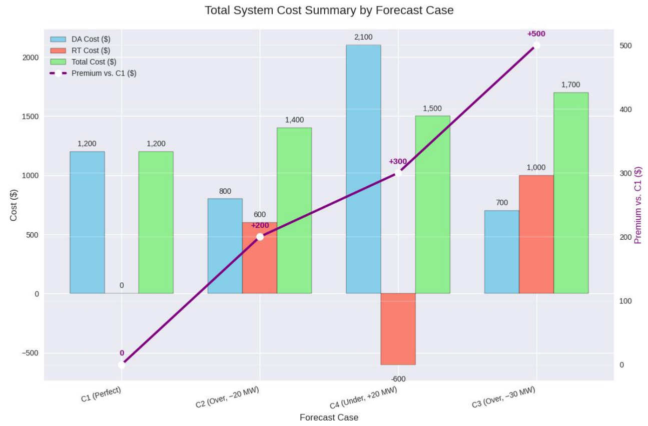

Fig. 1. Total system cost for each forecast case. Perfect forecast (C1) achieves the minimum cost of $1,200. Severe over-forecasting (C3) imposes the highest penalty at $1,700.

B. Ramp Capacity as a Binding Resource

The results highlight that ramp capacity—not generation capacity—is the binding resource in real-time balancing. Generator i_1, despite being the cheapest, contributes nothing to RT flexibility because $R_1^{\max} = 0$. This means the entire burden of balancing a 60 MW wind shortfall (Case C3) falls on i_2 (50 MW) and i_3 (10 MW), with i_3 setting the marginal RT price at $25/MWh. Operators must therefore value ramp capability highly when making DA commitments.

C. LMP Signal Quality

The LMP analysis shows that meaningful price signals ($10/MWh DA, $15–25/MWh RT) are generated in Cases C1–C3, where conventional generation is the marginal resource in both stages. These prices accurately reflect the opportunity cost of dispatched capacity and provide correct incentives for demand response. In Case C4, the zero LMP constitutes a market signal failure—the model over-commits generation relative to what is truly needed, leading to degenerate dual solutions. This failure mode underscores a structural weakness of DMC under under-forecast conditions.

D. Cost of Forecast Uncertainty

The spread between the best-case (C1, $1,200) and worst-case (C3, $1,700) outcomes represents a **41.67% cost range** attributable entirely to forecast inaccuracy. Even a moderate over-forecast of 20 MW per farm (C2) raises costs by $200 (16.7%). Improving short-term wind forecasts therefore has a direct and quantifiable economic benefit in the DMC framework.

VI. CONCLUSION

This paper presented a detailed sensitivity analysis of Deterministic Market Clearing under varying wind power forecasts on a 6-bus system. Four forecast scenarios—covering perfect prediction, moderate over-forecast, severe over-forecast, and under-forecast—were solved to optimality as two-stage Linear Programs implemented in GAMS.

The principal conclusions are:

1) **Forecast accuracy is the primary cost driver.** Total costs range from $1,200 (perfect forecast) to $1,700 (severe over-forecast), a 41.67% spread attributable solely to forecast error.
2) **Over-forecasting is more costly per unit of error than under-forecasting** when upward ramp resources are scarce, as the system must activate progressively more expensive flexible units.
3) **Ramp capacity, not generation capacity, is the binding real-time resource.** The zero-ramp generator i_1 contributes no flexibility, concentrating the balancing burden on i_2 and i_3.
4) **LMPs degenerate under under-forecast conditions**, producing zero prices that fail to signal the true scarcity of committed resources—a structural limitation of the deterministic framework.

These findings provide a quantitative motivation for investing in improved wind forecasting and for considering the adoption of forecast ensemble methods or robust optimization frameworks that can hedge against forecast errors at the day-ahead stage, particularly in power systems with high wind penetration.

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