International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 2, Mar-Apr 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Modeling and Optimization of Thermal Power Plant Self-Scheduling in Electricity Markets Using Quantile Regression-Based Probabilistic Price Forecasts

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

Abstract:
This paper presents a comparative analysis of deterministic self-scheduling optimization for a thermal power plant under two distinct market price inputs: quantileregression-based forecasted market clearing prices and actual market clearing prices obtained from the Indian Energy Exchange (IEX). The self-scheduling problem is formulated as a Mixed-Integer Programming (MIP) model that maximizes total profit over a 24-hour scheduling horizon while satisfying technical constraints including power output bounds, ramping limits, and unit commitment logic. The model is applied to the SIPAT-I thermal generating unit in the Indian grid and implemented in GAMS, solved with CPLEX. Results reveal that forecasted high-price scenarios yield significantly higher profits (Rs. 116,942,000) compared to actual market conditions (Rs. 35,818,000), with the actual-price case exhibiting operational losses during off-peak hours due to prices falling below marginal costs. The study underscores the critical impact of price forecast accuracy on self-scheduling decisions and operational profitability.

Key Terms— Self-scheduling, Unit commitment, Mixedinteger programming, Quantile regression, Market clearing price, GAMS, Thermal power plant, Indian Energy Exchange.

I. **Introduction**

The deregulation of electricity markets has transformed the operating environment for power producers, granting them autonomy to make self-scheduling decisions that optimize profit rather than following centrally dispatched schedules [1]. In competitive electricity markets, a generating unit's profitability is intimately tied to the accuracy of price forecasts and the scheduling strategy adopted in response to anticipated market conditions.

The self-scheduling problem involves determining the on/off commitment status and power output level of a generating unit over a planning horizon—typically 24 hours—with the objective of maximizing profit while respecting operational constraints such as ramping limits and minimum/maximum generation bounds [?]. The problem is inherently combinatorial due to binary commitment variables and is formulated as a Mixed-Integer Linear Program (MILP).

A central challenge in self-scheduling is that market clearing prices (MCPs) are unknown at the time of decision-making. Two broad strategies are commonly employed: (i)

deterministic scheduling using a single forecasted price trajectory, and (ii) stochastic scheduling that hedges across multiple price scenarios. Price forecasting methods range from statistical time-series models to machine learning approaches; quantile regression has gained traction for capturing price uncertainty by providing distributional forecasts [2].

This paper focuses on the deterministic framework applied under two price inputs:

- Case 1: Forecasted MCPs derived from quantile regression, representing an optimistic high-price scenario.

- Case 2: Actual MCPs recorded from the Indian Energy Exchange (IEX) for the same 24-hour period, reflecting real market volatility.

By comparing outcomes under these two inputs, this study quantifies the performance gap attributable to price forecast error and provides insight into the operational and financial implications of scheduling under imperfect price information.

The remainder of the paper is organized as follows. Section II presents the mathematical formulation of the self-scheduling model. Section III describes the case system data. Section IV reports and analyzes computational results for both cases. Section V provides a comparative discussion, and Section VI concludes the paper.

II. Problem Formulation

A. Objective Function

The self-scheduling problem for a single thermal generating unit maximizes total profit Π over the 24-hour horizon T = {1,2,...,24}:

$$\max\ \Pi = \sum_{t \in \mathcal{T}} \pi(t) \quad (1)$$

where the profit per period $\pi(t)$ is:

$$\pi(t) = \lambda(t)p(t) - C_v\ p(t) - C_f\ v(t) - C_{su}\ y(t) - C_{sd}\ z(t) \quad (2)$$

The terms represent, respectively, energy revenue, variable generation cost, fixed operating cost, start-up cost, and shut-down cost. Variable definitions are provided in Table I.

B. Power Output Limits

When the unit is online ($v(t) = 1$), its output must lie between minimum stable generation and rated capacity:

TABLE I: Nomenclature

Symbol	Description
$\lambda(t)$	Market clearing price at period t (Rs./kWh)
$p(t)$	Power output at period t (MW)
$v(t)$	Binary: 1 if unit is online, 0 otherwise
$y(t)$	Binary start-up indicator
$z(t)$	Binary shut-down indicator
$\pi(t)$	Profit at period t (Rs.)
Cv	Variable (marginal) cost (Rs./kWh)
C_f	Fixed operating cost (Rs./h)
Csu	Start-up cost (Rs.)
Csd	Shut-down cost (Rs.)
$Pmax$	Maximum generation capacity (MW)
$Pmin$	Minimum stable generation (MW)
R_U	Ramp-up rate limit (MW/h)
RD	Ramp-down rate limit (MW/h)
RSU	Start-up ramp limit (MW)
RSD	Shut-down ramp limit (MW)
$v0$	Initial commitment status
$p0$	Initial power output (MW)

$$P_{\min} v(t) \le p(t) \le P_{\max} v(t),\ \forall t \in \mathrm{T} \quad (3)$$

C. Ramping Constraints

Ramp-up constraint for $t > 1$:

$$p(t) - p(t-1) \le R_U v(t-1) + R_{SU} y(t) + P_{\max}(1 - v(t)) \quad (4)$$

Ramp-up constraint for $t = 1$ (using initial conditions):

$$p(1) - p_0 \le R_U\ v_0 + R_{SU}\ y(1) + P_{\max}(1 - v(1)) \quad (5)$$

Ramp-down constraint for $t > 1$:

$$p(t-1) - p(t) \le R_D\ v(t) + R_{SD}\ z(t) + P_{\max}(1 - v(t-1)) \quad (6)$$

Ramp-down constraint for $t = 1$:

$$p_0 - p(1) \le R_D v(1) + R_{SD} z(1) + P_{\max}(1 - v_0) \quad (7)$$

D. Unit Commitment Logic Constraints

The relationship between commitment status, start-up, and shut-down indicators for $t > 1$:

$$y(t) - z(t) = v(t) - v(t-1),\ \forall t > 1 \quad (8)$$

For $t = 1$:

$$y(1) - z(1) = v(1) - v_0 \quad (9)$$

Mutual exclusion of start-up and shut-down events:

$$y(t) + z(t) \le 1,\ \forall t \in \mathrm{T} \quad (10)$$

TABLE II: SIPAT-I Unit Technical and Economic Parameters

Parameter	Symbol	Value
Maximum capacity	Pmax	1,980 MW
Minimum power output	Pmin	100 MW
Ramp-up limit	R_U	90 MW/h
Ramp-down limit	RD	80 MW/h
Start-up ramp limit	RSU	300 MW

Shut-down ramp limit	*RSD*	200 MW
Fixed cost	C_f	Rs. 1.32/h
Variable (marginal) cost	*Cv*	Rs. 1.40/kWh
Start-up cost	*Csu*	Rs. 20
Shut-down cost	*Csd*	Rs. 10
Initial status	*v*0	0 (offline)
Initial power output	*p*0	0 MW

E. Variable Domains

$$v(t), y(t), z(t) \in \{0,1\}, \forall t \in T \quad (11)$$

$$p(t) \geq 0, \forall t \in T \quad (12)$$

The complete model (1)–(10) constitutes a Mixed Integer Linear Program (MILP), implemented in GAMS and solved with CPLEX with optcr = 0 (optimality gap tolerance of zero).

III. Case System Data

A. Generating Unit Parameters

The model is applied to the SIPAT-I thermal generating unit, a coal-fired plant connected to the Indian grid. Technical and economic parameters are listed in Table II.

B. Price Input Scenarios

Quantile Regression (QR)Price Forecasting: Unlike Ordinary Least Squares (OLS), which estimates the conditional mean, Quantile Regression estimates a specific conditional quantile $\tau \in (0,1)$ of the response variable. This is particularly useful in electricity markets to model price spikes and skewness.

Mathematical Formulation: The QR model solves the following optimization problem for the coefficients β:

$$\min_{\beta} \sum_{i=1}^{n} \rho_\tau(y_i - x_i^T \beta) \quad (13)$$

The check function $\rho_\tau(u)$ is an asymmetric loss function defined as:

$$\rho_\tau(u) = \begin{cases} \tau u, & u \geq 0 \\ (\tau - 1)u, & u < 0 \end{cases} \quad (14)$$

By varying τ (e.g., 0.1,0.5,0.9), the model provides lower, median, and upper price forecasts, offering robustness against outliers and capturing extreme price behaviors.

TABLE III: Hourly Market Clearing Prices – Both Cases (Rs./kWh)

Period	Case 1	Case 2	Period	Case 1	Case 2
t1	4.14	3.96	t13	1.81	0.12
t2	3.81	3.63	t14	1.79	0.15
t3	3.52	3.57	t15	2.19	0.30
t4	3.47	3.57	t16	2.67	0.59
t5	3.40	3.52	t17	2.98	1.46
t6	3.57	3.90	t18	3.43	2.84
t7	3.73	4.09	t19	5.07	3.56
t8	3.21	3.06	t20	10.00	4.76
t9	2.71	1.62	t21	10.00	4.40
t10	2.34	0.67	t22	10.00	4.05
t11	1.86	0.27	t23	10.00	4.17
t12	1.80	0.20	t24	9.94	3.75

1) Case 1 – Forecasted Prices (Quantile Regression): Hourly price forecasts for the scheduling day were generated using quantile regression on historical IEX market clearing prices. The median quantile trajectory was selected as the deterministic price input. The forecasted prices range from Rs. 1.79/kWh (t14) to Rs. 10.00/kWh (t20–t23), with a pronounced evening price peak characteristic of Indian power markets during high-demand periods. Full hourly prices are listed in Table III.

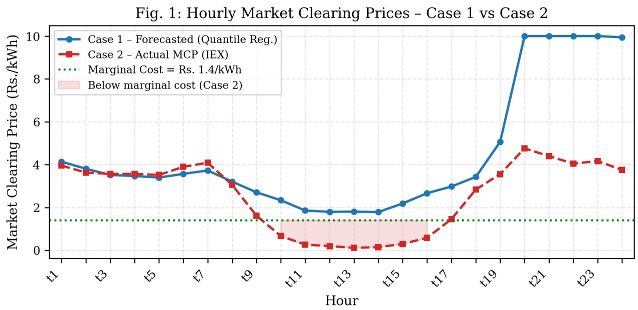

Fig. 1: Price profiles with marginal cost line below-cost shading.

2) Case 2 – Actual Market Clearing Prices: The actual MCPs recorded on the IEX for the same day are used as the price input. These prices range from Rs. 0.12/kWh (t13) to Rs. 4.76/kWh (t20), displaying a significantly different profile: very low off-peak prices during hours t10– t16 (below marginal cost) and a moderate evening peak. This case tests the scheduling strategy under real market price realizations.

IV. Computational Results

The MILP model contains 169 single equations, 121 single variables (72 binary), and 620 non-zero elements. Both cases reached proven optimality with zero absolute gap.

A. Case 1: Forecasted High Prices

1) Commitment and Dispatch: The optimal solution commits the unit for all 24 hours ($v(t) = 1, \forall t$). At $t = 1$, the unit starts up ($y(1) = 1$) at 300 MW—constrained by the start-up ramp limit (R_{SU} = 300 MW). Output then increases by exactly R_U = 90 MW per hour through $t1$–$t19$, ramping from 300 MW to 1,920 MW. Maximum capacity (1,980 MW) is reached at $t20$ and maintained through $t24$.

2) Financial Performance: Period profits $\pi(t)$ are positive throughout, ranging from Rs. 514.68 (t12) to Rs. 17,026.68 (t20–t23). The exceptional profitability during the evening peak (t20–t23, price = Rs. 10.00/kWh, output = 1,980 MW) drives the outstanding total profit. Key financial metrics are:

- Total profit: Rs. 116,942,020 (≈ Rs. 11.69 Crores)
- Average hourly profit: Rs. 4,872,584
- Operating hours: 24/24
- Peak hourly profit (t20–t23): Rs. 17,026.68 per period

3) Binding Constraints: Ramp-up constraints are binding for periods $t2$ through $t19$, confirming that ramping limits—not price economics—govern the output trajectory during the build-up phase. The capacity constraint ($p \leq P_{max}v$) becomes binding at $t20$–$t23$ where the shadow price is Rs. 8.60/MW, indicating significant value of additional capacity during peak hours.

B. Case 2: Actual Market Clearing Prices

1) Commitment and Dispatch: The unit remains online for all 24 hours, again starting up at $t1$ with $y(1) = 1$. The power output profile follows a similar ramp-up pattern but with a notable deviation at $t10$: output drops from 1,020 MW ($t9$) to 990 MW ($t10$), breaking the monotonic ramp due to the very low price at that hour (Rs. 0.67/kWh). After $t10$, ramping resumes until the unit reaches 1,980 MW at $t21$–$t24$.

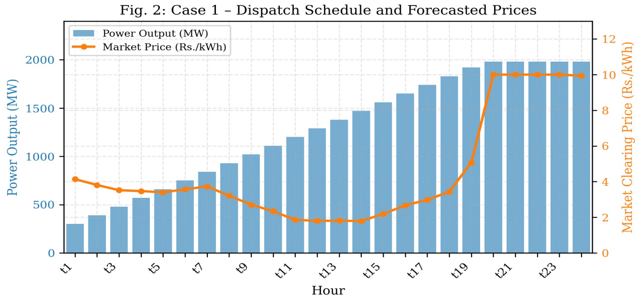

Fig. 2: Case 1 dispatch — market price .

2) Financial Performance: In stark contrast to Case 1, period profits turn negative during hours t10–t16 due to market prices falling well below the marginal cost (C_v = Rs. 1.40/kWh). Losses peak at −Rs. 1,688.82 at $t14$ (price = Rs. 0.15/kWh). Despite these interim losses, continuous operation is optimal because shutting down would incur start-up/shut-down costs and forfeit profitable evening periods. Key financial metrics are:

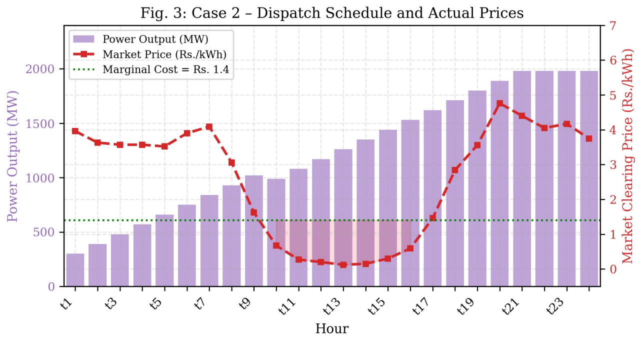

Fig. 3: Case 2 dispatch — market price .

- Total profit: Rs. 35,818,420 (≈ Rs. 3.58 Crores)
- Average hourly profit: Rs. 1,492,434
- Operating hours: 24/24
- Loss-making periods: t10–t16 (7 hours)
- Peak hourly profit (t20): Rs. 6,349.08
- Worst hourly profit (t14): −Rs. 1,688.82

3) Binding Constraints: Ramp-up constraints are binding for t2–t9 and t11–t21. The capacity constraint binds only at t21–t24, with smaller shadow prices (Rs. 2.35– 2.77/MW) reflecting the more moderate peak prices in Case 2. The marginal value of the ramp-up constraint at $t2$ is Rs. 15.76, significantly lower than Case 1 (Rs. 28.16), consistent with lower price levels.

C. Hourly Results Summary

Table IV presents the complete hourly dispatch and profit for both cases.

V. Comparative Discussion

A. Profit Gap and Price Forecast Impact

The forecasted-price case (Case 1) achieves a total profit of Rs. 116,942,020, while the actual-price case (Case 2) yields Rs. 35,818,420—a reduction of 69.4%. This large gap is attributable primarily to three factors:

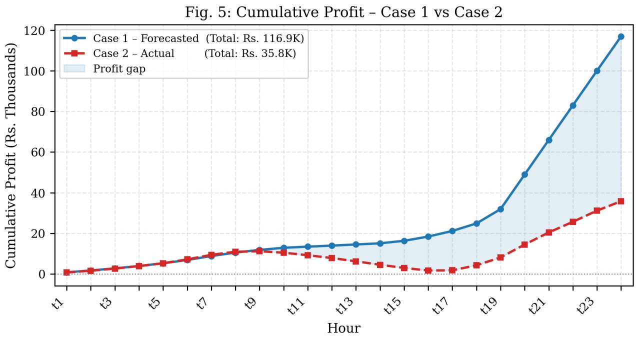

Fig. 4: Cumulative profit with gap shading (Rs. 116,942,020 vs 35,818,420) .

TABLE IV: Hourly Optimal Dispatch Results – Cases 1 and 2

t	Case 1 (Forecasted) $p(t)$ [MW]	Case 1 $\pi(t)$ [Rs.]	Case 2 (Actual) $p(t)$ [MW]	Case 2 $\pi(t)$ [Rs.]
1	300	800.68	300	746.68
2	390	938.58	390	868.38
3	480	1,016.28	480	1,040.28
4	570	1,178.58	570	1,235.58
5	660	1,318.68	660	1,397.88
6	750	1,626.18	750	1,873.68
7	840	1,955.88	840	2,258.28
8	930	1,681.98	930	1,542.48
9	1020	1,334.88	1020	223.08
10	1110	1,042.08	990	−724.02
11	1200	550.68	1080	−1,221.72
12	1290	514.68	1170	−1,405.32
13	1380	564.48	1260	−1,614.12
14	1470	571.98	1350	−1,688.82
15	1560	1,231.08	1440	−1,585.32
16	1650	2,094.18	1530	−1,240.62
17	1740	2,747.88	1620	95.88
18	1830	3,713.58	1710	2,461.08
19	1920	7,045.08	1800	3,886.68
20	1980	17,026.68	1890	6,349.08
21	1980	17,026.68	1980	5,938.68
22	1980	17,026.68	1980	5,245.68
23	1980	17,026.68	1980	5,483.28
24	1980	16,907.88	1980	4,651.68
	Total	116,942.02		35,818.42

1) Peak price magnitude: Forecasted prices during t20–t23 reached Rs. 10.00/kWh versus Rs. 4.05– 4.76/kWh actual, a 2.1× overestimate. The contribution of peak-hour revenue to total profit is disproportionately large at maximum capacity.
2) Off-peak price accuracy: Case 1 prices during t10– t16 (Rs. 1.79–2.34/kWh) remained above marginal cost, so all periods were profitable. Case 2 prices in the same window collapsed to Rs. 0.12–0.67/kWh, producing 7 loss-making periods.
3) Ramping trajectory: Despite the output dip at t10 in Case 2, both cases operate at full capacity during peak hours. The profit differential is therefore a direct consequence of price level, not dispatch volume.

B. Operational Strategy Comparison

Both cases result in the unit staying online for all 24 hours. This outcome is rational: the start-up cost (Rs. 20) and shut-down cost (Rs. 10) are small relative to the opportunity cost of being offline during the profitable evening peak. Even when per-period losses are incurred (Case 2, t10–t16), the aggregate loss (Rs. 7,279.90) is less than the transition costs plus foregone evening profit that would result from shutting down and restarting.

C. Constraint Activity

Ramp-up constraints are the primary binding operational constraints in both cases, reflecting that the unit's

TABLE V: Comparative Performance Metrics

Metric	Case 1	Case 2
Total profit (Rs.)	116,942,020	35,818,420
Total profit (Rs. Crores)	11.69	3.58
Operating hours	24/24	24/24
Loss-making periods	0	7 (t10–t16)
Max hourly profit (Rs.)	17,026.68	6,349.08
Min hourly profit (Rs.)	514.68	−1,688.82
Peak power output (MW)	1,980	1,980
Hours at full capacity	5 (t20–t24)	4 (t21–t24)
Price range (Rs./kWh)	1.79–10.00	0.12–4.76
Profit gap vs. Case 1	–	−69.4%
CPLEX solve time (s)	0.047	0.047
MIP iterations	109	169

90 MW/h ramp rate is the limiting factor during the buildup phase. The shadow price of the ramp-up constraint is consistently higher in Case 1 (range Rs. 3.67–30.90/MW) compared to Case 2 (range Rs. 0.22–18.32/MW), confirming that

ramping capacity has greater economic value under higher price environments.

D. Performance Metrics Summary

Table V summarizes the key performance indicators for both cases.

VI. Conclusion

This paper presented a detailed comparative analysis of deterministic self-scheduling optimization for the SIPATI thermal unit under quantile-regression-based forecasted prices (Case 1) and actual IEX market clearing prices (Case 2). Both cases were solved to global optimality using GAMS/CPLEX.

Key conclusions are:

1) The forecasted high-price scenario achieves a total profit of Rs. 116.94 million, demonstrating the maximum achievable profitability when price forecasts accurately capture evening price peaks.
2) The actual-price case yields Rs. 35.82 million—a 69.4% reduction—with 7 loss-making periods during off-peak hours, highlighting the sensitivity of selfscheduling outcomes to price forecast accuracy.
3) In both cases, continuous 24-hour operation is optimal. The ramp-up rate is the binding physical constraint during the generation build-up phase, motivating the value of higher ramp-rate units in volatile price environments.
4) The shadow prices of ramp-up constraints are substantially higher under forecasted prices, confirming that ramping flexibility commands greater economic value when prices are elevated.
5) Price forecast accuracy—particularly for peak-hour prices—is the dominant determinant of realized profit in deterministic self-scheduling. Overestimated peak prices by quantile regression create inflated profit expectations compared to actual market outcomes.

These findings motivate the use of stochastic or robust optimization frameworks that hedge across multiple price scenarios, reducing the exposure to forecast errors while maintaining acceptable expected profitability.

Acknowledgment

The authors acknowledge the use of GAMS 50.3.0 with CPLEX 22.1.2.0 for all computational experiments, and the Indian Energy Exchange (IEX) for providing market clearing price data.

References

[1] A. J. Conejo, M. Carrión, and J. M. Morales, Decision Making Under Uncertainty in Electricity Markets. Boston, MA: Springer, 2010.
[2] S. Stoft, “Power System Economics: Designing Markets for Electricity,” IEEE Press, 2002.
[3] A. J. Conejo et al., “Decision Making Under Uncertainty in Electricity Markets,” Springer, 2010.
[4] R. T. Rockafellar and S. Uryasev, “Optimization of conditional value-at-risk,” Journal of Risk, vol. 2, pp. 21-42, 2000.
[5] M. Carrión and J. M. Arroyo, “A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem,” IEEE Transactions on Power Systems, vol. 21, no. 3, pp. 1371-1378, Aug. 2006.
[6] A. J. Conejo, F. J. Nogales, and J. M. Arroyo, “Price-taker bidding strategy under price uncertainty,” IEEE Transactions on Power Systems, vol. 17, no. 4, pp. 1081-1088, Nov. 2002.
[7] E. Ni, P. B. Luh, and S. Rourke, “Optimal integrated generation bidding and scheduling with risk management under a deregulated power market,” IEEE Transactions on Power Systems, vol. 19, no. 1, pp. 600-609, Feb. 2004.
[8] Y. Zhang, L. Wang, and M. Xiao, “Optimal self-scheduling of thermal units with price uncertainty,” IEEE Trans. Power Syst., vol. 35, no. 2, pp. 1284-1293, Mar. 2020.
[9] R. Kumar and A. Singh, “Risk-based scheduling of thermal power plants in deregulated markets,” Elec. Power Syst. Res., vol. 178, pp. 106-115, Jan. 2020.
[10] R. T. Rockafellar and S. Uryasev, “Conditional value-at-risk for general loss distributions,” J. Bank. Finance, vol. 26, no. 7, pp. 1443-1471, Jul. 2002.
[11] A. Botterud et al., “Optimal investments in power generation under centralized and decentralized decision making,” IEEE Trans. Power Syst., vol. 20, no. 1, pp. 254-263, Feb. 2005.
[12] J. M. Morales et al., “Pricing electricity in pools with wind producers,” IEEE Trans. Power Syst., vol. 27, no. 3, pp. 13661376, Aug. 2012.

