



Power Marketing Customer Service Method based on Credit Score

Chao Zhang^{1,*}, Qirui Chen², Jianing Xu², Wei Zhang², Ying Jiang²

¹State Grid ZheJiang Province Co.Ltd DeQing Power Supply Company Zhejiang ,Huzhou, 313200, China

²State Grid Zhejiang Marketing Service Center, Zhejiang,Huzhou, 313200, China

*e-mail: 943328208@qq.com

Abstract. Driven by both the global energy structure transformation and the digital wave, the customer service system in the power industry is undergoing profound changes. The traditional integrated and non-differentiated service model has become difficult to meet the diverse and personalized service demands of emerging customer groups. Based on this, this paper focuses on constructing a customer service method for power marketing with credit scores as the core driving force. Firstly, a credit score system covering multiple dimensions such as payment behavior, stability of electricity load, and green electricity consumption behavior was designed, thereby achieving precise modeling of customer stratification and profiling. Subsequently, a dynamic assessment of customer credit is implemented based on machine learning algorithms, and a differentiated service push mechanism that matches customer characteristics is constructed. At the system architecture level, this paper designs a three-layer collaborative system of data collection - analysis and decision-making - service application to support the efficient operation of the model.

Keywords: Electricity marketing,Credit score System,Machine Learning,Service Model

1 Introduction

With the accelerated penetration of information technology into traditional industries, the customer service system in the power industry is transforming from a passive response type to an active perception type. In the new era, customers show diversified and dynamic characteristics in terms of energy consumption demands, interactive experiences and value recognition, and put forward higher requirements for the accuracy and flexibility of services. The traditional unified service model ignores customer heterogeneity, which not only leads to low efficiency in resource allocation, but also aggravates customer churn and default risks. Credit scores, as a comprehensive representation means of customer behavior and risk management, have been verified for their effectiveness in hierarchical management and personalized services in multiple fields. Introducing the credit score mechanism into the field of power marketing not only helps

© The Author(s) 2025

P. S. Borah et al. (eds.), *Proceedings of the 2025 5th International Conference on Enterprise Management and Economic Development (ICEMED 2025)*, Advances in Economics, Business and Management Research 346, https://doi.org/10.2991/978-94-6463-811-0_61

to achieve the precise identification and hierarchical operation of customer resources, but also provides quantitative support for the formulation of differentiated service strategies and risk control. However, the current research on customer credit management in the power industry is not systematic, and there is a lack of a service optimization system and dynamic implementation mechanism driven by credit scores. In response to this research gap, this paper proposes a customer service method for power marketing based on credit scores. Through the design of the index system, algorithm implementation and system construction, it explores the practical application path of credit management in the optimization of power services.

2 Construction of Power Customer Service Model Based on Credit Score

2.1 Design of Credit Score System

To scientifically assess the potential of customer service and credit risk, it is necessary to first establish a complete and quantified credit score system. This system should take the behavioral characteristics of customers in the power industry as the benchmark, comprehensively consider five dimensions including the timeliness of payment, default records, stability of power consumption load, historical complaint rate and green power consumption behavior, set specific indicators, and form the final credit score through weighted weights. [1-2]

Specifically, the credit score can be calculated according to the following formula: $\text{Credit Score} = w_1 \times x_1 + w_2 \times x_2 + \dots + w_i \times x_i$

Among them, w_i represents the weight coefficient of the i -th indicator, and x_i represents the standardized score of the customer on this indicator.

As shown in Table 1, it is an example of the representation of the integral index weights, all of which ensure the operability and transparency of the evaluation system.

Table 1. Weight Table of Integral Indicators

Indicator name	indicator description	Weight ratio
Timeliness of payment	Monthly bill payment punctuality rate	30%
Breach of contract record	The number of overdue and breach of contract times over the years	25%
Stability of electrical load	Fluctuation range of the electricity consumption curve	20%
Complaint record	Average annual number of complaints	15%
Green electricity consumption behavior	The proportion of new energy usage	10%

Through the above model, the credit level of customers can be quantified, providing a scientific basis for subsequent customer stratification.

2.2 Customer Stratification and Profiling Establishment

After the credit score assessment is completed, the customers need to be stratified systematically based on the score results. According to the points, they can be classified into four levels: A-level high-quality customers, B-level stable customers, C-level risk customers and D-level high-risk customers. Each level represents significant differences among customers in terms of payment capacity, standardization of electricity usage behavior, and service response demands. [3]

To support the formulation of precise service strategies, it is necessary to further construct the customer profiling system. The profile dimensions include but are not limited to: average monthly electricity consumption, preferred payment methods, frequency of fault reporting and repair, and selection of response channels, etc. The typical characteristics of each level of customers can be systematically presented through the credit rating classification standard table (table), and at the same time, the multi-dimensional characteristic differences can be visually displayed in the form of customer portrait diagrams (such as radar charts or feature matrix diagrams). Example table of credit rating classification (as shown in Table 2) :

Table 2. Example Table of Credit Rating Classification

Credit rating	Credit rating	Feature description
Grade A	90–100	Timely payment, stable load, and zero complaints
Grade B	70–89	Occasional delays, moderate load, and low complaints
Grade C	50–69	Frequent overdue payments, large load fluctuations and high complaint rates
Grade D	<50	Long-term breach of contract, abnormal load, frequent complaints

Through refined customer stratification and profiling construction, it provides data support and logical basis for the subsequent formulation of differentiated service strategies. [4]

2.3 Service Strategy and Differentiated Configuration Mechanism

Based on the classification of customer levels, a matching service strategy needs to be formulated to maximize resource utilization and optimize service efficiency. For Class A customers, VIP green channels, personalized energy efficiency optimization suggestions and customized electricity consumption packages should be provided. For B-level customers, the main promotion is the cross-sale of standardized services and value-added products. For C-level and D-level customers, the focus is on risk early warning, strengthening the collection mechanism and applying the guaranteed power supply policy. As shown in Table 3, the service contents, response priorities and resource allocation volumes of customers at each level in the differentiated services are presented.

Table 3. Differentiated Services Table

Credit rating	Service content	Response priority
Grade A	Personalized package push, dedicated customer manager	high
Grade B	Standard service, periodic reminders	In the
Grade C	Urgent collection, standard risk warning	low
Grade D	Default handling and guaranteed power supply	Extremely low

Furthermore, to maximize the overall customer satisfaction under resource-constrained conditions, a simple linear programming model can be introduced. Let the total amount of resources be R and the demand for service resources of various types of customers be r_i . Then the optimization objective is:

$$\max \sum_i (S_i \times r_i)$$

Among them, S_i represents the comprehensive service weight coefficient of the i -type customer. The constraint condition is:

$$\sum_i r_i \leq R$$

This model can guide the scientific allocation of resources among different customer groups, avoid resource waste and service blind spots, and improve the overall operational efficiency.

3 Algorithm Implementation and System Design

3.1 Customer Credit Assessment Algorithm

Credit scores, as the core basis for customer service stratification, must be continuously updated and optimized relying on reliable and dynamic credit assessment algorithms. Based on this, this paper designs and implements a customer credit prediction and correction mechanism dominated by machine learning. [5]

In terms of the specific algorithm selection, considering the structural characteristics of power customer data and the evolution law of credit behavior comprehensively, the decision Tree (CART, Classification and Regression Tree) model and the Random Forest (RF) model were adopted preferentially. Among them, the CART model is suitable for the credit rating prediction of a single customer because of its transparent decision-making process and strong interpretability of rules. The random forest, with its high accuracy rate and anti-overfitting ability, is suitable for the training and deployment of large-scale customer credit scoring systems.

The general process of customer credit score prediction can be expressed as:

$$\text{Predicted Credit Score} = f(X_1, X_2, \dots, X_M)$$

Among them, X_1, X_2, \dots, X_m respectively represent the customer behavior characteristics (such as payment interval, default frequency, load fluctuation coefficient, etc.), and f is the prediction function obtained through training.

To enhance the explanatory power and operability of the model, a decision tree branch diagram can be drawn to illustrate the credit scoring paths of customers under different credit indicators, and the key factors affecting the credit score can be identified through the feature importance ranking diagram (As shown in Figure 1). [6]

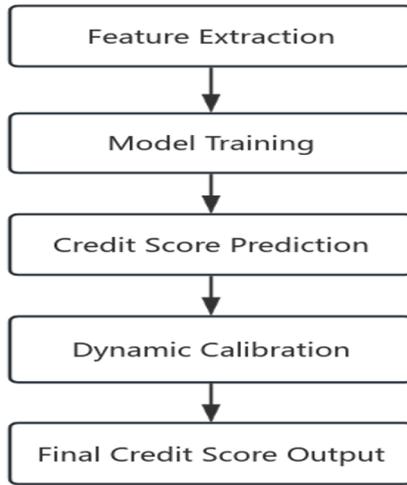


Fig. 1. Schematic diagram of the framework of the customer credit score assessment model

Furthermore, in order to avoid the degradation of the model due to data drift in practical applications, new customer behavior data need to be introduced regularly for model retraining to ensure the timeliness and robustness of the scoring system.

3.2 Customer Service Matching and Recommendation Mechanism

After completing the customer credit rating assessment, a precise and dynamic service recommendation mechanism should be designed based on the assessment results and the personalized demand characteristics of the customers to enhance the customer experience and marketing conversion rate.

This study adopts a hybrid recommendation strategy based on the combination of rule-driven and collaborative filtering. Firstly, set the basic service push rules based on the customer's credit score range and behavior labels, for example:

If it is greater than 90, the "Green Power Optimization Service Package" will be pushed.

If it is 7089, a "Standard Energy-saving Package Suggestion" will be pushed.

If it is less than 70, the "Abnormal Energy Use Warning and Risk Alert Service" will be pushed.

Based on rule push, a collaborative filtering algorithm is further introduced to comprehensively analyze customers' historical energy consumption behaviors, feedback records and preferences of similar customers, and dynamically adjust the recommended content to achieve differentiated service segmentation. The process of the customer service matching mechanism is as follows(As shown in Figure 2):

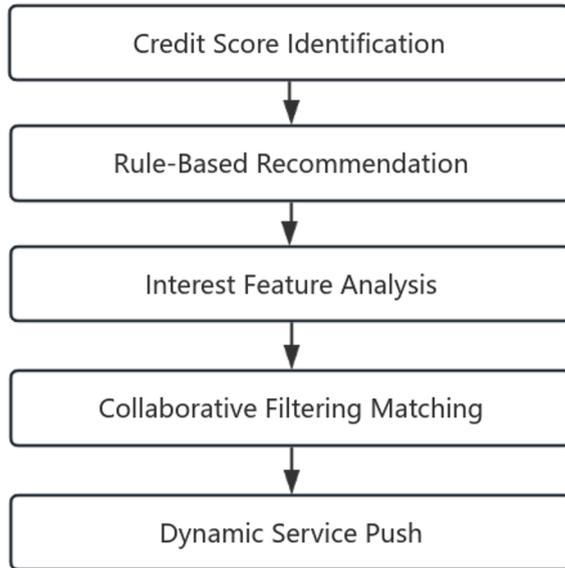


Fig. 2. Flowchart of the customer service recommendation mechanism

Through the above-mentioned mechanism, not only can the timeliness and accuracy of service responses be guaranteed, but also a closed loop of value mining based on credit assets can be formed on the marketing side.

C. Overall system architecture and division of functional modules

To support the efficient operation of the aforementioned credit assessment and service recommendation mechanism, this paper designs a three-layer overall system architecture, including the data acquisition layer, the analysis and decision-making layer, and the service application layer. Each layer collaborates and divides the work to ensure that the system has good scalability, reliability, and real-time performance. [7]

Data acquisition layer: It is responsible for the real-time collection and preprocessing of multi-source data, including customer basic information, electricity load curves, payment history, complaint records, etc. Standardized API interfaces and data synchronization technologies are adopted to ensure the integrity and consistency of data flow.

Analysis and decision-making level: It undertakes core functions such as credit score calculation, customer classification, and service recommendation decision-making. This layer introduces the machine learning training module and the rule engine module to implement model deployment and inference services. The system internally uses a

caching mechanism to accelerate the response to integral queries and improve decision-making efficiency.

Service application layer: Oriented towards end users and business operation ends, it provides functions such as personalized service recommendation and display, customer credit information query, and dynamic marketing content push. The asynchronous scheduling and load balancing of service tasks are achieved through message middleware to ensure the elastic scalability of the system.

In the overall architecture design, particular emphasis was placed on module decoupling and horizontal scalability to adapt to the evolution requirements of future expansion in the scale of power customers and increase in data complexity.

4 Case Analysis and Experimental Verification

4.1 Dataset and Experimental Setup

The sources of experimental data include two parts:

The first part consists of the actual customer behavior data collected by a provincial power company in the past two years (desensitized), covering five types of characteristics such as basic customer information, payment records, electricity load curves, historical default records, and complaint feedback. The total sample size is approximately 18,500 items.

The second part is the simulation data constructed based on the actual electricity consumption behavior rules, mainly used to supplement the small sample of customers with a high default rate and improve the representativeness of the low-credit customer sample in the experiment.

In the data preprocessing stage, outlier elimination, missing value filling and feature standardization processing are carried out respectively.

Among them, the standardized interval of the credit score is set as (0,100), and the fluctuation of the load curve is normalized using the standard deviation index.

To ensure the scientificity and comparability of the experiment, two groups of experimental subjects were set up (as shown in Table 4), and Table 5 is the description of the main features of the customer dataset.

Table 4. Two groups of experimental subjects

Group	Description
Baseline Group	Adopt the unified customer service model under the current rules of power companies, without distinguishing the credit ratings of customers
Proposed Group	Apply the credit score assessment and differentiated service recommendation mechanism proposed in this paper

Table 5. Description of the Main Characteristics of the customer Dataset

Feature	Description	Data Type	Summary Statistics
Customer ID	The code that uniquely identifies each customer	String	Unique ID
Monthly Average Electricity Consumption	The code that uniquely identifies each customer Average monthly electricity consumption of customers (kWh)	Continuous	Mean value: 456kWh, Standard deviation: 120kWh
Payment Timeliness Rate	Proportion of the number of times payment is made on time	Continuous	Mean: 94.5%, median: 96%
Historical Default Count	The number of default events of the customer in the past two years	Discrete	Average: 0.8 times, maximum: 5 times
Complaint Count	The cumulative number of complaint records	Discrete	Mean value: 0.3 times, maximum value: 3 times
Load Fluctuation Coefficient	Standard deviation of the fluctuation degree of the electricity consumption curve	Continuous	Mean value: 0.15, Standard deviation: 0.04
Green Energy Usage Ratio	The proportion of renewable energy used	Continuous	Mean: 22.3%, median: 20%

The entire experiment was carried out in accordance with the 5-Fold Cross Validation process to improve the robustness and generalization ability of the experimental results.

4.2 Definition of Key Performance Indicators

To comprehensively evaluate the effect of service optimization, the following key performance indicators (KPIs) are set in this study:

Customer satisfaction improvement rate To measure the improvement degree of customer service experience, based on the changes in the scores of the follow-up survey questionnaire, the calculation formula is as follows:

$$CSIR = \frac{S_{\text{proposed}} - S_{\text{baseline}}}{S_{\text{baseline}}} \times 100\%$$

Among them, S_{proposed} and S_{baseline} are the mean customer satisfaction values of the optimization group and the baseline group respectively.

Service Response Time Reduction Rate (SRTR)

Based on the average time from the customer's service request to the completion of the response, calculate the improvement range of the response timeliness.

Default Rate Decline (DRD) of customers

The effectiveness of risk control was evaluated by comparing the default occurrence frequency of the two groups of customer groups during the experimental period.

Furthermore, to verify the statistical significance of the results, the two-sided Independent Samples T-Test was used to analyze the differences between the two groups of data, and the significance level was set at 0.05.

4.3 Result Analysis and Comparison

The experimental results show that the customer stratification and differentiated service method driven by credit scores is significantly superior to the traditional unified service model in all key performance indicators.

The specific manifestations are as follows:

The improvement rate of customer satisfaction (CSIR) reached 18.6%, while that of the traditional group was only 3.5%. The improvement effect was significant ($p < 0.01$).

The average service response time has been shortened from the original 36 hours to 24 hours, and the efficiency improvement rate (SRTR) is approximately 33.3%. [8]

The customer default rate (DRD) decreased by 11.2 percentage points, especially among the C-level and D-level risk customer groups, the default rate decreased most significantly (as shown in Figure 3).

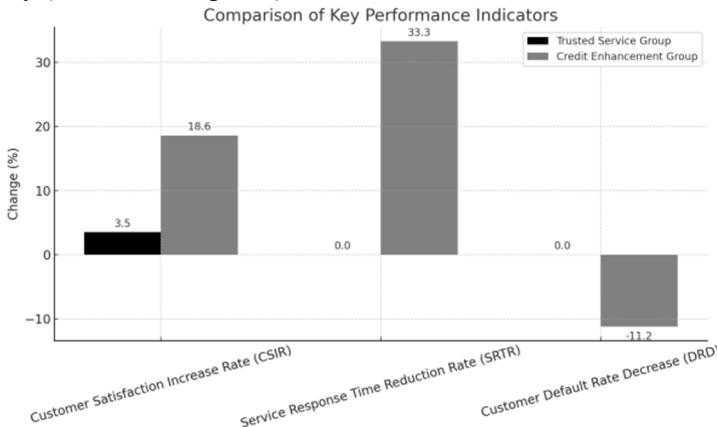


Fig. 3. shows the performance differences of the three indicators, CSIR, SRTR and DRD, in the two groups of experimental subjects

Further detailed analysis shows that the introduction of the credit score system not only enhances the service experience perception of high-credit customers, but also effectively identifies potential high-risk customers in advance, significantly reducing the rates of bad debts and service disputes.

Figure 4 shows the changing trends of satisfaction of customers of various credit ratings before and after the implementation of differentiated services. It can be clearly observed that the satisfaction improvement of the A-level and B-level customer groups is particularly prominent under the new service system.

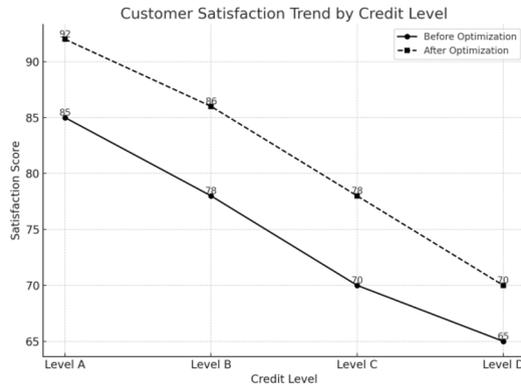


Fig. 4. shows the changing trend of customer satisfaction under different credit ratings

Overall, the experimental verification fully demonstrates that the power customer service optimization method based on credit scores has significant potential for efficiency improvement in practical applications and provides empirical support for subsequent large-scale promotion and application.

5 Conclusions

This paper focuses on the optimization of customer service in power marketing and proposes a service stratification and differentiated configuration method centered on credit scores. Through model construction, algorithm implementation and system design, the full-chain research from the theoretical framework to practical application has been completed. Empirical analysis shows that this method can effectively enhance the customer service experience, optimize the efficiency of resource allocation, reduce the risk of default, and has good potential for promotion and application. Future research can further combine real-time data streams, dynamic behavior modeling and multi-dimensional credit evolution mechanisms to deepen the adaptability and predictive ability of the credit score system, in order to cope with the increasingly complex customer service challenges and intelligent development demands in the power industry.

References

1. Wang Ningjing, Tang Tao Research on the Construction and Practice of Modern Electric Power Marketing Electricity Charge Management System [J]. *Electrical Engineering Technology*,2024,(S2):472-474.
2. Ma Chengjie. Research on Methods for Enhancing Customer Service Experience through Electric Power Marketing Information System [J] *Information and Computer*,2024,36(24):27-29.
3. Shen Zhihong, Zhang Liang, Shen Xuming, et al. Research on Strategies for Improving Quality Service in Electric Power Marketing Considering Customer Experience [J]. *Electric Times*,2024,(09):90-92.

4. Yin Qing, Liu Junling, Wang Yongli, et al. Analysis of Problems and Countermeasures in Electric Power Marketing Management [J]. *Electrical Technology & Economics*,2024,(06):241-242.
5. Wang Yue. Auxiliary Precision Analysis of Power Services Based on Customer Intelligent "Profiling" [J] *Rural Electrification*,2024,(06):1-4.
6. Gao Siyuan. Customer Service Management Strategies in the Field of Electric Power Marketing in the New Era [J]. *Marketing World*,2024,(07):50-52.
7. Shen Huazhou, Xu Jie, MAO Qianqian, et al. Analysis of Electric Power Marketing Management System Based on Big Data [J]. *Electronic Technology*,2024,53(02):100-101.
8. Shen Fengling, Yu Wenjin, Yin Qing, et al. Construction of Power Customer Group Segmentation Model Based on Semi-supervised Spectral Clustering [J]. *Automation Technology and Application*,2023,42(12):85-89.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

