Research on health assessment of electric power information system based on deep belief networks and cluster analysis

Haiqing Xu¹², Hongfa Li³, Shitong Chen² and Xiaohua Wu¹²⁴

¹ State Grid Corporation Power System Artificial Intelligence Joint Laboratory (State Grid Information and Communication Industry Group), Hefei, Anhui 230088;
² Anhui Jiyuan Software Co., Ltd., Hefei 230088, Anhui;
³ Information and Communication Branch of State Grid Fujian Electric Power Co., Ltd., Fuzhou, Fujian 350003
⁴ Email: jy_wxh@163.com

Abstract. It has been a hot issue for a long time to effectively ensure the safe and stable operation of the power service information system and make a reasonable evaluation of the healthy operation of the power service information system. Without relying too much on the subjective experience and scoring of experts, this paper introduces a health assessment method based on deep belief networks and cluster analysis for the power service information system. Firstly, cluster analysis is used to obtain corresponding cluster centers and evaluation index sets based on the selected evaluation indexes of the information system. Secondly, the entropy weight method is adopted to score different clustering categories and obtain the corresponding health evaluation categories. Finally, based on the score of the healthy operation, the samples are supervised and trained by the deep belief network model, and then the objective comprehensive evaluation of the system is completed. Experiment results show that this model is more accurate than traditional SVM, KNN, random forest and LSTM. The proposed model has theoretical significance and practical value for the healthy operation evaluation of the power service information system.

1. Introduction

Electricity power energy is an important foundation to support the efficient operation of the national economy. With the rapid development of emerging information technologies, it makes the production, operation and management of power enterprises closely integrated and improves the information level of the power system. The mentioned emerging information technologies refer to cloud computing, big data, and the internet of things, information technology, network technology and communication technology. As a result, a large number of system logs have been generated, including system network connection status, database status and equipment operation parameters. In addition, with the deepening reform of the power system in China, electricity market-oriented transactions being orderly liberalized make the information system more complex. From the above considerations, many researchers focus on analyzing the healthy operation of the power information system based on the massive operation information, supporting the safety [1], reliability [2] and economic operation of the system [3].

Similar to the health assessment of the information system in other fields, the health assessment of the power service information system needs to conduct a systematic and comprehensive analysis of system components such as system hardware, system software and network composition. The existing health assessment methods of the information system mainly include a subjective evaluation method...
and an objective evaluation method [5]. The subjective evaluation method needs to build the corresponding evaluation index system, and then determine the weight of each indicator in the evaluation system according to the scoring of experts, conducting a comprehensive evaluation. In order to improve the deficiency of traditional subjective model relying on expert experience. Combining Fuzzy Theory (FT) and Analytic Hierarchy Process (AHP) can evaluate and study the operating conditions of power transformers, thereby solving the problems of ambiguity, uncertainty, and even information conflicts [6]. In the past, each indicator of the indicator system was determined by experienced experts, but now, based on repeated simulations in the scene space, an indicator system calculated from quantitative data can be established [7]. By combining TOPSIS and Entropy Weight Method, the evaluation of system performance can be completed [8]. Interoperability can solve the problem of barriers to cross-domain information resource sharing. Therefore, a dynamic comprehensive evaluation method of interoperable trust constructed by fuzzy comprehensive evaluation and variable weight theory can solve the above resource sharing barriers [9]. In the evaluation index system, we can have multiple evaluation methods, such as single index attribute measurement, index weight calculation and multi-attribute comprehensive evaluation [10].

In recent years, the deep neural networks (DNN) [11], as a representative of the artificial neural networks, have been successfully applied in many fields due to its good nonlinear fitting ability and feature capture ability. Through the use of pattern recognition of the artificial neural network (ANN) algorithm, a probable methodology may be generated to address the impact of biofuels on the environment [12]. In terms of the operating status of the circuit breaker, a data-driven nonlinear method is proposed to formulate the best maintenance strategy [13]. In order to reduce the dependence as much as possible, Convolutional Neural Network (CNN) is used to automatically evaluate the quality of the target video [14]. In addition, the deep belief networks (DBN) model [15] is also a type of deep neural network model that has gradually received attention. with hidden layers, The DBN model has a strong feature learning ability. The obtained feature data is more representative than the original data [16]. The DBN model mainly conducts the tasks of feature recognition and data classification by establishing a joint distribution between observation data and data labels, therefore the DBN model is more suitable for classification and visualization problems. The DBN model has strong scalability and has been successfully applied to many fields such as font recognition, speech recognition and image processing [17]. Relying as little as possible on subjective information and using neural network models are both hotspots in the objective evaluation and analysis research area.

In summary, the existing research focuses on improving a single evaluation model, including subjective evaluation models like AHP or objective evaluation models like neural network evaluation. However, future research should consider index weight evaluation construction based on existing research. Based on the above considerations, this paper proposes a new objective modeling method to generate and divide the evaluation indicators by using deep belief network in the system health evaluation. This framework considers the subjectivity during the evaluation process, providing quantitative guidance to the operation and maintenance in the power business information system.

2. Proposed system health evaluation model
It is a very difficult task to analyze and evaluate the healthy operation state of the power service information system. Therefore, it is necessary to select and build a reasonable evaluation index system, and then objectively evaluate the power service information system. In this paper, we mainly follow the SMART principle [18,19], that is, the indicators must be specific, measurable, accessible, relevant and time-bound. Considering the DBN model has good feature recognition and pattern discrimination ability, this paper selects DBN model to be used in the health assessment of power service information system.

DBN [20-22] is a generative structural graph model with multiple hidden layers, which is composed of several layers of Restricted Boltzmann Machine (RBM) and one layer of BP neural network.
2.1. Restricted boltzmann machine

RBM is a two-layer recurrent neural network. Usually each RBM consists of a visible layer containing visible units \( v = \{v_1, v_2, \ldots, v_n\} \) and a hidden layer containing hidden units \( h = \{h_1, h_2, \ldots, h_m\} \). The elements of \( v \) and \( h \) are binary variables whose states are 0 or 1. There is a bidirectional connection weight between the visible unit and the hidden unit, but there is no connection between the visible unit and the visible unit and between the hidden unit and the hidden unit.

RBM is an energy-based model. The more orderly the system or the more concentrated the probability distribution, the smaller the energy of the system. The opposite is also true. The minimum value of the energy function corresponds to the most stable state of the system. For a given set of states \((v, h)\), the energy function of the visible unit and the hidden unit is:

\[
E(v, h | \theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n} \sum_{j=1}^{m} v_i w_{ij} h_j
\]

(1)

where \( \theta = (w, a, b) \) is the parameter of the RBM model; \( w \) is the weight of the layer connection, \( a \) and \( b \) are the deviations of the neurons in the visible layer and the hidden layer, respectively.

Since the value state of the network node is random, one energy state corresponds to a probability. Therefore, the joint probability distribution between the hidden layer and the visible layer can be obtained, the formula is as follows:

\[
P(v, h | \theta) = \frac{1}{Z(\theta)} \exp(-E(v, h | \theta))
\]

(2)

where \( Z(\theta) = \sum_{v, h} \exp(-E(v, h | \theta)) \) is called the partition function, which is obtained by adding up the energy values between all visible layer and hidden layer units. Similarly, given a randomly input hidden layer vector \( h \), the probability of the hidden layer vector \( h \) and the visible layer vector \( v \) can be obtained, and the formula is as follows:

\[
P(h_j = 1 | v, \theta) = \sigma(h_j + \sum_i w_{ij} v_i)
\]

(3)

\[
P(v_i = 1 | h, \theta) = \sigma(a_i + \sum_j w_{ij} h_j)
\]

(4)

where \( \sigma(x) = \frac{1}{1 + \exp(-x)} \) is the sigmoid activation function.

2.2. Structure of deep belief network

![Figure 1. structure of DBN.](image-url)
DBN is a representative DNN model, which is composed of several RBMs and a classification layer (BP neural network). Figure 1 shows the structure of DBN. The input layer has $q$ units, which means that there is $q$ input features, and the output layer has $p$ neurons, which means there are $p$ categories. The connection structure between the visible layer and the hidden layer in each RBM has an energy. When the value is different, the specific value of the energy is also different. RBM mainly uses input data for feature extraction, while the regression layer maps the feature probability distribution to the corresponding label.

The training of DBN mainly consists of two processes: unsupervised layer-by-layer pre-training and supervised fine-tuning. During DBN training, the unsupervised layer-by-layer pre-training process is the main difference between the DBN model and other models. Firstly, a vector is generated in the visible layer of the first RBM, and the value is passed to the hidden layer through the RBM network. In turn, the hidden layer is used to reconstruct the visible layer. According to the difference between the reconstruction layer and the visible layer, the weight between the hidden layer and the visible layer is updated until the maximum number of iterations is reached. After completing the unsupervised training between layers, the automatic learning features of DBN are input into the classification layer and finally perform fine-tuning on the BP layer. This training model can effectively reduce the space of parameter optimization through unsupervised training and greatly reduce the time of supervised training.

2.3. System health evaluation method based on deep belief network with hidden layers, The DBN model has a strong feature learning ability. The obtained feature data is more representative than the original data. Based on that, this paper proposes a power service information system health assessment method (KM-EW-DBN) based on deep belief network and cluster analysis. The basic idea of the method is to divide the class labels of the data according to clustering algorithm and entropy weight method, and determine the health level of all kinds of data. Multiple features and parameters are input, different health levels classified are output, and the deep belief network is trained based on historical samples. Through a large amount of training, the trained deep neural network is used to comprehensively evaluate the system operation log information and predict the objective evaluation score. Figure 2 shows the specific flow chart.

![Flow Chart](image-url)

**Figure 2. KM-EW-DBN model structure.**
3. Experimental setup
In order to verify the evaluation method based on deep belief network and cluster analysis proposed in this paper, this paper combines it with support vector machine (SVM), random forest (RF), k-nearest neighbor (KNN), long short-term memory (LSTM) algorithm Perform comparative analysis. The experimental environment of this paper is Win10 system, sharing 3.2GHz CPU, and the compilation environment is Python 3.6, Tensorflow 2.0.0 and Keras 2.3.1.

3.1. Data description and preprocessing
The experiment selected the log information data of a province-level power company for analysis. This data set represents each the value of each indicator of the system at different times, including 4 different types of attributes such as ID, Guideline_ID, Monitor_Date, and Monitor_Value, among which ID is the primary key. Guideline_ID contains 12 indicators, which represent log information data, 12 indicators are listed respectively as total number of CPU cores, remaining amount of memory, memory utilization, total physical memory, memory size, IOWAIT, memory allocation rate, average CPU usage, storage medium utilization, memory footprint, PING packet loss rate, continuous running time. Monitor_Date is the detection date (1/23/2019-1/25/2019). Monitor_Value represents the value of each indicator at different times.

In order to further analyze the healthy operation of the power information system, the original log information is first processed to obtain a data set with time as the main key and various indicators as attributes. Next, the data is cleaned and the data with empty index values is deleted. The final valid data is 1195.

3.2. Evaluation standard
This paper chooses the area under the curve (AUC), precision, recall rate and F1 as evaluation indicators to evaluate the accuracy of each classification algorithm. The definition of the confusion matrix is shown in Table 1, where TP indicates the true category of the sample is positive, and the result of the model prediction is also positive. TN indicates the true category of the sample is negative, and the corresponding forecasting result is negative. FP indicates the true category of the sample is negative, while the corresponding forecasting result is positive. FN indicates the true category of the sample is positive, but the corresponding forecasting result is negative.

| Confusion Matrix | True |
|------------------|------|
| Prediction       | positive | negative |
|                  | TP     | FP       |
|                  | FN     | TN       |

The following indicators can be obtained from the confusion matrix:

1) Accuracy

\[ \text{Precision} = \frac{TP}{TP + FP} \]  \hspace{1cm} (5)

2) Recall rate

\[ \text{Recall} = \frac{TP}{TP + FN} \]  \hspace{1cm} (6)

3) F1- Score

\[ F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \]  \hspace{1cm} (7)

4) Area under ROC curve

\[ AUC = \frac{TP + TN}{TP + FP + TN + FN} \]  \hspace{1cm} (8)
3.3. Parameter settings
In the deep belief network model of this paper, RBM adopts three hidden layers, the number of neurons is 64, the learning rate of RBM is 0.05, the learning rate of BP is 0.1, and the Dropout value set to 0.2. In this paper, the compared models, such as SVM, RF and KNN use grid search to find the best parameters of the model. The detailed parameters of comparative model are shown in Table 2. The training set and test set are divided into 9:1.

Table 2. The detailed parameters of comparative model.

| Models | Configuration |
|--------|---------------|
| LSTM   | LSTM_1(units=64) |
|        | LSTM_2(units=64) |
|        | Dropout(dropout=0.2) |
|        | dense(units=3) |
| SVM    | kernel = ['rbf', 'linear'] |
|        | C = [-1, 1], construct a geometric sequence with base 2 |
| KNN    | N = [5,50], step=5 |
| RF     | N = [5,70], step=5 |

4. Experimental results and analysis

4.1. Label determination

Table 3. Table of clustering results.

| Class | Number | Level |
|-------|--------|-------|
| 1     | 440    | Good  |
| 2     | 362    | Fair  |
| 3     | 393    | Poor  |

Firstly, classifying and determining the category. Three types of data are obtained by K-means clustering. The next is to determine each category's health level. The entropy weight method is used to calculate the weight of each indicator. Next, the average value of each type of score is calculated based on its weight and further the various types of health are ranked by the level of the average score. Table 3 shows the specific results.

4.2. Analysis of experimental results

Table 4. Comparison results between the proposed method and other algorithms (The result is t mean of three repeated experiments).

| Models | AUC Class1 | F1 | precision | recall | AUC Class2 | F1 | precision | recall |
|--------|------------|----|-----------|--------|------------|----|-----------|--------|
| DBN    | 0.9722     | 0.9714 | **1.0000** | 0.9444 | **0.9889** | 0.9677 | **0.9375** | **1.0000** |
| LSTM   | **0.9762** | 0.9756 | **1.0000** | 0.9524 | 0.9741    | 0.9279 | 0.8655    | **1.0000** |
| SVM    | 0.9698     | 0.9639 | 0.9756    | **0.9524** | 0.9833    | 0.9524 | 0.9091    | 1.0000 |
| KNN    | 0.9698     | 0.9639 | 0.9756    | **0.9524** | 0.9722    | 0.9231 | 0.8571    | 1.0000 |
| RT     | 0.9698     | 0.9639 | 0.9756    | **0.9524** | 0.9611    | 0.8955 | 0.8108    | 1.0000 |
| Class3 | Mean       | Mean   | Mean      | Mean   |
| DBN    | **0.9861** | 0.9827 | 0.9793    | **0.9861** | 0.9824    | 0.9739 | **0.9723** | 0.9769 |
| LSTM   | 0.9606     | 0.9571 | 0.9853    | 0.9306  | 0.9703    | 0.9535 | 0.9503    | 0.9610 |
| SVM    | 0.9792     | 0.9787 | **1.0000** | 0.9583 | 0.9774    | 0.9650 | 0.9616    | 0.9702 |
| KNN    | 0.9583     | 0.9565 | **1.0000** | 0.9167 | 0.9668    | 0.9478 | 0.9443    | 0.9563 |
| RT     | 0.9375     | 0.9333 | **1.0000** | 0.8750 | 0.9561    | 0.9309 | 0.9288    | 0.9425 |
After completing the parameter setting and label determination, the experimental model is analyzed through four indicators: AUC, F1, precision and recall. Specifically, the main evaluation methods are AUC and F1. In addition, considering the instability of machine learning results and other reasons, this paper carried out three repeated experiments to eliminate errors caused by the model. Table 4 shows the comparison results between the proposed method in this paper and the LSTM, SVM, KNN and RF algorithms. We can find that compared with LSTM, SVM, KNN, RF, the average AUC of the proposed model has increased by 1.21%, 0.50%, 1.56%, 2.63%. The average value of F1 has increased by 2.04%, 0.89%, 2.61%, 4.30% respectively. As shown in Table 4, the classification result of the proposed method is significantly better than that of traditional machine learning methods. This is mainly because the DBN model has good feature recognition and pattern discrimination ability.

![Figure 3. Comparison results of evaluation index AUC.](image1)

![Figure 4. Comparison results of evaluation index F1.](image2)

![Figure 5. Comparison results of evaluation index precision.](image3)

![Figure 6. Comparison results of evaluation index recall.](image4)

Figure 3-6 show the comparison results of different indicators regarding AUC, F1, precision and recall. The abscissa in the figure is the category, and the ordinate is accuracy. From Figure 3 and Figure 4, LSTM model is superior to the proposed model. But the AUC value of LSTM in class 2 and class 3 are lower than the proposed model. As seen from Figure 5 that the precision value of LSTM is the same as the proposed model in class 1. And F1 is the harmonic average of precision and recall. However, the recall value of class 1 for LSTM model is lower than that of the proposed model. Therefore, the F1 score of the proposed model is lower than that of LSTM.
5. Conclusions
This paper has introduced a new health evaluation modeling framework to the power business information system. This framework can be used to improve the information system from the following aspects, including quantify objectively evaluation index weight, simplify the comprehensive evaluation process and real-time dynamic modeling. The proposed modeling framework mainly consists of two parts: firstly, the objective quantitative method of evaluation index weight is used to make cluster analysis on massive system operation information. Secondly, based on above results, entropy weight method is adopted to score different cluster center indexes, scoring various indicators under different health conditions. The proposed evaluation model can effectively overcome the shortcomings of traditional methods relying on expert experience to score. In addition, the experimental results show that compared with the traditional pattern discrimination method, the method proposed in this paper can effectively improve the classification and recognition accuracy of the operation status of the power service information system. In the future research work, how to extract features from the massive log information and integrate them into the model, judging the operation status of the system, and how to trace the fault source based on the operation information of the information system are worth studying.

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