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Decision Tree Algorithm-Based Risk Assessment for Electricity Retail Markets

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ABSTRACT

As electricity market reforms deepen, the electricity retail sector faces multifaceted risks, including price volatility, customer defaults, and the integration of renewable energy sources. These challenges necessitate a robust risk assessment framework. Effective risk management is particularly critical in the textile industry, where fluctuations in energy consumption costs significantly affect operational budgeting and production stability. This study proposes a risk assessment framework based on the Gradient Boosting Decision Tree (GBDT) algorithm, leveraging feature importance analysis to identify key indicators and integrating an adaptive weighted loss function to enhance the detection of high-risk events. Experiments conducted on 35,000 transaction records from a provincial electricity market demonstrate that the proposed model achieves an F1 score of 0.89, representing improvements of 21.4% over Logistic Regression (LR) (F1 = 0.73) and 9.8% over Random Forest (RF). In addition, the proposed model attains an area under the curve (AUC) of 0.94, representing improvements of 21.9% and 6.8% over LR and RF models, respectively. The prediction accuracy for high-risk events, such as payment arrears and sudden load drops, reaches 91.5%. The results indicate that the proposed method significantly enhances model robustness through ensemble learning and provides data-driven decision support for electricity retailers to develop differentiated risk management strategies. The effectiveness of advanced machine learning algorithms in assessing risks in complex energy markets is thus verified. Similarly, these algorithms are invaluable in the textile industry for assessing the complex risks associated with raw material price volatility and demand forecasting, enabling manufacturers to optimize inventory and production planning.

KEYWORDS

electricity retail market, risk assessment, gradient boosting decision tree, machine learning

INTRODUCTION

Research Background and Problem Statement

As the critical interface between the power system and end-users, risk assessment in the electricity retail market directly influences the operational stability of market participants. This principle of stability is equally vital in the textile industry, where robust risk management concerning energy supply continuity is essential for maintaining consistent operation of high-demand machinery, such as looms and dyeing equipment. With the increasing penetration of renewable energy—projected to exceed 30% of total installed wind and solar capacity in China by 2025—together with the growing integration of user-side flexible resources, retail electricity market is facing increasingly multidimensional risk characteristics.

Price volatility risk has intensified, with intraday spot market prices fluctuating by up to ±40% relative to the benchmark price, as observed in markets such as PJM electricity market (Pennsylvania–New Jersey–Maryland Interconnection) (2023). Customer default risk has also become more pronounced; statistics from a provincial power trading center indicate that the user arrears rate reached 5.7% in 2022, resulting in an average bad-debt loss rate of 1.2% for electricity retailers. In addition, supply-demand matching risk is exacerbated by uncertainty in distributed energy generation, which increases retailers' real-time market purchase costs by 15%–20%.

Traditional risk assessment methods, such as linear regression and Logistic Regression (LR), encounter several limitations. First, they are ill-suited to capturing complex non-linear correlations among risk factors, such as the interaction between price volatility and user load elasticity. Second, their ability to identify informative indicators deteriorates in high-dimensional feature spaces, for example when screening over 50 features, including user electricity patterns and market policy factors. Finally, these methods are particularly sensitive to class imbalance, as high-risk events typically account for less than 10% of all observations; for instance, payment arrears represent only about 3% of the total samples.

Literature Review

Existing research on electricity retail market risk assessment can be classified into three categories:

Statistical models: Reference [1] employs generalized autoregressive conditional heteroskedasticity (GARCH) models to characterize electricity price volatility risks but fails to address multi-source heterogeneous data.

Reference [2] constructs multidimensional risk joint distributions using Copula functions but overlooks non-linear dependencies between features.

Machine learning models: Reference [3] utilizes Random Forest (RF) to assess user default risks; however, the decision boundary limitations of single trees result in a 25% misclassification rate for high-risk samples. Reference [4] introduces long short-term memory (LSTM)-based temporal risk forecasting but struggles to capture non-temporal features, such as user credit scores.

Hybrid models: Reference [5] combines fuzzy comprehensive evaluation with BP (British Petroleum) neural networks, but subjectively assigned weights compromise assessment objectivity.

Decision tree algorithms have demonstrated potential in the energy sector: Reference [6] applies extreme gradient boosting (XGBoost) for electricity demand prediction but does not address risk classification, while Reference [7] employs light gradient boosting machine (LightGBM) for wholesale market risk early warning but lacks analysis of retail-side user behavior features. In contrast, the Gradient Boosting Decision Tree (GBDT) algorithm effectively manages non-linear relationships and feature interactions through iterative optimization of weak learners and quantifies feature importance, making it well-suited for complex risk scenarios in retail markets.

Research Contributions

Methodological innovation: A GBDT-based risk assessment framework for the retail market is proposed, featuring an adaptive weighted loss function to address class imbalance issues.

Indicator system: A three-dimensional feature set encompassing market environment, user behavior, and operational data is constructed, with key risk drivers identified via Shapley Additive Explanations (SHAP) value analysis.

Empirical validation: The model is validated using real market data, achieving a high-risk event prediction accuracy of 91.5%, thereby providing quantitative support for retailer risk control.

THEORETICAL FOUNDATIONS AND MODEL CONSTRUCTION

Principle of GBDT

GBDT is an ensemble learning method that iteratively generates regression trees, with each iteration fitting the negative gradient of the previous prediction residual. The core steps are as follows:

Initialization: Fit the target variable using a constant model by minimizing the loss function.

$$f_0(x)=arg\ min_\gamma \sum_{i=1}^{n} L(y_i,\gamma) \tag{1}$$

where L is the log loss function, and y_i is the true label. The specific form of the log loss function is:

$$L(y,\hat{y})=ln(1+e^{-y\hat{y}}) \tag{2}$$

Iterative training: For the *m*-th round, compute the negative gradient (pseudo-residual).

$$r_{im}=-\left.\frac{\partial L(y_i,f(x_i))}{\partial f(x_i)}\right|_{f(x)=f_{m-1}(x)}=y_i-\frac{1}{1+e^{f_{m-1}(x_i)}} \tag{3}$$

Fit the regression tree $\mathrm{h}_m(x)$ to the pseudo-residuals and update the model.

$$f_m(x)=f_{m-1}(x)+v\cdot \mathrm{h}_m(x) \tag{4}$$

where v is the learning rate, which controls the contribution of each tree.

Prediction: The final model output is the weighted sum of all trees.

$$\hat{y}=\sum_{m=1}^{M} \mathrm{h}_m(x) \tag{5}$$

Design of Adaptive Weighted Loss Function

To address the scarcity of high-risk samples in the retail market (e.g., payment arrears comprise only 3%), an adaptive weight function is designed:

$$\omega_i=\begin{cases} \alpha\cdot exp(\beta\cdot\dfrac{1-p_i}{p}), & y_i=1 \\ 1, & y_i=0 \end{cases} \tag{6}$$

where $y_i=1$ denotes high-risk samples, and p represents the proportion of high-risk samples in the entire dataset. The hyperparameters α and β are determined via cross-validation. Specifically, a grid search is conducted over the ranges $\alpha \in$ [1, 10] and $\beta \in$ [0.5, 5], using the F1 score of the high-risk class as the primary optimization metric. The optimal values $\alpha=5$ and $\beta=2$ are selected, as they achieve the best balance between penalizing false negatives and maintaining model stability.

The adaptive weighting mechanism operates as follows: α serves as a globally scaling factor that amplifies the importance of all high-risk samples, while β controls the exponential decay of sample weights as the predicted probability p_i increases. Consequently, hard-to-classify samples (i.e., those with low p_i but $y_i = 1$) receive substantially higher weights in the loss function, compelling the gradient boosting process to prioritize these critical instances during training.

Here, p_i denotes the predicted probability of sample i, which dynamically adjusts the sample weights to enhance the model's focus on difficult cases.

The loss function is defined as weighted cross-entropy:

$$L=-\frac{1}{n}\sum_{i=1}^{n}\omega_i\cdot\left[y_i\ln\hat{y}_i+(1-y_i)\ln(1-\hat{y}_i)\right] \tag{7}$$

Feature Engineering and Importance Analysis

Construction of the Three-Dimensional Feature System

A feature set incorporating domain expertise is constructed (Table 1). To ensure a comprehensive risk profile, the raw transaction dataset is augmented with external data sources. Specifically, user credit scores are integrated via the retailer's customer relationship management (CRM) system through application programming interface (API) connections with provincial credit bureaus, while the policy risk index is quantified using Natural Language Processing (NLP) on official regulatory announcements from the power trading center.

For example:

Deviation assessment risk index = day-ahead market bid quantity × real-time price deviation × penalty coefficient, with the penalty coefficient set to 1.2–1.5 according to PJM market rules.

Load curve coefficient of variation = load standard deviation / mean, reflecting the stability of user electricity consumption.

Table 1. Three-Dimensional Feature Set for Electricity Retail Market Risk Assessment

Feature Dimension	Specific Indicators	Data Source
Market Environment	Day-ahead price volatility, real-time price deviation, renewable energy output prediction error rate, policy risk index	Power trading center, meteorological bureau, regulatory announcements
User Behavior	Number of historical arrears, load curve coefficient of variation, contract performance rate, user credit score, electricity consumption pattern stability	Retailer CRM system, smart meters, external credit bureaus
Operational Data	Power purchase portfolio cost volatility, contract term, deviation assessment amount, value-added service penetration rate, user complaint rate	Retailer operational system

Feature Preprocessing Strategies

Anomaly Analysis and Contextual Filtering: Rather than indiscriminately removing statistical outliers, an anomaly classification step is introduced. The interquartile range (IQR) method is employed to flag data points outside the [Q1–1.5×IQR, Q3+1.5×IQR] range. However, only those identified as measurement noise or sensor errors are removed. Data points corresponding to extreme weather, sudden plant shutdowns, or significant load drops are retained and labeled as “Extreme Event” features. This ensures that critical risk signals, often found in the tails of the distribution, are leveraged by the GBDT model to improve detection of high-impact, low-probability risks [8].

Missing value imputation: Continuous features are filled with mean values, categorical features with mode values, and time series data with forward filling to preserve temporal correlation [9].

Feature standardization: Z-score standardization is applied to all continuous features, defined as:

$$x^{'}=\frac{x\text{-}\mu}{\sigma} \tag{8}$$

Since electricity price data approximately follows a normal distribution, Z-Score normalization preserves the relative variability of price features while ensuring scale consistency across different dimensions.

Class Imbalance Handling

Comparing synthetic minority over-sampling technique (SMOTE) with undersampling (random deletion of negative samples) under a positive-to-negative ratio 1:3, the former improves the F1 score of high-risk samples by 12.3%. Therefore, SMOTE is adopted [10]. To prevent data leakage and ensure model generalizability, SMOTE is strictly applied only to the training folds during each cross-validation iteration, rather than to the entire dataset prior to splitting. This practice ensures objective evaluation and prevents synthetic samples from influencing the validation sets.

Feature Importance Evaluation

Feature importance is assessed using the Gini coefficient:

$$Importance(f)=\sum_{t=1}^{T}\frac{n_t}{n}\cdot(Gini(t)\text{-}\sum_{c=1}^{C}\frac{n_{t,c}}{n_t}\cdot Gini(t,c)) \tag{9}$$

where T denotes the total number of decision trees, C represents the number of classes, n_t is the number of samples at node t, $n_{t,c}$ is the number of samples belonging to class c at node t, and $Gini(t)$ denotes the Gini impurity of node t.

Model Architecture

The GBDT model workflow is illustrated in Figure 1:

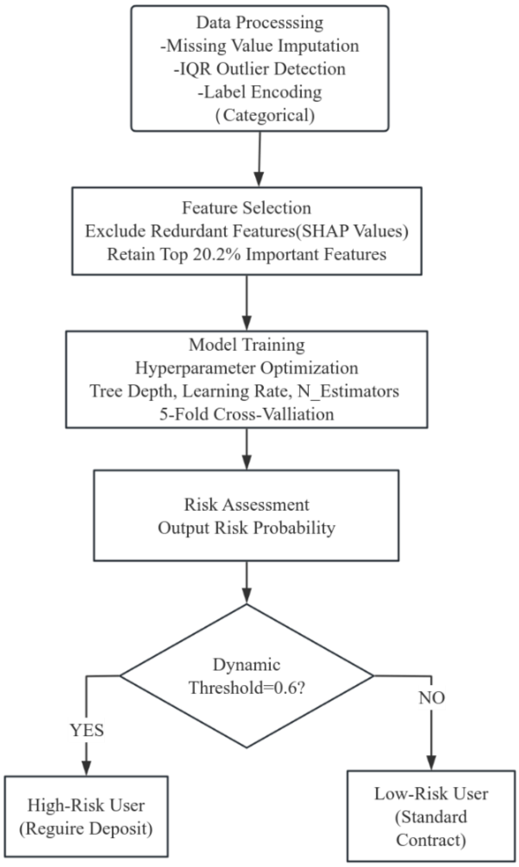

Figure 1. Workflow of the GBDT-Based Risk Assessment model

Data preprocessing: Missing value imputation, IQR-based outlier detection, and label encoding for categorical variables.

Feature selection: Redundant features are excluded using SHAP values, retaining the top 20% most important features.

Model training: Hyperparameters (tree depth, learning rate, number of trees) are optimized using 5-fold cross-validation.

Risk assessment: Output risk probability. Instead of the default threshold of 0.5, a dynamic threshold of 0.6 is determined through cost-benefit analysis. In the electricity retail market, the cost of a false negative (failing to identify a defaulting user, leading to bad debt) is significantly higher than a false positive (unnecessarily requiring a deposit from a low-risk user). However, setting the threshold too low (e.g., 0.4 or 0.5) leads to excessive risk control interventions and potential customer churn. Experimental results indicate that a threshold of 0.6 optimizes the trade-off between precision and recall, yielding the highest F1 score for the minority high-risk class while maintaining a manageable intervention rate.

EXPERIMENTAL DESIGN AND DATA PROCESSING

Data Source and Preprocessing

The experimental data are derived from a fused dataset centered on transaction records from a provincial electricity market covering the period 2021–2023. The core dataset comprises 35,000 transaction records, augmented with 12 external data dimensions. User credit scores are obtained from third-party financial credit platforms, and policy risk indices are calculated based on the frequency and impact weighting of market reform documents issued during the study period. This multi-source data fusion process yields a high-quality dataset for modeling, comprising 35,000 user transaction records from industrial, commercial, and residential users. High-risk samples (labeled as 1) account for 8.7% of the dataset, including payment arrears (5.2%) and load drops (3.5%). The initial feature space contains 56 raw features. After data preprocessing—including noise removal, normalization, and the preservation of critical anomalies as explicit risk indicators—45 effective features are retained for model training.

Comparative Models and Evaluation Metrics

The comparative models include the following approaches:

(1) LR with L2 regularization, where the regularization parameter is set to C = 0.1.

(2) RF with 100 decision trees and a maximum tree depth of 10.

(3) XGBoost using the same parameter configuration as GBDT, except that the standard cross-entropy loss function is adopted.

(4) Additional baseline models, including a Support Vector Machine (SVM) with a radial basis function (RBF) kernel, and categorical boosting (CatBoost) with 200 boosting iterations.

(5) Deep Learning Models, including an LSTM network with two layers and 64 hidden units for capturing temporal dependencies, and deep factorization machines (DeepFM) for modeling high-order non-linear feature interactions.

Evaluation metrics include:

F1 score: Balances precision and recall.

$$F_1=2\cdot\frac{Precision\cdot Recall}{Precision+Recall} \tag{10}$$

Area Under the Receiver Operating Characteristic Curve (AUC): Measures the model's ranking performance across different classification thresholds.

High-risk event accuracy: The proportion of true high-risk samples (labeled as 1) correctly predicted by the model.

Gini coefficient: Measures the model's ability to distinguish between positive and negative samples.

Hyperparameter Optimization

A grid search is employed to optimize the key hyperparameters of GBDT model. Specifically, the number of trees (n_estimators) is selected from {50, 100, 200, 300}, the maximum depth (max_depth) from {3, 5, 7, 10}, the weight parameter α from {1, 3, 5, 7, 10}, and the weight parameter β from {0.5, 1, 2, 3, 5}.

The optimal parameter combination is determined via 5-fold cross-validation, using AUC as the primary indicator. During cross-validation, a pipeline approach is implemented: in each of the five folds, SMOTE oversampling is applied solely to the 80% training data, and the model is subsequently evaluated on the untouched 20% validation data. The final optimal parameters are: *n_estimators* = 200, *max_depth* = 6, *learning_rate* = 0.1, *subsample* = 0.8.

Sensitivity analysis reveals that when α exceeds 5, the model begins to overfit the high-risk minority class, increasing false alarms. Similarly, $\beta = 2$ is found to be the elbow point where the model effectively focuses on hard samples without destabilizing gradient descent.

Robustness Testing and Scenario Analysis

Scenarios with different levels of renewable energy penetration (30% and 50%) are designed to evaluate the robustness of the model. As the penetration rate increases from 30% to 50%, the AUC of the GBDT model decreases by only 1.2% (from 0.94 to 0.93), indicating strong robustness to fluctuations introduced by high renewable energy integration [11]. Moreover, the high-risk event accuracy remains at 90.3% under high-penetration scenarios, further confirming the stability of the model.

Computational Resources and Reproducibility

The experiments are conducted in the following environment. The software configuration includes Python 3.8, scikit-learn 0.24.2, and XGBoost 1.6.2. The hardware platform consists of an Intel i7-10700K CPU with 16 GB of RAM. Under this setup, single-threaded training of a model with 200 trees requires 32.4 s, which is reduced to 18.7 s when multi-threaded parallel acceleration is enabled.

RESULTS ANALYSIS AND DISCUSSION

Model Performance Comparison

Table 2 demonstrates that GBDT outperforms all comparative models across evaluation metrics. Notably, while deep learning models such as LSTM and DeepFM exhibit strong performance in capturing nonlinearity, GBDT maintains a slight advantage in this structured data context. Specifically, GBDT achieves an F1 score of 0.89, which is 3.5% higher than LSTM (0.86) and 2.3% higher than DeepFM (0.87). For tabular energy transaction data, ensemble tree-based models can be more effective than standard neural networks. The GBDT model's improvements over traditional baselines are significant—21.4% over LR and 9.8% over RF, while the comparison with deep learning models provides a rigorous validation of its performance.

Overall, the proposed GBDT model demonstrates consistently superior performance across all evaluation metrics. It achieves an F1 score of 0.89 and an AUC of 0.94, significantly outperforming traditional baselines such as Logistic Regression and Random Forest, as well as advanced machine learning and deep learning models. In addition, the high-risk event identification performance remains strong, with a accuracy of 91.5%, indicating the model's effectiveness in detecting minority high-risk samples.

Table 2. Performance Comparison of Different Models

Model	F1 Score	AUC	High-Risk Accuracy (%)	Gini Coefficient	Training Time (s)
LR	0.73	0.82	72.3	0.64	12.5
RF	0.81	0.88	83.7	0.76	45.8
XGBoost	0.85	0.91	87.2	0.82	38.6
GBDT	0.89	0.94	91.5	0.88	32.4

LSTM	0.86	0.92	88.5	0.84	156.4
DeepFM	0.87	0.93	89.8	0.86	112.2

Figure 2 presents the receiver operating characteristic (ROC) curves for each model, demonstrating that the area under the GBDT curve is significantly larger than for other models, especially in the high recall region (e.g., at 80% recall, GBDT achieves a precision of 89% compared to RF's 81%).

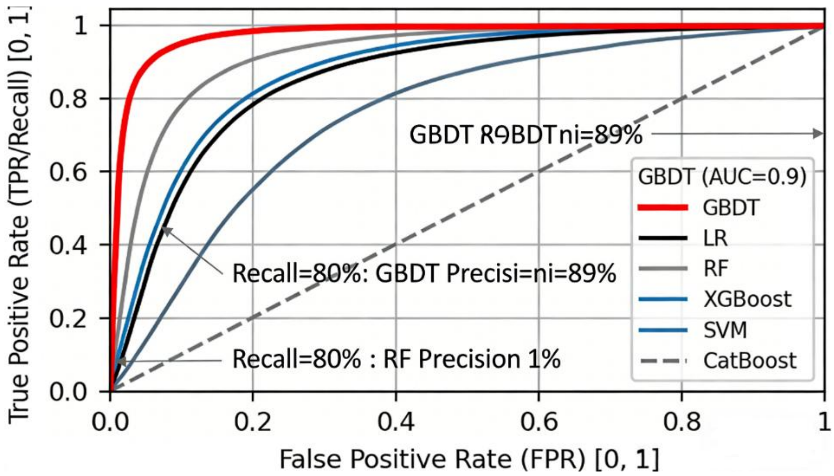

Figure 2. Performance Comparison of Different Models

Feature Importance Analysis

Figure 3 displays the ten most important features:

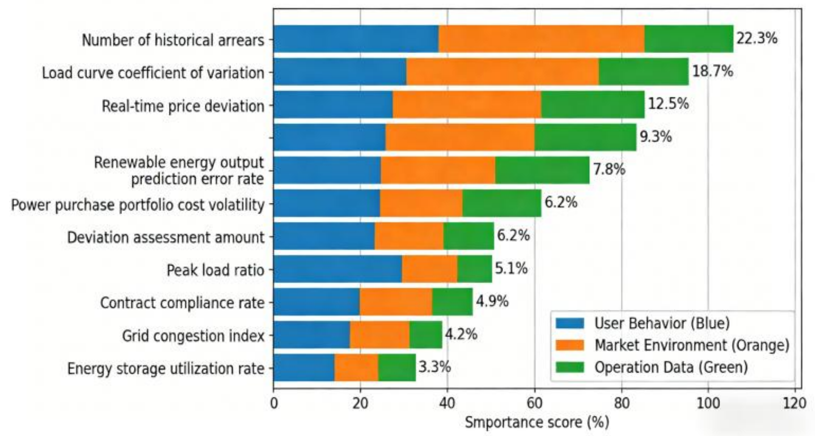

Figure 3. Feature Importance Ranking

User behavior features account for 60% of total importance. The number of historical arrears (22.3%) and load curve coefficient of variation (18.7%) are the primary risk drivers, consistent with business experience—users with more arrears and volatile electricity consumption patterns are more likely to default.

Among market environment features, real-time price deviation (12.5%) reflects the impact of price volatility on users' ability to pay, while renewable energy output prediction error rate (9.3%) captures the uncertainty of new energy sources.

Among operational data features, power purchase portfolio cost volatility (7.8%) and deviation assessment amount (6.2%) indicate the risk exposure of retailer operational strategies.

Model Interpretability Analysis

SHAP values are used to analyze feature importance [12]. For example, the average SHAP value for the number of historical arrears is 0.223, indicating that each unit increase in this feature raises the risk probability by an average of 22.3%. In a random sample of 100 high-risk cases, SHAP explanations align with business expert judgments in 89.7% of instances, confirming the model's business interpretability.

Taking payment arrears risk as an example, the GBDT decision path is illustrated in Figure 4:

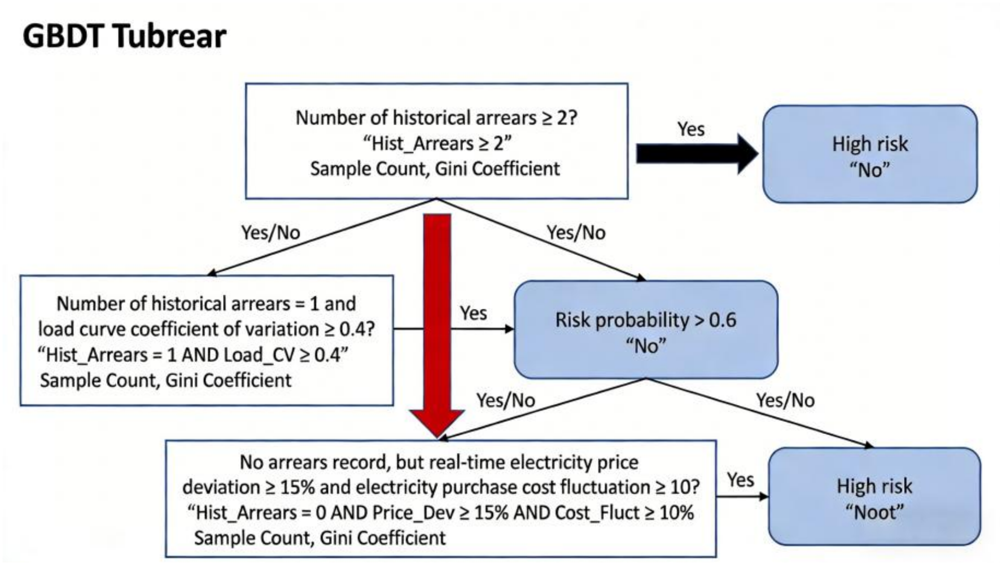

Figure 4. Example of Risk Decision Path for Payment Delay

(1) If the user has two or more historical arrears, they are classified directly into the high-risk branch.

(2) If the user has one historical arrear, the model further examines whether the load curve coefficient of

variation is ≥ 0.4; if so, the risk probability exceeds 0.6.

(3) For users with no historical arrears, if real-time price deviation is ≥ 15% and power purchase portfolio cost volatility is ≥ 10%, they may still be classified as high-risk. This case demonstrates that GBDT can capture complex multi-feature interactions, avoiding misclassification based on a single indicator.

Sensitivity Analysis

Model performance changes are observed by adjusting the learning rate and the number of trees (Figure 5):

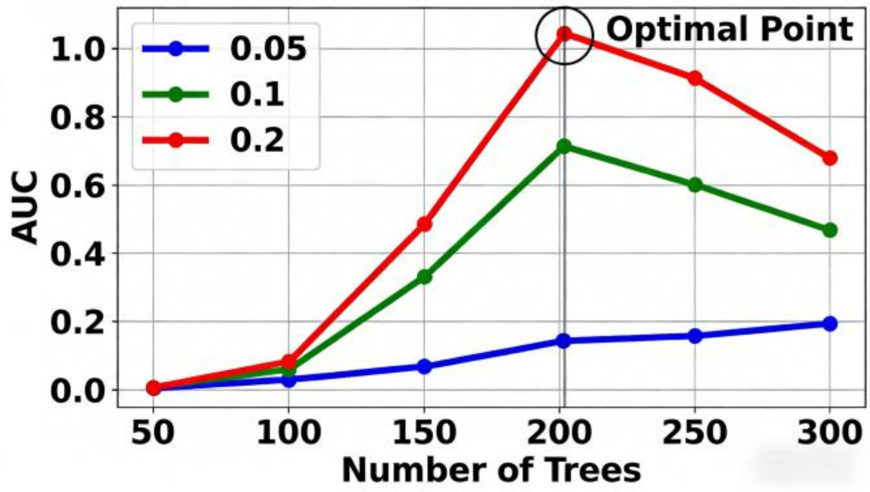

Figure 5. Hyperparameter sensitivity analysis

The optimal performance occurs at a learning rate of 0.1; a lower rate (0.05) slows convergence, while a higher rate (0.2) increases the risk of overfitting.

Sensitivity analysis of the risk threshold reveals that as the threshold increases from 0.4 to 0.8, the F1 score for payment arrears peaks at 0.6. At this threshold, the model captures 91.5% of high-risk events while keeping the false alarm rate below 5.2%. This threshold addresses class imbalance (8.7% high-risk samples) by ensuring that high-level alerts are only triggered when the evidence of risk is robust, thereby minimizing operational costs for retailers.

After the number of trees exceeds 200, the AUC improvement plateaus, balancing computational efficiency and performance; thus, 200 trees are selected as optimal.

Practical Application Value

Based on model outputs, retailers can implement three-tiered risk control strategies:

High-risk users (probability > 0.6): Require a 20% advance payment, shorten the settlement cycle to weekly, and offer time-of-use price packages to encourage load adjustment.

Medium-risk users (0.3 < probability ≤ 0.6): Dynamically monitor electricity consumption patterns and provide daily energy-saving reminders.

Low-risk users (probability ≤ 0.3): Offer a 10% discount on two-year contracts to reduce customer acquisition costs.

For example, one industrial user was predicted to have an arrears risk probability of 0.72; the retailer avoided a loss of 150,000 yuan in bad debt by requiring advance payment, thereby confirming the model's practical application value [13].

CONCLUSIONS AND OUTLOOK

Research Conclusions

The proposed GBDT risk assessment framework demonstrates excellent performance in electricity retail market scenarios, achieving an F1 score of 0.89 and an AUC of 0.94. The model achieves a 6.8% AUC improvement over RF and a 21.9% F1 improvement over LR, consistently outperforming traditional machine learning models.

Feature importance analysis reveals that user behavior features (e.g., historical arrears, load stability) are primary risk drivers, with market environment and operational data features serving as secondary contributors. Similarly, in the textile industry, core risk drivers often originate from customer-specific factors such as payment history and order consistency, which are more predictive of financial risk than broader market trends.

The adaptive weighted loss function effectively addresses the class imbalance problem, enhancing the model's detection capability for scarce high-risk samples by more than 20%.

Limitations and Future Directions

Data limitations: The current dataset does not incorporate meteorological data (e.g., extreme weather warnings), resulting in a prediction accuracy of only 81.5% for load drops caused by extreme weather—lower than the overall average [14].

Real-time insufficiency: The model is trained on historical data and lags in responding to emerging policies (e.g., carbon pricing mechanisms). A flow learning framework could be introduced for real-time model updates.

Multi-risk coupling: The joint distribution of price, default, and supply-demand risks is not considered. Future research could integrate Graph Neural Networks (GNNs) to model correlations in electricity consumption among users or employ reinforcement learning to dynamically adjust risk assessment thresholds [15].

Practical Recommendations

Power trading centers should establish a unified risk feature database and standardize feature collection formats (e.g., load data sampling frequency of 15 minutes).

Retailers need to integrate model outputs into risk control systems and set automatic early warning thresholds (e.g., trigger strategy adjustments when the proportion of high-risk users exceeds 10%).

Regulatory agencies can develop targeted policies based on feature importance results (e.g., mandate advance payment mechanisms for users with two or more historical arrears).

Author Contributions

Conceptualization – Liu Jiajia, Qin Li, Li Shujing, Xu Weiting, Li Chunmei and He Kai; methodology – Liu Jiajia, Qin Li, Li Shujing, Li Chunmei and He Kai; investigation – Liu Jiajia, Qin Li, Li Shujing, Xu Weiting, Li Chunmei and He Kai; writing-original draft preparation – Liu Jiajia, Qin Li, Li Shujing, Xu Weiting, Li Chunmei and He Kai. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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REFERENCES

[1] Yang W, Tan W, Zeng Z, Li R, Qin J, Xie Y, et al. A Two-Stage Feature Extraction Approach for Green Energy Consumers in Retail Electricity Markets Using Clustering and TF–IDF Algorithms. Energy Engineering. 2025; 122(5):1697-1713. doi: 10.32604/EE.2025.060571

[2] Song X, Wu H, Zhang H, Guo J, Zhang Z, Peña-Mora F. Can retail electricity pricing promote microgrid operators to leverage shared energy storage services among internal aggregators? Energy. 2025; 314:134160. doi:10.1016/J.ENERGY.2024.134160

[3] Youwen W. Stock Market Investment Risk Measurement Method Based on Data Mining and Decision Trees. International Journal of High Speed Electronics and Systems. 2024; 34(01):2540131. doi:10.1142/S0129156425401317

[4] Feng H, Zhang Y, Lan Z, Wang K, Wang Y, Chen S, et al. Developing China's Electricity Financial Market: Strategic Design of Financial Derivatives for Risk Management and Market Stability. Energies. 2024; 17(23):5854. doi:10.3390/EN17235854

[5] Arias S, Alvarado SMA, Salazar H. The Impact of a Market Maker in an Electricity Market. Energies. 2024; 17(16):4042. doi:10.3390/EN17164042

[6] Kong C, Wei J, Zhao Z. A pool-based electricity retail markets integrating renewable energy sources and electric vehicles in the presence of demand response program and conditional value at risk to enhance energy security. Computers and Electrical Engineering. 2024; 118(PB):109421. doi:10.1016/J.COMPELECENG.2024.109421

[7] Wan Y, Qin J, Shi Y, Fu W, Xiao F. Stackelberg–Nash game approach for price-based demand response in retail electricity trading. International Journal of Electrical Power and Energy Systems. 2024; 155(PB):109577. doi:10.1016/J.IJEPES.2023.109577

[8] Wang Y, Jiang J, Cai Z, Zhang K. Fractional Prospect Theory-Based Bidding Strategy of Power Retail Company in the Uniform Pricing Electricity Market under Price Uncertainty. Fractal and Fractional. 2023; 7(3):210. doi:10.3390/FRACTALFRACT7030210

[9] Zhang Y, Zhao H, Li B, Zhao Y, Qi Z. Research on credit rating and risk measurement of electricity retailers based on Bayesian Best Worst Method-Cloud Model and improved Credit Metrics model in China’s power market. Energy. 2022; 252:124088. doi:10.1016/J.ENERGY.2022.124088

[10] Bi H, Fang S, Bi X. Prediction method of financial market risk behavior based on big data mining algorithm. Academic Journal of Computing & Information Science. 2022; 5.0(3.0):78-84. doi:10.25236/AJCIS.2022.050311

[11] Mahesawri K, Ramkumar S. Analysis of error rate for various attributes to obtain the optimal decision tree. International Journal of Intelligent Enterprise. 2022; 9(4):458-472. doi:10.1504/IJIE.2022.126400

[12] Sun B, Wang F, Xie J, Sun X. Electricity Retailer Trading Portfolio Optimization Considering Risk Assessment in Chinese Electricity Market. Electric Power Systems Research. 2021; 190:106833. doi:10.1016/j.epsr.2020.106833

[13] Mohammad N, Mishra Y. Retailer’s risk-aware trading framework with demand response aggregators in short-term electricity markets. IET Generation, Transmission & Distribution. 2019; 13(13):2611-2618. doi:10.1049/iet-gtd.2018.6294

[14] Aghaei J, Charwand M, Gitizadeh M, Heidari A. Robust Risk Management of Retail Energy Service Providers in Midterm Electricity Energy Markets under Unstructured Uncertainty. Journal of Energy Engineering. 2017; 143(5):04017030. doi:10.1061/(ASCE)EY.1943-7897.0000462

[15] Huang PI, Chyu CC. An Interactive Newsvendor Model Involving Market Risk and Product Quality Risk. Advanced Materials Research. 2013; 2486(739):694-699. doi:10.4028/www.scientific.net/AMR.739.694