Research on Reliability Evaluation of Intelligent Energy Integrated Service Platform Based on Hierarchical Linear Model

Wen-Lin Xu[1(✉)], Xiao-xiao Liu[2], Chao Li[2], Zi-peng Hu[2], and Kai Liu[2]

[1] Marketing Department, State Grid Hunan Electric Power Co., Ltd., Changsha 410000, China
dsf2541521@163.com
[2] State Grid Hunan Integrated Energy Service Co., Ltd., Changsha 410000, China

Abstract. Intellectualization is a new form of energy services, which can accelerate the integration of different energy services, expand the scope of traditional energy services, and meet the various service requirements of users. In order to improve the use effect of the platform, the reliability evaluation method of the intelligent energy integrated service platform based on hierarchical linear model is studied. The hierarchical linear model is used for data mining and prediction of the intelligent energy integrated service platform, and the functional structure of the platform is optimized, so as to better improve the security of the platform and the utilization efficiency of the intelligent energy integrated service platform, so as to better meet the growing demand of smart energy services of users.

Keyword: Hierarchical linear model · Smart energy · Service platform

1 Introduction

The deep integration of Internet technologies such as the Internet of Things, big data and cloud computing with information technology and digital technology has brought about profound changes in the energy system. The deepening of electric power system reform and diversified market service demand further promote the transformation of energy enterprises into intelligent energy comprehensive service providers. The strategic goal of “three types and two networks” put forward by State Grid Corporation of China, as well as the strategic deployment of ubiquitous power Internet of Things, pose new challenges to power enterprises. The development of smart energy integrated services has become a growth point to improve energy efficiency, expand new business, and become an important development direction to promote competition and cooperation.

Many countries comprehensive service platform for intelligent energy research started earlier, the European focus on a variety of energy cooperation between collaborative optimization of complementary, energy system has more exploration, such as Germany's e-energy project is mainly to carry out the energy system and

S. Wang et al. (Eds.): IoTCare 2021, LNICST 414, pp. 136–153, 2022.
https://doi.org/10.1007/978-3-030-94185-7_10

communication between information system integration, including smart power, smart grid, smart consumer and smart energy storage four aspects; The typical integrated energy system (IES) development plan in the United States aims to increase the proportion of clean energy supply and utilization, and further improve the reliability and economy of the social energy supply system. Japan focuses on optimizing its energy mix and improving energy efficiency, while promoting the large-scale development of renewable energy. At present, China has also accelerated the research and application of comprehensive energy services. Traditional energy enterprises and market-oriented energy enterprises have set up their operations in transportation, medical care, airports, large industrial parks and communities to carry out research and application of platform construction and business model exploration.

At this stage, the smart energy integrated service platform collects business data and optimizes the platform structure framework, so as to better promote the construction of new energy. In order to ensure the data reliability of the smart energy integrated service platform, it does a good job in external data acquisition and management, and analyzes the platform data sharing service and data reliability mining, as well as the platform data operation reliability evaluation and detection [1]. In order to better build the energy big data sharing and operation service platform and ensure the safe and stable operation of the platform, it is necessary to realize the safe processing of the whole chain data with the support of data standardization management, so as to enhance the agile development ability of the intelligent energy integrated service platform and effectively improve the reliability evaluation effect of the intelligent energy integrated service platform [2].

2 Reliability Evaluation of Smart Energy Integrated Service Platform

2.1 Information Management of Smart Energy Integrated Service Platform

The reliability evaluation of intelligent energy integrated service platform is the core content of reliability engineering. According to the structural relationship and failure data of each component of intelligent energy integrated service platform, the level of existing platform reliability is quantitatively estimated and evaluated [3]. According to the different evaluation objects, the reliability evaluation methods are divided into: intelligent energy integrated service platform reliability evaluation, platform reliability evaluation and service reliability evaluation, and the evaluation methods, means and tools used by different evaluation objects are also different [4]. Data reliability mining of intelligent energy integrated service platform is the core of energy prediction and energy information discovery based on intelligent energy service. After the preliminary processing steps, the target data set is transformed into the data form suitable for mining. Based on this, the hierarchical linear model is used to mine the energy data to be mined on the platform. The hierarchical linear model is formed by the continuous iteration of the multi-layer linear model. The whole iteration process is a machine learning process. For example, the energy data will continue to iterate until all the residuals are equal to or close to 0. Based on this, we can effectively form a high accuracy intelligent energy prediction model [5]. Using smart energy services to predict energy data has high efficiency and accuracy, which can well realize the energy demand forecast proposed by users at the initial stage of energy information discovery.

Using hierarchical technology to mine the security data of intelligent energy integrated service platform, in the process of mining, each level becomes very independent, especially easy to expand. Using the asynchronous computing function of intelligent energy integrated service platform, the distributed storage of files is realized.

The following is a very detailed introduction of cloud service platform for data reliability mining based on intelligent energy integrated service platform [6]. In the distributed computing platform layer, the intelligent energy integrated service platform is used to complete the data storage function and calculation and analysis function of the cluster. The intelligent energy integrated service platform controls the distributed platform and provides the distributed file platform and parallel operation mode. At the same time, we need to submit the task to the server node. The data reliability mining platform layer is the top priority of the whole architecture, and its general task is to realize the parallel computing of the algorithm. In the process of executing various tasks, the tasks are assigned to the distributed computing layer of the intelligent energy integrated service platform for mining calculation [7]. And the results are fed back to the business application layer. It provides the business application layer with the data of each module needed in each stage of mining business process, including the data collection process, data reliability mining process, pattern evaluation process, data preprocessing process, result display process and other functional modules [8]. Based on this, the overall structure of big data external cloud services is optimized, and the specific structure of smart energy integrated service platform security data mining model is shown in the figure below.

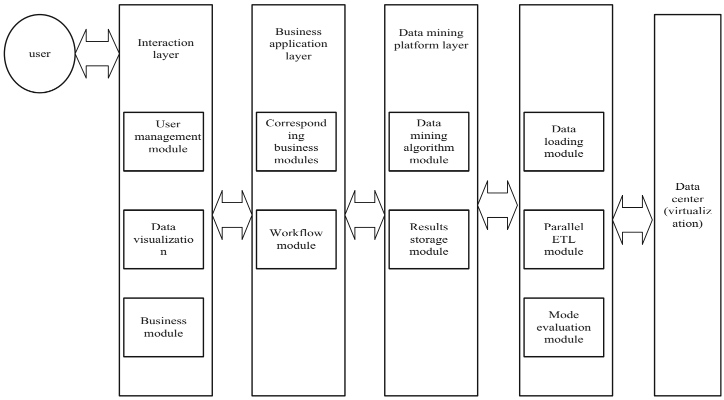

Fig. 1. Security data mining model framework of smart energy integrated service platform

As can be seen from Fig. 1, during the operation of the smart energy integrated service platform, it is affected by the complex environment, weak risk tolerance and other factors by the way of alliance sharing to obtain core data, so the possibility of better obtaining core competence is reduced. However, through the flow, transfer, learning and other processes of energy information among alliances, the possibility of better obtaining core competence is reduced, quickly realize the complementary of the collected data to ensure the information security. According to the concept definition and elements of enterprise core competence proposed by panhand and hammer, the mining data is screened and classified, and the platform reliability evaluation architecture is optimized according to data resource capability, data technology capability and data service capability, as shown in Fig. 2.

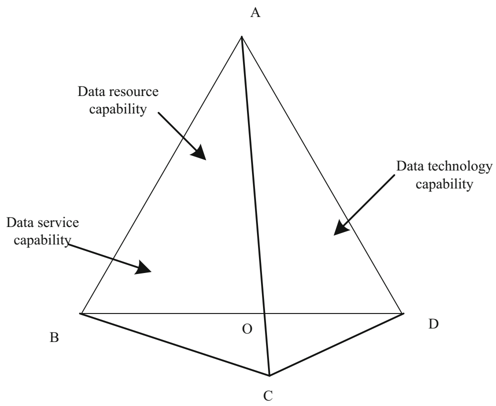

Fig. 2. Platform reliability evaluation architecture

In the actual operation process, the smart energy integrated service platform has experienced the decentralized development stage *A*, bilateral cooperation stage *B*, multilateral cooperation stage *C*, alliance network stage *D* and cross-development stage *O*, and each stage has different characteristics at the base level, organizational level, management level and information level. It is reflected in the network core, network node, organization mode, cooperation mode, management mechanism, information communication and so on. Therefore, the platform data processing capacity is relatively large. Therefore, the hierarchical linear model is needed to be combined for data processing. The specific platform data processing data is shown in Table 1 below:

Table 1. Characteristic information management of smart energy service platform

Stage category	Bilateral cooperation stage	Multilateral cooperation stage	Decentralized development stage	Alliance network stage
Information layer	Simple docking	Interconnection	Nothing	Building information platform
Organizational layer	Bilateral cooperation, limited number of members	Multilateral cooperation with a large number of members	Single member	Multilateral cooperation with a large number of members
Management layer	Limited scope of cooperation and standardized management	Risk sharing control, relationship management and benefit distribution mechanism	Nothing	More attention should be paid to the synergy effect, stability and strategic execution effect of the alliance
Foundation layer	Simple dual core network	Multi core network with various organizational forms	No network or simple single core network	Multi level network structure

The starting point of energy prediction information discovery process is the user, and the user is also the end point of energy information discovery [9]. The whole information mining and management process of smart energy platform needs to be carried out around the users, so the energy information discovery starts from the users. Through the analysis of user needs, the task and target of energy information discovery as well as the type of source data are clarified, so as to simplify the complexity of energy information discovery source data collection and help to locate the data source more effectively and accurately.

2.2 Intelligent Energy Integrated Service Reliability Data Optimization Algorithm

The energy prediction and energy information discovery process in smart energy service platform is different from the traditional information discovery process. It is a prediction and discovery process for energy data based on new network environment and high-density electronic data [10]. On the basis of following the general rules of information discovery based on smart energy service platform, the flexible and robust advantages of hierarchical linear model are used to effectively consider the problem of how to select huge data sources on the Internet, and the conversion of initial data source format is added in the process of energy information discovery, which improves the compatibility of energy information discovery process [11]; The predictive energy information contained in the data source is effectively found through the gradient elevator, and the feedback mechanism is added in the platform information discovery process, forming a set of closed-loop and feasible operation for the predictive energy information. The specific process is shown in Fig. 3.

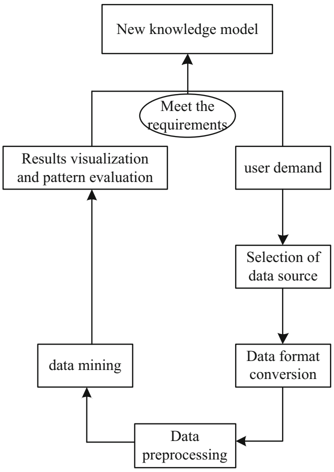

Fig. 3. Steps of reliability information stability prediction of service platform

In the process of evaluating the reliability of smart energy integrated services, we need an additive model composed of multiple weak classifiers in the platform. By accumulating several basic classifiers, the optimized objective function and the exponential reliability loss function related to the class spacing distribution are trained in the gradient direction [12]. The strong prediction parameter $h(x)$ is constructed by the ensemble prediction model. In the m steps of gradient promotion, if there is some weak interference F_m in the smart energy integrated service platform, which will affect the reliability of the platform, the platform information prediction model is calculated by adding a predictor. The details are as follows:

$$F_{m+1}(x) = F_m(x) + h(x) - m \tag{1}$$

The way to find the platform information is as follows:

$$R = SF_m(x) + h(x) = F_{m+1}(x) - y \tag{2}$$

In the above algorithm, y is the eigenvector and S is the interference value.

The results are as follows:

$$W = Sy - RF_m(x) \tag{3}$$

The approximate function of the reliability of the selected data is further calculated [13]. The specific algorithm is as follows:

$$F_{ij}(x) = \arg WR \min_F E_{x,y}[L(y, F(x))] = \sum_{i=1}^{n} \gamma_i h_i(x) + WRconst \tag{4}$$

In the above formula, W represents the reliability loss coefficient, and R represents the calculation error. $\min_F$ represents the minimum value of weak interference, $E_{x,y}$ represents the sample data processing function, L represents the average loss of sample data, γ_i represents the feature vector of sample data, and $h_i(x)$ represents the reliability evaluation function of sample data [14].

Furthermore, the average loss limit $L(y_i, \gamma)$ of the information training set samples collected in the smart energy service platform is standardized, and the greedy strategy expansion model is further used to expand the loss function:

$$F_0(x) = F_{ij}(\mathrm{x})\mathrm{argmin}_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma) \tag{5}$$

$$F_m(x) = F_{m-1}(x) + F_0(x)\mathrm{argmin}_{h \in H} \sum_{i=1}^{n} L(y_i, F_{m-1}(x) + h(x_i)) \tag{6}$$

Intelligent energy integrated service platform is a complex data analysis platform which integrates multiple application sub platforms. Its main task is to build a data storage, processing and network publishing platform of web service monitoring center based on XML, receive all the monitoring data of existing experiments, and store them in the database [15]. The heterogeneous data conversion platform is developed to convert the original heterogeneous data of different regions and different resource climate regions into XML format. By comparing and analyzing the original data of each monitoring point, the smart energy evaluation model of the contribution rate of smart energy to energy consumption is established to comprehensively evaluate the use of equipment and resources in the climate zone, and provide the function of network publishing to provide the latest data and historical data browsing, data import and export, data collection and management different data, various forms of graphics and tables display and report functions [16]. Based on this, the topological structure of platform reliability information evaluation is optimized, and the specific structure is shown in Fig. 4 below.

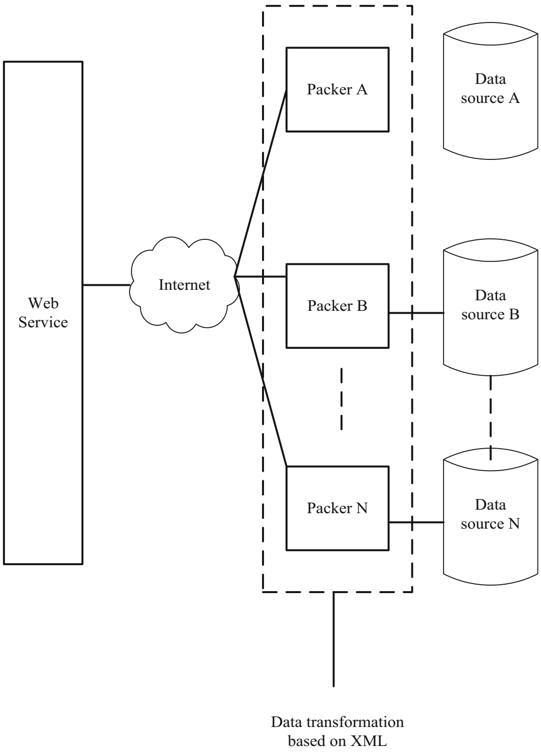

Fig. 4. Topology

On this basis, the function of the intelligent energy integrated service platform is optimized, and the specific function structure is shown in the following Fig. 5.

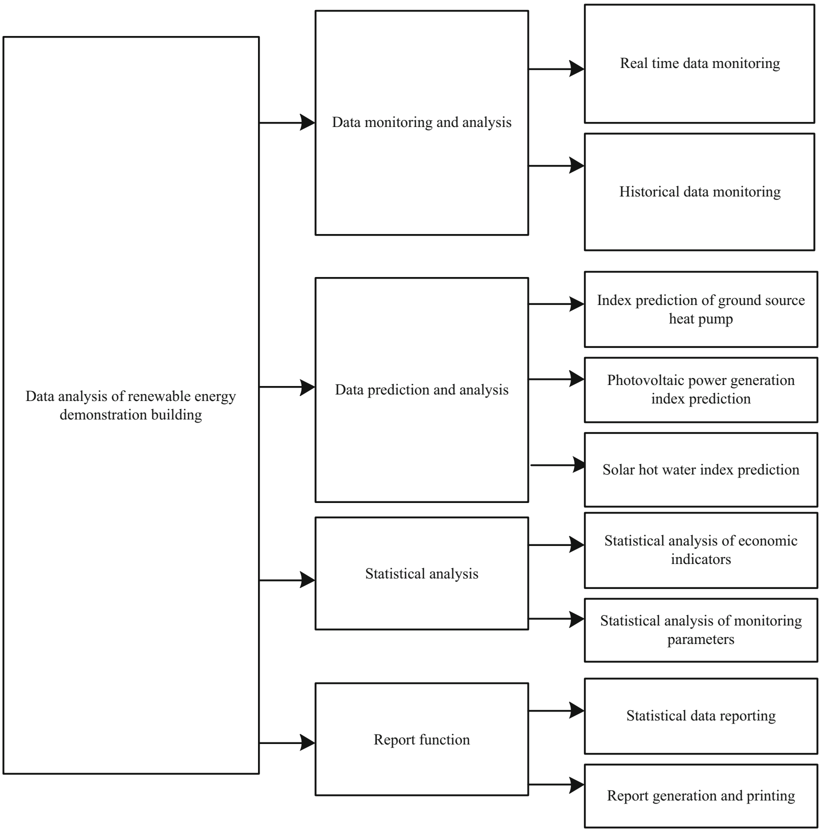

Fig. 5. Function structure optimization of smart energy integrated service platform

In order to realize the above functions, considering the use of intelligent energy integrated service platform and project progress, and considering the database and development tools, we decided to use SQL Server database and C# language as the development environment. Before building the energy reliability prediction energy information discovery model based on intelligent energy service, the model construction should follow the construction principle of the model to ensure the smooth progress of the process of energy information discovery [17]. The construction principles of the model mainly include the basic principles and design principles.

2.3 Optimization of Reliability Evaluation Algorithm for Smart Energy Service Platform

In the process of energy prediction, feature engineering is needed. The so-called feature engineering is the process of using the relevant energy information in the data field to make the hierarchical linear model achieve the best performance. Feature engineering is an art, and its selection is the key to the success of hierarchical linear model prediction.

Therefore, before data reliability mining, we need to design a K dimensional feature vector for the original data set. Selecting different feature vectors will usually represent different information sets, which will affect the performance of the whole smart energy service on energy prediction. If the information represented by the smart energy service feature engineering can accurately meet the requirements of the prediction dependent variables, the reliability prediction performance of the model will be improved, otherwise it will be reduced. Therefore, in the intelligent energy service feature engineering of energy prediction and energy information discovery, we need to pay attention to the following principles: whether the feature is emitted or not. For example, in the prediction of power consumption, the variance of a feature is close to 0, that is, there is basically no difference in the original data on this feature, so this feature is not emitted. Whether the features are related or not, that is, the correlation between the features and the prediction target, the features with high correlation should be selected first. To sum up, feature engineering has the advantages of improving prediction accuracy, avoiding over fitting and reducing irrelevant features. According to the above steps and principles of feature engineering, a feature framework is designed, as shown in the figure. Generally, energy prediction is closely related to energy users, regions and other factors, so the characteristics are constructed according to the interaction characteristics of users, regions and user regions (Fig. 6).

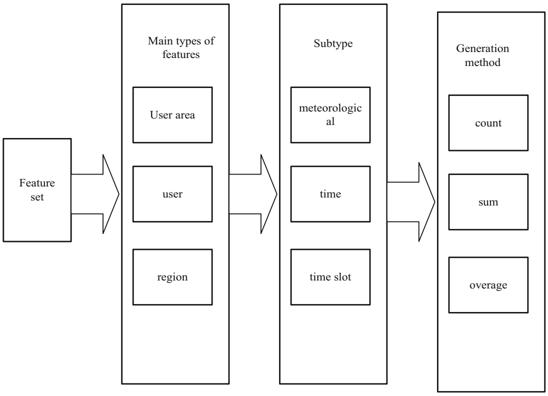

Fig. 6. Platform reliability information processing structure

In the process of smart energy service modeling, historical data is used to build models to analyze and test the lag effect of time series data. The specific modeling process is as follows: initialize the estimated values of all samples of energy data in category $K, f_{k0}(x)$ represents a vector of k, specifically represents the estimated values of energy sample data x in category k, where k is also the k feature of energy processing engineering, then:

$$\{F_m(x) - f_{k_0}(x) \geq 0,\ k = 1, 2, 3, \ldots K\} \tag{7}$$

By making logistic regression transformation for each estimated sample value, $f_{k0}(x)$ is converted into the probability value between $0-1$, and repeated calculation K times, the reliability probability sequence is obtained:

$$P_k(x) = \exp(f_k(x)) / \sum_{t=1}^{K} \exp(F_l(x)),\ k = 1, K \tag{8}$$

In the above formula, $f_k(x)$ represents the current classification estimate and $F_l(x)$ represents the logistic regression transformation function.

Traverse the probability of each category in the energy data sample, find the gradient of each sample on category K, and establish the cost function, which is expressed as:

$$L\left(\{y_k, f_k(x)\}_1^k\right) = -\sum_{k=1}^{K} y_k \log p_k(x) \tag{9}$$

In the above formula, y_k represents the sample gradient.

Through derivation, the hierarchical linear model is used to learn the energy data, and the gradient form, namely residual form, is obtained. If the energy data belongs to class i, then residual = true probability - estimated probability. Based on this, R square, mean absolute error and mean absolute percentage error are introduced as the error measurement index of energy consumption prediction

$$R_2 = \frac{\Sigma\left(y_{pre} - y_{avg}\right)^2}{\sum L\left(\{y_k, f_k(x)\}_1^k\right) - \left(y_{ori} - y_{avg}\right)^2} \tag{10}$$

$$MAE = \frac{1}{R_2 n_{sam}} \sum_{i=0}^{n_{sam}-1} \left| y_{pre,i} - y_{avg,i} \right| \tag{11}$$

$$MAPE = R_2 \sum_{i=1}^{n_{sam}-1} \left| \frac{y_{pre,i} - y_{avg,i}}{y_{avg,i}} \right| \tag{12}$$

where $y_{pre,i}$ and y_{pre} represent the predicted value of energy consumption, y_{avg} and $y_{avg,i}$ represent the mean value of sample data, and n represents the number of samples. The value of R_2 is between $0-1$, and the larger the value is, the better. However, MAE, MAPE will produce different values according to the data of training set, and the smaller the value is, the better. The probability of no failure operation in the specified operation environment and within the specified time. The reliability of the platform is represented by the function $R(t)$, the time of the failure of the platform is represented by the random variable t, the probability density function of the random variable t is represented by the function $F(t)$, and the probability of the failure of the program from the initial time to t_1 is represented by $\Pr o < t < y$:

$$F(t) = \int_0^t \mathrm{MAE} - f(x)dx \tag{13}$$

$$f(t) = \mathrm{MAPE} - \frac{dF(t)}{dt} \tag{14}$$

From 0 to t_1, the probability of program failure is expressed by $Pf(t_1)$:

$$Pf(t_1) = P - f(t)(0 \le t \le t_1) = F(t_1) - F(0) - f(t) = F(t_1) - f(t) \tag{15}$$

If the probability of successful operation of the program in interval $[0, t]$ is $Ps(t)$ and the probability of failure is $Pf(t)$, then:

$$\sum F(t_1)\mathrm{Ps}(t) + Pf(t) = e \tag{16}$$

In the above formula, e represents the overall error. It can be deduced from the above formula that:

$$R(t) = 1 - Pf(t)e = 1 - F(t)e = 1 - \int_0^l f(x)edx \tag{17}$$

The definition shows that the platform reliability is defined as a probabilistic measure, and the probability of no failure operation should be used to describe the reliability. The platform reliability is a function of time. When the residual error value is fixed, the longer a platform runs, the greater the probability of failure and the smaller the reliability of the platform. Because reliability is affected by many factors, it is difficult to evaluate reliability with one parameter. For different applications, there may be different parameters. For the evaluation of platform reliability, it can be evaluated from the aspects of management reliability and technical reliability. Management reliability is mainly for management personnel, and less considered in the evaluation of platform reliability. The evaluation indexes of platform reliability are mainly elaborated from the perspective of technical reliability. The indexes commonly used to characterize platform reliability are reliability, failure efficiency, failure strength, reliability, etc. Based on this, the platform reliability information management method is further optimized, as shown in Fig. 7.

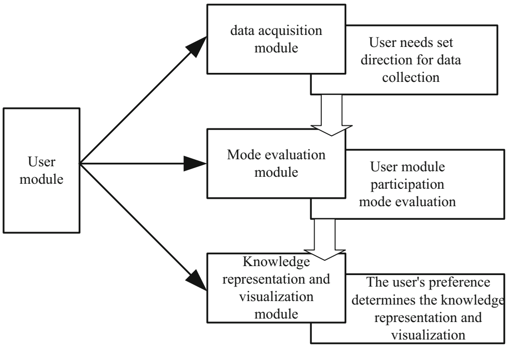

Fig. 7. Platform reliability information management method

Data preprocessing based on the above methods is mainly the preliminary processing of the source data, which mainly includes two steps: data cleaning and integration and data selection and transformation. Among them, data cleaning is mainly to fill missing values in data sources, correct inconsistent data and remove data noise. The data integration is when the data comes from multiple data sources, it needs to integrate the data, that is, simply integrate and overlay the data, integrate the data from different data sources into a data set, and improve the consistency and accuracy of the source data. The data preprocessing module is the data processing stage of the energy prediction and energy information discovery model based on smart energy services. It primarily processes and analyzes the collected data by means of data conversion, data cleaning, data aggregation, data integration and data specification, so as to form an orderly data warehouse and make full preparation for data reliability mining. This module is mainly aimed at the noise, missing and other problems of the target data set, using the corresponding technical means to process the target data set, so as to form a suitable data warehouse. Therefore, data conversion, data cleaning, data aggregation, data integration and data specification technologies are used in this module, as shown in Table 2.

Table 2. Data reliability preprocessing

Data reduction	Simplified representation of data sets
Data aggregation	Simple classification of messy data
Data conversion	The format of the source data set is converted uniformly
Data integration	Merge multiple data
Data cleaning	Filling missing values, identifying discrete points and so on

Platform data selection is to select the appropriate sample from the source data set, and the sample analysis can produce almost the same analysis results as the source data set. Data transformation is realized through discretization, standardization and other technologies to ensure that data can be mined from multiple abstract levels, which is conducive to improving the quality of data reliability mining. Data reliability mining is the core of this model. The core algorithm of this model is hierarchical linear model, and the content of energy information discovery in this model is time series data, that is, predictive data. Through the analysis of the status and trend of historical data, we find the change trend of future data. Comparing the content of the energy information discovery with the actual data in the first mock exam, it is found that the deficiency of the model is feedback to the former module, and the energy information discovery result is optimized. Based on this, the reliability correction process of platform reliability data is optimized, and the specific process is shown in Fig. 8.

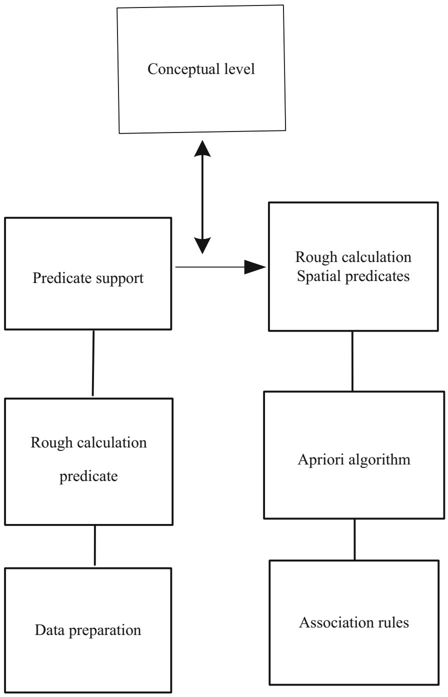

Fig. 8. Reliability correction process of platform reliability data

After data query and analysis, it is necessary to collect the target related objects and reference sets into the database. The expected confidence of $X \Rightarrow Y$ is the percentage of all things contained in association rule $X \Rightarrow Y$ in database; The confidence is compared with the expected confidence

$$\mathrm{D} = \frac{R(t) + X \Rightarrow Y}{\text{expected value: } X \Rightarrow Y} \tag{18}$$

Interestingness can measure the X, Y relevance of all things. Predicate calculation is carried out at the rough level. The target is set as the minimum rectangle, the extraction distance falls within the predetermined threshold as the object, the predicate of object relationship is stored in the database, and the attribute value is set as a single value or a group of values. Different predicates have different support

$$\xi = \mathrm{D} \times (X - Y) \tag{19}$$

The threshold with lower support is excluded, and then the common database is formed. In order to perform accurate spatial calculation in common databases, MBR technology is used to check the relationship between predicates, exclude the predicate relationship that does not conform to the actual situation, and then form the topological data table, so as to calculate the support of predicates, exclude the items with less support, and then form the optimal database. Through the model evaluation, we can make appropriate trade-offs on the results of energy information discovery, and can feed back the poor results of energy information discovery, so as to conduct a new round and more detailed energy information discovery on this part of energy information. In the hierarchical variable weight cloud service reliability evaluation model, the reliability of service reflects the reliability of users getting the best service resources. The greater the reliability of service, the better the quality of cloud service; The mathematical expectation of service reliability reflects the average value of service reliability provided by service resources when users get service; The mean square error of service reliability reflects the deviation degree between the reliability of service resources and the mean value of service reliability. The greater the fluctuation is, the worse the effect of reliability is. Therefore, the reliability quality of cloud service can be evaluated by one or several aspects of reliability, mathematical expectation of reliability and mean square error of reliability. According to the platform analysis idea of holism and reductionism, the reliability evaluation model based on hierarchical variable weight realizes that the weight of reliability factors changes with the change of cloud service status. According to different actual needs, it can use incentive type and punishment type state variable weight to build a reasonable reliability weight adjustment mechanism, which provides an efficient and effective way for cloud service reliability evaluation flexible technical means, with strong operability and flexibility.

3 Analysis of Experimental Results

In order to verify the feasibility and accuracy of the evaluation method of intelligent energy integrated service platform based on hierarchical linear model, the experiment is divided into 5 user demand analysis, data acquisition, data preprocessing, data reliability mining, data visualization and pattern evaluation. The environment of this experiment is Mac-OS10.13 platform, and the environment is PyCh development environment experiment. It calls the Scrapy crawler of python2.7 to collect data, and pandas database is used for data processing, scidit learn library for linear regression fitting, numpy database for scientific calculation, Matplotlib database for visualization and result export. The hardware environment is 2.7 GHz IntelCorei5CPU and 8 GB

RAM. With the change of parameters, the error amplitude of the model decreases. Based on this, the trend of platform data reliability is investigated. The specific results are shown in Fig. 9 below:

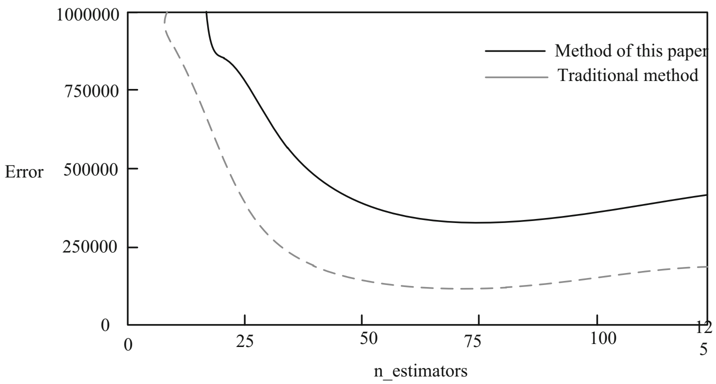

Fig. 9. Trend of platform data reliability

Generally, it is necessary to understand the influence of the constructed features on the model prediction. Therefore, six features, such as summer, minute, Dow, day, year, etc., are selected to draw the feature importance diagram. It can be seen that the summer feature has the least influence on the model, and the influence of minute and doy on the model is relatively large (Fig. 10).

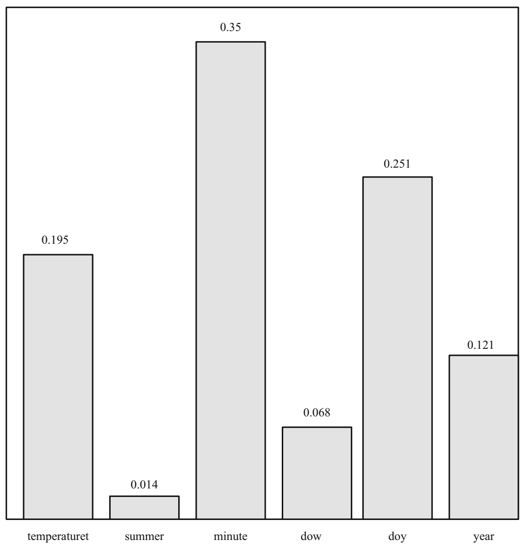

Fig. 10. Influencing factors and influencing degree of platform stability

Through the above steps, this experiment draws the final visualization results, and compares the reliability of data mining speed. The specific detection results are shown in Fig. 11.

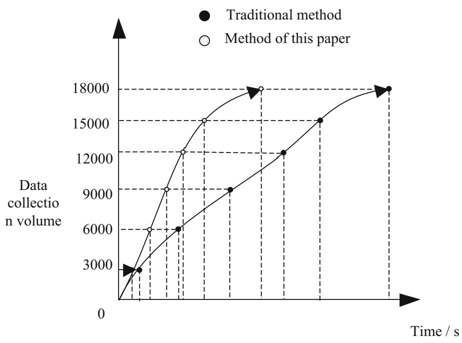

Fig. 11. Comparison of platform reliability evaluation efficiency results

It can be seen from the figure that the reliability and efficiency of the smart energy service platform proposed in this paper is obviously higher than that of the traditional platform, which can better guarantee the rational use of smart energy and avoid the waste of resources.

Taking the reliability evaluation accuracy and evaluation time of the comprehensive smart energy service platform as experimental indexes, the actual application effects of the traditional method and the method presented in this paper are compared. The specific experimental results are shown in Table 3.

Table 3. Comparison of practical application effects

Number of experiment	Evaluation accuracy/%		Evaluation time/s	
	Traditional method	Method of this paper	Traditional method	Method of this paper
1	85.6	98.6	1.9	0.5
2	81.3	99.3	1.8	0.2
3	82.4	98.9	1.4	0.4
4	86.3	97.8	1.6	0.2
5	84.1	98.5	1.7	0.3
6	82.5	98.6	1.5	0.4
7	81.7	98.4	1.2	0.5
8	85.6	97.4	1.8	0.3
9	84.7	97.6	1.4	0.2
10	82.6	98.3	1.7	0.3
Average	83.7	98.3	1.6	0.3

It can be seen from the analysis of Table 3 that the average reliability evaluation accuracy of the comprehensive intelligent energy service platform of the traditional method is 83.7%, and the average reliability evaluation accuracy of the comprehensive intelligent energy service platform of this paper is 98.3%, which is much higher than that of the traditional method. The reliability assessment time of the integrated intelligent energy service platform of the traditional method is 1.6 s, while that of the proposed method is 0.3 s, much lower than that of the traditional method. The above data prove that the proposed method has better comprehensive performance and better practical application effect.

4 Concluding Remarks

In recent years, the application requirements of the comprehensive intelligent energy service platform have been increasing. In order to better realize the whole process management of smart energy service projects, realize the objectives of data visualization, online monitoring and early warning, and effective response, and with the help of mobile data collection, big data analysis and index management, etc. The reliability evaluation method of intelligent energy integrated service platform based on layered linear model is proposed in order to provide users with new service experience. Finally, through energy efficiency improvement, energy saving transformation, creating stable revenue, expanding profit source, the ultimate goal of bringing high efficiency, clean, reliable, convenient personality and intelligent interaction to customers in the whole society can be achieved.

References

1. Abiri, R., Borhani, S., Kilmarx, J., et al.: A usability study of low-cost wireless brain-computer interface for cursor control using online linear model. IEEE Trans. Hum.-Mach. Syst. 1–11 (2020)
2. Yang, W., Chen, Y., Chen, Y.C., et al.: Intelligent agent-based predict system with cloud computing for enterprise service platform in IoT environment. IEEE Access 1 (2021)
3. Zhang, C.: Design and application of fog computing and Internet of Things service platform for smart city - ScienceDirect. Futur. Gener. Comput. Syst. **112**(4), 630–640 (2020)
4. Lei, J., Zhou, C., Li, X., et al.: Energy management considering energy storage and demand response for smart energy hub in Internet of Things. IEEE Access 1 (2020)
5. Carli, R., Dotoli, M.: Decentralized control for residential energy management of a smart users' microgrid with renewable energy exchange. IEEE/CAA J. Automatica Sinica **6**(3), 36–51 (2019)
6. Li, Z., Li, H., Feng, Y.: Research on big data mining based on improved parallel collaborative filtering algorithm. Clust. Comput. **22**(5), 1–10 (2019)
7. Arafat, Y., Hoque, S., Xu, S., et al.: Machine learning for mining imbalanced data. IAENG Int. J. Comput. Sci. **46**(2PT.264–383), 332–348 (2019)
8. Campo-Vila, J.D., Takilalte, A., Bifet, A., et al.: Binding data mining and expert knowledge for one-day-ahead prediction of hourly global solar radiation. Expert Syst. Appl. **8**, 114147 (2020)

9. Nali, J., Martinovi, G., Agar, D.: New hybrid data mining model for credit scoring based on feature selection algorithm and ensemble classifiers. Adv. Eng. Inform. **45**(11), 101130 (2020)
10. Lin, M., Chen, X., Wang, Z., et al.: Global profiling and identification of bile acids by multi-dimensional data mining to reveal a way of eliminating abnormal bile acids. Anal. Chim. Acta **32**(11), 74–82 (2020)
11. Lu, N.: Reliability evaluation model of network resource sharing information consulting service platform. Environ. Technol. **37**(2), 45–48+52 (2019)
12. Fei, Q.: SOA complex network system reliability evaluation. Comput. Technol. Dev. **29**(11), 113–117 (2019)
13. Jiang, J.L., Guan, T.T.: RESTful service reliability evaluation optimization based on Markov chain. Mod. Comput. **23**(8), 17–21 (2018)
14. Xuan, J.J., Xiao, Y., Lu, W.S., et al.: Reliability evaluation method for regional integrated energy system applying complex network theory. Electr. Power Constr. **41**(4), 1–9 (2020)
15. Lu, Z.K., Jian, X.H., Zhang, M.H.: Reliability and economic evaluation of multi-terminal flexible DC distribution network. South. Energy Constr. **7**(4), 67–74 (2020)
16. Pan, J., Shen, Y.Y., Duan, R.C.: Interval estimation of power supply reliability evaluation for planned power outage projects. Power Energy **40**(4), 62–66 (2019)
17. Ni, W., Lv, L., Xiang, Y., et al.: Reliability evaluation of integrated energy system based on Markov process Monte Carlo method. Power Syst. Technol. **44**(1), 150–158 (2020)