Research and Analysis of Power Outage Dispatch Control System Based on Customer Zero-Blackout Awareness

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Abstract. The paper deeply analyzes the sensitivity of customer blackout perception and the user perception model. The K-Means clustering algorithm is used for clustering. By analyzing and summarizing the user's perception of the blackout event, the user is divided into perceptions. By constructing the user perception model, the user perception classification of fault events is realized for the first time, and the decision basis for personalized active services is provided. The user perception model is of great significance to the customer service business application. Based on the perception segmentation result, the user can be provided with personalized and active services. Finally, the paper proposes to establish a power outage management system with no power outage, aiming to improve the service quality of current power customers.

1. Introduction
Customer demand is the starting point for all service activities. In recent years, the power supply bureau's survey report on the satisfaction of power customers has revealed that the customer's electricity demand is more concerned with the impact of power outages on customer value, in addition to the power outage time and number of power outages that we have previously recognized. In order to reduce the customer's unsatisfactory power outage perception, further optimize and improve the power supply enterprise power outage management mode. The power supply bureau began to conduct a questionnaire survey on the customers who use electricity to learn more about the customer's perception of power outage management. In order to ensure the rationality and operability of this research, the power supply company conducted a survey on commercial, agricultural, and residential users to gain an in-depth understanding of the impact of power outages on customers and the need for customers to power outages. In addition, in order to further optimize the customer service quality, this paper proposes a working idea based on user perception analysis to optimize customer service level. The purpose of this paper is to summarize and analyze the user's perception of the blackout event, and divide the user's perception. When a failure occurs, the result can be divided based on the perception to provide a personalized service for the user. It is of great significance to improve the quality of customer service center's active service and reduce the risk of customer complaints.

2. User Perceptual Clustering Model Construction
Customer classification based on the perception of fault events, select fault repair, business consultation, opinions, suggestions, customer reminders, praises, complaints, report work order data and fault handling data, based on the fault repair user's phone, repair time, repair completed Time, in the work
order data, statistically analyze the total number of work orders generated by the user for each fault event, the average interval of multiple calls, and the number of complaints generated, using a clustering algorithm based on the fault to repair the user's fault event. The degree of perception is classified into high-aware users, medium-aware users, and low-sensing users. The higher the perception, the higher the sensitivity of the user to the blackout event and the lower tolerance. Synthesizing historical data, taking the highest perceived performance of the user in the historical failure event as the final perception of the user.

2.1. Cluster Analysis Algorithm

(1) Basic ideas. Initially, k cluster centers are randomly given, and the sample points to be classified are divided into clusters according to the nearest neighbor principle, and then the centroid of each cluster is recalculated according to the averaging method to determine a new cluster core. Iterate until the distance of the cluster heart is smaller than a given value [1]. The specific data preprocessing process is shown in Figure 1.

![Data preprocessing process](image)

Figure 1. Data preprocessing process

(2) Implementation steps. 1) Find k cluster centers [2] for the points to be clustered. Specify the number k of clusters and randomly select k initial center points \( O_{1}, O_{2}, \ldots, O_{k} \) in all cases. 2) Calculate the distance from each point to the cluster center, cluster each point into the cluster closest to the point, classify according to the nearest distance principle, and calculate each sample data point to the initial center point of k classes. The Euclidean distance, and all samples are assigned according to the principle of the nearest distance from the k center points to form the k class. The Euclidean distance formula from the sample point to the initial center point of the class is:

\[
EUCLID[(O_{i}, T_{i}), (O_{k}, T_{k})] = \sqrt{(O_{i} - O_{k})^2 + (T_{i} - T_{k})^2}
\]  

\( (O_{i}, T_{i}) \) Is the initial center point of the selected k classes, and \( (O_{i}, T_{i}) \) is the sample point. Determine the minimum distance to which type of initial center point the sample point is, and classify this sample into this class.

3) Calculate the coordinate average of all points in each cluster and use this average as the new cluster center. Repeat steps 2) and 3) until the cluster center no longer performs large-scale movement or the number of clusters reaches the required level. The mean values of the k variables in each category are
calculated in turn, and the mean points are used as the center points of the k categories. Re-determine the class center point \( (C_k, T_k) \) and calculate the formula as:

\[
C_k = \left( \frac{\sum_{i=1}^{n} C_i}{n} \right)
\]

\[
T_k = \left( \frac{\sum_{i=1}^{n} T_i}{n} \right)
\]

\( (C_k, T_k) \) is the new class center point, and \( n \) is the number of sample points in each category. To set termination clustering, the following principles must be followed: A. When the current number of iterations is equal to the specified number of iterations, the clustering is terminated; B. When the newly determined class center point is less than the specified amount from the center of the last class, the maximum offset is less than the specified amount. Stop clustering. When any of the number of iterations and the class center offset degree is satisfied, the clustering is ended. If the above two conditions are not satisfied, the steps 2) and 3) are repeatedly performed.

2.2. User Perceptual Model Construction

(1) Data preprocessing. 1) Linked data. The raw data for the two-year work order data and troubleshooting table data, the type of ticket amount for each of the user occurs during this time period associated based on user phone numbers fault repair work order, fault repair processing time, fault repair completion time and more than The average interval between calls made by the user, where the total number of work orders generated by the user is the number of times the user makes a call. The data table is the source data for user perception analysis; the data fields are user phone number (CALLING_NO), administrative area code (AREA), number of user calls (ORDER_NUM), average time interval for multiple calls (AVG_TIME), and complaint ticket Number of times (CONSULT_NUM).

2) Eliminate outliers. The user perception analysis source data is data in which the user telephone number (CALLING_NO) is "12345" or "PRIVATE".

3) Screening data. The data source is the data after the outliers are eliminated: A. The user A who screened the complaint ticket (CONSULT_NUM>0) is marked as high-aware user A; B. the number of users who dialled the number of calls (ORDER_NUM=1) is 1 for low-aware user B; C. A complaint work order (CONSULT_NUM=0) is 0, and the number of times the user dials the number of calls (ORDER_NUM>1) greater than 1 is used for clustering model analysis to model the data.

4) Descriptive statistics. The data source is modelling data: the number of calls made by the user (ORDER_NUM) and the average interval of multiple calls (AVG_TIME) are described and counted. The variables are sorted in ascending order and the cumulative frequency of the two variables is analysed [3].

(2) Data selection and parameter setting of model construction. 1) Determine the entry model data. A. Determine the number of calls made by users entering the model analysis (ORDER_NUM). The minimum number of times a user makes a call (ORDER_NUM) is \( X_1=2 \). The maximum value needs to be selected according to the frequency cumulative percentage. The selected frequency cumulative percentage is less than \( X_2 \) and is closest to the corresponding ORDER_NUM value at \( X_2 \). The initial value of \( X_2 \) is set to 99.85%, incrementing by 0.01% for each correction, and the range is set between (99.85% and 99.90%). B. Determine the range of the average time interval (AVG_TIME) of multiple calls made to enter the model analysis. The minimum interval and maximum value of the average interval (AVG_TIME) of multiple calls must be selected according to the cumulative percentage of frequencies. The minimum value of the selected frequency is less than 1% and is closest to the corresponding AVG_TIME value at \( Y_1 \). The initial value of \( Y_1 \) is set to 98%, incrementing by 0.1% for each correction, and the range is set between (98.0% and 99.0%). C.
Filter the data \( P \) that matches the number of times the user makes a call (ORDER_NUM) and the average interval of multiple calls (AVG_TIME) enters the K-Means model analysis.

2) Data processing that does not enter the model analysis. The non-entry model data \( Q=(C–P) \) is defined as the medium-aware user \( Q \).

3) K-Means clustering algorithm. A. Model parameter setting: the number of clusters is 2, the number of iterations is 40, and the degree of class center point offset is 0. B. Model input fields: administrative area code (AREA), user phone number (CALLING_NO), number of user calls (ORDER_NUM), average time interval for multiple calls (AVG_TIME); model output field: administrative area code (AREA), User phone number (CALLING_NO), number of user calls (ORDER_NUM), average time interval for multiple calls (AVG_TIME), user perception level (CLASS_EXP); analysis variable: number of user calls (ORDER_NUM) marked 0, multiple times The average interval for making calls (AVG_TIME) is marked as \( T \); the tag variable: user phone number (CALLING_NO).

\[ O_k \]  

1) Specify the number of clusters (\( k=2 \)). 2) Randomly select 2 initial center points, \( (O_1, T_1), (O_2, T_2) \), in all cases. 3) Classification according to the nearest distance principle. Calculate the Euclidean distance from each sample data point to the initial center point of the 2 classes, and assign all samples according to the principle of the closest distance from the 2 center points to form 2 categories. The Euclidean distance from the sample point to the initial center point of the class is given by equation (1). 4) Re-determine 2 class center points. The average of the two variables in each category is calculated in turn, with the mean point as the center point of the two classes. Re-determine the class center point \( (C_1, T_1) \), and calculate the formula with reference to formulas (2) and (3). 5) Set the conditions for terminating the cluster. A. The number of iterations is 40. When the current number of iterations is equal to the specified number of iterations, the clustering is terminated. B. The class center point offset degree is 0, and the newly determined class center point stops clustering when the maximum offset from the center of the last class is less than the specified amount. If any of the above two conditions is satisfied, the clustering [4] is ended. If the above two conditions are not satisfied, the process returns to step 3). 6) Output the final class center point, the class to which each sample belongs, the variance analysis table, and analyze the final output result. 7) Model verification. A. Whether the final class center point can distinguish categories. Judgment criteria: number of calls made by users of type 1 (ORDER_NUM) > number of calls made by type 2 users (ORDER_NUM), and average interval of calls made by multiple types of users (AVG_TIME) < average time interval for multiple types of calls by type 2 users (AVG_TIME). The result is that the category can be distinguished, and the type 1 perception is > class 2 perception, that is, the type 1 user is a high-aware user, and the type 2 user is a medium-aware user (a type 1 user and a class 2 user are interchangeable). B. Whether the variance analysis variable is significant. The number of calls made by users (ORDER_NUM) and the average interval of multiple calls (AVG_TIME) are less than 0.05, indicating that the model works well. 8) Model judgment. When the conditions of A and B in step 7) are satisfied at the same time, the class of each sample output by the model is accepted, and the medium-aware user \( P_1 \) and the high-sensing user \( P_2 \) are obtained; if any of the conditions A and B in step 7) are not satisfied, the process returns to the step. 1) Determine the process of entering the model data, adjust the parameters \( X_2, Y_2 \), re-select the data into the model analysis, and repeat the K-Means algorithm process [5].

3. Application examples

Based on a province’s fault repair, business consultation, opinions, suggestions, customer reminders, praises, complaints, report work order data and fault handling data, statistical analysis of the total number of work orders generated by the user for each fault event, multiple calls The average interval duration and the number of complaints generated are used as source data for user perception analysis. K-Means clustering algorithm is used to divide the user’s perception, and the provincial (city) power customer perception is divided into three categories: high, medium and low. Statistics and comparison of the perceived user distribution in each region (prefecture, district, county) the business personnel
carry out active services according to the user perception category. The data from September to November 2018 was analyzed by the user perception analysis model (see Table 1).

Table 1. Initial data analysis

| month     | Number of complaints occurred | No complaints occurred | The number of users dialed 1 | Total number of users |
|-----------|-------------------------------|------------------------|-----------------------------|-----------------------|
| 2018.9    | 5945                          | 92985                  | 98930                       | 1084254              | 1183184              |
| 2018.10   | 5959                          | 95459                  | 101418                      | 1120623              | 1222041              |
| 2018.11   | 5963                          | 97956                  | 103919                      | 1157189              | 1261108              |

The initial data is divided into perceptual users by K-Means clustering algorithm. The perceived user situation in September, October and November 2018 is shown in Figure 2.

Figure 2. User perception distribution of a province from September to November 2018

Through initial data analysis and the distribution of perceived users in a province for 3 months, it can be seen that about 90% of users in the province's perceived users are low-aware users, and about 10% of users are high-sensing and medium-sensing users. By mining the model results and combining the detailed information of the perceptual users, the customer service personnel can provide personalized and proactive services to different perceptual users in a targeted manner, thereby reducing the number of perceptual users, improving the proactive service quality of the customer service center, and reducing the customer's risk of complaints.

4. Customer zero blackout sensing power outage management system establishment

4.1. Establishing the sensitivity factor of the customer's power outage period

Due to the different customer's electricity habits, their sensitivity coefficients are different in different production periods. For industrial and commercial customers, the production of their products in the light, peak season and their daily production and use of electricity is the main factor determining the sensitivity factor of the blackout period. We set different proportions for the above two factors and use the weighted method to calculate the sensitivity factor of the customer's power outage period according to the characteristics of different customers. Sensitivity coefficient during power outage period, commercial=production season sensitivity coefficient×20%+period sensitivity coefficient×80%. For residential customers, only the daily electricity consumption is the main factor for the analysis of the sensitivity of the blackout period.
4.2. Establishing the social impact sensitivity coefficient of blackouts
A power outage will result in a loss of customer value. It will also have a certain impact on society. Therefore, we have established a social impact sensitivity coefficient. Based on the unique characteristics of customers, we describe the sensitivity of customer blackouts to social impacts. Similarly, we also use 5 levels for division. From party and government organs, hospitals, schools, residents to commercial users, there are 10 categories, and the social impact sensitivity coefficient score ranges from 4.5 to 2 points.

4.3. Establish special factors additional coefficient
Due to the wide variety of customers and their respective characteristics, in addition to the above perceptions, there are still many specialties in the customer's perception of power outages. For example, power outages will cause significant loss of the economy, major safety hazards, or power outages to local pillar enterprises. At the same time, we will also need to consider the complexities of industrial intensity (number of customers). Therefore, we have designed a special figure 3 customer power outage demand delivery platform additional coefficient, to modify and supplement the customer blackout sensitivity coefficient, the set unit value is 0.1, can be accumulated according to the actual situation.

![Figure 3. Customer power outage demand delivery platform](image)

4.4. Establish comprehensive power outage management decision
After proposing the initial blackout plan, we will send a "Customer blackout Consultation Letter" to the user. If the customer has objection to the power outage arrangement, both parties can negotiate the power outage plan [6]. Additional measures for power outage management. The power outage plan developed through the power outage management decision process meets the needs of most of the more sensitive customers, but it will inevitably affect a small number of customers. To this end, we have also developed a series of supplementary measures to minimize customer satisfactory factor. Centralized maintenance management methods. When conditions permit, the same power outage line during the same power outage period, even for the same interval or the same voltage level, the equipment is considered to be integrated, and a number of maintenance operations are concentrated to reduce the number of repeated power outages. Actively promote live working [7]. In the distribution network expansion, technical transformation, infrastructure, repair and other projects, priority is given to live working, and active
operation is actively promoted to minimize the impact of power outages [8]. Standardize the power supply work. Strictly follow the principle of "can turn to turn". For the line with the power supply condition, the power supply is turned on to ensure the power supply of the customer with higher blackout sensitivity coefficient. Provide on-board generator service [9]. For the important customers who can't take care of the power outage plan, we can guarantee the power supply plan, or provide the on-board generator power supply service, and make every effort to ensure the power supply of individual important customers during the power outage [10].

5. Conclusion
The active service scenario based on the user perception of the fault event provides real-time display of the real-time fault blackout area of the selected district and county, the distribution of the user's perceived situation and the detailed information, and provides reference information for realizing the user's active service. The user is divided into perceptions. When the blackout occurs, the user is provided with personalized and active services based on the results of perceptual division, which improves the active service quality of the customer service center and reduces the risk of customer complaints. By applying an active service scenario based on the user perception of the fault event, the user perception classification of the fault event is implemented for the first time, and the decision basis for the personalized active service is provided.

Acknowledgments
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