Valuing Electricity Customers of Electricity Retailers Based on Bayesian BWM-Inverse Entropy-Cloud Model

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Abstract. With the continuous reform of electricity market, the competition in the retail market is becoming more and more intense. How to select high quality customers will become an important issue for the development of electricity retailers. At present, the value assessment of customers by electricity retailers is subjective and arbitrary. The establishment of a scientific and reasonable evaluation system for the value of customers will be conducive to the development of targeted marketing strategies and the realization of differentiated services. The paper constructs a value assessment system for customers based on their characteristics such as load curve, profit contribution and credit risk. By combining Bayesian BWM and the entropy weighting method, the indicators are comprehensively assigned. Then the two-dimensional cloud model is applied to determine the distribution level of customer value. Finally, it realizes the comprehensive assessment of the value of electricity customers. The paper uses ten customers for case studies to validate the proposed model. Targeted marketing measures are proposed to improve the retailers' operating profitability.

Keywords: electricity retailers · customer value assessment · Bayesian · BWM · anti-entropy rights

1 Introduction

As China's electricity system reform continues to deepen, the retail market is gradually being liberalised and the marketisation process is accelerating. The challenges faced by electricity retailers have also become more complex. There are three main sources of sustainability for the operations of retailers. The first is market-based competition in the wholesale and retail markets. The second is the ability of the retailer to manage its operations. The third is the value rating of electricity customers. As an emerging player in the market, the retailer needs to select more reliable customers in order to have stable and sustainable revenues. It is therefore particularly important to assess the

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value of customers, to select quality customers and to develop differentiated packages of services for different classes of customers.

The retail electricity market in China is still in its infancy. The basis for retailers to select their customers comes from the economic value and the market share mainly. Currently, domestic and international experts have also conducted studies on the assessment of the value of customers of electricity retailers. The literature [1] uses improved hierarchical analysis based on the reliability needs of electricity consumers and proposes the reliability needs of customers in different power supply areas of power supply companies. Literature [2] establishes two evaluation index systems for individual power sales companies and the industry of power sales companies, starting from the market behaviour of power sales companies. Jiangsu is used as a case study to provide guidance to electricity sales companies in the market. The literature [3] establishes a comprehensive evaluation model for the customer classes of electricity sales companies based on the cloud model and proposes optimisation suggestions for each customer class. The literature [4] proposed a hybrid neural network approach to H-LSTM for electricity customer segmentation. Literature [5, 6] all used K-means algorithm for customer data segmentation, which improved the accuracy of customer segmentation. Literature [7] based on fuzzy clustering analysis for credit evaluation algorithm of electricity customers. Literature [8] constructs an electricity customer evaluation index system, applies multi-objective optimisation weights to obtain customer evaluation results, and classifies customers into categories to develop differentiated service packages. The literature [9] considers the carbon reduction level of electricity customers, constructs electricity customer value indicators, and combines dynamic model clustering to subdivide electricity customer categories. Literature [10] addresses the content, clustering approach and problems of electricity customer service and constructs an evaluation system for electricity customer service quality. Literature [11, 12] used entropy weight method to calculate the weights of indicators and proposed an improved PCA clustering algorithm to classify the value of electric power customers, which provided auxiliary support for power supply enterprises to develop differentiated service strategies.

These studies have all improved the accuracy and scientific validity of customer value assessment, but there are still certain shortcomings. Firstly, the main indicator chosen for the customer value assessment is the economic value, but the impact of the customer's own electricity consumption characteristics, such as the volatility of the load curve, is ignored. Secondly, the cost of customer value is measured mostly in terms of arrears, but the cost of deviations due to the uncertainty of consumption is ignored. Thirdly, the models currently used are rated according to the final combined weighting results. However, discrete models that ignore the characteristics of each user will not have all the relevant assessment indicators, so the rating of the evaluation should be multidimensional and discrete.

This paper first analyses the key features of the embodied customer value, constructs an indicator system and further improves the evaluation content. On the basis of the customer mechanism index system, a customer value evaluation model is constructed to rank the customer value. Finally, corresponding service suggestions are made for each class of electricity customers, which is conducive to better marketing business development for electricity retailers.

2 Construction of the Customer Value Assessment Index System for Electricity Retailers

2.1 Selection of Customer Value Assessment Indicator System

The value of the electricity customer is the basis for the electricity retailers to develop its marketing strategy and differentiate its services to its customers. Electricity customer value assessment indicators need to reflect customer characteristics and also provide a basis for differentiated services for electricity retailers. In this paper, three categories of indicators are selected to develop the customer value assessment index system, including economic indicators, load characteristics indicators and low carbon indicators, and the three categories of indicators are further refined into 11 secondary indicators, as shown in Table 1.

2.2 Description of Customer Value Assessment Indicators

The customer value assessment indicator system reflects customer value in terms of economy, load characteristics and low carbon, as described below.

The economics value is analysed in terms of customer impact on the revenue of the electricity retailers. We have selected contracted tariffs, contracted electricity, contracted tariff revenue, tariff arrears and payment defaults as the economic breakdown indicators. For electricity retailers, the higher the price of the retail contract with the electricity customer and the larger the contracted electricity, the higher relative economic revenue they can earn. At the same time, the operating income of the electricity retailers is not only subject to the retail contract, but also to the market assessment. Therefore, it is necessary to gradually break down the revenue minus the deviation assessment to restore the financial authenticity of the electricity retailers. Finally, due to the economic nature of customers, there can be delinquencies in the payment of electricity bills. All of these can affect the revenue of the electricity retailers.

The customer's electricity load characteristics can directly affect the normal operation of the electricity retailers. If the load fluctuation is too drastic, it will make the operation of retailers more difficult and will also increase the probability of deviation assessment. In terms of load value, the secondary indicators selected in this paper include historical electricity consumption volatility, historical electricity consumption growth rate, frequency of defaulted electricity consumption and the percentage of deviation assessment electricity.

In terms of future energy efficiency services provided by retailers, some high energy-consuming enterprises will become potential customers in the future. The willingness of customers to make low-carbon retrofits is also an important indicator of whether there is room for trading. In this paper, the cost of purchasing a green certificate is chosen as an indicator to express the willingness of customers to make low-carbon retrofits.

3 Customer Value Assessment Model

The customer value indicator systems are all quantitative indicators, but each indicator has different measurement dimensions. Therefore, the different indicator data need to be dimensionless and normalised to determine a scientific judgement matrix to achieve the

Table 1. Indicator system for customer value assessment

Target level	First level indicator layer	Second level indicator layer	Description
Customer value	Economic value	Contracted tariffs	Contracted price between electricity retailers and customers for a fixed period
		Contracted electricity	Contracted electricity between electricity retailers and customers for a fixed period
		Contracted revenue	The difference between the electricity retailers' contract revenue and the assessment fee
		Delinquent fees	Total customer arrears for a fixed period
		Delinquent payment time	The maximum period of time a customer can be in arrears
	Load value	Historical volatility of electricity consumption	Deviation of the daily fluctuation of the load curve of the customer in a fixed period
		Historical growth rate of electricity consumption	Trends in customer electricity consumption over a period of time
		Frequency of default electricity use	Number of customer defaults on electricity bills for a fixed period
		Percentage of deviation assessment electricity	The proportion of deviations in electricity consumption due to non-compliance with contractual requirements to the total deviations
	Low carbon value	Green Certificate Purchase fees	Cost to the customer for purchase of green certificates

rationality and standardisation of the evaluation object data. In addition, the importance of each indicator also requires subjective human understanding. This paper uses a combination of subjective and objective methods to assign weights to evaluation indicators.

Finally, due to the diversity of user evaluation criteria, which leads to a discrete user rating in different intervals, this paper uses a multi-dimensional cloud model to grade customer value.

3.1 Bayesian Best-Worst Method

The Best Worst Method is a new multi-criteria decision making method proposed by the Dutch scholar Rezaei. BWM is a structured comparison compared to AHP, where only the reference indicator needs to be compared with other alternative indicators. In this paper, a Bayesian best worst model is used to find a reasonable set of weights based on the preferences of multiple experts.

The BWM provides two vectors for each expert, representing the best and worst indicator systems, which is performed as follows.

First, construct a system of evaluation indicators $\{c_1, c_2, ..., c_n\}$ and select the best criterion CB and the worst criterion CW among the many indicators.

Second, the degree of preference of the optimal criterion over the other criteria is determined using a scale scoring from 1 to 9. Comparison vector $A_B = (a_{B1}, a_{B2}, ..., a_{Bn})$ is constructed. Where a_{Bi} represents the degree of preference of the best criterion compared to criterion *i*, expressed using a number between 1 and 9. The number 1 indicates equal importance and the number 9 indicates extreme importance.

Third, to determine the degree of preference of other criteria over the worst criteria. Comparison vector $A_W = (a_{W1}, a_{W2}, ..., a_{Wn})^T$ is constructed. Where a_{Wi} represents the degree of preference of the worst criterion compared to criterion *i*, expressed using a number between 1 and 9.

Fourth, construct a mathematical planning problem and solve it to derive the optimal weights $w^* = (w_1^*, w_2^*, ..., w_n^*)$. Given A_B and A_W, the best set of weights for the indicators is minimised by a linear model such that the maximum absolute difference of $\left\{|w_B^d - a_{Bj}w_j^d|, |w_j^d - a_{jw}w_W^d|\right\}$ is satisfied. Where w_B^d denotes the weight of the best indicator B, w_W^d denotes the weight of the worst indicator W and w_j^d denotes the weight of the j indicator. Thus, the problem can be transformed into solving the optimal solution to a constrained optimisation problem.

$$\begin{cases} \min\limits_{w} \max\limits_{j} \left\{|w_B^d - a_{Bj}w_j^d|, |w_j^d - a_{jw}w_W^d|\right\} \\ \qquad\qquad j \\ \sum\limits_{j=1}^{n} w_j = 1 \\ w_j \geq 0 \end{cases} \tag{1}$$

Suppose that there are K experts who have given different criteria for the best and worst indicators in the indicator system. We use sets $A_B^{1:K}$ and $A_B^{1:W}$ to express the set of experts' best and worst indicators. Find w^{agg} in the set of all indicator comparisons to represent the overall best weight. The conditional independence between the various variables is clear. Considering all the independence between the different variables, the

Bayes' rule is applied to the joint probabilities as follows.

$$\begin{aligned} &P(w^{agg}, w^{1:K}|A_B^{1:K}, A_W^{1:K}) \propto P(A_B^{1:K}, A_W^{1:K}|w^{agg}, w^{1:K})P(w^{agg}, w^{1:K}) \\ &= P(w^{agg})\Pi P(A_W^k|w^{agg})P(A_B^k|w^{agg})P(w^k|w^{agg}) \end{aligned} \tag{2}$$

A probabilistic model with a Bayesian model is used to replace the optimisation model of the best-best method. Bayesian models provide more information on the confidence level of the relationship between each pair of indicators. The information can be obtained by Bayesian testing.

3.2 Inverse Entropy Method

The concept of entropy was originally derived from system thermodynamics and was later introduced into information theory to represent the degree of disorder of a system. If the system may be in n different states and the probability of each state occurring can be known as $p_i(i = 1, 2, ..., n)$, for n assessment metrics and m assessment objects, the entropy of the system can be expressed as

$$e_{ij} = -\theta \sum_{i=1}^{n} p_{ij} \ln(p_{ij}) \tag{3}$$

where $0 \leq p_{ij} \leq 1$, $\sum\limits_{i=1}^{n} p_{ij} = 1$.

The inverse entropy method is an improved method of assigning weight to indicators based on the entropy method. In the concept of inverse entropy, the inverse entropy value increases as the variability of the indicators increases. The following are two different expressions for inverse entropy.

$$e_{j\prime} = -\theta \sum_{i=1}^{n} p_{ij} \ln(1 - p_{ij}) \tag{4}$$

$$e_{j\prime} = -\theta \sum_{i=1}^{n} (1 - p_{ij}) \ln(p_{ij}) \tag{5}$$

The steps for assigning weights in the inverse entropy weighting method are as follows.

(1) Form a standardised matrix of programme indicators.

$$p_{ij} = x_{ij\prime} \Big/ \sum_{i=1}^{n} x_{ij\prime} (i = 1, 2, ..., n; j = 1, 2, ..., m) \tag{6}$$

(2) Determine the inverse entropy of each indicator based on the matrix of assessment indicators.

$$e_{j\prime} = -\theta \sum_{i=1}^{n} (1 - p_{ij}) \ln(p_{ij}) \tag{7}$$

where $0 \le p_i \le 1, \sum_{i=1}^{n} p_i = 1$. $\theta > 0$, and $\theta = 1 \big/ \ln(n)$.

(3) Calculation of the inverse entropy weighting of indicators.

$$\omega_i^{''} = e_{j'} \Bigg/ \sum_{i=1}^{n} e_{j'} \tag{8}$$

3.3 Cloud Model

The Cloud Model was introduced in 1995 and uses natural language to express the uncertainty between qualitative and quantitative concepts. It describes and analyses the ambiguity and randomness of things in a unified way through mathematical expressions. Let Π be a quantitative domain and $\tilde{A}$ is a qualitative concept of Π. If x is a quantitative value and it is a random realization on $\tilde{A}$. The affiliation of x to $\tilde{A}$ is $\lambda(x) \in [0, 1]$, then x can be regarded as a cloud droplet distributed on Π.

$$\lambda : \Pi \to [0, 1], \forall x \in \Pi, x \to \lambda(x) \tag{9}$$

The cloud model further expresses the qualitative concept by using three numerical characteristics of the cloud. Cloud droplet expectation *Ex*, entropy *En* and super-entropy *He*. Where, *Ex* reflects the centre of gravity of the cloud droplet population for the qualitative concept; *En* is a measure of the uncertainty of the qualitative concept, determined by the randomness and ambiguity of the concept; and the super-entropy *He* describes the uncertainty of *En*, which can be expressed by the dispersion of the cloud droplets. The individual cloud droplet affiliation can be further expressed according to the numerical characteristics of the cloud.

$$\lambda(x_i) = \exp[-\frac{(x_i - Ex)^2}{2En^2}](i = 1, 2, \ldots, M) \tag{10}$$

In order to make the indicator indicate the certainty of the data while also indicating the importance of the indicator, we use multiple weight overlays to assign weights to the data. Using ω_0 to denote the combined weights, the original indicator weights are first assigned, and then the normalised indicator weights are used to form the normalised weighted decision weights. Finally, the numerical characteristics of the weighted cloud, Ex', En' and He' can be obtained.

In this paper, the fuzziness of the cloud model is expressed in terms of grading the characteristics of the subject of the assessment, and a specific cloud model standard cloud needs to be set for the different levels of characteristics. The position in which each cloud is located indicates the state under that rank and can be denoted by $\eta[Ex, En, He]$. The numerical characteristics of the cloud can be specifically calculated as follows.

$$\begin{cases} Ex = (F_{\max} + F_{\min})/2 \\ En = (F_{\max} - F_{\min})/3 \\ He = k \end{cases} \tag{11}$$

We set five evaluation levels based on data characteristics. These are very poor, poor, medium, good and very good. As the matrix of judgment indicators in this paper

Table 2. The customer's value level

Rank	Scope	Evaluation criteria cloud	Strategies
Very good	(0.2, + ∞)	(0.25,0.017,0.05)	Priority in securing customer resources
Good	(0.1,0.02]	(0.15,0.017,0.05)	Securing customer resources
Medium	(0,0.1]	(0.05,0.017,0.05)	Maintaining customer resources
Poor	(−0.1, 0]	(−0.05,0.017,0.05)	Provide differentiated services in moderation. Transforming the way customers use energy
Very poor	(−∞, −0.1]	(−0.15,0.017,0.05)	Excluding customers

is normalised and weighted, the constant term of super-entropy is taken as 0.05. The customer value grades are shown in Table 2.

We grade the value of customers for electricity retailers. On the one hand, it reflects the importance of the indicators for customer value assessment, i.e. the indicator weights. On the other hand, it reflects the discrete degree and modeling of the customer data. Therefore, we adopts a comprehensive subjective and objective weighting approach. Firstly, we determine the indicator weights. Then, we use the cloud model to determine the distribution level of customer value. The specific process is shown below.

(1) Industry experts were selected to construct a subjective judgement matrix of indicator weights. The model we mainly use is Bayesian BWM. Therefore, each expert has to choose the most important indicators and the least important indicators in his or her opinion. Combined with the Bayesian model, the scoring matrices of multiple experts are solved to form subjective weighting indicator weights.
(2) As the Bayesian best and worst method is still a subjective assessment, the features of the data itself need to be extracted. Firstly, the units of the customer value assessment indicators are all different, and the data from multiple customers need to be normalised. Secondly, the inverse entropy weighting method is applied to the indicator data.
(3) A combination of subjective and objective indicators is assigned, and we mainly use a stacking approach to assign subjective and objective weights.
(4) Determine the value hierarchy interval to which each user belongs. Firstly, a reasonable standard normal cloud is developed. Secondly, the expectation, entropy and super-entropy of each user are derived from the user data and the cloud drops for each user are constructed.

4 Case Study

We selected 10 customers of a retailer in Shanxi province as the research object, mainly including industry (K1), science and technology industry (K2), building materials (K3), renewable energy (K4), metallurgy (K5), aluminium and silicon (K6), coal and chemical (K7), chemical industry (K8), new materials (K9) and power generation (K10). At the same time, we selected six experts to score the indicator system and selected the best and worst indicators. The Bayesian BWM was used to solve for the subjective weights, and then the inverse entropy weighting method was applied to solve for the objective weights of these 10 different electricity customers. Finally, the multidimensional cloud model was used to rate.

The indicators are first scored using Bayesian BWM to construct a scoring matrix. As different experts will have different views on the indicators, the best and worst indicators are chosen differently. The best matrix is as follows.

$$A_B = \begin{pmatrix} 2 & 3 & 1 & 4 & 5 & 2 & 6 & 5 & 4 & 8 \\ 3 & 2 & 1 & 5 & 6 & 1 & 6 & 5 & 6 & 9 \\ 2 & 4 & 1 & 3 & 7 & 3 & 5 & 7 & 7 & 6 \\ 4 & 3 & 2 & 1 & 3 & 5 & 3 & 3 & 5 & 7 \\ 1 & 3 & 2 & 5 & 6 & 5 & 6 & 7 & 5 & 8 \\ 2 & 1 & 3 & 7 & 6 & 5 & 5 & 6 & 5 & 7 \\ 2 & 3 & 1 & 3 & 4 & 6 & 6 & 5 & 6 & 8 \end{pmatrix}$$

The worst matrix is as follows.

$$A_W = \begin{pmatrix} 6 & 5 & 8 & 5 & 7 & 7 & 4 & 2 & 3 & 1 \\ 8 & 6 & 7 & 4 & 5 & 8 & 4 & 3 & 3 & 1 \\ 6 & 7 & 8 & 4 & 3 & 5 & 1 & 2 & 4 & 2 \\ 8 & 7 & 7 & 8 & 4 & 6 & 2 & 3 & 5 & 1 \\ 8 & 7 & 7 & 5 & 3 & 3 & 2 & 5 & 1 & 2 \\ 6 & 8 & 6 & 4 & 3 & 5 & 4 & 3 & 4 & 1 \\ 6 & 7 & 8 & 6 & 5 & 7 & 4 & 4 & 1 & 2 \end{pmatrix}$$

A comparison of the weights obtained by applying the different methods is shown in Table 3.

The combined indicators show that the actual operating profile of the retailers focus on contracted tariff revenue and contracted electricity. This is in line with the way in which retailers are now developing. However, the importance of historical electricity consumption volatility has gained some traction. This suggests that the volatility of electricity consumption by actual customers has an important impact on the operations of retailers.

The evaluation matrix of the cloud model base data indicators is constructed based on the combined indicator weights. The expectation, entropy and super entropy of the cloud of each user are calculated to obtain the cloud drops of each part. The results of the customer value assessment level distribution are obtained as shown in Table 4.

Table 3. Comparison of the results of each weighting

Indicators	Weight		
	Combined weights	Bayesian BWM	Inverse entropy rights
Contracted tariffs	0.138	0.149	0.092
Contracted electricity	0.144	0.140	0.103
Contracted revenue	0.172	0.167	0.103
Delinquent fees	0.103	0.101	0.101
Delinquent payment time	0.077	0.079	0.097
Historical volatility of electricity consumption	0.112	0.112	0.100
Historical growth rate of electricity consumption	0.071	0.069	0.102
Frequency of default electricity use	0.069	0.068	0.100
Percentage of deviation assessment electricity	0.069	0.068	0.102
Green Certificate Purchase fees	0.046	0.046	0.100

Table 4. Level distribution results of electricity customer value assessment

Customers	Distribution characteristics of assessment results
K1	(0.0658,0.615,0.008)
K2	(0.0332,0.02,0.012)
K3	(0.0498,0.0618,0.007)
K4	(0.0564,0.0624,0.09)
K5	(0.0465,0.0397,0.01)
K6	(0.048,0.0584,0.012)
K7	(0.0351,0.335,0.006)
K8	(0.0429,0.324,0.07)
K9	(0.0391,0.0399,0.08)
K10	(0.0312,0.292,0.07)

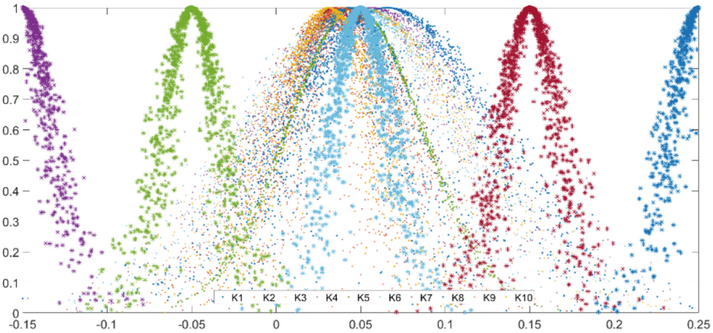

Fig. 1. Evaluation Level Cloud

The evaluation level cloud is shown in Fig. 1.

The value evaluation objects in this paper include industry (K1), technology industry (K2), building materials (K3), renewable energy (K4), metallurgy (K5), aluminium and silicon (K6), coal and chemical (K7), chemical (K8), new materials (K9) and power generation (K10). The cloud model results show that all customers are currently in the medium range. They can be divided into three categories, the first with a good tendency, mainly K1 and K4. The second with a medium tendency, mainly K3, K6, K5 and K8; and the last with a relatively low tendency, mainly K9, K7, K2 and K10.

As can be seen from the combined indicators and the actual data from the users, the main difference between these three user groups is the variability in user contract prices, contracted electricity, contracted revenue and historical electricity consumption volatility. The first group of customers has relatively high contract revenue and low historical volatility. The second group of users has slightly lower returns compared to the first group of users and the first group of users, but with some increased volatility. This results in a further increase in the final deviation assessment of electricity for the second group of users as well. The third group of customers is relatively more volatile and has a relatively low return, and some customers also show negative growth in electricity consumption.

Therefore, different strategies have to be developed for different customers. Firstly, it is important to make clear whether the choice is economic efficiency or load stability when selecting the customer. According to the load characteristics, on the original pricing mechanism, consider the economic and security issues arising from load volatility and develop a composite tariff package. Secondly, the process of screening customers according to their economy, safety and environmental friendliness also assists in enhancing their value. Customers are provided with relative differentiation, such as energy efficiency services, to improve the stability of their electricity consumption. Finally, electricity sales companies also take into account their environmental factors when considering the selection of customers to ensure their sustainability.

5 Conclusions

This paper develops a system for evaluating the value of electricity customers. We combine the subjective model Bayesian BWM and the objective assessment model inverse entropy weight method to evaluate customers. In order to ensure the scientific and reasonable description of the objective indicators, after discussion with experts, the indicators are scored objectively. A subjective evaluation index system is constructed and subjective weights are obtained. Finally, combining these two approaches, the weights of each indicator are reasonably allocated. Finally, the multi-dimensional cloud model is applied to classify the value of different customers. Through arithmetic examples, the value of different types of customers is verified, and the characteristics of different customers are described and rationalised. With the continuous promotion of the electricity market, the electricity sales side is gradually liberalised. Retailers must first select high quality customers and ensure customer quality. Secondly, they should develop differentiated services for different customers to improve the quality of services, attracting more customers and achieving sustainable development.

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