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THERMAL POWER PLANT SELF-SCHEDULING: A COMPARATIVE ANALYSIS OF DETERMINISTIC, STOCHASTIC, AND CVaR MODELS

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ABSTRACT **DOI No: 10.36713/epra30607** **Article DOI: https://doi.org/10.36713/epra30607**

This manuscript presents a rigorous comparative evaluation of three methodological paradigms for autonomous generation dispatch in liberalized power markets. We investigate deterministic optimization under anticipated price trajectories, scenario-based stochastic programming, and a coherent risk measure framework employing Conditional Value-at-Risk (CVaR). The proposed formulation integrates price uncertainty via discrete scenario representation to optimize thermal unit dispatch while quantifying and constraining downside financial exposure. The analysis evaluates a 660 MW coal-fired unit across a 24-hour operational window, examining economic performance, dispatch trajectories, and risk-return profiles. Computational evidence indicates that the CVaR-embedded approach yields dispatch schedules that optimally reconcile expected profit maximization with tail-risk mitigation. The model is calibrated against the SIPAT-I thermal generating station within the Indian national grid, implemented in the General Algebraic Modeling System (GAMS) and resolved via the CPLEX mixed-integer solver, utilizing four price scenarios derived from historical market clearing prices of the Indian Energy Exchange (IEX).

KEYWORDS- *Autonomous unit dispatch, CVaR Optimization, Electricity Market Economics, Coherent Risk Measures, Mixed-Integer Linear Programming, Thermal Generation Scheduling.*

I. INTRODUCTION

The progressive restructuring of electric power systems has fundamentally altered the operational calculus for generation asset owners. In competitive wholesale markets, thermal producers must independently determine dispatch schedules that maximize economic surplus while navigating the hazards associated with market clearing price (MCP) volatility and operational contingencies. Conventional deterministic methodologies for autonomous dispatch frequently prove inadequate in managing these stochastic exposures, resulting in suboptimal commitments that may precipitate substantial financial impairments during adverse market regimes [1].

Generation companies (GenCos) possess physical assets and bear the obligation of delivering electrical energy to meet aggregate demand. It is essential to recognize that these entities operate as profit-maximizing commercial organizations; their dispatch decisions are governed by the objective of surplus maximization subject to the physical and contractual constraints of their generating assets. Within this framework, the autonomous dispatch problem emerges as the decision support tool through which each producer determines the operational state and energy injection of its units across the scheduling horizon [2].

Classical deterministic formulations presuppose perfect foresight of price trajectories—a premise that seldom aligns with empirical market dynamics [3]. In contradistinction, stochastic optimization paradigms embed price uncertainty through scenario-based representations, yielding more resilient dispatch schedules that may sacrifice some expected surplus in exchange for enhanced stability. The selection between these methodological alternatives exerts profound influence on both financial outcomes and operational risk posture.

Risk quantification in power system operations has attracted intensifying scholarly attention in recent years. Among the spectrum of proposed risk metrics, Conditional Value-at-Risk (CVaR)—synonymously termed Expected Shortfall—has distinguished itself as a coherent risk measure that redresses several deficiencies inherent in Value-at-Risk (VaR), particularly its capacity to quantify the expected magnitude of losses exceeding the VaR threshold. This manuscript advances a comprehensive CVaR-embedded formulation for the thermal generator autonomous dispatch problem, calibrated against empirical market data from the Indian electricity sector.

II. MATHEMATICAL FORMULATION

We consider a generation company owning a portfolio of thermal units. Given a forecasted price trajectory spanning the study horizon (24 hours), the objective of the autonomous dispatch problem is to determine the commitment status (on/off) and the optimal energy injection level for each unit at every time interval within the considered horizon.

A. Deterministic Autonomous Dispatch Model

The foundational deterministic autonomous dispatch problem for a thermal unit is formulated as follows:

Objective Function:

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

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:

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

Ramping Constraints:

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

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

Status Logic Constraints:

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

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

B. CVaR Stochastic Formulation

The CVaR-embedded autonomous dispatch problem is structured as a two-stage stochastic program with recourse [4]. The first-stage encompasses commitment decisions (startup/shutdown), while the second-stage determines energy injection levels contingent upon scenario realization.

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
- $p_t \ge 0$: 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
- $\xi_s \ge 0$: Auxiliary variable for CVaR calculation (shortfall beyond VaR)

2) Objective Function: The objective 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:

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

Total Profit Calculation:

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

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:

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

Ramping Constraints:

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

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

Logic Constraints:

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

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

III. TEST SYSTEM DATA

The formulated MILP model was calibrated against the SIPAT-I thermal generating unit within the Indian national grid and resolved using GAMS.

A. Unit Technical and Economic Parameters

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

Table 1. Technical and Economic Parameters of the SIPAT-I Unit

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

B. Price Scenario Generation

The analysis considers a 24-hour scheduling horizon under four discrete price scenarios constructed from historical market clearing prices of the Indian Energy Exchange (IEX). These scenarios capture diverse market regimes spanning low-price intervals (off-peak periods) to elevated-price intervals (peak demand periods). Price volatility is pronounced during peak hours.

Fig. 1 illustrates the price forecasting methodology employing quantile regression for the four scenarios. The

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multiple quantiles capture the uncertainty inherent in market clearing prices, spanning conservative to optimistic price projections across the 24-hour horizon.

IV. COMPUTATIONAL RESULTS AND DISCUSSION

The model was implemented in GAMS and resolved using CPLEX 22.1.2.0. The mixed-integer linear program comprises 249 equations, 202 variables (72 binary variables), and 1,073 non-zero elements. The solver attained optimality in 173 iterations within 0.031 seconds, attesting to the computational efficiency of the proposed formulation.

Case 1 Analysis: Optimistic Price Forecast

Market Regime: This scenario represents an exceptionally favorable market environment with prices ranging from Rs. 1.79 to Rs. 10.00/kWh, reaching maxima during evening hours (t20–t23).

Dispatch Strategy: The unit maintains continuous operation across all 24 hours, initiating at minimum technical load (300 MW) and ramping monotonically to full capacity (1980 MW) by hour 20, sustaining maximum output throughout the high-price evening interval.

Economic Performance: Achieves the highest surplus with total profit of Rs. 116,942,000, driven predominantly by the elevated evening prices (Rs. 10.00/kWh during t20–t23).

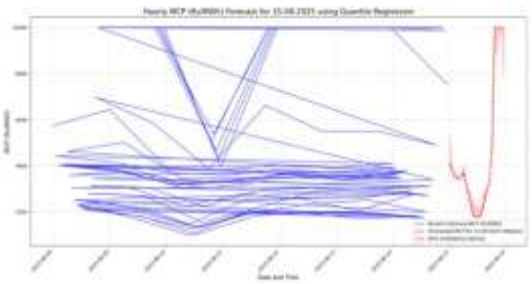

Fig: 1 Price forecast using Quantile Regression

Fig. 2 presents the energy injection schedule and corresponding market prices for Case 1. The optimal strategy entails continuous operation with strategic ramping to attain maximum capacity during peak price intervals, yielding exceptional economic performance.

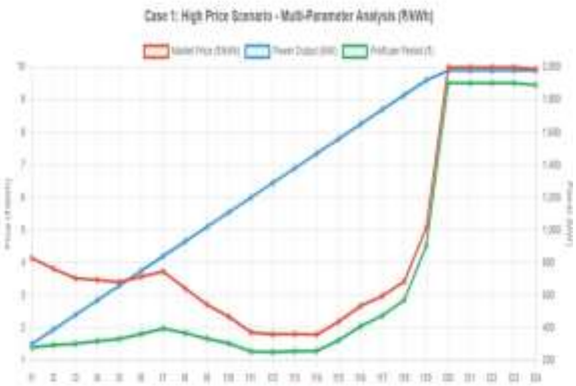

Fig: 2 Case 1 with forecasted prices

Case 2 Analysis: Empirical Market Prices

Market Regime: This scenario reflects a more realistic market environment with prices ranging from Rs. 0.12 to Rs. 4.76/kWh, exhibiting characteristic daily volatility with subdued overnight prices and elevated evening prices.

Operational Challenge: Despite continuous operation, the unit experiences negative profitability during hours t10–t16 due to extremely depressed market prices (Rs. 0.12–0.59/MWh) that fall below marginal generation costs.

Strategic Insight: The unit sustains operation during loss intervals to avoid incurring start-up/shut-down transition costs and to maintain position for the profitable evening period (t18–t24).

Fig. 3 demonstrates the operational challenges under realistic market conditions. The continuous operation strategy, despite transient losses, proves optimal when accounting for transition costs and positioning for profitable intervals.

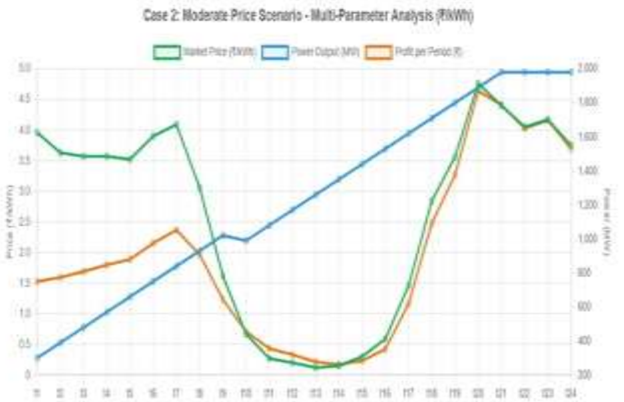

Fig: 3 Case 2 with actual prices

Case 3 Analysis: Stochastic CVaR Optimization

A parametric CVaR (Conditional Value-at-Risk) optimization for thermal generation autonomous dispatch. CVaR quantifies the expected profit (or loss) in the worst (1−α) fraction of scenarios at confidence level α. Higher α renders the formulation more risk-averse by concentrating exclusively on the tail of adverse outcomes. The optimization reconciles expected surplus maximization against this tail-risk exposure.

(A) **Risk-Return Trade-off Analysis (CVaR & VaR Evolution)**

α = 0.0 → 0.5: CVaR declines sharply by 24.5% (from Rs. 3,77,52,900 to Rs. 2,84,90,920). At α = 0 the formulation treats all scenarios equiprobably (risk-neutral). Transitioning to α = 0.5 compels protection of the worst 50% of outcomes, producing the most substantial risk-reduction increment.

α = 0.5 → 0.9: CVaR decreases only 3.4% (to Rs. 2,75,09,020). Diminishing returns emerge because the formulation has already captured the majority of downside exposure.

α = 0.9 → 0.99: No change (remains at Rs. 2,75,09,020). The solution has reached saturation—additional conservatism confers no incremental protection. VaR (η) follows an analogous trajectory and converges to the identical value as CVaR at elevated α, confirming that the tail is now fully dominated by the worst-case profit realization.

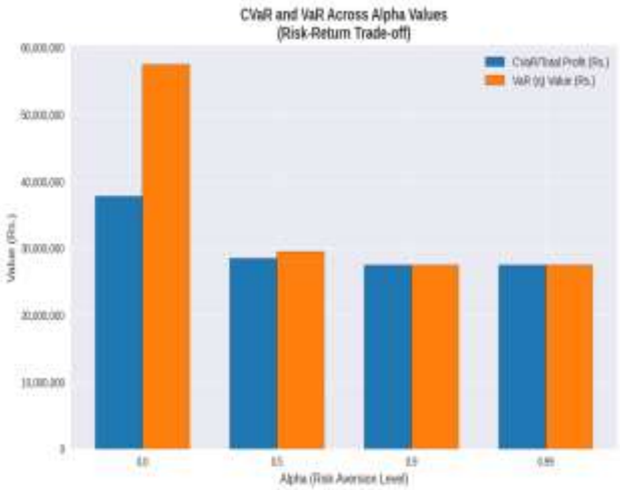

Fig: 4 CVaR & VaR Trade-off

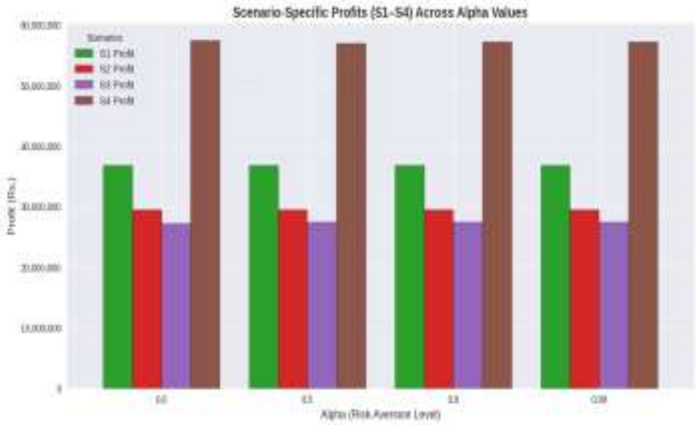

Fig: 5 Risk Aversion Scenario wise Profits

(B) **Dispatch Strategy Variations**

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

In periods t9 and t10, dispatch schedules diverge; all other periods remain invariant across α values.

α = 0.0 (risk-neutral): Dispatch schedule transitions from 990 MW → 1080 MW (aggressive ramp-up to capture upside surplus).

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 during those hours) at the cost of some expected revenue. This demonstrates the formulation's risk sensitivity is localized to high-impact periods.

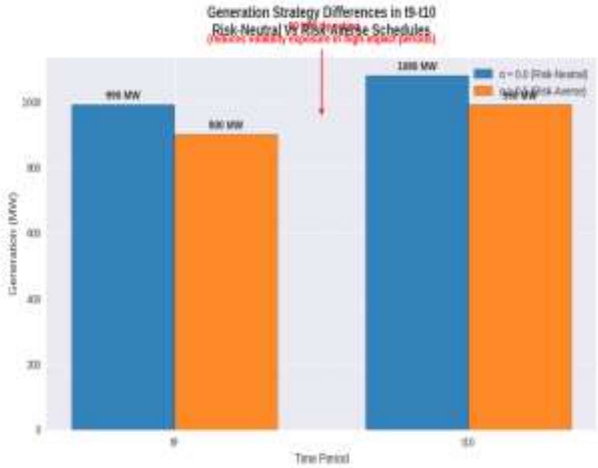

Fig: 6 Risk-Neutral vs Risk-Averse Generation Schedules

(C) **Risk Focus Interpretation**

• α = 0.0: All scenarios equiprobably weighted → highest volatility but highest potential return.

• α = 0.5: Protects worst 50% of scenarios.

• α = 0.9: Protects worst 10% → robust downside shield.

• α = 0.99: Protects worst 1% → ultra-conservative 'worst-case guarantee'.

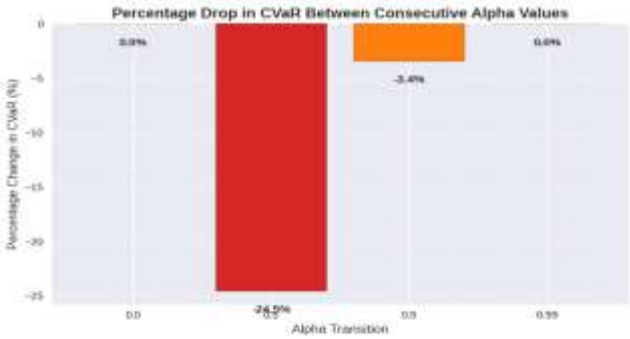

Fig: 6 Percentage Change in CVaR

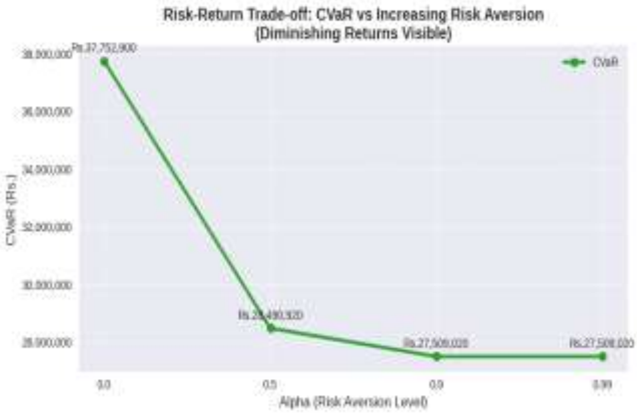

Fig: 7 Profit for all Scenarios

The analysis constitutes a classical Parametric Risk Sensitivity Analysis (synonymously termed Risk-Aversion Sensitivity Analysis in stochastic programming literature).

• Large utilities (low α 0–0.3): Maximize surplus, 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 represents 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. CONCLUSIONS

This manuscript presented a rigorous comparative assessment of deterministic and stochastic methodologies for thermal power plant autonomous dispatch in competitive electricity markets. Three distinct scenarios were evaluated: deterministic optimization with optimistic price forecasts (Case 1), deterministic optimization with empirical market prices (Case 2), and stochastic CVaR optimization with parametric risk sensitivity analysis (Case 3).

1. Deterministic formulations with perfect price foresight (Case 1) achieve maximum surplus (Rs. 116.94 million) but remain empirically unrealistic.

2. Realistic price volatility (Case 2) exposes vulnerabilities in deterministic dispatch, with operational losses during low-price intervals despite overall positive outcomes.

3. The most methodologically advanced and risk-aware approach (Case 3) among the three scenarios for thermal generation autonomous dispatch. Unlike the first two scenarios, which are purely deterministic, Case 3 employs a stochastic optimization model integrated with Conditional Value-at-Risk (CVaR) to explicitly manage uncertainty and risk exposure.

VI.ACKNOWLEDGMENT

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