Two-Stage CVaR-Based Stochastic Energy Procurement Strategy for Electric Vehicle Charging Network Operators

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***Abstract*—Increasing adoption of electric vehicles (EVs) introduces significant uncertainty in charging demand and energy procurement decisions for EV Charging Network Operators (CNOs). Effective coordination between day-ahead (DA) and real-time (RT) markets is essential to minimize cost and manage risk under volatile conditions. This paper presents a data-driven framework for risk-aware day-ahead energy procurement for EV CNOs operating under real-time price uncertainty. A Conditional Value-at-Risk (CVaR) based stochastic optimization model is solved across a spectrum of risk-aversion levels using one year of ERCOT market data. Each daily optimization is followed by RT simulation to identify the best-performing risk level. To interpret and predict risk behavior, three classifiers are trained to forecast the optimal risk class for future days. The proposed hybrid framework integrates stochastic optimization with machine-learning prediction to support efficient bidding decisions in real-time electricity markets.**

***Index Terms*—CVaR, day-ahead and real-time markets, energy procurement, EV CNOs, risk-aware optimization, stochastic programming.**

NOMENCLATURE

Sets and Indices

k	Scenario index
t	Time index

Parameters

ω	Risk trade-off parameter ($0 \leq \omega \leq 1$)
α	CVaR confidence level
η	VaR threshold for the daily cost distribution
ρ_k	Probability of scenario k
cap_t	Max RT trading capacity at hour t
β	RT volume budget fraction
$\lambda_{DA}^{k,t}$	Day-ahead price (\$/MWh)
$\lambda_{RT}^{k,t}$	Real-time price (\$/MWh)
$L^{(k,t)}$	Realized demand (MWh)

Decision Variables

P_{DA}^{t}	DA energy purchase at hour t (MWh)
$P_{p}^{k,t}$	RT up-regulation purchase (MWh)
$P_{n}^{k,t}$	RT down-regulation sell (MWh)
s_k	CVaR slack (excess cost above VaR)
$C_{DA}^{k,t}$	DA cost at (k,t)
$C_{RT}^{k,t}$	RT settlement cost at (k,t)
$C_{tot}^{k,t}$	Total cost at (k,t)
$\delta^{k,t}$	Imbalance $L^{(k,t)} - P_{DA}^{t}$ (MWh)

Derived Quantities

$cost_k$	Total daily cost in scenario k
$\mathbb{E}[cost_k]$	Expected daily cost
CVaR_α	Conditional Value-at-Risk at level α

I. INTRODUCTION

The restructuring of wholesale electricity markets has created an increasingly dynamic environment in which market participants seek to optimize their operational and financial strategies. Energy imbalances, defined as the deviation between actual and forecasted energy, are a major source of economic risk in markets with high shares of Renewable Energy Sources (RES) and highly variable load profiles [1]. With the rapid growth of electric transportation, charging demand has become an increasingly significant and uncertain component of modern power systems. Electric Vehicle (EV) Charging Network Operators (CNOs), or EV Aggregators (EVAs), procure energy from wholesale markets and coordinate charging schedules to minimize total cost and maximize profit. In doing so, they serve as an operational link between EV users and the grid through their participation in both the day-ahead (DA) and real-time (RT) electricity markets. Given the inherent stochasticity in electricity demand and market conditions, CNOs face substantial exposure to price uncertainty and potential financial losses [2].

In the DA market, participants commit to buying or selling energy one day in advance, which typically reduces exposure to short-term volatility [3]. By contrast, the RT market reflects immediate supply–demand conditions through continuous intra-day trading [4]. Although coordinated charging and active market participation can reduce operational cost, CNOs remain vulnerable to sudden demand fluctuations and abrupt RT price spikes. Even relatively simple charging scenarios require managing uncertainty in both forecasts and price trajectories, which can substantially affect operational revenue.

This challenge is similar to that faced by large industrial consumers, which balance day-ahead contracts with uncertain real-time market purchases using two-stage procurement strategies [5]. For EV CNOs, the central operational difficulty lies in managing financial risk across DA-RT markets, where stochastic optimization is essential for capturing uncertainty in both vehicle behavior and market conditions.

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Several studies have examined market participation strategies for CNOs. In [6], a two-stage optimal charging model based on a transactive control framework is presented, in which EV owners submit flexibility offers through response curves and are compensated accordingly. The day-ahead stage minimizes expected cost using forecasted EV behavior and price scenarios, while the real-time stage applies Model Predictive Control (MPC) to adapt to updated conditions. However, the model does not account for aggregator market power or uncertainty in real-time prices within its control framework. A two-stage stochastic scheduling model for a risk-averse EV aggregator is presented in [7], which uses historical fleet data from Norway and Sweden to maximize expected profit while accounting for uncertainties in EV availability and RT prices. Although effective for DA scheduling, the framework does not capture real-time operational adaptation or the co-simulation of DA decisions with realized RT deviations, both of which are essential for evaluating risk exposure and imbalance costs. Optimal bidding strategies under price and demand uncertainty are further explored in [2], where CVaR is used to analyze the impact of risk aversion on bidding behavior.

While existing literature provides valuable contributions to stochastic and risk-aware EV charging strategies, DA optimization and RT operation are typically studied in isolation. The interaction between realized RT performance, risk aversion, and imbalance costs remains insufficiently explored. In this paper, we address this gap by proposing a data-driven, risk-aware framework for day-ahead energy procurement by EV charging network operators. We first solve a CVaR-based day-ahead optimization over a full year of ERCOT data across multiple risk-aversion levels. We then evaluate each solution using realized prices to identify the best-performing risk level for each day. This enables practical day-ahead risk selection without requiring manual tuning. Together, these components form a closed-loop optimization, evaluation, and prediction pipeline for operational risk management in EV energy procurement.

The remainder of the paper is organized as follows. Section II presents the proposed methodology. Section III describes the case studies and experimental setup. Section IV discusses key results and analysis. Section V concludes with final remarks and directions for future work.

II. Methodology

A. Problem Description

Under uncertain EV demand and prices, charging network operators risk high procurement costs when relying heavily on real-time transactions. A coordinated DA-RT strategy helps manage this risk while supporting reliable charging operations.

B. Model Framework

The proposed framework uses a two-stage stochastic optimization approach. The first stage determines DA energy purchase quantities based on forecasted demand and historical RT price data. After uncertainty is realized, RT adjustments are made in the second stage. The objective function minimizes a risk-adjusted total cost, where CVaR balances the expected cost and tail risk through the parameter ω. This approach supports risk-aware planning by penalizing high-cost scenarios and limiting exposure to unfavorable market outcomes.

The cost for each scenario k, defined as cost_k, is expressed as

$$\mathrm{cost}_k = \sum_{t=0}^{23} \Big(\lambda_{\mathrm{DA}}^{k,t}\, P_{\mathrm{DA}}^{t} + \lambda_{\mathrm{RT}}^{k,t} \big(P_p^{k,t} - P_n^{k,t} \big) \Big). \qquad (1)$$

The CVaR-based two-stage stochastic optimization problem is then formulated as

$$\min\ \omega\, \mathbb{E}[\mathrm{cost}_k] + (1-\omega) \left(\eta + \frac{1}{1-\alpha} \sum_k \rho_k s_k \right), \qquad (2)$$

subject to

$$P_{\mathrm{DA}}^{t} + Pp_p^{k,t} - P_n^{k,t} = L^{(k,t)}, \quad \forall k, t, \qquad (3)$$

$$s_k \geq \mathrm{cost}_k - \eta, \quad \forall k, \qquad (4)$$

$$P_p^{k,t} \leq \mathrm{cap}_t, \quad P_n^{k,t} \leq \mathrm{cap}_t, \quad \forall k, t, \qquad (5)$$

$$\sum_k \rho_k \left(P_p^{k,t} + P_n^{k,t} \right) \leq \beta\, \mathbb{E}[L_t], \quad \forall t. \qquad (6)$$

In the objective function (2), the first term captures the expected scenario cost across all load and price realizations, while the second term represents the CVaR component. This combines a central tendency measure with a tail-risk penalty weighted by the parameter ω. The term η denotes the CVaR threshold, and s_k are the auxiliary slack variables associated with the tail region beyond η.

The equality constraint in (3) enforces hourly supply-demand balance for every scenario by matching DA purchases and RT adjustments with the realized load, using a simplified form of the balance equation adapted from [8], where the original model also includes storage, renewables, network losses, and demand shifting. The CVaR linearization constraint in (4) follows the standard Rockafellar-Uryasev formulation in [9], where the slack variables s_k capture any excess of the scenario cost above the threshold η and enable a linear representation of the tail-risk term.

The RT magnitude limits in (5) at cap_t, which are introduced to prevent excessive dependence on RT transactions and improve operational robustness. Finally, the expected RT volume constraint in (6) limits the total expected RT energy traded at each hour to a fraction β of the expected load. Together, these constraints ensure that the day-ahead schedule remains the primary procurement decision, while RT trading is used only for limited corrections.

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III. Case Studies and Experimental Setup

This study evaluates the proposed two-stage CVaR-based model across two settings: a one-month synthetic experiment and a one-year real-data experiment. Both cases treat DA and RT prices as stochastic inputs and use the same queuing-derived charging demand model [10]. The RT magnitude cap is set to $\mathrm{cap}_t = 0.60\mathbb{E}[L_t]$ and the expected RT budget is limited by $\beta = 0.25$, consistent with the operational considerations described earlier.

A. One-Month Data

Uncertainty arises from both charging demand and wholesale market prices. To represent price uncertainty, historical ERCOT DA and RT prices from January 2025 [11] are used as the base dataset. One hundred synthetic DA and RT price scenarios are generated using a Gamma-distributed multiplicative noise factor to preserve typical daily patterns while capturing realistic variability. To represent both typical stress-related price jumps and rare extreme price events, two stress modifications are applied. The *top-p spike* method represents scarcity events by increasing only the highest RT prices and forcing them to be higher than DA prices, while the *lognormal-rare* method represents rare, unpredictable volatility by adding occasional large price spikes with a right-skewed distribution [12].

Charging demand is modeled using an $M_t/M/c$ queuing model that captures stochastic EV arrivals and service durations at a charging facility [10]. One hundred synthetic daily demand profiles are produced by applying multiplicative Gaussian noise to the base queuing output. Hourly means and variances derived from these samples are then used to create one thousand Gamma-based demand scenarios, which represent possible future realizations and serve as the stochastic load inputs to the optimization model.

For each synthetic day k, summary metrics are computed from the price scenarios, including the DA-RT spread, volatility, the ninety-fifth percentile tail price, and the fraction of hours where RT prices fall below DA prices. Based on these metrics and percentile thresholds, each day is assigned to a price-type category: *spike*, *cheap*, *expensive*, *flat*, or *normal* to evaluate performance under a diverse set of market conditions.

The CVaR-based two-stage linear program is solved for each day and each risk weight $\omega \in \{0.2, 0.4, 0.6, 0.8, 1.0\}$ using Pyomo with the HiGHS solver. The optimization yields an optimal DA procurement schedule P^t_{DA} for each risk level. To evaluate realized performance, a real-time simulation is conducted. At every fifteen-minute interval, the imbalance between the realized load and the DA bid is computed as $\delta_{k,t}$. The corresponding RT settlement cost is given by

$$C^{RT}_{k,t} = \begin{cases} \delta_{k,t}\,\lambda^{k,t}_{RT}, & \text{if } \delta_{k,t} > 0, \\ -|\delta_{k,t}|\,\lambda^{k,t}_{RT}, & \text{if } \delta_{k,t} < 0, \end{cases} \tag{7}$$

and the total cost for each interval is

$$C^{tot}_{k,t} = C^{DA}_{k,t} + C^{RT}_{k,t}. \tag{8}$$

The total daily cost in scenario k is then

$$\mathrm{cost1}_k = \sum_t C^{tot}_{k,t}. \tag{9}$$

The distribution of daily costs across risk levels is summarized using mean, median, ninety-fifth percentile, and worst-case values, grouped by the previously assigned day-type categories.

B. One-Year Real-Data Experiment

The second case uses a full year of real ERCOT hourly DA and RT prices. For each calendar day, sixty candidate price scenarios are generated by resampling historically similar days within the same month and weekday. To preserve intra-day variability while maintaining appropriate mean levels, a multiplicative Gamma noise term with five percent dispersion is applied. A spike stress inflates the top two percent of RT prices above DA prices to represent rare but impactful volatility.

The demand model from the first case is reused, but the number of demand scenarios is reduced to one hundred to improve computational tractability for year-long analysis. The combination of sixty price scenarios and one hundred demand scenarios forms the stochastic inputs to the daily CVaR optimization problem. For each day, the model is solved for multiple values of $\omega \in [0, 1]$, which yields the expected cost, CVaR, and optimal DA procurement associated with each risk preference. This creates a year-long dataset of optimal daily outcomes and their corresponding risk classifications: Risk-Averse ($\omega = 0$), Balanced ($\omega = 0.6$), and Risk-Neutral ($\omega = 1.0$).

Real-time co-simulation is then performed using the actual realized load and DA–RT prices. Daily imbalance and settlement costs are computed using the same equations (7)–(9). The risk level ω^*_d that achieves the lowest realized daily cost is recorded as the oracle choice for that day and serves as the ground-truth label for the subsequent classification task.

A set of twenty-two ex-ante features is constructed to capture how the market is expected to behave and provide the basis for predicting each day's optimal risk preference. These features include descriptive statistics of DA and RT prices such as mean, standard deviation, quantiles, and spreads, along with short-horizon forecasts generated from a twenty-eight-day, weekday-matched historical estimator that predicts next-day RT price mean, volatility, and RT–DA spreads, refined using an exponentially weighted moving-average adjustment [13]. Additional inputs include calendar indicators for month and weekday and short-term dynamics derived from lagged values, three-day moving averages, and first-difference trends.

Three machine learning models are trained to predict the risk class: logistic regression [14], calibrated random forest [15], and gradient boosting [16]. Group K-Fold cross-validation [17] is conducted with folds grouped by month to avoid temporal leakage. Regret, measured as the difference between the realized cost under the predicted risk level and the oracle cost, is used to evaluate performance.

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The predicted strategy is then compared with fixed baselines $\omega = \{0.2, 0.6, 1.0\}$ and the oracle to demonstrate the value of adaptive, risk-aware planning.

IV. Results and Analysis

The results of the CVaR-based day-ahead optimization and the subsequent learning framework for adaptive risk selection are presented in this section. The one-month synthetic experiment introduced in Section III is first used to examine the model under controlled price conditions.

Fig. 1 summarizes the realized daily costs under different values of ω for the five day types. In each subplot, the costliest outcome is highlighted using a red bar, while lower-cost outcomes are shown in green. The results indicate that lower values of ω (risk-averse strategies) perform better on volatile or spike days, whereas higher values (risk-neutral strategies) reduce costs when RT prices consistently exceed DA prices.

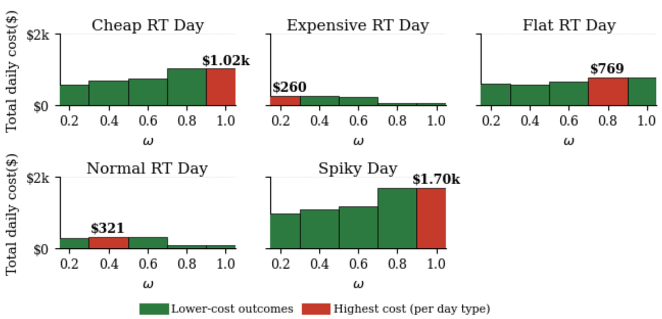

Fig. 1. Realized cost comparison under different risk settings for 30 synthetic days.

Table I summarizes the observed relationship between RT–DA price patterns and the corresponding optimal choice of ω to demonstrate how the model adapts risk levels to market conditions.

Although the one-month experiment illustrates the model's ability to identify day-level risk preferences, it remains descriptive and does not provide a predictive mechanism. To address this, the study is extended to a full year of ERCOT data. The classification results presented in this section rely on the 22 ex-ante features described in Section III. Among the three classifiers tested, the calibrated Random Forest achieved the highest accuracy at 55.7%, outperforming Gradient Boosting (49.5%) and Logistic Regression (34.4%).

Fig. 2 presents the row-normalized confusion matrix for the calibrated Random Forest classifier. The model shows strong performance for Risk-Neutral days, correctly identifying stable market conditions where $\omega = 1$ is optimal. However, the classifier tends to over-predict the Risk-Neutral class, misclassifying 89 percent of Balanced days and 86 percent of Risk-Averse days. This behavior aligns with the class imbalance in the training data: 56.01 percent of historical days are Risk-Neutral, while 26.5 percent are Risk-Averse and 17.48 percent are Balanced. Since learning algorithms typically optimize overall accuracy, they often favor the majority class, leading to high

TABLE I
Observed Day Types and Corresponding Risk Behavior in the One-Month Experiment

Day Type	Rationale
Cheap RT Day	When RT $<$ DA most of the day, heavy DA purchases are wasteful. Safer to buy less in DA ($\omega = 0.2$–0.4).
Expensive RT Day	When RT $>$ DA consistently, it pays to lock in with a full DA hedge ($\omega = 1.0$).
Flat RT Day	When RT and DA are close, costs do not vary much across ω. Moderate ω avoids unnecessary risk.
Normal Day	When RT is slightly above DA, higher ω (more DA purchase) protects against RT costs.
Spiky Day	Rare RT spikes create volatile outcomes. CVaR preference ($\omega \leq 0.6$) reins in extreme losses compared to $\omega = 1.0$.

precision for that class and lower recall for minority classes which occur less frequently and exhibit greater variability. The uneven results indicate that the model struggles to identify Balanced and Risk-Averse days because their characteristics are not distinct enough, and thus tends to predict Risk-Neutral days, which are easier to recognize. Similarly, our features, based on past returns and volatility, may miss important information about what drives different risk regimes. Fig. 3 shows

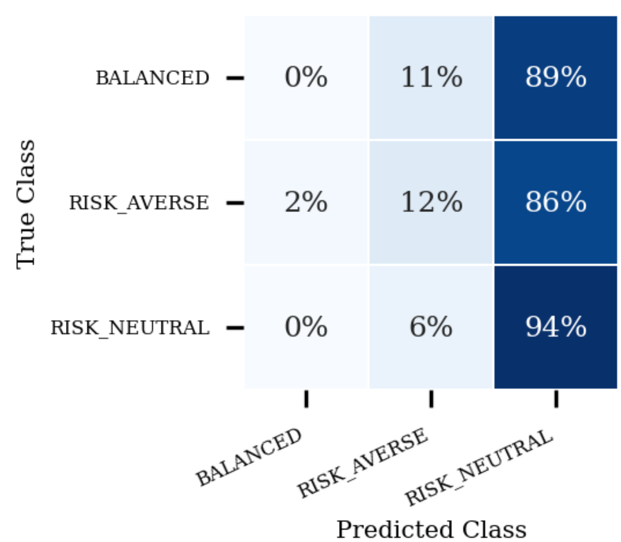

Fig. 2. Row-normalized confusion matrix for the calibrated Random Forest classifier.

the economic impact of misclassification in terms of regret. The costliest error occurs when Risk-Averse days are classified as Risk-Neutral, producing a median regret of approximately \$50 and a ninety-fifth percentile near \$200. In comparison, when Balanced days are predicted as Risk-neutral, the median regret is about forty dollars and the P-ninety-five regret is near eighty dollars. However, the overall penalty remains modest, with tight dispersion, suggesting that the predicted strategy still performs close to optimal. All correct classification cases

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exhibit nearly zero regret, and the model achieves correct predictions for Risk-Neutral days about 94 percent of the time.

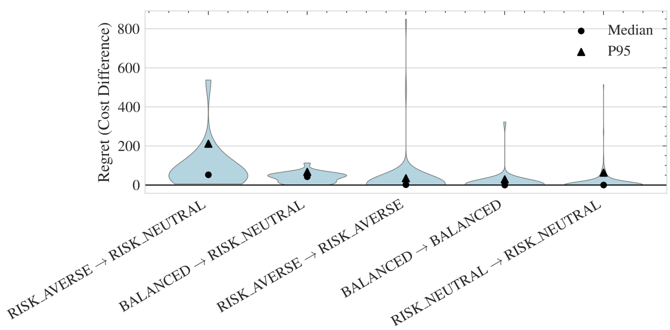

Fig. 3. Distribution of daily regret across all true–predicted ω class pairs

The cumulative savings curve in Fig. 4 shows three clear phases: steady gains from January to April, rapid gains from May to July when adaptive bidding is most effective, and continued gradual improvement throughout the remaining months. This pattern demonstrates that the predicted strategy consistently outperforms all fixed-risk alternatives under varying market conditions.

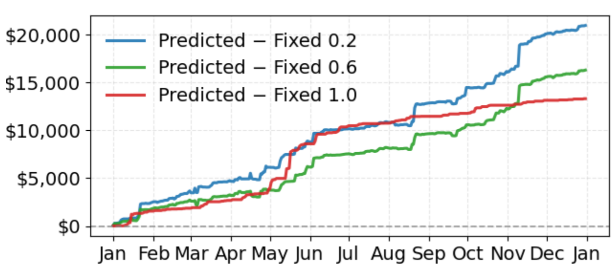

Fig. 4. Cumulative savings of the predicted ω-policy versus fixed strategies throughout the year

TABLE II
STATISTICAL SUMMARY OF DAILY COST PERFORMANCE ACROSS ALL STRATEGIES.

Metric	Optimum ω	Predicted	Fixed 0.2	Fixed 0.6	Fixed 1.0
Mean Cost ($)	267.02	287.45	344.70	331.95	323.79
Median Cost ($)	243.95	260.64	288.99	287.07	276.66
Std. Dev.	480.16	517.43	502.06	500.92	556.01

Table II shows that the predicted policy achieves a mean daily cost within approximately twenty dollars of the optimum. It also outperforms all fixed-ω strategies by about thirty six-fifty seven dollars per day. Although these savings appear modest on a daily basis, they accumulate over time and scale with portfolio size. This results in meaningful annual cost reductions. The predicted policy also shows lower cost variability which indicates improved risk control in addition to cost savings.

V. Conclusions and Future Work

This study presents a CVaR-based day-ahead optimization framework with supervised learning for adaptive risk management in EV charging operations. Results from month-long and year-long real-data studies show that the CVaR model captures clear cost–risk trade-offs across market conditions and can infer daily risk preferences from ex-ante features.

Future work will focus on addressing limitations of class imbalance by adding stronger ex-ante features and more enhanced training ML models to improve accuracy. Expanding the approach to coordinate multiple EV stations will help assess scalability in networked environments. Additionally, this study is implemented on ERCOT data for a preliminary feasibility study. Future work will expand and scale this to other markets.

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