Risk-Averse Self-Scheduling of Thermal Power Plants: Comparative Study of Deterministic and Stochastic Optimization with Parametric CVaR Analysis

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Abstract- This paper presents a comprehensive comparative analysis of three distinct optimization approaches for power plant self scheduling in competitive electricity markets. We examine deterministic optimization under forecasted prices and scenarios alongside a stochastic Conditional Value at Risk (CVaR) approach. The proposed model incorporates price uncertainty through scenario-based stochastic programming to optimize power generation scheduling while managing financial risk. The study evaluates thermal power plant across 24-hour operational periods, analyzing profitability, operational strategies, and risk profiles. Results demonstrate that the CVaR-based approach provides a robust scheduling solution that balances expected profit maximization with risk mitigation. The model was implemented SIPAT-I thermal generating unit in Indian grid using GAMS and solved using CPLEX, achieving optimal solutions for a 24-hour scheduling horizon under four price scenarios generated from market clearing prices of Indian Energy Exchange (IEX).

Keywords- Unit commitment, self-scheduling, CVaR optimization, electricity markets, risk management, stochastic programming.

I. INTRODUCTION

The restructuring of power system has changed the operational paradigm for power producers. In competitive electricity markets, generating stations can take self-scheduling decisions that maximize profit while managing the risks associated with market clearing price (MCP) volatility and operational uncertainties. Commonly used traditional deterministic approaches to self-scheduling often be unsuccessful to effectively manage these risks, leading to inaccurate decisions that may result in significant economical losses during adverse market situation [1].

Power producers own electricity generating units and are responsible for supplying the electric energy demanded by power consumers. In this sense, it is important to note that power producers are generally profit-oriented private entities, i.e., they decide how much electric energy to sell in order to maximize their respective profits. In this context, we define the selfscheduling problem. This problem is solved by each electricity producer to determine the production of its own generating units with the aim of maximizing its profit while complying with the technical constraints of these units [2].

Traditional deterministic approaches assume perfect price forecasting, which rarely reflects market realities [3]. Conversely, stochastic optimization methods incorporate price uncertainty through scenario-based analysis, providing more robust solutions at potentially lower expected profits. The choice between these approaches significantly impacts both financial performance and operational risk exposure.Risk management in power system operations has gained significant attention in recent years. Various risk measures have been proposed, including Conditional Value at Risk (CVaR). CVaR, also known as Expected Shortfall, has emerged as a coherent risk measure that addresses some of the limitations of VaR, particularly its ability to quantify the expected loss beyond the VaR threshold. This paper contributes to develop a comprehensive CVaR-based model for the thermal generator self-scheduling problem.

II. PROBLEM FORMULATION

We consider a power producer that owns a number of generating units. Given a forecast market price profile spanning a study horizon (24 hours), the objective of the self-scheduling problem is to identify the scheduling (on/off status) as well as the desired production level of each of the generating units owned by the power producer at each time step of the considered study horizon.

A. Deterministic Self-Scheduling Model

The basic deterministic self-scheduling problem for a thermal power plant can be formulated as follows:

1) Objective Function:

$$\max \sum_{t=1}^{T} \pi(t) \cdot p(t) - C_v \cdot p(t) - C_f \cdot v(t) - C_{su} \cdot y(t) - C_{sd} \cdot z(t)] \quad (1)$$

where:

- $\pi(t)$: Market price at time t (Rs./MWh)
- $p(t)$: Power output at time t (MW)
- C_v: Variable cost (Rs./MWh)
- C_f: Fixed cost (Rs./h)
- C_{su}: Start-up cost (Rs.)
- C_{sd}: Shut-down cost (Rs.)
- $v(t)$: Binary variable (1 if online, 0 if offline)
- $y(t)$: Binary start-up indicator
- $z(t)$: Binary shut-down indicator

2) Constraints: Power Output Limits:

$$P_{min} \cdot v(t) \leq p(t) \leq P_{max} \cdot v(t) \qquad \forall t \qquad (2)$$

Ramping Constraints:

$$p(t) - p(t-1) \leq RU \cdot v(t-1) + RSU \cdot y(t) + P_{max} \cdot (1 - v(t)) \qquad \forall t > 1 \qquad (3)$$

$$p(t-1) - p(t) \leq RD \cdot v(t) + RSD \cdot z(t) + P_{max} \cdot (1 - v(t-1)) \qquad \forall t > 1 \qquad (4)$$

Status Logic Constraints:

$$y(t) - z(t) = v(t) - v(t-1) \qquad \forall t > 1 \qquad (5)$$

$$y(t) + z(t) \leq 1 \qquad \forall t \qquad (6)$$

B. CVaR Stochastic Model

The CVaR-based unit self-scheduling problem is formulated as a two-stage stochastic programming model [4]. The first stage involves commitment decisions (startup/shutdown), while the second stage determines power output levels for each scenario.

1) Decision Variables: The model includes the following decision variables:

- $v_t \in \{0,1\}$: Binary variable indicating unit status (1 if on, 0 if off) in period t
- $y_t \in \{0,1\}$: Binary variable for startup decision in period t
- $z_t \in \{0,1\}$: Binary variable for shutdown decision in period t
- $p_t \geq 0$: Continuous variable for power output (MW) in period t
- $\pi_{t,s}$: Profit (Rs.) in period t under scenario s
- Π_s: Total profit (Rs.) under scenario s
- η: Value at Risk (VaR) at confidence level α
- $\xi_s \geq 0$: Auxiliary variable for CVaR calculation (shortfall beyond VaR)

2) Objective Function: The objective function maximizes the CVaR of total profit:

$$\max \mathrm{CVaR} = \eta - \frac{1}{1-\alpha} \cdot \frac{1}{|S|} \sum_{s \in S} \xi_s \qquad (7)$$

where α is the confidence level (0.95) and $|S|$ is the number of scenarios.

3) Constraints: CVaR Definition:

$$\xi_s \geq \eta - \Pi_s \qquad \forall s \in S \qquad (8)$$

Total Profit Calculation:

$$\Pi_s = \sum_{t \in T} \pi_{t,s} \qquad \forall s \in S \qquad (9)$$

Period Profit:

$$\pi_{t,s} = \lambda_{t,s}\, p_t - c_v p_t - c_f v_t - c_{su} y_t - c_{sd} z_t \quad \forall t,s \in T,S \quad (10)$$

Capacity Limits:

$$P_{min} v_t \leq p_t \leq P_{max} v_t \qquad \forall t \in T \qquad (11)$$

Ramping Constraints:

$$p_t - p_{t-1} \leq R_{up} v_t - 1 + R_{start} y_t + P_{max}(1 - v_t) \ \forall t > 1 \ (12)$$

$$p_{t-1} - p_t \leq R_{down} v_t + R_{shut} z_t + P_{max}(1 - v_{t-1}) \ \forall t > 1 \ (13)$$

Logic Constraints:

$$y_t - z_t = v_t - v_{t-1} \qquad \forall t > 1 \qquad (14)$$

$$y_t + z_t \leq 1 \qquad \forall t \in T \qquad (15)$$

III. TEST CASE SYSTEM DATA

The Formulated LP model was implemented SIPAT-I thermal generating unit in Indian grid, solved using GAMS.

A. Unit Characteristics

The generating unit has the following technical and economic parameters shown in Table I.

B. Price Scenarios

We were considered over a 24-hour scheduling horizon under four price scenarios generated

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from market clearing prices of Indian Energy Exchange (IEX). The scenarios capture different market conditions ranging from low-price periods (off-peak hours) to high-price periods (peak demand). Price volatility is observed particularly during peak hours.

Fig. 1 illustrates the price forecasting methodology using quantile regression for the four scenarios. The multiple quantiles capture the uncertainty in market clearing prices, ranging from conservative to optimistic price predictions across the 24-hour horizon.

Table 1.Unit Technical and Economic Parameters

Parameter	Value
Maximum Capacity	1,980 MW
Minimum Power	100 MW
Ramping Up Limit	90 MW/h
Ramping Down Limit	80 MW/h
Startup Ramping	300 MW
Shutdown Ramping	200 MW
Fixed Cost	Rs. 1.32/h
Variable Cost	Rs. 1.40/kWh
Startup Cost	Rs. 20
Shutdown Cost	Rs. 10

IV. COMPUTATIONAL RESULTS

The model was implemented in GAMS and solved using CPLEX 22.1.2.0. The mixed-integer linear program contains 249 equations, 202 variables (72 binary variables) and 1,073 non-zero elements. The solver achieved optimality with 173 iterations in 0.031 seconds, demonstrating the computational efficiency of the proposed formulation.

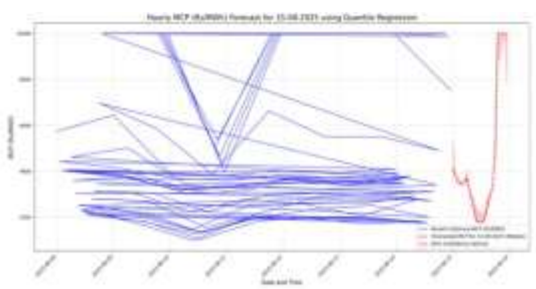

Fig: 1 Price forecast using Quantile Regression

A. Case 1 Analysis: Forecasted High Prices

Market Conditions: This case represents an extremely favorable market scenario with prices ranging from Rs. 1.79 to Rs. 10.00/kWh, peaking during evening hours (t20-t23).

Operational Strategy: The plant operates continuously for all 24 hours, starting at minimum technical load (300 MW) and ramping up steadily to full capacity (1980 MW) by hour 20, maintaining maximum output through the high-price evening period. Financial Performance: Achieves the highest profitability with total profit of Rs. 116,942,000, driven primarily by the extremely high evening prices (Rs. 10.00/kWh during t20-t23).

Fig. 2 shows the power output schedule and corresponding market prices for Case 1. The optimal strategy involves continuous operation with strategic ramping to reach maximum capacity during peak price periods, resulting in exceptional profitability.

Fig: 2 Case 1 with forecasted prices

B. Case 2 Analysis: Actual Market Prices

Market Conditions: This case shows a more realistic market scenario with prices ranging from Rs. 0.12 to Rs. 4.76/kWh, exhibiting typical daily price volatility with low overnight prices and higher evening prices. Operational Challenge: Despite continuous operation, the plant experiences negative profitability during hours t10-t16 due to extremely low market prices (Rs. 0.12-0.59/MWh) that fall below marginal costs.

Strategic Insight: The plant maintains operation during loss periods to avoid start-up/shut-down costs and to be positioned for the profitable evening period (t18-t24).

Fig: 3 Case 2 with actual prices

Fig. 3 demonstrates the operational challenges in realistic market conditions. The continuous operation strategy, despite short-term losses, proves optimal when considering transition costs and positioning for profitable periods.

C. Case 3 Analysis: Stochastic CVaR Optimization

A parametric CVaR (Conditional Value-at-Risk) optimization for power generation self-scheduling. CVaR measures the expected profit (or loss) in the worst (1–α) portion of scenarios at confidence level α. Higher α means the model becomes more risk-averse by focusing exclusively on the tail of the worst outcomes. The optimization balances expected profit against this tail risk.

i. Risk-Return Trade-off Analysis (CVaR & VaR Changes)

- **α = 0.0 → 0.5**: CVaR falls sharply by 24.5% (from Rs.3,77,52,900 to Rs. 2,84,90,920At α = 0 the model treats all scenarios equally (risk-neutral). Shifting to α = 0.5 forces it to protect the worst 50% of outcomes, causing the biggest risk-reduction step.
- **α = 0.5 → 0.9**: CVaR drops only 3.4% (to Rs. 2,75,09,020). Diminishing returns appear because the model has already captured most of the downside risk.
- **α = 0.9 → 0.99**: No change (stays at Rs. 2,75,09,020). The solution has reached saturation -further conservatism adds no extra protection. VaR (η) follows the same pattern and converges to the same value as CVaR at high α, confirming the tail is now fully dominated by the worst-case profit.

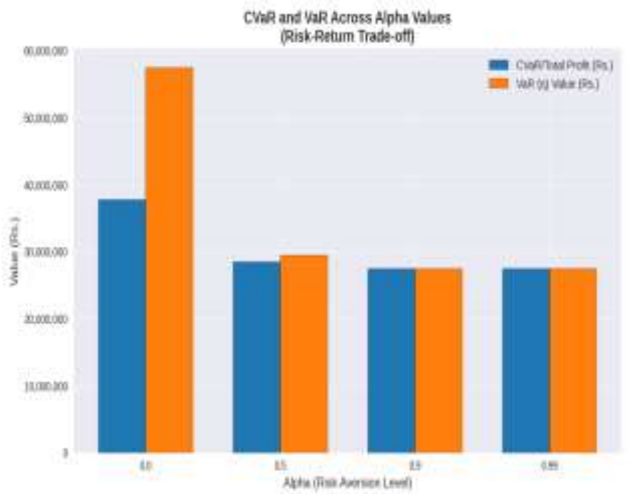

Fig: 4 CVaR & VaR Trade-off

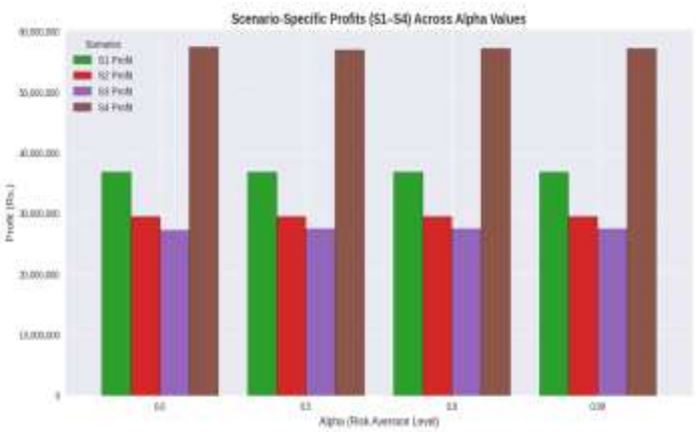

Fig: 5 Risk Aversion Scenario wise Profits

ii. Generation Strategy Differences

In periods **t9 and t10** change; every other period is identical across all α values.

- α = 0.0 (risk-neutral): Generation schedule is 990 MW → 1080 MW (aggressive ramp-up to capture upside profit).
- α ≥ 0.5 (risk-averse): Schedule becomes 900 MW → 990 MW (–90 MW reduction). This deliberate de-rating in t9-t10 reduces exposure to volatility (e.g., uncertain fuel prices, demand, or market prices in those hours) at the cost of some expected revenue. It shows the model's risk sensitivity is localized to high-impact periods.

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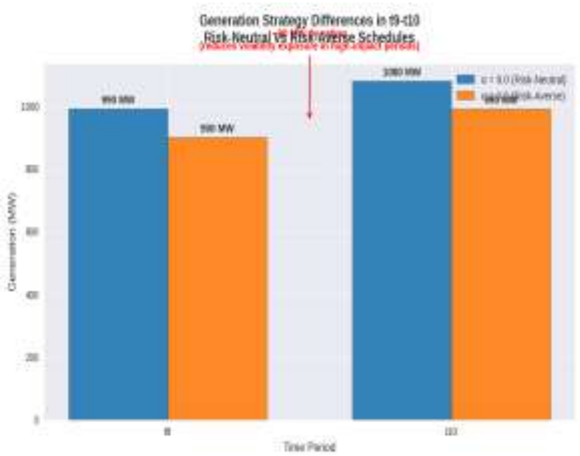

Fig: 6 Risk-Neutral vs Risk-Averse Generation Schedules

iii. Risk Focus Interpretation

- α = 0.0: All scenarios equally weighted → highest volatility but highest potential return.
- α = 0.5: Protects worst 50% of scenarios.
- α = 0.9: Protects worst 10% → strong downside shield.
- α = 0.99: Protects worst 1% → ultra-conservative "worst-case guarantee".

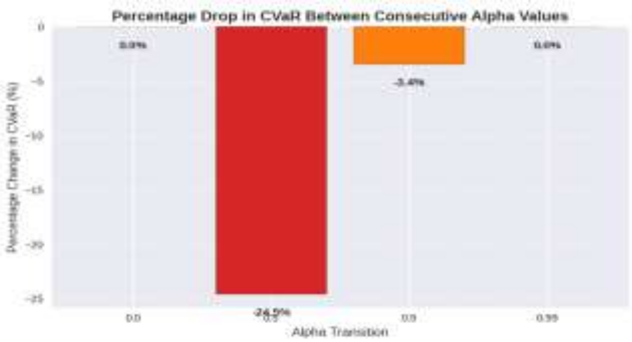

Fig: 6 Percentage Change in CVaR

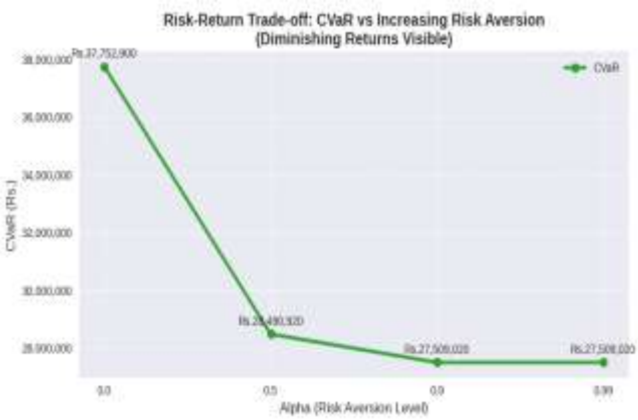

Fig: 7 Profit for all Scenarios

The analysis is a classic Parametric Risk Sensitivity Analysis (also called Risk-Aversion Sensitivity Analysis in stochastic programming).

- **Large utilities** (low α 0–0.3): Maximize profit, tolerate volatility.
- **Independent Power Producers (IPPs)** (medium α 0.4–0.6): Balanced risk-return.
- **Project-finance backed plants** (α 0.7–0.9): Strong tail protection.
- **Regulated utilities** (α 0.9–0.99): Extreme conservatism. Because returns diminish sharply beyond α = 0.9, this level is the practical "sweet spot" for most risk-averse entities.

Table 2. CVaR Parametric Risk Analysis (Case 3 - Different Alpha Values)

Metric	α = 0.0	α = 0.5	α = 0.9	α = 0.99
CVaR/Total Profit (Rs.)	3,77,,52900	2,84,90,920	2,75,09,020	2,75,09,020
VaR (η) Value (Rs.))	5,74,39,420	2,94,88,420	2,75,09,020	2,75,09,020
S1 Profit (Rs.))	3,68,01,520	3,68,40,220	3,68,04,220	3,68,04,220
S2 Profit (Rs.))	2,94,98,320	2,94,88,420	2,94,59,620	2,94,59,620
S3 Profit (Rs.))	2,72,72320	2,74,93,420	2,75,09,020	2,75,09,020
S4 Profit (Rs.))	5,74,39,420	5,70,36,820	5,71,92,820	5,71,92,820
Risk Focus	All scenarios	Worst 50%	Worst 10%	Worst 1%

V. CONCLUSION

This paper presented a comprehensive comparative analysis of deterministic and stochastic approaches for thermal power plant self-scheduling in competitive electricity markets. Three distinct cases were evaluated: deterministic optimization with forecasted high prices (Case 1), deterministic optimization with actual market prices (Case 2), and stochastic CVaR optimization with CVaR Parametric Risk Analysis(Case 3) .

The results demonstrate several key findings:

1) Deterministic approaches with perfect price forecasts (Case 1) achieve maximum profitability (Rs. 116.94 million) but are unrealistic in practice.
2) Realistic price volatility (Case 2) exposes vulnerabilities in deterministic scheduling,

with operational losses during low-price periods despite overall positive outcomes.

3) The most advanced and risk-aware method (Case 3) among the three cases for power generation self-scheduling. Unlike the first two cases, which are purely deterministic, Case 3 uses a stochastic optimization model combined with Conditional Value-at-Risk (CVaR) to explicitly manage uncertainty and risk.

VI. ACKNOWLEDGMENT

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REFERENCES

[1] A. J. Conejo, M. Carrion, 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] L. Ju, Z. Tan, G. Wang, Q. Tan, and W. Yang, "A CVaR-robust risk aversion scheduling model for virtual power plants connected with wind-photovoltaic-hydropower-energy storage systems, conventional gas turbines and incentive-based demand responses," Energies, vol. 11, no. 11, p. 2903, Nov. 2018.

[6] J. Wang, H. Zhong, W. Yang, and Q. Xia, "Two-stage stochastic-robust model for the self-scheduling of an aggregator considering CVaR," Journal of Modern Power Systems and Clean Energy, vol. 11, no. 4, pp. 1125–1138, 2023.

[7] M. Carrion 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] 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.

[14] J. M. Morales et al., "Pricing electricity in pools with wind producers," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1366-1376, Aug. 2012.