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OPTIMIZATION METHOD OF CALIBRATION CYCLE BASED ON STATE EVALUATION RESULTS OF ELECTRIC ENERGY METERS

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Abstract. In order to solve the problems of heavy workload, weak planning, and repetitive maintenance in the periodic rotation of smart energy meters, the author proposes a verification cycle optimization method based on the evaluation results of energy meter status. This method first obtains data on six indicators of smart energy meters: regional factors, reliability, full event, abnormal metering events, battery overload, and clock battery undervoltage; Subsequently, on the one hand, the coefficient of variation assignment method is used to obtain the status score of each electricity meter, and on the other hand, these six indicator data are used as input data, and the K means clustering algorithm is used to classify and obtain the corresponding categories. Finally, the two algorithms are combined to obtain a new method for evaluating the status of smart energy meters, and the final evaluation result is output. The experimental results indicate that: The number of electricity meters scored below 80 points obtained by this method accounts for 22.08% of the total number of electricity meters, while electricity meters scored above 80 points account for 77.93% of the total number of electricity meters. This indicates that this method is in line with the actual situation and objective laws. Constructing a state evaluation model for electric energy meters, using historical data and on-site calibration data as state variables, analyzing the annual operational quality of electric energy meters, and providing reference basis for adjusting the calibration cycle of electric energy meters.

Key words: State evaluation methods, K means, Coefficient of variation method, Electricity meter, Error, Verification cycle

1. Introduction. Electricity meters are a bridge between power supply enterprises and electricity customers for billing and settlement, and an important measuring tool for people's daily electricity consumption [1]. With the rapid development of smart grids, smart energy meters are widely used due to their powerful functions, high measurement accuracy and sensitivity. The quality of their operation directly affects the economic benefits of power grid enterprises and the vital interests of users [2]. With the application of new technologies and methods, the level of power management is also constantly improving. Improving the lean management level of electricity metering and rational allocation of human, financial and resources have become important needs in the new era. The following uses big data analysis methods to explore and study the optimization of the re inspection cycle of electricity meters [3]. Mining data on electricity meter calibration and resource loss, based on discrete degree analysis and EUAC (equivalent comprehensive cost) analysis method, provides reference for optimizing calibration cycle, improving management level, assisting departmental decision-making, and provides ideas for wider applications [4].

Create a state evaluation model to evaluate the status of electricity meters. This model is based on the current and historical data of the electricity meter, and applies membership function to establish and solve fuzzy technology to design a state quantity evaluation model. It combines entropy weight method to objectively evaluate the operation quality of the electricity meter [5]. The state evaluation model includes the selection of state variables, normalization of state variables, evaluation of state components, and overall state evaluation of smart energy meters.

With the improvement of the production level of smart energy meters, the drawbacks of the traditional one size fits all disassembly and calibration method for periodic calibration of energy meters have become increasingly apparent [6]. In order to solve the problem of dismantling and re calibrating smart energy meters

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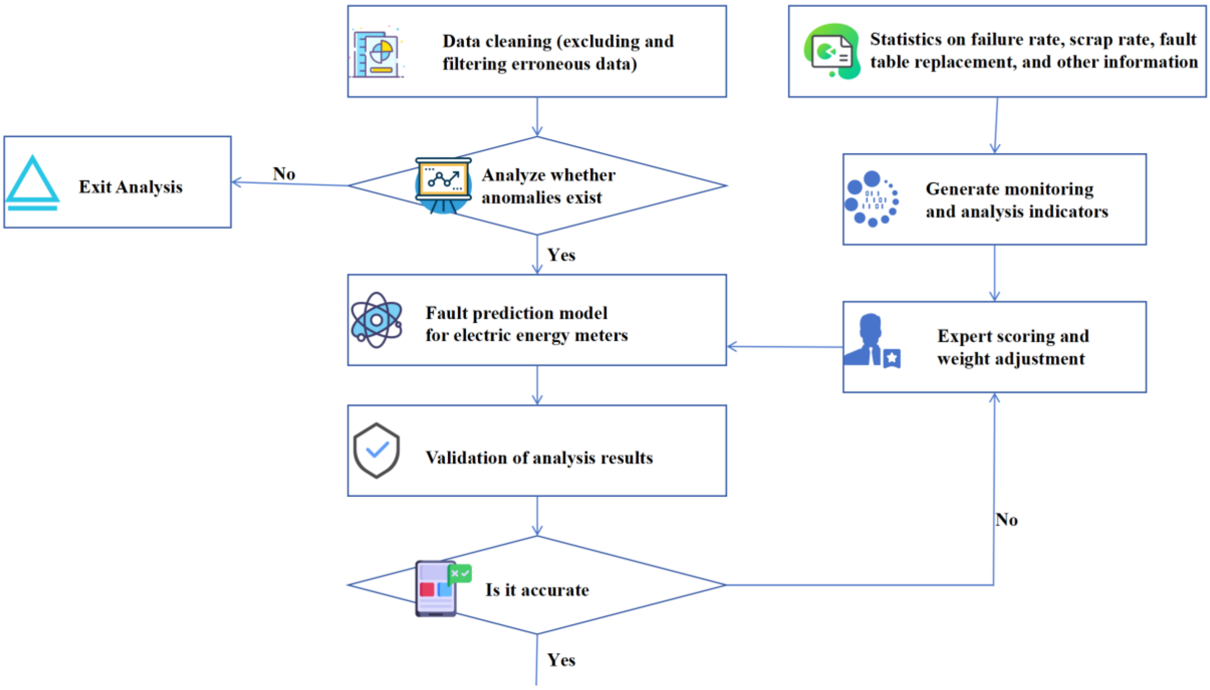

Fig. 1.1: Energy meter status evaluation

within an eight year calibration cycle, the author conducted a research on quality supervision and evaluation of energy meters based on full life cycle testing data. Based on the first inspection data of the electricity meter, big data analysis technology is used to assess the risk of the electricity meter; Conduct periodic verification through on-site verification based on risk screening results; Analyze the calibration error of the electric energy meter based on the first inspection and on-site verification data; Establish a state evaluation model to evaluate the operational quality of electric energy meters, providing a reference basis for extending the cycle of electric energy meters. As shown in Figure 1.1.

2. Literature Review. As a measuring and recording device for power supply and consumption, the operation status of smart energy meters not only directly affects the development and operational efficiency of power grid companies, but also affects the fairness and safety of user electricity consumption [7]. At present, smart energy meters have been widely used in important links such as power generation, transmission, distribution, and consumption. As a key component of the smart grid, smart energy meters play an important role in real-time measurement, load control, and response to power demand in power grid companies [8]. The power grid company vigorously promotes the comprehensive construction of big data technology in the smart grid, and various emerging technologies are widely applied in the power industry. Among them, the establishment of databases such as substation data, distribution data, electricity consumption data, and marketing data is also becoming increasingly perfect, providing a good research environment for the research and development of big data technology [9].

At present, Power Grid Co., Ltd. has completed the construction and operation of the corresponding data management platform, gradually leveraging the role of big data technology in electricity data management and analysis [10]. However, current data analysis techniques cannot fully utilize smart energy meter data to achieve ideal analysis results, and continuous research and practice are still needed. Therefore, using big data technology to analyze electricity meter data is the development trend of future smart grid technology, and the increasingly perfect big data platform and corresponding technology make it have great potential for development. Pazderin,

A. V. used a state estimation method based on the direct measurement data of EE in watt hours (volt ampere reactive hours) provided by an electricity meter to determine the EE flow rate. EFP solutions are essential for a wide range of applications, including instrument data validation, zero imbalance EE billing, and non-technical EE loss checks [11]. Singh, M. provides a detailed description of some of the challenges faced by electricity consumption data, including saving large amounts of data, deleting, manipulating, and adjusting data. Blockchain is a promising technology that can use encryption algorithms to address issues of data integrity and confidentiality [12]. Dakyen, M. M. et al. used big data technology to analyze the electricity consumption data of smart energy meters, in order to better evaluate the status of smart energy meters [13]. Jie YANG has modularized various data, evaluation index systems, and evaluation methods for the current state evaluation indicators of electric energy metering devices, aiming to address the uncertainty of the evaluation indicators and the inconsistency of the results of various evaluation methods. He has dynamically built an electric energy metering device state evaluation system, which provides a comprehensive description of the state indicators, but does not involve the detailed differences in the state indicators of each component of the electric energy metering device [14]. The multi-objective comprehensive evaluation method for smart meter suppliers based on grey correlation degree described in Zhu, X, while retaining the advantages of the multi-objective comprehensive evaluation model, solves the problems of cumbersome indicators and strong subjectivity in traditional smart meter supplier comprehensive evaluation [15]. But this method only analyzes the overall batch of electricity meters, ignoring the evaluation of individual electricity meter states.

A new method for evaluating the status of smart energy meters is proposed by combining the coefficient of variation assignment method and K-means clustering algorithm. The evaluation results of smart energy meters are obtained by analyzing six indicators: regional impact index, all events, measurement anomalies, meter overload, and clock battery undervoltage. The rationality of the method is analyzed based on the results.

3. Method.

3.1. Design Concept. Firstly, based on the previous statistical analysis and research, six indicators that have a significant impact on the evaluation of the status of smart energy meters were identified, namely meter reliability, regional factors, all events, measurement anomalies, meter overload, and clock battery undervoltage. Then, these indicators were analyzed using two methods: One was weighted using the coefficient of variation method, by analyzing the impact of different indicators on the operating status of electricity meters, assign corresponding weights to each indicator, and finally reflect the operating status of each electricity meter in the form of a score; Another approach is to use these indicators as features of the electricity meter, treating the meter as points in space, where these indicators are the coordinates of the points. Clustering methods are used to classify these points and obtain different evaluation states of the electricity meter [16]. Combine the evaluation results of these two methods to obtain the final evaluation result of the operating status of the electricity meter. The process is shown in Figure 3.1.

3.2. Indicator data.

1) Reliability of electric energy meters. The reliability calculation formula for electric energy meters is:

$$M_r = 1 - \frac{\sum_1^t f(1)}{N} \tag{3.1}$$

In the formula: M_r is the reliability index of the electric energy meter; $f(i)$ is the number of faulty meters in the i-th month of the current batch of electricity meters; N is the total number of electricity meters in the current batch; t is the current month.

2) Regional factors. The formula for calculating regional factor indicators is:

$$M_t = 1 + \frac{H_x}{H} \times lg(\frac{H_x}{H} \cdot \frac{J}{J_x}) \tag{3.2}$$

In the formula: M_t is the regional factor indicator; H_x is the number of electricity meters installed in the x-th city; J_x is the total number of installed energy meters; J is the number of faulty energy meters in the x-th city; is the total number of faulty energy meters.

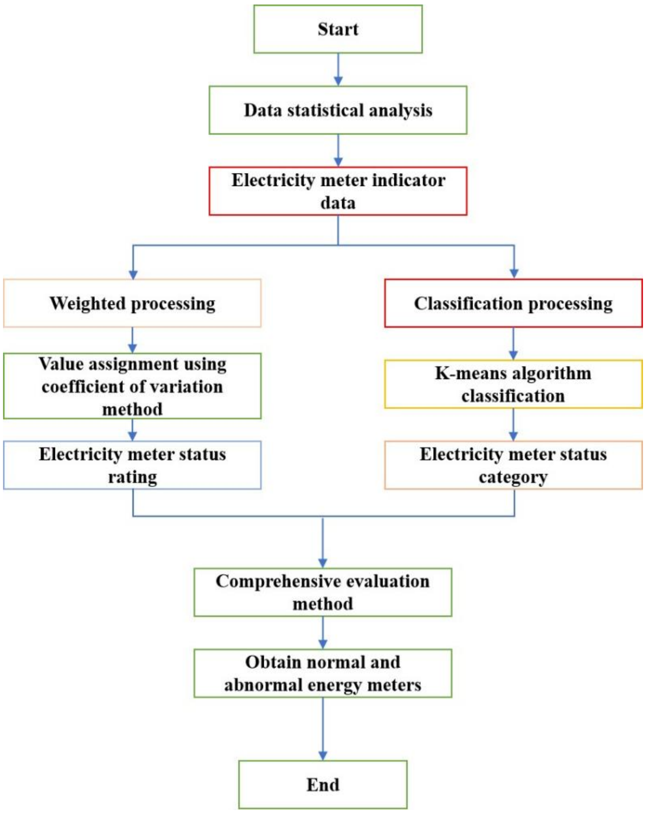

Fig. 3.1: Design process of state evaluation method

3) Full event. The calculation formula for all event indicators is:

$$M_q = \begin{cases} 100 \times \sum_{i=1}^{11} P(A_2|C_i), \sum_{i=1}^{11} P(A_2|C_i \leqslant 1) \\ 100, \sum_{i=1}^{11} P(A_2|C_i > 1) \end{cases} \tag{3.3}$$

In the formula, M_q represents the overall event indicator; A_2 indicates that the calibration result of the electric energy meter is faulty; C_i $(i = 1, 2, \cdots, 11)$ refers to 11 events, including meter shutdown, meter runaway, meter deviation, meter reverse connection, meter time deviation, meter power outage frequency change, meter phase failure frequency, magnetic field anomaly, meter transformer rate change, cover opening recording, and time synchronization; $P(A_2|C_i)$ represents the probability of C_i occurring under A_2 conditions.

4) Abnormal measurement. The formula for calculating abnormal measurement indicators is:

$$M_a = \begin{cases} 100 \times (\sum_{i=1}^{6} P(A_2|B_j) + \sum_{k=1}^{5} y_k), \sum_{i=1}^{6} P(A_2|B_j) + \sum_{k=1}^{5} y_k \leqslant 1 \\ 100, \sum_{i=1}^{6} P(A_2|B_j) + \sum_{k=1}^{5} y_k > 1 \end{cases} \tag{3.4}$$

In the formula, M_a represents the measurement anomaly indicator; $B_j (j = 1, 2, \cdots, 6)$ refers to uneven energy representation, meter flying, meter reversing, meter stopping, abnormal reverse power and clock; $y_k (k = 1, 2, \cdots, 5)$ represents the correlation between voltage exceeding limits, voltage loss, current overcurrent, voltage disconnection, and reverse flow events and anomalies; $P(A_2|B_j)$ represents the probability of A_2 occurring under B_j conditions.

5) The electricity meter is overloaded. The formula for calculating the overload index of an electric energy meter is:

$$M_1 = \begin{cases} 100K_w \times log_2(\frac{W_0}{W_N}), K_W > 0 \\ 0, K_W = 0 \end{cases} \tag{3.5}$$

In the formula: M_1 is the overload indicator of the electric energy meter; W_N is the amount of electricity measured within 24 hours of normal rated operation of the energy meter; K_W is the proportion of days in which the daily electricity consumption exceeds the standard metering electricity of the electricity meter within 6 months; W_0 is the average daily electricity consumption of the portion of electricity consumption that exceeds the standard measurement of the electricity meter within 6 months.

6) Clock battery undervoltage. The formula for calculating the undervoltage index of the clock battery is:

$$M_c = \frac{100 - 100e^{-x}}{1 + e^{-z}} \tag{3.6}$$

In the formula, M_c represents the undervoltage indicator of the clock battery; Z is the number of clock undervoltages that occur within 6 months.

3.3. Principle of coefficient of variation method. The coefficient of variation assignment method directly utilizes the information contained in various indicators to calculate the weights of the indicators, and is an objective weighting method [17]. Based on the impact of changes in indicator data on the evaluation results of electricity meters, further analyze the importance of this indicator in the evaluation of results [18]. Reflected in numerical terms, the greater the degree of variation of the indicator data, the greater the assigned value to the indicator.

The coefficient of variation chosen by the author is the standard deviation, and its main calculation steps are as follows.

1). Assuming there are m objects to be evaluated and a total of n evaluation indicators, the evaluation matrix X of the indicators can be expressed as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{3.7}$$

In the formula, x_{ab} represents the characteristic data of the $a(a = 1, 2, \cdots, n)$ evaluation indicator for the b (b=1,2, m) th evaluation object.

2). Calculate the average value $\overline{x_a}$ of the a-th indicator as follows:

$$\overline{x_a} = \frac{1}{m} \sum_{b=1}^{m} x_{ab} \tag{3.8}$$

3). Calculate the standard deviation σ_a of the a-th indicator as:

$$\sigma_a = \sqrt{\frac{1}{m} \sum_{b=1}^{m} (x_{ab} - \overline{x_a})^2} \tag{3.9}$$

4). Calculate the coefficient of variation for the a-th indicator as:

$$v_a = \frac{\sigma_a}{\overline{x_a}} \tag{3.10}$$

5). Normalize the obtained coefficient of variation and calculate the objective weight β_a of the a-th indicator as follows:

$$\beta_a = \frac{v_a}{\sum_{a=1}^{n} v_a} \tag{3.11}$$

3.4. K-means clustering principle. The core idea of the K means algorithm is to randomly select data from the dataset as the initial clustering center, and calculate the distance from other data points to these data points. These data points are divided into the closest clustering centers. After traversing all the data, the average value of each class of data is used as the new clustering center, and the above operation is repeated again until a certain threshold is met or a predetermined number of iterations are reached before stopping [19].

The specific steps of the K-means algorithm are mainly divided into the following steps:

1. Based on a known dataset, use k data points as the initial cluster center C, where these k data points are arbitrarily selected;
2. Calculate the Euclidean distance between data samples other than the cluster center and the cluster center;
3. Using Euclidean distance as the basis for judgment, divide the data samples into clusters belonging to the cluster center closest to them;
4. Calculate the mean of the data samples in each cluster and use it as the new cluster center for each cluster to calculate the sum of squared errors for this dataset;
5. Determine whether the total sum of squared errors of the entire dataset remains unchanged or fluctuates within a small range. If so, end the clustering and output the final clustering result; Otherwise, go back to step 2) and loop in the order of steps until the requirements are met or the set number of iterations is reached.

In practical calculations, all events, measurement anomalies, meter overload, and clock battery undervoltage are converted into indicator data of 1-100 using equations 3.3-3.6 to achieve unity of magnitude, and then clustering algorithm calculations are performed [20]. The Euclidean distance formula is:

$$D(z, E_p) = \sqrt{\sum_{q=1}^{Q} (z_q - E_{pq})^2} \tag{3.12}$$

In the formula: z is the data sample; E_p is the p-th cluster center; Q is the dimension of the data sample; z_q, E_{pq} is the qth feature of z and E_p.

4. Results and Discussion. Select the operating data of all dismantled and calibrated electricity meters in a certain area for the 6 months before the evaluation time, and analyze and process these data to obtain the indicator data for the evaluation of smart electricity meters, this includes the reliability of smart energy meters, regional factors, all events, metering anomalies, meter overload, and clock battery undervoltage. The reliability indicators and regional factors are obtained based on the data analysis of the entire province's electricity meters from installation to evaluation time, while the weights of each indicator are obtained using the coefficient of variation assignment method based on the average indicator data of each batch of electricity meters in each month throughout the year, including all events, measurement anomalies, meter overload, and clock battery undervoltage. And based on the data from the 6 months before the evaluation time, obtain the indicator data of the current status of each smart energy meter, and finally calculate the current operating status of each smart energy meter by combining reliability indicators and regional factors.

The state evaluation of smart energy meters is defined as:

$$R = (100 - w_1 M_q - w_2 M_q - w_3 M_q - w_4 M_q) \times M_r \times M_t \tag{4.1}$$

In the formula, R represents the evaluation result of each energy meter; $w_1 - w_4$ is its corresponding weight, obtained by the coefficient of variation assignment method.

The experimental case analysis is based on data from 12 batches of electricity meters evaluated in July 2021, each batch including disassembled and still running electricity meters. The weight of the indicators is calculated

Table 4.1: Energy meter status evaluation Table

Score	Number of electricity meters/piece	Proportion/%	Predicted number of faults/block	Predicted proportion of faults/%	Normal quantity/block in the predicted number of faults
0∼60	4250	5.15	808	29.22	0
60∼70	11050	13.34	877	31.67	0
70∼80	2967	3.59	342	12.34	0
80∼90	12867	15.55	526	18.94	19
90∼100	51587	62.37	235	7.83	198
amount	69854	100.00	2788	100.00	217

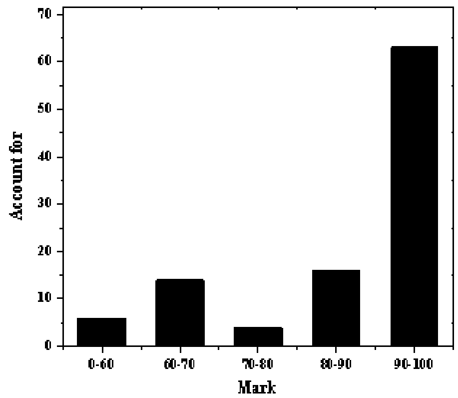

Fig. 4.1: Distribution of Energy Meter State Evaluation

based on the average monthly indicator data of the batch of electricity meters in 2021. As the dismantling of smart electricity meters requires a certain process and time, the quality of the evaluation results is evaluated based on the dismantling of the meters within 3 months after the evaluation results. The evaluation results are shown in Table 3.1, Figure 4.1, and Figure 4.2.

Table 4.1 shows the specific quantity of each score segment, where the number of faults is based on the number of fault tables obtained through disassembly and detection within three months after the current evaluation time point, and the normal number is based on the number of normal tables obtained through disassembly and detection within three months after the current evaluation time point. Figures 3.2 and 3.3 are visualizations of the distribution of all meter quantities and the distribution of fault meter quantities for the evaluation of the energy meter status in Table 4.1, respectively.

From Table 4.1 and Figure 4.1, it can be seen that 22.08% of the total number of electricity meters are scored below 80 points according to this method, and 77.93% are scored above 80 points. At the same time, it can be seen from Table 4.1 and Figure 4.2 that the number of faults in electricity meters scored below 80 points accounts for 73.26% of the total number of faulty electricity meters. This indicates that the method is in line with the actual situation and objective laws.

4.1. K-means algorithm analysis. This evaluation method considers smart energy meters as points in space, and considers the reliability, regional factors, all events, measurement anomalies, meter overload, and clock battery undervoltage as the coordinates of points in the space. These coordinates are used as inputs to the K-means algorithm, and points with similar distances can be clustered in the same area based on the distance between points to achieve classification results.

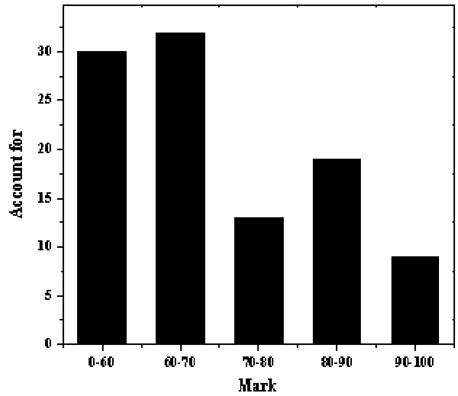

Fig. 4.2: Distribution of the number of faulty energy meters

Table 4.2: Energy meter status evaluation Table

Score	Number of electricity meters/piece	Proportion/%	number of faults/block	Fault proportion of faults/%	Normal quantity/block in the predicted number of faults
Class I	63905	77.26	798	28.18	215
Class II	207	0.26	12	0.35	0
Class III	867	1.06	62	2.23	1
Class IV	2437	2.96	291	10.47	0
Class V	15303	18.46	1625	58.77	0
total	82719	100.00	2788	100.00	216

Using the data from the smart electricity meter batch mentioned above for analysis, referring to the analysis results of the coefficient of variation method, based on data characteristics and the principle of facilitating result comparison and analysis, this method determines that the K-means clustering algorithm has 5 categories. The clustering results are shown in Table4.2, Figure 4.3, and Figure 4.4.

Table 4.2 shows the specific quantity of each score segment, where the number of faults is based on the number of fault Tables detected by dismantling within 3 months after the current evaluation time point, and the normal number is based on the number of normal Tables detected by dismantling within 3 months after the current evaluation time point. Figures 4.4 and 4.5 visualize the distribution of the number of all meters and the distribution of the number of faulty meters in the state classification of electricity meters in Table 4.2, respectively.

From Table 4.2 and Figure 4.5, it can be seen that Class I electricity meters have the most data, as the analysis includes both disassembled and still running smart electricity meters, so normal electricity meters account for the majority. Obviously, Class I should be considered as a normal energy meter category, while Class II-V should be considered as an abnormal energy meter category. The classification here is for comparison with the coefficient of variation method. According to the K-means clustering algorithm, 77.26% of energy meters are classified as normal energy meters, and 71.82% of actual faulty energy meters are included in the category of abnormal energy meters. The abnormal energy meters analyzed in the K-means algorithm's energy meter status evaluation include most of the actual faulty energy meters, which is consistent with the actual situation, indicating that the evaluation result has a certain degree of scientific and rationality.

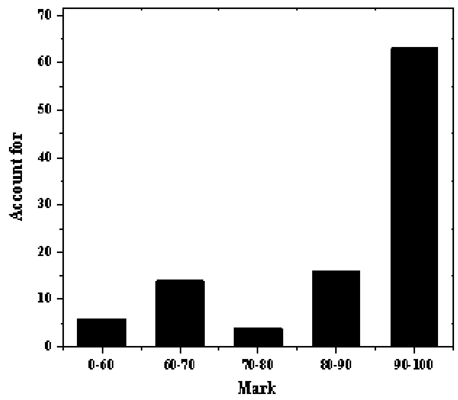

Fig. 4.3: K-means clustering distribution of all electricity meters

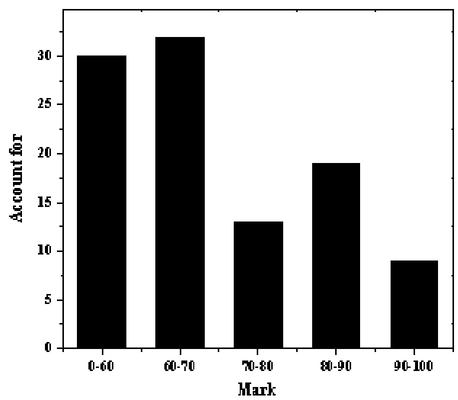

Fig. 4.4: K-means clustering distribution of fault Table

5. Conclusion. The author proposes a study on the optimization method of calibration cycle based on the evaluation results of electricity meter status, introduces the principles of coefficient of variation algorithm and K-means algorithm, and evaluates the status of electricity meters based on these two algorithms. After comparing the evaluation results of coefficient of variation method and K-means algorithm, combined with the characteristics of electricity meter evaluation parameters, a new state evaluation method is constructed by integrating the coefficient of variation method and K-means algorithm, prove its scientific and feasibility through data analysis, providing new ideas for the state evaluation of smart meters. This method has been recognized by the power supply company in practical experiments.

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REFERENCES

[1] Yan, R., Zheng, Y., Yu, N., & Liang, C. (2024). Multi-smart meter data encryption scheme basedon distributed differential privacy. Big Data Mining and Analytics, 7(1), 131-141.
[2] Jiang, T., Shen, Z., Jin, X., Zhang, R., Parisio, A., & Li, X., et al. (2023). Solution to coordination of transmission and distribution for renewable energy integration into power grids:an integrated flexibility market. Journal of Electric Power and Energy Systems, Chinese Society of Electrical Engineering, 9(2), 444-458.
[3] Naeemah, A. J., & Wong, K. Y. (2023). Selection methods of lean management tools: a review. International Journal of Productivity and Performance Management, 72(4), 1077-1110.
[4] Jie YANG, Xiaoshu CAO, Jun YAO, Zhewen KANG, Jianxia CHANG, & Yimin WANG. (2024). Geographical big data and data mining: a new opportunity for "water-energy-food" nexus analysis. Journal of Geography (English Edition), 34(2), 203-228.
[5] Zhang, J., Li, B., Peng, Q., & Gu, P. (2023). Product specification analysis for modular product design using big sales data. Chinese Journal of Mechanical Engineering: English Edition, 36(1), 19-33.
[6] Liao, Y., Weng, Y., Tan, C. W., & Rajagopal, R. (2022). Quick line outage identification in urban distribution grids via smart meters. CSEE Journal of Power and Energy Systems, 8(4), 1074-1086.
[7] Kong, F., Yin, S., Sun, C., Yang, C., Chen, H., & Liu, H. (2022). Design and optimization of a maglev electromagnetic ribo-electric hybrid energy converter for supplying power to intelligent sensing equipment. Sustainable Energy & Fuels, 6(3), 800-814.
[8] Ahmed, M., Khan, A., Ahmed, M., Tahir, M., Jeon, G., & Fortino, G., et al. (2022). Energy theft detection in smart grids:taxonomy,comparative analysis,challenges,and future research directions. Journal of Automation: English Edition, 9(4), 23.
[9] vorah. (2022). A comparison on pso optimized pid contro11er for inter area osci11ation contro1 in an interconnected power system. Technology and Economics of Smart Grids and Sustainable Energy, 7(1), 1-14.
[10] Bhaskar, U., Mishra, B., Yadav, N., & Sinha, P. (2023). Who uses deceptive impression management to succeed at job interviews? the role of ethical ideologies and work locus of control. International Journal of Manpower, 44(3), 453-469.
[11] Pazderin, A. V., Polyakov, I. D., & Samoylenko, V. O. (2022). Energy flow problem solution based on state estimation approaches and smart meter data. Global Energy Internet: English, 5(5), 551-563.
[12] Singh, M., Ahmed, S., & Sharma, S. (2022). Blockchain-based smart electricity measurement and monitoring system: a survey. i-Manager s Journal on Embedded Systems, 11(1), 12-16.
[13] Dakyen, M. M., Dagbasi, M., & Zdenefe, M. (2022). Energy models for cost-optimal analysis: development and calibration of residential reference building models for northern cyprus:. Indoor and Built Environment, 31(3), 657-681.
[14] Li, X., Hu, Y., Xue, B., Wang, Y., Zhang, Z., & Li, L., et al. (2022). State-of-health estimation for the lithium-ion battery based on gradient boosting decision tree with autonomous selection of excellent features. International Journal of Energy Research, 46(2), 1756-1765.
[15] Zhu, X., Cui, J., & Li, Y. (2023). Energy savings bottleneck diagnosis of cooling system based on integrated correlation analysis. The Canadian Journal of Chemical Engineering, 101(8), 4762-4770.
[16] Wang, C., Qin, D., Wen, Q., Zhou, T., Sun, L., & Wang, Y. (2022). Adaptive probabilistic load forecasting for individual buildings. iEnergy, 1(3), 341-350.
[17] Meng, F., & Tian, K. (2022). Interval type-2 fuzzy logic based radar task priority assignment method for detecting hypersonic-glide vehicles. Frontiers of Information Technology & Electronic Engineering, 23(3), 488-501.
[18] Kok, K., Paterakis, N. G., & Giraldo, J. S. (2022). Development, application, and evaluation of an online competitive simulation game for teaching electricity markets. Computer Applications in Engineering Education, 30(3), 759-778.
[19] Bennaceur, H., Almutairy, M., & Alhussain, N. (2023). Genetic algorithm combined with the k-means algorithm:a hybrid technique for unsupervised feature selection. Intelligent Automation and Soft Computing, 37(9), 2687-2706.
[20] Bai, R., Shi, Y., Yue, M., & Du, X. (2023). Hybrid model based on k-means++ algorithm, optimal similar day approach, and long short-term memory neural network for short-term photovoltaic power prediction. Global Energy Internet: English, 6(2), 184-196.

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