An Integrated Decision-Support Framework for Risk-Aware Electricity Procurement in Indian Power Systems

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Abstract - *The increasing integration of renewable energy sources and electricity exchange markets has transformed electricity procurement practices in India's power sector. While traditional Power Purchase Agreements (PPAs) provide supply reliability, exchange-based procurement mechanisms, including the Day-Ahead Market (DAM), Green Day-Ahead Market (GDAM), and Real-Time Market (RTM), offer greater flexibility under dynamic market conditions. However, rising renewable penetration, market volatility, and supply–demand uncertainty create significant challenges for distribution companies (DISCOMs) in achieving cost-effective, reliable, and risk-aware procurement decisions. This study proposes a data-driven adaptive electricity procurement framework using Central Electricity Authority (CEA) operational datasets and electricity exchange market analytics. The framework integrates operational stress assessment, market-risk analysis, procurement optimization, and machine learning to model procurement behavior under varying market and system conditions. Results indicate that procurement behavior is strongly influenced by the combined effects of operational stress, market risk, and resource characteristics, with renewable-rich and lower-stress conditions supporting greater exchange market participation, while elevated stress conditions encourage increased reliance on long-term PPAs. A comparative Bihar–Gujarat case study further demonstrates the framework's ability to capture heterogeneous procurement patterns, with predicted exchange participation increasing from 26.4% in Bihar to 39.2% in Gujarat under contrasting system conditions. Overall, the proposed framework contributes to the development of adaptive and risk-aware procurement decision-support systems for India's evolving electricity markets.*

Key Words: Electricity Procurement, Power Purchase Agreements (PPAs), Market Risk, Procurement Optimization, Renewable Integration, Machine Learning, Operational Stress

1. INTRODUCTION

India's electricity demand has grown rapidly in recent years due to increasing electrification, economic development, rising cooling requirements, and expanding industrial activity [1]. The national power system recently recorded peak demand levels approaching 270 GW, highlighting the increasing challenge of maintaining reliable and cost-effective electricity supply under evolving operating conditions [2]. To meet this growing demand while advancing national clean-energy objectives, India has significantly expanded the deployment of renewable energy resources, particularly solar and wind generation, resulting in a progressively evolving generation mix [3]. While renewable-energy expansion strengthens sustainability and energy security, the variable nature of renewable generation introduces additional uncertainty into power-system operations and procurement planning [4]. As demand continues to grow and the generation mix becomes increasingly diverse, Distribution Companies (DISCOMs) face increasing pressure to secure adequate power resources while balancing procurement cost, reliability requirements, and operational uncertainty.

Traditionally, Indian DISCOMs have relied primarily on long-term Power Purchase Agreements (PPAs), which provide supply reliability and procurement certainty through contracted electricity purchases from generating companies. However, while PPAs ensure supply security, they offer limited flexibility in responding to short-term variations in demand, renewable generation, and market conditions [6]. To improve procurement flexibility, utilities increasingly participate in electricity exchange markets operated through platforms such as the Indian Energy Exchange (IEX). These include the Day-Ahead Market (DAM), where electricity is traded one day in advance; the Real-Time Market (RTM), which supports short-term balancing close to delivery; and the Green Day-Ahead Market (GDAM), which facilitates trading of renewable electricity [7]. In practice, DISCOMs commonly utilize electricity exchange markets to manage anticipated power shortfalls and operational imbalances, with participation patterns varying across DAM, GDAM, and RTM according to procurement requirements, renewable availability, and prevailing market conditions. Exchange markets also provide opportunities to liquidate surplus contracted power, enabling utilities to reduce procurement losses or benefit from favourable spot-market prices.

The growing importance of exchange-based procurement has coincided with increasing renewable-energy integration within Indian power systems [3,5]. Renewable resources such as solar and wind exhibit variable generation behavior, creating additional balancing requirements and operational uncertainty [4,5]. Consequently, utilities must continuously balance PPAs with short-term market participation while maintaining supply reliability and controlling procurement risk. In this context, hydroelectric generation provides important balancing flexibility during fluctuating operating conditions, while thermal generation continues to support system reliability during periods of elevated stress [8].

1.1 Indian Electricity Market Challenge

Electricity procurement in India is influenced by a combination of market dynamics, operational constraints, and regional system characteristics. Variations in demand patterns, renewable-generation output, fuel-dependent thermal availability, transmission limitations, and state-level infrastructure differences can significantly affect procurement decisions and system reliability. During evening peak-demand periods, power systems frequently experience elevated operational stress due to the simultaneous contribution of residential, commercial, and cooling loads [9]. Under such conditions, utilities must manage procurement decisions while responding to changing renewable-generation availability, balancing requirements, and fluctuations in market prices. Although the Real-Time Market (RTM) provides a mechanism for managing short-term balancing requirements, its utilization is influenced by prevailing market conditions because procurement costs may increase during periods of system stress as market-clearing prices respond to supply-demand imbalances and transmission constraints [10]. Consequently, DISCOMs must carefully balance long-term contractual procurement with short-term market participation. Excessive dependence on long-term PPAs may reduce procurement flexibility and limit the ability to benefit from favorable market opportunities, whereas excessive reliance on exchange markets may increase exposure to price volatility, balancing risk, and procurement uncertainty [11].

In response to these challenges, several Indian utilities have begun adopting advanced forecasting, smart-grid, and digital operational technologies to improve decision-making and system management. Power Trading Corporation (PTC) has adopted machine-learning-based forecasting techniques for day-ahead and intraday electricity demand prediction to support power procurement and operational decision-making [12]. Tata Power Delhi Distribution Limited (TPDDL) has implemented smart-grid infrastructure, automated monitoring systems, and demand-response initiatives to enhance operational reliability and peak-load management [13]. Similarly, TP Central Odisha Distribution Limited (TPCODL) has undertaken network-strengthening and reliability-improvement programs to support more efficient system operations and electricity management [14]. These developments indicate a gradual transition from purely contract-driven procurement toward data-driven operational planning, renewable-energy integration, intelligent forecasting, and market-responsive procurement strategies.

1.2 AI-Based Energy Analytics and Research Motivation

Artificial intelligence (AI) and machine learning (ML) have demonstrated significant potential for addressing complex decision-making problems in modern power systems. Recent studies have shown that AI-based approaches can improve electricity-demand forecasting, renewable-energy management, anomaly detection, and other data-driven power-system applications by identifying nonlinear relationships and hidden patterns within large-scale datasets [15-17]. Such capabilities are particularly valuable in electricity markets where procurement decisions are influenced by multiple interacting factors, including demand uncertainty, renewable variability, market volatility, and system is operating conditions. The growing adoption of intelligent analytics within the power sector further highlights the potential of AI-enabled decision support. For example, NTPC has adopted artificial intelligence and advanced analytics techniques for load forecasting, renewable-generation forecasting, and operational optimization to support more efficient power-system planning and decision-making [18]. Building upon such forecasting and optimization capabilities, Rajasthan Urja Vikas and IT Services Ltd. (RUVITL) has initiated the development of an AI-enabled integrated energy portfolio management system incorporating forecasting, scenario analysis, scheduling, trade optimization, and power-purchase cost optimization capabilities to improve procurement planning under demand uncertainty, renewable-energy variability, forecasting errors, and market-volatility conditions [19]. These developments reflect a broader transition toward data-driven power-system operation and demonstrate the growing role of AI-enabled analytics in supporting forecasting, renewable integration, operational optimization, and decision support within modern electricity networks.

Despite these developments and the growing adoption of AI-enabled analytics within the power sector, electricity procurement remains a complex decision-making problem involving the interaction of market behavior, operational stress, renewable variability, and procurement risk. Existing studies have contributed significantly to electricity-market forecasting, procurement flexibility, renewable-energy integration, market reforms, and operational analytics within power systems. However, limited research has integrated exchange market forecasting, market-risk assessment, operational stress modeling, procurement optimization, and machine learning-based decision support within a unified framework for Indian electricity markets. This gap motivates the development of an adaptive and risk-aware electricity procurement framework capable of supporting decision-making under varying market and operational conditions.

1.3 Proposed Framework and Contributions

To address the challenges associated with electricity procurement under renewable variability, market uncertainty, and operational stress, this study proposes a machine learning-driven adaptive electricity procurement framework for Indian power markets. The framework integrates electricity-market forecasting, operational stress assessment, procurement optimization, and machine-learning-based decision support within unified procurement intelligence architecture. The main contributions of this study are:

- A State Stress Index is developed to quantify operational and structural stress in Indian power systems using demand–supply, generation, capacity, and renewable-integration indicators.

- A risk-aware procurement optimization framework is proposed to determine adaptive allocation between long-term PPAs and multiple electricity exchange markets (DAM, GDAM, and RTM) under varying market and system conditions.

- A machine learning–based procurement modeling framework is developed to predict adaptive allocations between PPAs and exchange markets under varying market and operational conditions, validated through a Bihar–Gujarat case study demonstrating distinct procurement strategies under contrasting stress and renewable-integration conditions.

2. LITERATURE REVIEW

Several studies have investigated individual dimensions of electricity procurement, market operation, and risk management in the Indian power sector. However, most existing works focus on specific components of the procurement process rather than developing an integrated decision-making framework.

Tiwari et al. [20] proposed ensemble machine-learning models for forecasting electricity prices in the Indian Energy Exchange (IEX). Their study demonstrated that advanced forecasting techniques can effectively capture the non-linear relationships between demand, supply conditions, and market prices, thereby improving short-term price prediction accuracy. However, the study was limited to forecasting performance and did not examine how forecast outputs could be incorporated into procurement planning or risk-aware decision-making.

Jindal and Shrimali [21] examined the challenges associated with large-scale renewable energy integration and battery storage adoption in the Indian power sector. Their study highlighted the limitations of conventional procurement and contracting mechanisms under evolving power-system conditions and emphasized the need for more flexible market and policy frameworks. However, the study primarily focused on policy and market-enabling mechanisms and did not propose a quantitative framework for adaptive procurement decision-making under uncertainty.

Saran et al. [22] analyzed the impact of the Real-Time Market (RTM) on India's Day-Ahead Market (DAM), providing insights into evolving market behavior and the interactions between short-term electricity trading mechanisms. Their study highlighted the implications of RTM implementation for market participants, stakeholders, and electric utilities within the Indian electricity market. However, the analysis primarily focused on market interactions and market performance and did not address how utilities can utilize these market signals to optimize procurement decisions under uncertain operating conditions.

Gupta and Singh [23] examined flexible contracting mechanisms, including market-based Power Purchase Agreements (PPAs), Contracts-for-Difference (CfDs), and revenue-sharing arrangements, in the context of modernizing India's electricity market. Their study highlighted the potential of alternative contractual structures to support market adaptability and address emerging challenges associated with evolving electricity market conditions. However, the proposed mechanisms were primarily evaluated from a contractual and market-design perspective and did not integrate electricity price forecasting, operational stress indicators, or optimization-based procurement decision models.

Goud et al. [24] proposed a two-step chance-constrained day-ahead portfolio optimization framework for DISCOM scheduling under renewable energy uncertainty. Their approach incorporated stochastic renewable generation and scenario-based reconciliation to improve resource adequacy and scheduling decisions. However, the framework was limited to day-ahead operational planning and did not integrate real-time market dynamics, electricity price forecasting, or adaptive multi-market procurement strategies.

The reviewed studies demonstrate the growing importance of electricity price forecasting, flexible contracting mechanisms, renewable-energy integration, and market participation in modern power systems. Collectively, these works indicate that effective procurement decisions require consideration of multiple interacting factors, including market conditions, operational constraints, and renewable-generation variability. The findings also highlight the increasing need for analytical approaches capable of supporting procurement decisions under dynamic and uncertain operating environments.

3. METHODOLOGY

This study proposes a data-driven framework for analyzing electricity procurement behaviors in Indian electricity markets under varying operational and market conditions. Electricity exchange data, power-system indicators, renewable-energy characteristics, and state-level infrastructure information were integrated for procurement analysis. The framework incorporates market-risk analysis, operational stress modeling, procurement optimization, and machine learning-based forecasting to evaluate procurement behavior across long-term and exchange-based electricity markets. Weighting parameters used in aggregated indicators were selected using domain-informed engineering judgment while maintaining model interpretability. The overall architecture is illustrated in Fig. 1.

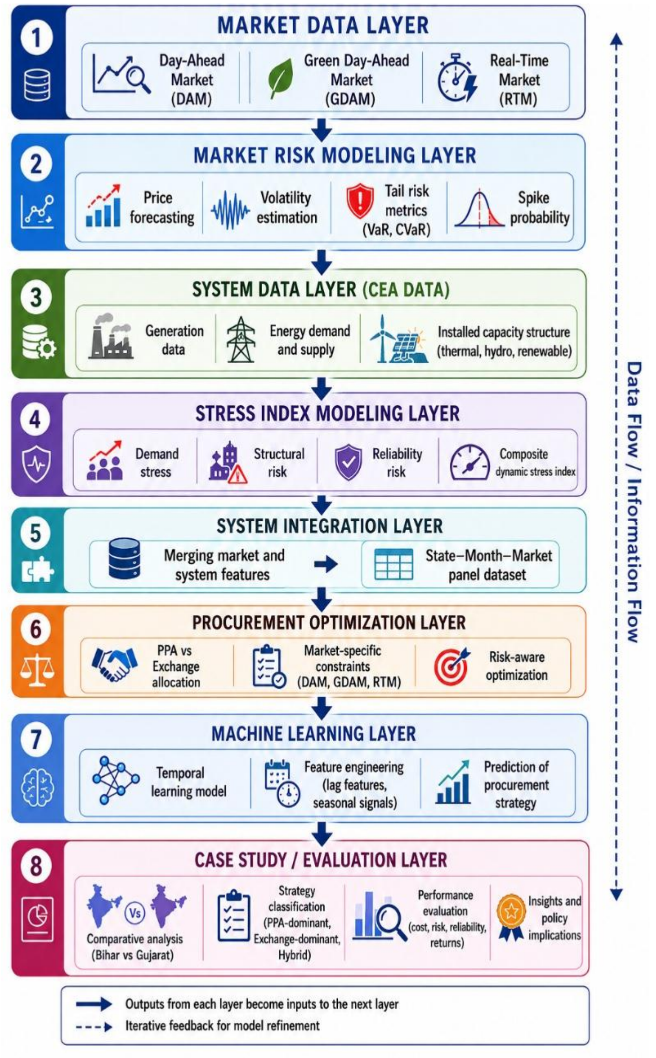


Fig -1: Proposed Adaptive Electricity Procurement Framework.

3.1 Exchange Market Modeling and Forecasting

The exchange market modeling component captures electricity price dynamics and procurement risk across the Day-Ahead Market (DAM), Green Day-Ahead Market (GDAM), and Real-Time Market (RTM) operating within the Indian Energy Exchange (IEX). Market clearing price, traded volume, purchase bids, and sell bids were extracted from exchange-level market records and organized at a 15-minute temporal resolution.

Lag-based historical price features, rolling volatility measures, bid-pressure ratios, volume-intensity indicators, and temporal variables including hour-of-day, day-of-week, and month were used to model short-term market behavior. DAM, GDAM, and RTM datasets were modeled independently to preserve market-specific trading characteristics and price behavior.

3.1.1 Market Forecasting Framework

Separate Random Forest regression models were developed for DAM, GDAM, and RTM price forecasting using lag-based historical prices, rolling volatility indicators, bid-pressure behavior, trading-volume intensity, and temporal market features as predictive inputs. The models were trained using exchange market observations from 2024 and evaluated on unseen market data spanning January 2025 to January 2026. Forecasting performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) metrics against a lag-based naïve forecasting baseline, and the resulting exchange-price forecasts were subsequently integrated into downstream procurement optimization and market-risk analysis modules.

3.1.2 Monthly Exchange Risk Profiling

Monthly exchange risk profiles were constructed using both realized and forecasted market observations to characterize short-term market uncertainty and procurement exposure. Market-risk behaviors were analyzed using realized log-return volatility, forecast-error statistics, spike-event probability, and peak-hour pricing characteristics.

Tail-risk conditions were evaluated using Value-at-Risk (VaR95), Conditional Value-at-Risk (CVaR95), exceedance-based CVaR, and price-cap event probability measures derived from monthly market price distributions. Operational spike thresholds were determined using monthly price-distribution characteristics to identify abnormal market conditions across DAM, GDAM, and RTM segments.

3.2 State-Level Operational Data Processing

State-level operational datasets were constructed using three categories of Central Electricity Authority (CEA) reports: (i) state-wise energy demand and supply reports, (ii) monthly generation performance reports, and (iii) installed capacity reports. The datasets covered the period from February 2024 to January 2026 and were integrated at monthly temporal resolution for stress analysis and procurement modeling, although January 2026 was excluded from the final stress-index dataset as installed-capacity observations were unavailable. Energy demand-supply reports were used to derive operational indicators including energy requirement, energy supplied, energy deficit, and shortage percentage across different electricity systems.

Generation and installed-capacity reports were used to derive generation and infrastructure indicators including total generation output, thermal Plant Load Factor (PLF), thermal, hydro, and renewable generation shares, hydro-to-thermal generation ratio, month-on-month generation variation, thermal capacity share, renewable capacity share, hydro capacity share, and total installed capacity. Additional indicators including PLF deviation and generation trend variation were incorporated to represent operational variability and generation-side conditions for subsequent state-level stress modeling and procurement analysis.

3.3 State-Level Stress Index

A state-level stress index was developed to quantify operational and structural stress across electricity systems. The framework integrated demand-supply imbalance behavior, infrastructure composition, generation flexibility, and reliability risk into a composite index. Demand-side indicators included gap percentage, demand growth, and shortage-volatility measures derived from state-level energy requirement and supply data. Structural indicators included thermal share, renewable share, hydro share, total installed capacity, capacity adequacy indicators, and renewable integration risk measures. In this study, renewable share represents non-hydro renewable capacity categories reported by CEA, while hydro share was modeled separately to capture balancing and flexibility. Accordingly, renewable integration risk (RIR) was modeled as a function of renewable penetration moderated by hydro and thermal capacity:

Equation (1): $\text{RIR} = \text{Renewable Share} \times [1 - (0.5 \times \text{Hydro Share} + 0.5 \times \text{Thermal Share})]$

Equal weighting was assigned to hydro and thermal capacity to reflect their complementary balancing roles. Hydro resources provide flexibility and rapid response capability, while thermal resources offer dispatchable generation support during sustained system stress. Prior to aggregation, features were normalized using rolling historical distributions, with global historical distributions applied when state-level history was limited. The final stress index combined demand stress, structural risk, and reliability risk through weighted aggregation:

Equation (2): $\text{Base Stress} = 0.5(\text{Demand Stress}) + 0.3(\text{Structural Risk}) + 0.2(\text{Reliability Risk})$

The weighting scheme assigns greater importance to demand stress (0.5) due to the direct influence of supply–demand imbalances and shortage conditions on procurement decisions. Structural risk (0.3) captures medium-term system characteristics, while reliability risk (0.2) represents supporting operational conditions.

A nonlinear transformation was applied to the base stress score to amplify higher-stress operating conditions while preserving differentiation among lower-stress states:

Equation (3): $\text{Stress Score} = (\text{Base Stress})^{1.8}$

The resulting scores were classified into high-, medium-, and low-stress categories using percentile-based thresholds. Monthly rankings were additionally computed to evaluate relative stress conditions across states and time periods.

3.4 Integrated Data Representation for Procurement Modeling

Exchange market observations, state-level operational indicators, generation statistics, installed-capacity characteristics, and stress-index measurements derived from Central Electricity Authority (CEA) and Indian Energy Exchange (IEX) reports were integrated and temporally aligned at a monthly resolution to construct a unified dataset for procurement modeling. Monthly exchange-risk observations were retained separately for different market segments to preserve market-specific pricing dynamics and risk behavior. State-level operational variables, infrastructure characteristics, and stress indicators were aligned with exchange-risk profiles using common temporal and state-wise mappings, while national-level generation statistics were incorporated to capture system-wide operating conditions. The resulting dataset represents state–month–market observations for subsequent procurement analysis. Although forecasting models were trained using 2024 data and generated forecasts through January 2026, the final procurement dataset was limited to the common overlapping period of January–December 2025 after temporal alignment of all variables.

3.5 Procurement Optimization Framework

A procurement optimization framework was developed to determine electricity procurement allocation between long-term PPAs and exchange-based markets under varying operational and market conditions. The framework utilizes the integrated state–month–market dataset described in Section 3.4 and incorporates forecasted exchange prices, market-risk indicators, renewable integration characteristics, and state-level stress conditions into a unified decision structure. Procurement allocation is modeled across the DAM, GDAM, and RTM to preserve exchange-specific trading behavior and volatility characteristics.

3.5.1 Procurement Risk Modeling and Regime Characterization

Procurement risk was modeled by integrating market risk and state-level operational risk. Market risk captures volatility, spike probability, tail-risk exposure, forecast uncertainty, and price-cap event likelihood, while state-level risk represents stress conditions, shortage behavior, and generation mix characteristics. The total procurement risk is defined as:

Equation (4): Total Risk = 0.60 × Market Risk + 0.40 × State Risk

A higher weight was assigned to market risk due to its direct influence on short-term procurement decisions through price volatility and trading uncertainty. State-level risk was assigned a lower weight as its influence is primarily reflected through broader system conditions. Based on these risk characteristics and underlying system conditions, procurement environments were classified into distinct operational regimes, as summarized in Table 1.

Table-1: Procurement Behavior across Operational Regimes

Operational Regime	**Condition Basis**	**Procurement Behavior**
Stable	Normal operating conditions	Balanced procurement
Renewable-Rich	High renewable penetration, low volatility	Increased exchange participation
Stress	Elevated shortage or system stress	Increased reliance on PPAs
Crisis	Concurrent market and system stress	Conservative, PPA-dominant procurement

3.5.2 Procurement Allocation across Markets

A baseline procurement share was determined between PPA and exchange markets using regime-dependent parameters and operational indicators. The remaining exchange share was allocated across exchange markets using market-specific capacity limits and risk-adjusted cost terms. These limits and adjustments were formulated using renewable share, stress score, and shortage conditions to enable differentiated allocation behavior across DAM, GDAM, and RTM while preserving market-specific characteristics. GDAM participation was increased under higher renewable availability, whereas RTM participation was restricted under elevated stress and shortage conditions due to higher balancing uncertainty and volatility exposure.

3.5.3 Constrained Procurement Optimization

The allocation of exchange procurement across markets was formulated as a constrained optimization problem that balances procurement cost, risk exposure, and diversification:

Equation (5):

$$\min_{x}\left[(1-\lambda)\sum_{i} x_i C_i + \lambda\sum_{i} x_i R_i + \gamma\sum_{i} x_i^2\right]$$

subject to:

Equation (6):

$$\sum_{i} x_i = \omega$$

and

Equation (7):

$$0 \le x_i \le Cap_i,\ \forall i \in \{DAM, GDAM, RTM\}$$

where x_i represents the procurement allocation share for market i, C_i denotes normalized procurement cost relative to the PPA benchmark tariff, R_i represents market-adjusted procurement risk, Cap_i denotes the dynamic allocation limit for each exchange market, and ω represents the total exchange participation share. The parameter λ is a regime-dependent risk-aversion coefficient controlling the trade-off between procurement cost minimization and risk reduction, while γ represents the diversification penalty coefficient. Procurement costs were normalized relative to the benchmark PPA tariff to enable consistent comparison across exchange markets. The quadratic penalty term reduces excessive dependence on a single exchange market by encouraging more balanced allocation across DAM, GDAM, and RTM under varying market conditions. The optimization problem was solved using Sequential Least Squares Programming under equality and bound constraints.

3.5.4 Procurement Behavior Characterization

Optimized allocation shares were converted into procurement quantities using state-level demand, and the resulting exchange participation levels were categorized into procurement behavior classes, as summarized in Table 2. These generated procurement allocations and behavior categories were subsequently utilized within the machine learning framework described in Section 3.6 to model and predict procurement behavior under varying operational and market conditions.

Table-2: Procurement Behavior Classification Based on Exchange Participation

Exchange Share (ω)	Procurement Profile
$\omega \leq 0.20$	Strong PPA Dominant
$0.20 < \omega \leq 0.35$	Moderate PPA Dominant
$0.35 < \omega \leq 0.50$	Balanced Adaptive
$\omega > 0.50$	High Exchange Participation

3.6 Machine Learning Framework for Procurement Strategy

A machine learning framework was developed to model procurement behavior using the state–month dataset generated by the procurement optimization framework described in Section 3.5. The resulting procurement allocations were treated as target procurement responses for subsequent machine learning modeling. The objective was to learn the relationship between market conditions, operational stress factors, and resulting procurement decisions, enabling predictive modeling of exchange participation. Input features comprised market indicators (price, volatility, and risk measures), operational variables (stress score, shortage conditions, and generation characteristics), seasonal signals, and lag-based temporal features. Additional engineered features captured demand shocks, reliability pressure, renewable variability, stress persistence, hydro availability patterns, and market–risk interactions to represent higher-order system dynamics.

The target variable was defined as the exchange procurement share, bounded between 0 and 1, and was transformed using a logit function to enable stable regression modeling, with predictions mapped back to the original scale using the inverse logistic transformation. A rolling temporal validation strategy was employed, wherein the first six months of 2025 were used as the initial training window and models were subsequently evaluated on rolling observations from July–December 2025 to ensure temporal generalization. For predictive modeling, a Gradient Boosting Regressor was used to estimate continuous exchange participation, while a Random Forest classifier was employed to model broader procurement-behavior regimes derived from the procurement profiles defined in Table 2. Specifically, Strong and Moderate PPA Dominant profiles were consolidated into a PPA-dominant regime, Balanced Adaptive was retained as a balanced regime, and High Exchange Participation was classified as an exchange-oriented regime. Model performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2) for regression, along with accuracy, precision, recall, and F1-score for classification.

4. CASE STUDY: COMPARATIVE ANALYSIS OF BIHAR AND GUJARAT

To examine procurement behavior under different system conditions, a comparative case study was conducted for Bihar and Gujarat. Since electricity procurement decisions are executed by DISCOMs at the state level, procurement strategies are influenced by variations in system stress, resource availability, and generation structure. The two states were selected based on their contrasting State Stress Index values (Section 3.3), enabling analysis across distinct operational environments.

Bihar represents a relatively high-stress power system characterized by persistent demand–supply imbalances and higher shortage levels. In contrast, Gujarat exhibits lower system stress, stronger capacity adequacy, and a more diversified generation-resource portfolio. The two states also differ in resource composition and system flexibility, providing a suitable basis for evaluating procurement behavior under contrasting electricity-system conditions. Such differences are expected to influence the balance between supply-security considerations and opportunities for flexible market participation.

The machine learning framework (Section 3.6) was applied to the state–month dataset developed through the integrated framework (Sections 3.4–3.5) to estimate exchange participation and procurement patterns for both states. The analysis compares exchange participation, PPA dependence, and procurement characteristics under differing system conditions, evaluating the ability of the proposed framework to distinguish procurement behavior across contrasting operational environments.

5. RESULTS AND DISCUSSION

This section presents the experimental evaluation and analytical findings of the proposed electricity procurement framework. The results examine exchange market forecasting performance, market-risk characteristics, state-level stress assessment, procurement optimization outcomes, machine learning-based procurement prediction, and comparative procurement results for Bihar and Gujarat.

5.1 Exchange Market Forecasting Performance

The forecasting framework was evaluated on unseen market observations across the DAM, GDAM, and RTM. As summarized in Table 4, the proposed framework achieved strong predictive performance across all market segments, with R^2 values exceeding 0.95 and consistently lower forecasting errors than the corresponding lag-based naïve baseline models. RTM achieved the highest forecasting accuracy, with an RMSE of 389.83 Rs/MWh and an R^2 of 0.973, while the corresponding naïve baseline RMSE exceeded 757 Rs/MWh, highlighting the framework's ability to capture market dynamics beyond persistence-based estimation. The dominant predictive drivers and their operational significance across markets are summarized in Table 3. Forecasting performance in DAM and GDAM was primarily associated with lag-based temporal persistence, reflecting relatively structured trading behavior, whereas RTM forecasting exhibited stronger dependence on bid-pressure dynamics linked to immediate market imbalance conditions. As illustrated in Chart 1, the proposed framework effectively captured the overall temporal behavior and exchange-price trends across varying demand and market conditions.

Table-3: Dominant Predictive Drivers Across Exchange Markets

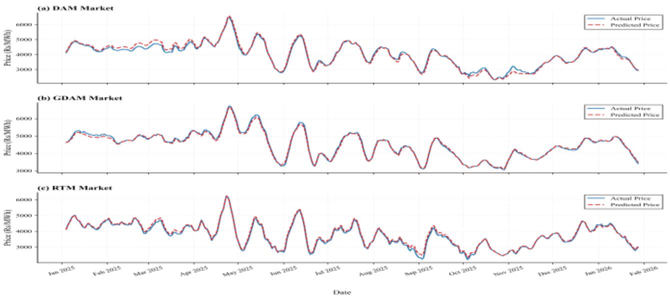
Market	Dominant Predictive Driver	Operational Interpretation
DAM	Previous-Period Market Price (Lag-1)	Strong short-term temporal persistence in scheduled exchange trading
GDAM	Previous-Period Market Price (Lag-1)	Structured and relatively stable renewable-oriented market behavior
RTM	Bid Pressure Ratio	High sensitivity to immediate balancing and supply-demand conditions

Table-4: Forecasting Performance across Exchange Markets

Market	MAE	RMSE	R^2	Naïve MAE	Naïve RMSE
DAM	223.34	511.49	0.961	239.30	681.11
GDAM	257.16	543.42	0.954	243.44	686.42
RTM	225.41	389.83	0.973	338.12	757.90

Note: All error metrics are reported in Rs/MWh

Chart-1: Daily Average Forecast Comparison across DAM, GDAM, and RTM Markets.



5.2 Monthly Exchange Risk Profile Analysis

Monthly exchange risk analysis revealed distinct behavior across DAM, GDAM, and RTM segments as summarized in Table 5. RTM exhibited the highest short-term volatility (0.245), reflecting the balancing-oriented nature of real-time electricity trading, whereas GDAM showed higher tail-risk exposure and peak-hour pricing behavior, likely influenced by renewable-generation variability. In contrast, DAM displayed comparatively stable market behavior with lower procurement-risk exposure. These differences highlight the importance of incorporating market-specific risk characteristics within the procurement optimization framework.

Table-5: Comparative Exchange Market Risk Profile across Exchange Markets

Market	Avg Volatility	Avg Spike Probability	Avg CVaR95	Avg Peak-Hour Price
DAM	0.133	0.130	6967.76	6457.13
GDAM	0.125	0.130	7914.15	7099.65
RTM	0.245	0.112	6412.29	5574.71

Note: CVaR95 and Peak-Hour Price are reported in Rs/MWh

5.3 State-Level Stress Index Analysis

The state-level stress index analysis revealed substantial variation in operational stress conditions across Indian electricity systems over the study period. Fig. 2 illustrates the temporal evolution of stress scores for selected high-stress states. Higher stress persistence was observed in states such as Bihar, Uttarakhand, and Jharkhand, reflecting persistent shortages, higher demand pressure, and comparatively lower operational flexibility. In contrast, Gujarat and Andhra Pradesh exhibited lower and more stable stress behavior, consistent with stronger capacity adequacy, diversified generation portfolios, and improved operational flexibility. These observations indicate that states exhibiting persistent shortages, higher demand pressure, and lower operational flexibility tended to record higher stress scores, whereas states with stronger capacity adequacy and diversified generation portfolios generally maintained lower stress levels. Stress patterns were further influenced by renewable integration, thermal dependence, hydro flexibility, and infrastructure characteristics.

Elevated stress conditions were particularly concentrated during the summer and high-demand months of March–July 2024, where multiple states simultaneously exhibited increased operational stress and procurement pressure.
While Bihar demonstrated relatively sustained stress persistence across several intervals, states such as

Uttarakhand, Puducherry, and Manipur exhibited comparatively episodic stress spikes during specific periods.

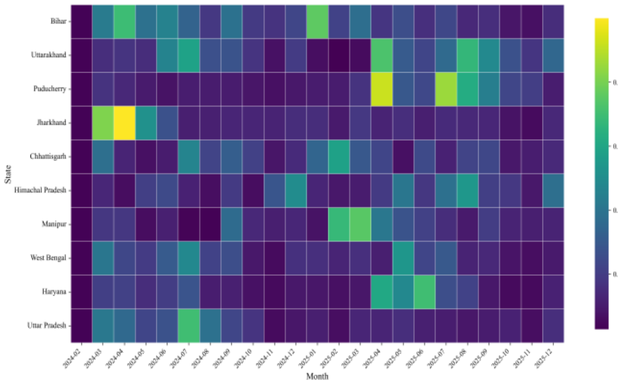
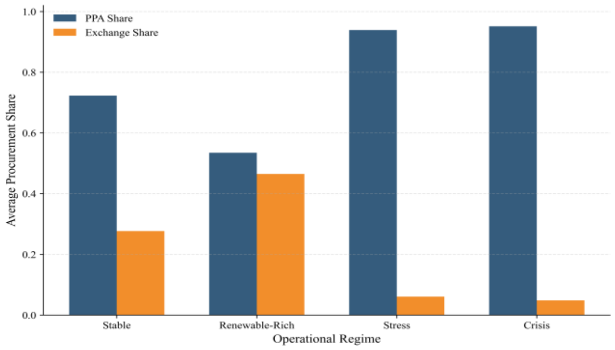


Fig-2: Monthly variation in stress scores across selected high-stress states during the study period.

5.4 Procurement Optimization Analysis

The procurement optimization framework exhibited regime-dependent allocation behavior across electricity-system conditions. Chart 2 illustrates the procurement allocation between PPAs and exchange markets across operational regimes. Under stable operating conditions, procurement remained balanced between PPAs and exchange markets, whereas the Renewable-Rich regime exhibited the highest exchange participation, indicating increased utilization of short-term markets under higher renewable availability and lower balancing risk. In contrast, the Stress and Crisis regimes showed PPA-dominant procurement patterns, with PPA shares exceeding 90%, reflecting greater reliance on long-term supply under shortage conditions, market volatility, and operational uncertainty. These results indicate that procurement allocation was jointly influenced by market risk, renewable availability, and operational stress rather than cost considerations alone, enabling adaptive shifts in procurement behavior that increased flexibility during favorable operating periods while preserving supply security under elevated stress conditions. Additional optimization results further revealed variation in procurement behavior across states. Gujarat and Tamil Nadu exhibited higher exchange participation, supported by stronger renewable integration and grid flexibility, whereas Uttarakhand, Himachal Pradesh, and Uttar Pradesh demonstrated higher dependence on PPAs. RTM participation remained limited under high-stress conditions, while GDAM utilization increased in renewable-rich environments.

Chart-2: Average procurement allocation between PPAs and exchange markets under different operating regimes.



5.5 Machine Learning-Based Procurement Behavior Analysis

5.5.1 Prediction Performance

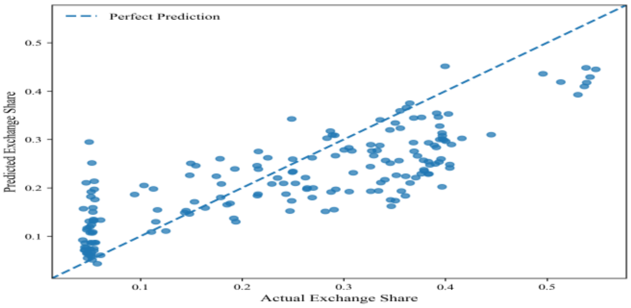
The proposed framework demonstrated stable predictive capability across varying operational and market conditions, achieving an overall MAE of 0.0734, RMSE of 0.0901, and R^2 of 0.6092, while the procurement-behavior classification framework achieved an overall accuracy of 91%. As summarized in Table 6, predictive performance remained relatively consistent across validation periods, indicating reasonable temporal generalization under changing market-risk and operational-stress conditions.

Table-6: Rolling Temporal Validation Performance of the Procurement Prediction Framework

Test Month	**MAE**	**RMSE**	**R^2**	**Classification Accuracy**
2025-07	0.0643	0.0811	0.7099	0.9000
2025-08	0.0664	0.0827	0.5481	0.8667
2025-09	0.0623	0.0802	0.7188	0.9333
2025-10	0.0748	0.0874	0.6686	0.9000
2025-11	0.0876	0.1071	0.1576	0.8667
2025-12	0.0850	0.0984	0.4563	1.0000

Predictive performance remained generally stable across the rolling validation periods, with the highest R^2 values observed in July, September, and October 2025. The lower performance observed during November and December suggests that procurement behavior during these periods was more difficult to model using historical patterns alone. Despite these variations, classification accuracy remained consistently high across all validation windows, demonstrating reliable identification of broader procurement-behavior regimes even when regression performance varied. As illustrated in Chart 3, predicted exchange participation closely followed observed procurement behavior across the validation period, indicating stable temporal generalization.

Chart-3: Actual versus predicted exchange procurement share



5.5.2 Feature Importance Analysis

The dominant factors influencing procurement behavior are summarized in Table 7. The results indicate that electricity procurement decisions in Indian power systems are influenced by the combined effects of market risk, operational stress, and renewable-integration characteristics, highlighting the multidimensional nature of procurement planning. The strong influence of total risk and stress-related indicators suggests that utilities prioritize supply security and operational reliability when facing demand–supply imbalances, shortage conditions, and infrastructure constraints. Furthermore, the importance of renewable- and hydro-related variables highlights the increasing influence of generation-mix composition and system flexibility on procurement decisions, particularly as renewable-energy deployment continues to expand across the electricity sector. While greater renewable availability can create opportunities for increased exchange market participation, the associated variability reinforces the need for flexible resources such as hydro generation to support balancing and operational adaptability.

Table-7: Dominant Factors Influencing Procurement Behavior Prediction

Dominant Feature	**Importance**	**Operational Interpretation**
Total Risk	0.246	Procurement behavior strongly depended on integrated market and operational risk exposure.
Stress Score	0.070	Elevated stress conditions increased conservative procurement behavior and reliance on secure supply sources.
Renewable Share	0.056	Renewable-rich conditions encouraged adaptive exchange participation and reduced dependence on long-term contracts.
Reliability Pressure	0.055	Reliability constraints influenced procurement conservatism and preference for supply security.
Renewable Variability	0.054	Variability in renewable availability affected exchange participation stability and procurement flexibility.
Demand Shock Index	0.050	Demand-side operational shocks influenced procurement adaptation under changing system conditions.
Energy Requirement	0.047	Higher electricity demand levels increased procurement pressure and influenced exchange participation decisions.
Stress Rolling Mean	0.046	Persistent operational stress over time contributed to longer-term conservative procurement behavior.
Hydro Share	0.046	Greater hydro-generation availability improved operational flexibility and supported adaptive procurement strategies.
Hydro Lag1	0.036	Historical hydro availability exhibited persistence effects that influenced subsequent procurement decisions.

5.5.3 Baseline Comparison

The procurement outcomes were compared against fixed and static procurement baselines, including Exch-80 (80% exchange procurement), PPA-80 (80% procurement through long-term PPAs), and Hybrid-50 (fixed 50:50 allocation between PPAs and exchange markets), as summarized in Table 8. The proposed framework achieved the lowest portfolio risk among practical procurement strategies while maintaining competitive procurement costs and improved renewable utilization relative to conservative procurement approaches. Although the exchange-heavy strategy achieved slightly lower average procurement cost, it exhibited substantially higher portfolio-risk exposure, reflecting greater sensitivity to market volatility and uncertainty.

Table-8: Comparison of Proposed and Baseline Procurement Strategies

Strategy	**Cost**	**Risk**	**Ren.**	**PPA**	**Exch.**
Proposed	4164.95	0.102	0.064	0.770	0.230
Exch-80	4125.78	0.273	0.190	0.200	0.800
PPA-80	4181.44	0.106	0.048	0.800	0.200
Hybrid-50	4153.61	0.190	0.119	0.500	0.500

Note: Cost = procurement cost per unit (Rs/MWh), Risk = portfolio risk, Ren. = renewable utilization, PPA = PPA procurement share, Exch. = exchange procurement share.

5.6 Comparative Case Study Results: Bihar and Gujarat

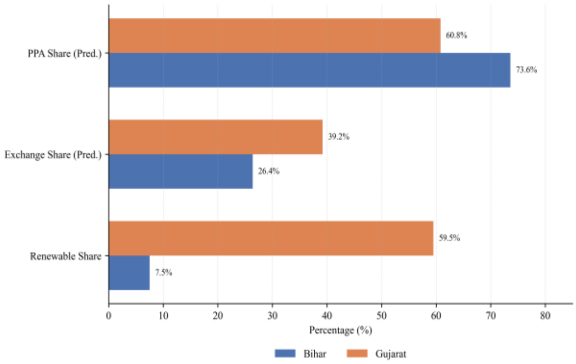
As summarized in Table 9 and illustrated in Chart 4, Bihar exhibited a more PPA-oriented procurement profile, with a predicted PPA share of 73.6%, whereas Gujarat showed relatively higher participation in exchange-based procurement, with a predicted exchange share of 39.2%. These contrasting procurement patterns suggest that the framework adapts procurement allocations according to differing electricity-system conditions. The larger PPA share observed for Bihar indicates a greater emphasis on supply adequacy and procurement stability, while Gujarat's higher exchange participation reflects increased procurement flexibility and greater utilization of short-term market opportunities. Although Gujarat exhibited lower operational stress, its greater reliance on exchange-based procurement resulted in a marginally higher procurement-risk score.

The results further highlight the influence of renewable integration on procurement strategy. Gujarat's higher renewable share was associated with increased exchange market participation and reduced dependence on long-term PPAs, suggesting that greater renewable availability can support more active engagement with short-term electricity markets. However, the framework did not recommend excessive reliance on exchange procurement, indicating that renewable-rich systems still require a diversified procurement portfolio to manage generation variability and maintain reliability. In contrast, the stronger dependence on PPAs observed for Bihar indicates the continuing importance of long-term contracted supply under more constrained operating conditions.

Table-9: Comparative Electricity-System Characteristics and Procurement Outcomes for Bihar and Gujarat

Metric	Bihar	Gujarat
Stress Score	0.138	0.085
Renewable Share	0.075	0.595
Shortage Ratio	0.017	0.000
Procurement Risk	0.225	0.245
Current Exchange Share	0.351	0.445
Predicted Exchange Share	0.264	0.392
Predicted PPA Share	0.736	0.608

Chart-4: Comparison of renewable share and predicted procurement allocation for Bihar and Gujarat.



6. CONCLUSIONS

This study proposed a data-driven adaptive electricity procurement framework for Indian power systems by integrating exchange market forecasting, market-risk assessment, state-level operational stress modeling, procurement optimization, and machine learning-based procurement prediction within a unified decision-support framework. The proposed approach combined electricity exchange market data, operational indicators, generation characteristics, and infrastructure information to analyze procurement behavior under varying market and system conditions.

The exchange markets forecasting frame work achieved strong predictive performance across DAM, GDAM, and RTM segments, with R^2 values exceeding 0.95 and consistently lower forecasting errors than lag-based baseline models. Market-risk analysis identified distinct risk characteristics across exchange markets, while the state-level stress framework differentiated operational conditions across electricity systems through variations in stress persistence, capacity adequacy, and operational flexibility. Together, these components provided the foundation for adaptive procurement analysis under diverse operating environments.

The procurement optimization framework demonstrated clear regime-dependent allocation behavior, balancing procurement cost, risk exposure, and diversification across PPA and exchange market procurement options. Results showed that renewable-rich and lower-stress operating environments supported greater exchange market participation, whereas elevated stress conditions encouraged increased reliance on long-term PPAs to maintain procurement stability and supply security. Machine learning models further demonstrated the ability to learn and predict procurement behavior generated by the optimization framework under varying market and operational conditions. The Bihar–Gujarat comparative case study further confirmed the framework's ability to capture heterogeneous procurement patterns across contrasting electricity-system environments. Bihar exhibited a more conservative and PPA-oriented procurement profile associated with higher system stress and shortage conditions, whereas Gujarat demonstrated greater exchange market participation under comparatively lower stress and more flexible operating conditions. Overall, the results indicate that procurement behavior is strongly influenced by the combined effects of operational stress, market risk, and resource characteristics, supporting the need for adaptive procurement strategies rather than fixed procurement allocations.

The proposed framework contributes to the development of risk-aware procurement decision-support systems for India's evolving electricity markets by integrating market intelligence, operational stress assessment, and adaptive procurement planning within a unified analytical framework. While the framework relies on historical market and operational datasets together with domain-informed weighting assumptions, it provides a practical foundation for adaptive procurement analysis under varying market and system conditions. Future work may extend the framework through the incorporation of longer historical datasets and higher-resolution renewable-energy information, including technology-specific solar and wind generation characteristics, to further improve model generalization and representation of renewable variability in increasingly renewable-rich power systems.

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