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# APPLICATION OF AHP-ENTROPY METHOD AND LSSVM IN THE ASSESSMENT AND FORECASTING OF TRANSFORMER OPERATING STATUS

Niu Guocheng<sup>1,3</sup>, Hu Zhen<sup>1\*</sup>, Hu Dongmei<sup>2</sup><sup>1</sup>College of electronic information engineering, Changchun University Science and Technology, Weixing Street, Changchun, China.<sup>2</sup>College of Electronic and information Engineering, Beihua University, Xinshan Street, Jilin, China.\*Corresponding Author Email: [huzhen21st@sina.com](mailto:huzhen21st@sina.com)

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### ABSTRACT

In order to meet the needs of fault troubleshooting, maintenance decision and on-line prediction, the method of the transformer health index based on AHP-entropy is proposed. The cross complex matter elements are established between the transformer health index and dissolved gases and typical faults. The subjective and objective weights affecting the transformer health index are determined by Analytic Hierarchy Process (AHP) and information entropy respectively, and the transformer health index is calculated quantitatively by matter element-maximum information entropy, the calculation is used as the predicting information, and the Least Squares Support Vector Machine (LSSVM) is used to predict the transformer operation status. The scheme provides a new feasible method to evaluate, quantify and forecast the transformer operation status.

#### KEYWORDS

Transformer, Health Index, Analytic Hierarchy Process (Ahp), Complex Matter Element, Support Vector Regression (Lssvm).

## 1. INTRODUCTION

As a hub equipment for power systems, the operation status of large-scale oil-impregnated power transformers is directly related to the safety and stability of the power grid, and the sudden failure of transformers will bring huge economic losses [1, 2]. During the operation of the oil immersed transformer, there will be overheating or discharging faults, which will produce hydrogen gas such as CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub>, C<sub>2</sub>H<sub>6</sub>, H<sub>2</sub> [3, 4]. The dissolved gas analysis (DGA) technology in oil can detect the dissolved gas in the oil without interrupting maintenance. It can reduce the time of transformer interruption maintenance and is beneficial to the development of transformer status monitoring technology [5]. The classification, diagnosis and evaluation of transformer faults can be realized by the use of dissolved gas in oil. At present, the research on transformers mainly focuses on the classification, diagnosis and assessment of their faults. In the literature, ABB company realizes the monitoring of power transformer operation state, fault classification, operation state analysis and confirmation, and evaluation of operation risk and life. In the literature, the fuzzy comprehensive evaluation method is used to evaluate the health state and GIS [6-9]. In the literature [9,10]. The artificial neural network and information fusion technology are used to evaluate the transformer operation status. The existing methods have greatly promoted the research of the equipment status assessment, but there is also a problem which is not comprehensive and has a high dependence on the knowledge of experts [11]. However, there are few study on the health status prediction of transformers.

With the development of data mining technology, it is possible to accurately evaluate and predict the operation state of transformers. The health status of transformers is quantitatively calculated from both subjective and objective aspects based on gases data in transformer oil. According to the historical health index data, the support vector machine with parameters optimization is used to predict the running state of the transformer, and the scientific management of the transformer from regular maintenance to state maintenance is carried out.

## 2. ENTROPY AND COMBINED WEIGHT EVALUATION MODEL

### 2.1 Subjective weight calculation

Analytic Hierarchy Process (AHP) is a multi-objective decision analysis method, which combines qualitative and quantitative analysis, and is proposed by T. L. Saaty of Pittsburgh University in the United States [12]. It introduces the experts' experience into different levels and quantifies some complex and difficult decision problems. Calculation, the process is simple and easy. In this paper, AHP is used to calculate the subjective weights of health index. The main steps are as follows:

#### 2.1.1 Establishment of composite matter element hierarchical structure model

In order to study the subjective factors affecting the operating state of the transformer, the AHP is used to establish the complex element model of the transformer faults, which reflects the mutual influence between the gas and the common faults.

The model is divided into three layers, and the decision layer C is "H<sub>2</sub> (C<sub>1</sub>), CH<sub>4</sub>(C<sub>2</sub>), C<sub>2</sub>H<sub>6</sub> (C<sub>3</sub>), C<sub>2</sub>H<sub>4</sub> (C<sub>4</sub>), C<sub>2</sub>H<sub>2</sub> (C<sub>5</sub>), ΣCH(C<sub>6</sub>). The criterion layer B is six transformer faults. "General overheating (B<sub>1</sub>), severe overheat (B<sub>2</sub>), partial discharge (B<sub>3</sub>), spark discharge (B<sub>4</sub>), arc discharge (B<sub>5</sub>), overheating and arc discharge (B<sub>6</sub>)", the target level A is the transformers' health index.

#### 2.1.2 Construction of Judgment Matrix

Establish the AHP Weight Matrices for the target layer A and the criterion layer B. The square root method is used to calculate the maximum eigenvalue root  $\lambda_{\max}$  of the judgement matrix. Its corresponding normalized eigenvector  $W = (\omega_1, \omega_2 \cdots \omega_n)^T$ , and  $AW = \lambda_{\max} W$ .

2.1.3 Consistency Test

a. Calculating the consistency index  $C.I. : C.I. = (\lambda_{max} - n) / (n - 1)$ .

Where, n is the order of judgment matrix.

b. Calculating the average random consistency index  $RI$ .

c. Calculating the conformance ratio  $C.R. : C.R. = CI / RI$ . If  $CR \leq 0.1$ , it is considered that the consistency of the judgment matrix is acceptable.

2.1.4 Calculation of objective weight

The weight of each decision is calculated as:

$$\omega' = W_C \times W_A \tag{1}$$

Where,  $W_C = [\omega_{C1}, \omega_{C2}, \dots, \omega_{Cn}]$  is the feature vectors of each decision parameters,  $W_A = [\omega_{A1}, \omega_{A2}, \dots, \omega_{An}]^T$  is the feature vectors of the target layers.

2.2 Subjective weight calculation

Information entropy is used to measure the uncertainty of random variables and can be used to solve the problem of information quantity measurement [12]. The entropy method is used to eliminate the human interference in calculating the weights of each index when applying the AHP method, so that the evaluation results are closer to reality.

2.2.1 Establishment of the stereoscopic cross compound matter element

The detection data of the transformer oil at different times is used as m evaluation schemes, and n is the parameters related decision making. Thus, the n-Dimensional Compound Element of the m Stereoscopic Cross Schemes of the Evaluation Index is:

$$R_{mm} = \begin{bmatrix} M_1 & M_2 & \dots & M_n \\ C_1 & x_{11} & x_{21} & \dots & x_{m1} \\ C_2 & x_{12} & x_{22} & \dots & x_{m2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_n & x_{1n} & x_{2n} & \dots & x_{mn} \end{bmatrix} \tag{2}$$

$M_i$  is the  $i$ -th stereoscopic cross scheme to be evaluated;  $C_j$  is the  $j$ -th evaluation index of the stereoscopic cross scheme;  $x_{ij}$  is the corresponding  $j$ -th index value of the  $i$ -th scheme to be evaluated.

2.2.2 The Standardization of the Stereoscopic Cross Matter-Element

In the calculation, it is necessary to standardize the evaluation index. The formula (3) will be used to standardize the one who has the propelling effect on the evaluation index. The formula (4) will be used to standardize the one who can weaken the evaluation index

$$\delta_{ij} = (x_{ij} - \min_{1 \leq i \leq n} x_{ij}) / (\max_{1 \leq i \leq n} x_{ij} - x_{ij}) \tag{3}$$

$$\delta_{ij} = (\max_{1 \leq i \leq n} x_{ij} - x_{ij}) / (\max_{1 \leq i \leq n} x_{ij} - \min_{1 \leq i \leq n} x_{ij}) \tag{4}$$

( $i = 1, 2, \dots, n; j \in J^-$ )

2.2.3 Subjective weight calculation

In the evaluation factors system, the importance of each factor to the objectives and functions of the system is expressed by weight, and the correlation entropy method is used to determine it. The correlation function uses maximum entropy theory

then the correlation function of the  $j$ -th item index  $C_j$  of the compound matter element is:

$$\zeta_{ij} = \frac{\min_i \min_j |\delta_{ij} - y_j| + 0.5 \max_i \max_j |\delta_{ij} - y_j|}{|\delta_{ij} - y_j| + 0.5 \max_i \max_j |\delta_{ij} - y_j|} \tag{5}$$

The entropy value of the  $j$ -third index of the stereoscopic cross is:

$$F_j = K \sum_i f_{i,j} \ln f_{i,j} \tag{6}$$

Where,  $K = -(H_{max}) = -(\ln n)^{-1}$ ,

$f_{i,j} = \zeta_{i,j} / \sum_{i=1}^m \zeta_{i,j}, j = 1, 2, \dots, m; F_j \in [0, 1]$ . The weight

coefficient of the index is  $\omega''$  as follows:

$$\omega'' = e_j / \sum_{j=1}^n e_j \tag{7}$$

The deviation degree of entropy value is:

$$e_j = 1 - F_j \tag{8}$$

2.3 Joint weight of information entropy

The subjective weight calculated by AHP method is  $\omega'$ , the objective weight calculated by entropy method is  $\omega''$ . Considering the shortcomings of subjective weight and objective weight, the compound matter-element entropy of the photoacoustic spectroscopy is used. The ultimate weight is the joint weight of two weights.

$$\omega_i = \omega'_i \omega''_i / \sum_{i=1}^n \omega'_i \omega''_i \tag{9}$$

2.4 Calculation and analysis of the health index

The experimental data is derived from the 110KV distribution transformer of the Jilin Songhua River thermal power plant. The photoacoustic spectroscopy is used to detect the sample data of the in-transformer oil in every week during the operation of the transformer. 48 sets of experimental gases (CH<sub>4</sub>, C<sub>2</sub>H<sub>2</sub>, C<sub>2</sub>H<sub>4</sub>, C<sub>2</sub>H<sub>6</sub>, H<sub>2</sub>, total hydrogen gas) samples are collected [13].

According to the relevance between different levels, the AHP weight matrixes of target layer matrix A and index layer matrix B<sub>1</sub>, B<sub>2</sub>, B<sub>3</sub>, B<sub>4</sub>, B<sub>5</sub> and B<sub>6</sub> are constructed by 1-9 scale method [14]. The values of each element in the matrix is determined by the current guidelines for analysis and determination of dissolved gases in transformer oil (DL/T722-2000) and the modified three ratio method.

The average random consistency index obtained after 1000 calculations is shown in Table 1, the fifth order value is 1.12.

Table 1: Consistency verification each parameter value

Judgment matrix	$\lambda_{max}$	CI	RI	CR
A	6.873	0.017	1.12	0.016
B <sub>1</sub>	4.033	0.011	1.12	0.009
B <sub>2</sub>	5.079	0.002	1.12	0.002
B <sub>3</sub>	3.004	0.002	1.12	0.002
B <sub>4</sub>	3.136	0.068	1.12	0.061
B <sub>5</sub>	4.046	0.015	1.12	0.014
B <sub>6</sub>	4.027	0.009	1.12	0.008

From table 1, it is known that the CR values are much less than 0.1, so the discriminant matrices are all satisfactory. After the hierarchical single sorting and the hierarchical total sorting of the matrix, the subjective weight  $\omega'$  is shown in Table 2.

**Table 2:** AHP weights of evaluation Indexes

Decision	Criterion Weight	B1	B2	B3	B4	B5	B6	$\omega'$
C1		0.455	0.157	0.309	0	0	0	0.096
C2		0.257	0.314	0	0.188	0	0	0.092
C3		0.118	0.057	0	0.263	0.358	0.135	0.17
C4		0	0.157	0.582	0.547	0.23	0.288	0.327
C5		0	0	0.109	0	0.11	0.107	0.069
C6		0.171	0.314	0	0	0.302	0.47	0.247

**Table 3:** Entropy weights of evaluation Indexes

evaluation indicators	$F_j$	$e_j$	$\omega''$
C1	0.636	0.364	0.168
C2	0.638	0.362	0.168
C3	0.638	0.362	0.163
C4	0.648	0.352	0.172
C5	0.648	0.352	0.162
C6	0.613	0.387	0.169

**Table 4:** Complex weights of evaluation Indexes

evaluation indicators	$\omega'$	$\omega''$	$\omega$
C <sub>1</sub>	0.096	0.167	0.097
C <sub>2</sub>	0.092	0.166	0.091
C <sub>3</sub>	0.170	0.166	0.168
C <sub>4</sub>	0.327	0.162	0.316
C <sub>5</sub>	0.069	0.162	0.067
C <sub>6</sub>	0.247	0.178	0.262

**Table 5:** The calculation results of different weight health index

health index ranking	NO.1	NO.2	NO.3	NO.4	NO.5	NO.6	NO.7	NO.8	NO.9	NO.10	NO.11	NO.12
Index_ $\omega''$	1.69	1.7	1.7	1.701	1.702	1.704	1.704	1.705	1.706	1.706	1.747	1.77
Index_ $\omega$	1.535	1.56	1.567	1.58	1.583	1.59	1.599	1.606	1.61	1.644	1.669	1.681

The entropy value is used to reflect the disordered degree of the parameters, so, the entropy method is used to quantitatively analyze the health index of transformers. For a certain indicator, the information entropy is:

$$H = -\sum_{j=1}^N P(\omega_j \delta_{ij}) \ln P(\omega_j \delta_{ij}) \tag{10}$$

$$P(\omega_j \delta_{ij}) = \omega_j \delta_{ij} [\sum_{j=1}^n \omega_j \delta_{ij}]^{-1} \tag{11}$$

$i = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$ ,  $\omega_j$  Represents the weight

of the impact of decision-making on the health of the target.

By formula (10) and (11), the health index of each month of the transformer is  $H_{\omega''}$  (the health index under the objective weight) and the  $H_{\omega}$  (health index under the compound weight). The ranking results are shown in Table 5.

### 3. HEALTH INDEX PREDICTION OF PRODUCTION CONDITION

#### 3.1 Forecast data samples

The dissolved gas in the weekly transformer oil per month are measured by photoacoustic spectroscopy. The health index of the transformer obtained by Formula (10) and (11) are the original data samples. The health index of three weeks in a month are the training set, and the last week's health index are the testing set.

#### 3.2 Predictive modelling

In order to realize the prediction of transformer operation status, the prediction model of transformer's historical health index is built in Matlab 7.11.0. LSSVM is used. The optimal combination of the kernel function parameters  $\sigma^2$  and the super parameters  $\gamma$  is determined by the grid-search with the cross validation, Finally, the estimation function is

$$f(x) = \sum_{i=1}^l \alpha_i K(x, x_i) + b$$

Where,

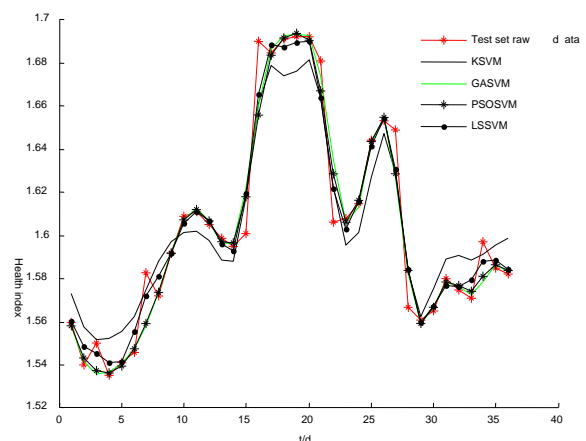
$$K(x, x_i) = \exp\left(-\|x - x_i\|^2 / 2\sigma^2\right) \quad (\sigma > 0)$$

is a kernel function,

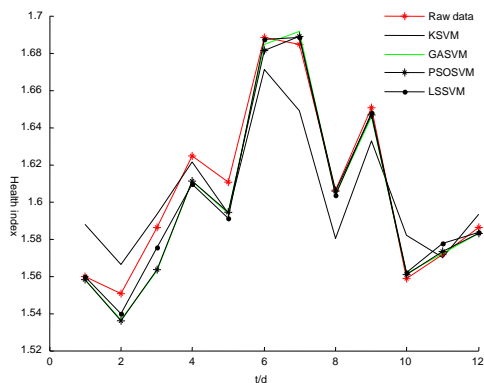
$\alpha_i$  is a Lagrange multiplier, b is a threshold, and it is a constant.

In order to demonstrate the superiority of the method, the support vector machine (SVM) is used, the kernel function is the same to above, using genetic algorithm (GA), grid search (grid-search) and particle swarm optimization (PSO) to optimize the parameters (the penalty parameter  $c$ , the span coefficient  $g$  of the RBF function). The training simulation curves

are shown in Figure 1, and the testing simulation curves are shown in Figure 2.



**Figure 1:** Training simulation curves


**Figure 2:** Testing set simulation curves

### 3.3 Performance Comparison of Modelling Methods

The evaluation indicators are shown in table 6, ( $c$  and  $g$ ) and ( $\sigma^2$  and  $\gamma$ ) are the optimal parameters. Train-MSE and Train-R are the errors and correlation coefficients in fitting [15]. Test-MSE and Test-R are the error and correlation coefficient in testing. T is the simulation run time.

**Table 6:** Performances comparison of four methods

evaluation indicators	SVM			LSSVM
	KC	GA	PSO	KC
optimal parameters	$c=0.0625$	$c=2.084$	$c=1.5492$	$\sigma^2=0.03$
	$g=0.25$	$g=156.87$	$g=173.5$	$\gamma=9.1269$
TRMSE	0.6564	0.0686	0.0653	0.0594
TRC	93.86 %	98.46%	98.51%	98.61%
TEMSE	0.6525	0.0617	0.0625	0.0616
TEC	97.35%	97.4%	97.66%	97.81%
T (s)	7.74	13.732	14.015	0.099

It is known from the table 8 and the Figure 1 and Figure 2 that the prediction effect of LSSVM optimized by cross validation, is better, when  $\sigma^2=0.03$ ,  $\gamma=9.1269$ , the training error and the correlation coefficient are 0.0594/98.61%, and the prediction error and the correlation coefficient are 0.00616/97.81%, and the running time is less 0.01s, and it can meet the demand of actual application of the online prediction.

#### 4. CONCLUSION

In this paper, the evaluation and prediction of the operation status of the transformer are studied. First, the subjective weight of the transformer index are calculated by AHP. Secondly, the objective weight of the transformer index are determined by the information entropy method, and then the joint weight are determined, and the composite element maximum entropy theory is used to calculate the transformer index. At last, the health index of the transformer is used as the prediction set and the verification set, and the prediction model of the transformer operation status is established by the least square support vector machine. In this way, the quantitative analysis of the transformer operation status can be realized, and the operation status of the transformer can be predicted, so as to achieve the better transformer. It provides theoretical and data support for troubleshooting, maintenance decision-making and online prediction.

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#### APPENDIXES

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#### ABOUT THE AUTHORS

Niu Guocheng (1977-), male, associate professor, doctoral student. The main research is intelligent information processing, reliability analysis of complex systems. E-mail [Niuguochengjilin@163.com](mailto:Niuguochengjilin@163.com);

Corresponding author: Hu Zhen (1962-), female, professor, doctor, The main research is intelligent information processing. E-mail: [Huzhen21st@sina.com](mailto:Huzhen21st@sina.com) Hu Dongmei(1979-), female, professor, doctor, The main research is intelligent information processing. E-mail: [haitianme@163.com](mailto:haitianme@163.com)

