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# Research on Multi-Attribute Decision-Making in Condition-Based Maintenance for Power Transformers Based on Cloud and Kernel Vector Space Models

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**Abstract:** Decision-making for the condition-based maintenance (CBM) of power transformers is critical to their sustainable operation. Existing research exhibits significant shortcomings; neither group decision-making nor maintenance intention is considered, which does not satisfy the needs of smart grids. Thus, a multivariate assessment system, which includes the consideration of technology, cost-effectiveness, and security, should be created, taking into account current research findings. In order to address the uncertainty of maintenance strategy selection, this paper proposes a maintenance decision-making model composed of cloud and vector space models. The optimal maintenance strategy is selected in a multivariate assessment system. Cloud models allow for the expression of natural language evaluation information and are used to transform qualitative concepts into quantitative expressions. The subjective and objective weights of the evaluation index are derived from the analytic hierarchy process and the grey relational analysis method, respectively. The kernel vector space model is then used to select the best maintenance strategy through the close degree calculation. Finally, an optimal maintenance strategy is determined. A comparison and analysis of three different representative maintenance strategies resulted in the following findings: The proposed model is effective; it provides a new decision-making method for power transformer maintenance decision-making; it is simple, practical, and easy to combine with the traditional state assessment method, and thus should play a role in transformer fault diagnosis.

**Keywords:** smart grid; cloud model; kernel vector space model; condition-based maintenance; power transformers

## 1. Introduction

The power transformer greatly affects the stability and security of electrical power systems (EPS). In order to enhance maintenance efficiency and lower costs, it is necessary to improve transformer operation and maintenance strategy. Traditional maintenance strategies usually consist of regular maintenance, which takes into account time but ignores the specific state of the equipment, causing the over-repair or lack of repair of the transformer. This affects the cost and also does not satisfy the need of smart grids [1]. The condition-based maintenance (CBM) of power transformers commonly includes condition monitoring, condition assessment, and maintenance decision-making. During condition monitoring, the electrical and chemical parameters are monitored to evaluate the condition of the voltage transformer insulation [2–4]. Dissolved gas analysis (DGA) is used in the actual field diagnosis of engineering to assess the condition of a transformer. Classical machine-learning methods related

to DGA, such as support vector machine (SVM) and particle swarm optimization (PSO) are used to classify and identify failures of the oil-immersed transformer [5].

Decision-making based on CBM has been gradually developing in the power grid in recent years. CBM is a transformer maintenance strategy that has low costs, short outage times, and high equipment-utilization rates, all of which are favored by domestic and foreign power enterprises [6]. CBM requires tracking and forecasting the state of the equipment. When the equipment has a potential fault state, the potential fault point can be determined by means of state evaluation, prediction of the development trend, and fault diagnosis, in order to clarify the location and time of maintenance and to ensure timely measures to avoid functional failure. The mathematical model and the heuristic model have been investigated extensively to determine the maintenance type or maintenance interval. Sim put forward a Markov model, which achieves the best maintenance spaces by comparing different maintenance cost rates [7]. Khac Tuan Huynh et al. espoused a deterioration-based maintenance (DBM) model based on proportional-resonant integrators to reduce costs [8]. In addition, on the basis of life cycle cost calculation, a genetic algorithm and other artificial intelligence methods have been used to compare different maintenance types [9]. There are several deficiencies in this research: it mainly considers reliability, economy, and unilateral research results, without taking into account security and the maintenance intention of decision-makers. This leads to inaccurate modeling processes and decision results. Therefore, multiple-attribute decision-making (MADM) [10] should be developed for risk management and cost–benefit control to aid in decision-making.

MADM can be characterized as a process of selecting the best strategy among all feasible alternatives based on multiple attributes [11,12]. The persistent problem with MADM is that it is not able to accurately express the preferences of decision experts for the alternatives under different attributes. There are various ways to evaluate the state of a power transformer, including fuzzy overall judgment, cloud model theory, evidence theory, association rules, and neural networks (NNs) [13–15]. The fuzzy sets theory and NN model were developed to solve the problem of MADM. The fuzzy sets theory proposed by Zadeh has made great progress in many areas [16–18], but it has no set standard for identifying suitable membership functions. The cloud model was therefore developed as an offshoot of the fuzzy sets theory and is able to integrate both fuzziness and randomness into the concept extraction process [19–23].

The NN model proposed by Rosenblatt is one of the most famous artificial intelligence methods currently in use. The NN model approximates any continuous function infinitely and performs well in response to decision-making problems [24–26]. However, NN training usually requires a large amount of manually labeled data; thus, the process can be time-consuming, expensive, and inefficient in engineering application. Consequently, the SVM model was proposed. Considering both experience risk minimization and the complexity of the learning machine, it is effective for less sample optimization [27,28].

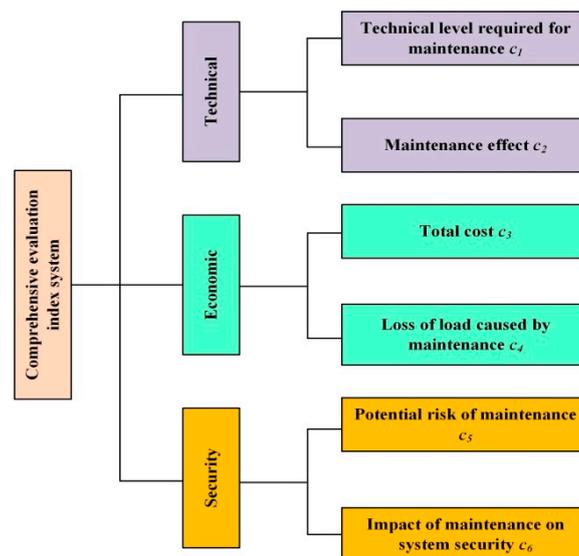
The kernel vector space model put forward in this paper was inspired by SVMs. It seeks to map the input data from low-dimensional space to high-dimensional space through the kernel function, and to realize a linearization method for settling the nonlinear questions in low-dimensional space. Thus, the computational problem of NNs can be effectively solved, and the calculation speed can be increased [29].

This paper proposes an integrated evaluation model composed of the cloud and kernel vector space models. The assessment system consists of three factors and six indices. The cloud model is used to convert qualitative linguistic concepts into quantitative expression for the purpose of obtaining quantitative decision information. The kernel vector space model maps low-dimensional input spaces to high-dimensional spaces and uses the weighted cosine calculation to produce evaluation results. The maintenance decision-making resulting from the proposed model is verified by the consistency of the on-site results.

## 2. Establishment of the Transformer Condition Maintenance Evaluation System

### 2.1. Comprehensive Evaluation Index System

The maintenance strategy for a power transformer is determined by many factors. Following the scientific, independence, and operability principles, a comprehensive evaluation index system was set up according to technical, economic, and security considerations. The selected assessment indices are shown in Figure 1.



**Figure 1.** The comprehensive evaluation index system.

Six indicators are used:  $c_1$  to  $c_6$  represent the required technical level for maintenance, the maintenance effect, the total cost, the economic impact of the loss of load due to maintenance, the potential security risk, and the impact of maintenance on system security, respectively.

### 2.2. Cloud Model

The cloud model, proposed by Li et al. [19], is a mathematical model of fuzzy exchange between a qualitative concept and its numerical expression; this model combines the uncertainty of fuzzy theory with the randomness of probability theory, the mathematical characteristics of which can be denoted by three indices:  $E_x$ ,  $E_n$ , and  $H_e$ .  $E_x$  is central to the concept of attributes in the discourse domain and represents the concept of the attributes.  $E_n$  is a measurement metric of the blurring level of property concept and represents the numerical region of intervals in which the property concept is applicable.  $H_e$  represents the degree of dispersion of cloud droplets and reveals the association of the concept of natural language properties between randomness and fuzziness. For example, if  $E_x = 0.5$ ,  $E_n = 0.15$ , and  $H_e = 0.01$ , the quantitative concepts represented by the cloud model can be described as  $C(0.5, 0.15, 0.01)$ .

There are many qualitative indicators in the comprehensive evaluation index system that need to be converted into quantitative indicators for subsequent analysis and calculation. The qualitative indicators  $c_1$  to  $c_6$  are classified in accordance with the following levels: very good, good, average, bad, and very bad. These levels can be represented by five classes under the golden section method. Assuming that  $C_0(E_x^0, E_n^0, H_e^0)$  is the middle cloud, with the neighboring clouds being  $C_{-1}(E_x^{-1}, E_n^{-1}, H_e^{-1})$ ,  $C_{+1}(E_x^{+1}, E_n^{+1}, H_e^{+1})$ ,  $C_{-2}(E_x^{-2}, E_n^{-2}, H_e^{-2})$ , and  $C_{+2}(E_x^{+2}, E_n^{+2}, H_e^{+2})$ , these five clouds can be defined by the golden section method in Formulas (1)–(3):

$$\begin{cases} E_x^0 = \frac{1}{2}(x_{\min} + x_{\max}) \\ E_x^{-2} = x_{\min} \\ E_x^{+2} = x_{\max} \\ E_x^{-1} = E_x^0 - \frac{1}{2}\left(1 - \frac{\sqrt{5}-1}{2}\right)(x_{\min} + x_{\max}) \\ E_x^{+1} = E_x^0 + \frac{1}{2}\left(1 - \frac{\sqrt{5}-1}{2}\right)(x_{\min} + x_{\max}) \end{cases} \quad (1)$$

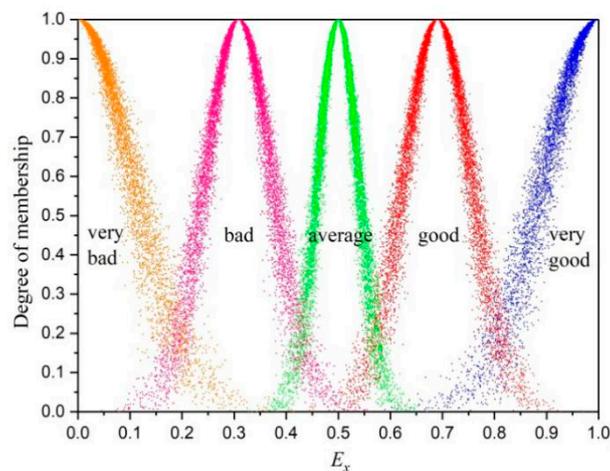
$$\begin{cases} H_e^{+1} = H_e^{-1} = \frac{2}{\sqrt{5}-1}H_e^0 \\ H_e^{+2} = H_e^{-2} = \frac{2}{\sqrt{5}-1}H_e^{+1} \end{cases} \quad (2)$$

$$\begin{cases} H_e^{+1} = H_e^{-1} = \frac{2}{\sqrt{5}-1}H_e^0 \\ H_e^{+2} = H_e^{-2} = \frac{2}{\sqrt{5}-1}H_e^{+1} \end{cases} \quad (3)$$

With  $H_e$  set as constant 0.006 and a valid discourse domain defined as [0, 1], the calculation outcomes are listed in Table 1. The corresponding cloud model image is shown in Figure 2.

**Table 1.** The corresponding cloud model of the qualitative indicators.

$c_1, c_3$	$c_2$	$c_4-c_6$	Cloud Model
Lower	Very Good	Smaller	$C(1, 0.104, 0.015)$
Low	Good	Small	$C(0.691, 0.064, 0.009)$
Average	Average	Average	$C(0.5, 0.039, 0.006)$
High	Bad	Big	$C(0.309, 0.064, 0.009)$
Higher	Very Bad	Bigger	$C(0, 0.104, 0.015)$



**Figure 2.** Normal cloud model image.

Assuming that the qualitative indicators are evaluated by  $h$  experts, the language-based evaluation information given by each expert has a corresponding cloud model. The individual cloud models of each expert are combined as an integrated cloud model in Formulas (4) and (5).

$$E_x = \frac{E_{x1}E_{n1} + E_{x2}E_{n2} + \dots + E_{xh}E_{nh}}{E_{n1} + E_{n2} + \dots + E_{nh}} \quad (4)$$

$$E_n = E_{n1} + E_{n2} + \dots + E_{nh} \quad (5)$$

### 3. Determination of Evaluation Index Weight

#### 3.1. Grey Correlation Analysis

The weight coefficient of each assessment indicator in the comprehensive assessment index system of maintenance decision-making greatly affects the final evaluation results. It is important to establish an objective and comprehensive decision-making process. The grey relational method, originating from the grey system theory, can resolve issues related to fuzzy information, less data, and data shortage [30–33]. Grey correlation analysis can determine different information between sequences and can calculate the degree of correlation by establishing the different information intervals.

The comprehensive evaluation system of the CBM consists of numerous evaluation indicators. The grey correlation analysis method can be used to objectively determine the principal contradiction of the system. It is therefore used to calculate the objective weight of evaluation indicators.

Assuming that  $G_i$  ( $i = 1, 2, \dots, m$ ) is the selected maintenance strategy, and  $G_0 = (g_{01}, g_{02}, \dots, g_{0n})$  is the best reference strategy,  $G_{ij}$  and  $G_{0j}$  denote the quantified evaluation indicators of the maintenance strategy and the corresponding indicator value of the best reference strategy, respectively. Thus, the selection criteria of the benefit indicators can be calculated using Formula (6):

$$g_{0j} = \max_{1 \leq i \leq m} \{g_{ij}\}, j = 1, 2, \dots, n \quad (6)$$

Moreover, the selection criteria of the cost indicators can be calculated using Formula (7):

$$g_{0j} = \min_{1 \leq i \leq m} \{g_{ij}\}, j = 1, 2, \dots, n \quad (7)$$

The correlation coefficient matrix  $(\zeta_{ij})_{m \times n}$  between the maintenance strategy  $G_i$  and the best strategy  $G_0$  can be calculated using Formulas (8) and (9):

$$\zeta_{ij} = \frac{\Delta(\min) + \rho \Delta(\max)}{\Delta_{ij} + \rho \Delta(\max)} \quad (8)$$

$$\Delta_{ij} = |g_{0j} - g_{ij}| \quad (9)$$

where  $\Delta_{ij}$  is the absolute difference between  $g_{ij}$  and  $g_{0j}$ ,  $\Delta(\min)$  is the minimum difference between the two levels,  $\Delta(\max)$  is the maximum difference between the two levels, and  $\rho$  is the resolution coefficient, which was set to 0.5 in this paper as an optimal value.

The objective weight vector  $w_j$  is calculated by Formulas (10) and (11) based on the correlation matrix  $(\zeta_{ij})_{m \times n}$  and the correlation coefficient  $r_j$ :

$$r_j = \frac{1}{m} \sum_{i=1}^m \zeta_{ij} \quad (10)$$

$$w_j = \frac{r_j}{\sum_{j=1}^n r_j} \quad (11)$$

#### 3.2. Determination of the Comprehensive Index Weight

The analytic hierarchy process (AHP) is combined with grey correlation analysis, and the comprehensive weight of the assessment index is calculated by the principle of additive integration. The AHP introduces the subjective prior knowledge of experts as well as their preference information to reach the subjective weight, while grey correlation analysis reflects the inherent correlation of maintenance decision-making for power transformers in an objective and comprehensive manner.

Assuming that  $W_S$  represents the subjective weight vector and  $W_O$  represents the objective weight vector, according to the additive integration principle, the comprehensive weight can be expressed as specified in Formulas (12) and (13):

$$W = aW_S + bW_O \quad (12)$$

$$\begin{cases} a = \frac{P_1 + 2P_2 + \dots + mP_m}{m-1} - \frac{m+1}{m^2-m} \\ a + b = 1 \end{cases} \quad (13)$$

where  $P_i$  is the value of subjective weight sorted from small to large, and  $m$  is the whole number of indicators.

#### 4. Kernel Vector Space Model

In this paper, the kernel vector space model derived from the support vector machine theory was applied to map the input data from low-dimensional space to high-dimensional space through kernel function. This model increases the difference and distance between samples to gain more objective and scientific evaluation results.

At present, there is no theory that can explain the selection of kernel functions perfectly, though the Gaussian kernel function is commonly used. The expression of the function is as specified in Formula (14):

$$Ker(x, y) = \exp\left(-\frac{\|x - y\|^2}{2\sigma^2}\right) \quad (14)$$

where  $\sigma$  is the radial basis parameter of the Gaussian kernel function and the parameters  $x$  and  $y$  are the corresponding space vectors.

By calculating the cosine of the angle of the vectors, the proximity between the vectors can be calculated using Formula (15):

$$\cos \theta = \frac{Ker(R, R_0)}{\sqrt{Ker(R, R)} \sqrt{Ker(R_0, R_0)}} \quad (15)$$

where  $R$  and  $R_0$  are the quantitative indicator and the best quantitative index mentioned in Section 2, respectively. The angle between the space vector  $R$  and  $R_0$  is defined as  $\theta$ .

Considering the difference between the factors and the weight distribution of each evaluation index, the space vector affected by the combined weight should be taken into account, and the comprehensive weight should be added before each space vector, as specified in Formula (16):

$$Q = \cos \theta' = \frac{Ker(WR, WR_0)}{\sqrt{Ker(WR, WR)} \sqrt{Ker(WR_0, WR_0)}} \quad (16)$$

where  $\cos \theta'$  is the weighted cosine of the space vector after the allocation of the index weights in the kernel space.

The calculated weighted cosine value can be regarded as the proximity of each decision candidate and the optimal decision. Thus, the maintenance decision evaluation result of a power transformer should be based on a close degree of proximity.

#### 5. Case Analysis

The case analysis was based on the equipment failure of a 110 kV transformer. Monitoring of the transformer showed that the total amount of hydrocarbon oil exceeded the alert value.

Three kinds of maintenance strategies were developed according to the results of the fault diagnosis and production planning arrangement, denoted as  $M_1$  to  $M_3$ .  $M_1$  overhauls in advance; maintenance items are established by the relevant guidelines.  $M_2$  uses targeted overhauling; the maintenance

schedule is arranged by the fault diagnosis and the trend forecasting results.  $M_3$  tracks and monitors the transformer continuously; it does not arrange the overhauling until the overhauling cycle.

After analysis and comparison, four experts published their own viewpoint of the alternative strategy according to the indices mentioned in Section 2. The evaluation of the qualitative indices is shown in Table 2, with each row of  $M_1$ ,  $M_2$ , and  $M_3$  corresponding to the evaluation of the qualitative indicators of one expert.

**Table 2.** Evaluation results of qualitative index  $c_1$ – $c_6$ .

Strategy	$c_1$	$c_2$	$c_3$	$c_4$	$c_5$	$c_6$
$M_1$	High	Very Good	Higher	Bigger	Bigger	Bigger
	Higher	Very Good	Higher	Bigger	Bigger	Bigger
	High	Very Good	Higher	Big	Bigger	Big
	Higher	Good	Higher	Bigger	Big	Big
$M_2$	High	Good	High	Medium	Big	Bigger
	Low	Very Good	Average	Big	Big	Bigger
	High	Very Good	Average	Medium	Big	Big
	Average	Good	Good	Small	Big	Bigger
$M_3$	Average	Very Bad	Low	Small	Smaller	Bigger Bigger
	Average	Bad	Low	Smaller	Smaller	Bigger
	High	Very Bad	Low	Smaller	Small	Bigger
	High	Bad	Average	Medium	Small	

The determination process of the optimal maintenance strategy is described as follows:

The natural language evaluation information of the experts should first be pre-processed. The quantification of the of technical, economic, and security qualitative indices should be calculated using Equations (1)–(5), and the initial decision matrix ( $D$ ) of the three strategies should be composed of six indicators, as follows:

$$D = \begin{pmatrix} 0.8823 & 0.9474 & 1.0000 & 0.9474 & 0.7821 & 0.8823 \\ 0.5529 & 0.8823 & 0.6588 & 0.6919 & 0.6910 & 0.9474 \\ 0.6187 & 0.1177 & 0.3412 & 0.1023 & 0.1177 & 1.0000 \end{pmatrix}$$

According to the criterion of the best program as established in Section 2, the best quantitative sequence was constructed as follows:

- (1) Based on the influence of maintenance in power transformers, the expected results of qualitative index  $c_2$  were calculated using Equation (6), as follows:

$$g_{02} = \max_{\substack{i=1 \leq i \leq 3 \\ j=2}} \{g_{ij}\} = g_{12} = 0.9474$$

- (2) The expected results of qualitative indicators  $c_1$  and  $c_3$  to  $c_6$  were calculated using Equation (7), as follows:

$$g_{01} = \min_{\substack{i=1 \leq i \leq 3 \\ j=1}} \{g_{ij}\} = 0.5529$$

$$g_{03} = \min_{\substack{i=1 \leq i \leq 3 \\ j=3}} \{g_{ij}\} = g_{33} = 0.3412$$

$$g_{04} = \min_{\substack{i=1 \leq i \leq 3 \\ j=4}} \{g_{ij}\} = g_{34} = 0.1023$$

$$g_{05} = \min_{\substack{i=1 \leq i \leq 3 \\ j=5}} \{g_{ij}\} = g_{35} = 0.1177$$

$$g_{06} = \min_{\substack{i=1 \leq i \leq 3 \\ j=6}} \{g_{ij}\} = g_{16} = 0.8823$$

Therefore, the best decision-making vector of the six quantitative indices ( $D_e$ ) can be expressed as follows:

$$D_e = \left[ \begin{array}{cccccc} 0.5529 & 0.9474 & 0.3412 & 0.1023 & 0.1177 & 0.8823 \end{array} \right]$$

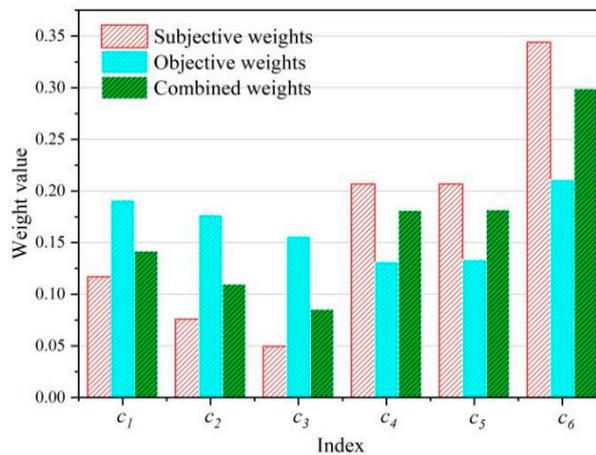
Additionally, the augmented matrix ( $M_z$ ) can be expressed as:

$$M_z = \left[ \begin{array}{cccccc} 0.5529 & 0.9474 & 0.3412 & 0.1023 & 0.1177 & 0.8823 \\ 0.5529 & 0.8823 & 0.6588 & 0.6910 & 0.6910 & 0.9474 \\ 0.6187 & 0.1177 & 0.3412 & 0.1023 & 0.1177 & 1.0000 \\ 0.5529 & 0.9474 & 0.3412 & 0.1023 & 0.1177 & 0.8823 \end{array} \right]$$

According to the process mentioned in Section 2, the final weight coefficients are shown in Table 3, and a bar diagram of the comprehensive weight is shown in Figure 3.

**Table 3.** Weight of the evaluation indices.

Index	Subjective Weights	Objective Weights	Combined Weights
$c_1$	$1.169 \times 10^{-1}$	$1.912 \times 10^{-1}$	$1.420 \times 10^{-1}$
$c_2$	$7.590 \times 10^{-2}$	$1.769 \times 10^{-1}$	$1.100 \times 10^{-1}$
$c_3$	$4.960 \times 10^{-2}$	$1.560 \times 10^{-1}$	$8.550 \times 10^{-2}$
$c_4$	$2.067 \times 10^{-1}$	$1.315 \times 10^{-1}$	$1.813 \times 10^{-1}$
$c_5$	$2.067 \times 10^{-1}$	$1.335 \times 10^{-1}$	$1.820 \times 10^{-1}$
$c_6$	$3.441 \times 10^{-1}$	$2.109 \times 10^{-1}$	$2.991 \times 10^{-1}$



**Figure 3.** Combined weights of the qualitative indicators.

The weighted proximity ( $Q$ ) between decision vector  $R$  and  $R_0$ , as calculated by Equations (14)–(16), is listed in Table 4, with  $\sigma$  set to 1.12.

**Table 4.** The proximity of evaluation strategies.

Maintenance Strategy	Proximity
$M_1$	0.9836
$M_2$	0.9906
$M_3$	0.9963

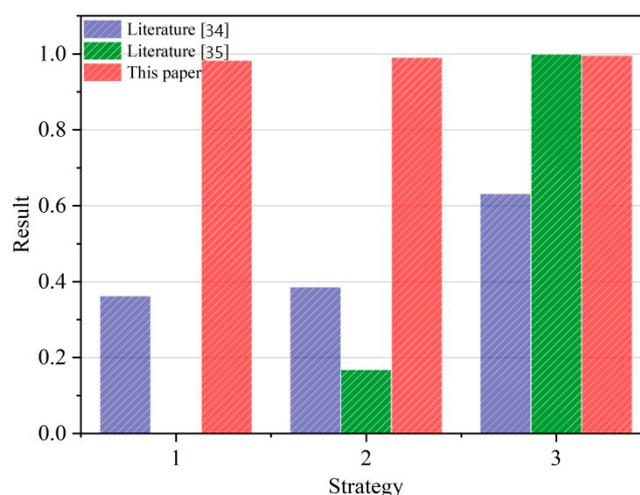
The optimal membership degrees of each maintenance strategy were sorted, and the result was  $Q_3 > Q_2 > Q_1$ . The third maintenance scheme,  $Q_3$ , was the relative optimum strategy, which is the same as the results of [34,35].

The above example takes the technical, economic, and security aspects into consideration. It can also be concluded that  $M_1$ ,  $M_3$ , and  $M_2$  are the relative optimum strategies for the technical, economic, and security aspects, respectively, where aspects are considered individually. Decision-makers should consider various evaluation indicators and the potential risk of loss comprehensively, synthetically, and systematically before making the final decision to avoid unnecessary economic loss. The model proposed in this paper offers a good interpretation of the psychology of power enterprise decision-makers, and thus reflects expected human behavior in the selection of the maintenance strategies.

Table 5 and Figure 4 show comparisons of the results obtained based on the strategies in [34,35] and those obtained by the proposed strategy in this paper.

**Table 5.** Comparison of the evaluation results.

Strategy	Ref. [34]	Ref. [35]	Proposed Strategy
$M_1$	0.3624	0	0.9829
$M_2$	0.3857	0.1685	0.9908
$M_3$	0.6317	1	0.9962



**Figure 4.** Comparison of the evaluation results.

According to the results of Table 5 and Figure 4, although in both [34,35] the third maintenance strategy was used as a relatively optimal scheme, the degree of uncertainty in [34] was still relatively high and the determination of the strategy in [35] was too absolute, which resulted in a deviation from reality. In comparison to the conclusions in [34,35], the model put forward in this paper is more suitable for practical engineering applications. The results obtained by the proposed model reflect the psychology of decision-makers in power companies when choosing maintenance strategies. More importantly, the implementation of the model is achieved with a solid mathematical foundation.

## 6. Conclusions

This paper proposed an integrated evaluation model for decision-making for power transformers that includes the cloud and kernel vector space models. It also suggested a comprehensive evaluation system based on technical, economic, and security indices. The cloud model allows for the quantitative expression of the qualitative language assessment index. The subjective weight of the assessment index is calculated by the analytic hierarchy process, while the objective weight is calculated by

the grey relational analysis method. In terms of the principle of the additive synthesis method, the comprehensive weight, including the influence of subjective judgment and objective information, can be obtained.

The results of the case analysis show that the proposed strategy is applicable. It is characterized by a simple model and practical method, and it is convenient to combine with traditional condition assessment method to play a greater role in the CBM of power transformers. The constructed comprehensive evaluation system is able to reflect the complexity of the maintenance decisions in the field and provides scientific and reasonable evaluation results. The model outlined above is considered an efficient model for maintenance decision-making of the power transformer and offers a new means of CBM decision-making for power enterprises.

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## References

1. Lösch, A.; Schneider, C. Transforming power/knowledge apparatuses: The smart grid in the German energy transition. *Innov. Eur. J. Soc. Sci.* **2016**, *29*, 262–284. [[CrossRef](#)]
2. Fofana, I.; Hemmatjou, H.; Meghnefi, F. Effect of thermal transient on the polarization and depolarization current measurements. *IEEE Trans. Dielectr. Electr. Insul.* **2011**, *18*, 513–520. [[CrossRef](#)]
3. Wada, J.; Ueta, G.; Okabe, S. Method to evaluate the degradation condition of transformer insulating oil—establishment of the evaluation method and application to field transformer oil. *IEEE Trans. Dielectr. Electr. Insul.* **2015**, *22*, 1266–1274. [[CrossRef](#)]
4. Abu-Siada, A.; Lai, S.P.; Islam, S.M. A novel fuzzy-logic approach for furan estimation in transformer oil. *IEEE Trans. Power Deliv.* **2012**, *27*, 469–474. [[CrossRef](#)]
5. Shintemirov, A.; Tang, W.; Wu, Q.H. Power transformer fault classification based on dissolved gas analysis by implementing bootstrap and genetic programming. *IEEE Trans. Syst. Man Cybern. Part C* **2008**, *39*, 69–79. [[CrossRef](#)]
6. Singh, J. The influence of service aging on transformer insulating oil parameters. *IEEE Trans. Dielectr. Electr. Insul.* **2012**, *19*, 421–426. [[CrossRef](#)]
7. Sim, S.H.; Endrenyi, J. A failure-repair model with minimal and major maintenance. *IEEE Trans. Reliab.* **1993**, *42*, 134–140. [[CrossRef](#)]
8. Huynh, K.T.; Grall, A. A condition-based maintenance model with past-dependent imperfect preventive repairs for continuously deteriorating systems. *J. Risk Reliab.* **2020**, *234*, 333–358. [[CrossRef](#)]
9. Hinow, M.; Mevissen, M. Substation maintenance strategy adaptation for life-cycle cost reduction using genetic algorithm. *IEEE Trans. Power Deliv.* **2010**, *26*, 197–204. [[CrossRef](#)]
10. Tang, W.H.; Spurgeon, K.; Wu, Q.H. An evidential reasoning approach to transformer condition assessments. *IEEE Trans. Power Deliv.* **2004**, *19*, 1696–1703. [[CrossRef](#)]
11. Li, D. A fuzzy closeness approach to fuzzy multi-attribute decision making. *Fuzzy Optim. Decis. Mak.* **2007**, *6*, 237–254. [[CrossRef](#)]
12. Bisoi, R.; Chakravorti, T.; Nayak, N.R. A hybrid Hilbert Huang transform and improved fuzzy decision tree classifier for assessment of power quality disturbances in a grid connected distributed generation system. *Int. J. Power Energy Convers.* **2020**, *11*, 60–81. [[CrossRef](#)]
13. Sivaperumal, P.; Subranhsu-Sekhar, D.; Saravanan, K. Enhancing the power of quality issues using superconducting magnetic storage devices—Based dynamic voltage restorer—Aided switched coupled inductor inverter with space vector pulse width modulation techniques. *Meas. Control.* **2019**, *52*, 1329–1343. [[CrossRef](#)]
14. Xiang, Z.; Ji, V.; Hai, Z.; Jie, D.; Fang, C.; Xin, Z. Very short-term prediction model for photovoltaic power based on improving the total sky cloud image recognition. *J. Eng.* **2017**, *2017*, 1947–1952. [[CrossRef](#)]

15. Yang, J.B.; Singh, M.G. An evidential reasoning approach for multiple-attribute decision making with uncertainty. *IEEE Trans. Syst. Man Cybern.* **2002**, *24*, 1–18. [[CrossRef](#)]
16. Rodriguez, R.M.; Martinez, L.; Herrera, F. Hesitant fuzzy linguistic term sets for decision making. *IEEE Trans. Fuzzy Syst.* **2012**, *20*, 109–119. [[CrossRef](#)]
17. Bovea, M.D.; Wang, B. Identifying environmental improvement options by combining life cycle assessment and fuzzy set theory. *Int. J. Prod. Res.* **2003**, *41*, 593–609. [[CrossRef](#)]
18. Dixit, V.; Chaudhuri, A.; Srivastava, R.K. Assessing value of customer involvement in engineered-to-order shipbuilding projects using fuzzy set and rough set theories. *Int. J. Prod. Res.* **2019**, *57*, 6943–6962. [[CrossRef](#)]
19. Li, D.; Liu, C.; Gan, W. A new cognitive model: Cloud model. *Int. J. Intell. Syst.* **2009**, *24*, 357–375. [[CrossRef](#)]
20. Lv, P.; Yuan, L.; Zhang, J. Cloud theory-based simulated annealing algorithm and application. *Eng. Appl. Artif. Intell.* **2009**, *22*, 742–749. [[CrossRef](#)]
21. Li, W.; Zhao, J.; Xiao, B. Multimodal medical image fusion by cloud model theory. *Signal Image Video Process* **2018**, *12*, 437–444. [[CrossRef](#)]
22. Shi, Y.; Zhou, H. Research on monthly flow uncertain reasoning model based on cloud theory. *Sci. China Technol. Sci.* **2010**, *53*, 2408–2413. [[CrossRef](#)]
23. Wang, J.Q.; Wang, P.; Wang, J. Atanassov's interval-valued intuitionistic linguistic multicriteria group decision-making method based on the trapezium cloud model. *IEEE Trans. Fuzzy Syst.* **2015**, *23*, 542–554. [[CrossRef](#)]
24. Gleue, C.; Eilers, D. Decision support for the automotive industry: Forecasting residual values using artificial neural networks. *Wirtschaftsinformatik* **2019**, *61*, 385–397. [[CrossRef](#)]
25. Zhao, B.; Chen, S. Maintenance decision methodology of petrochemical plant based on fuzzy curvelet neural network. *Appl. Soft Comput.* **2018**, *69*, 203–212. [[CrossRef](#)]
26. Saeed, Y.; Ahmed, K.; Zareei, M. In-vehicle cognitive route decision using fuzzy modeling and artificial neural network. *IEEE Access* **2019**, *7*, 20262–20272. [[CrossRef](#)]
27. Tan, Y.; Niu, C.; Tian, H. A one-class SVM based approach for condition-based maintenance of a naval propulsion plant with limited labeled data. *Ocean Eng.* **2019**, *193*, 106592.1–106592.12. [[CrossRef](#)]
28. Nie, F.; Zhu, W.; Li, X. Decision tree SVM: An extension of linear SVM for non-linear classification. *Neurocomputing* **2019**, *11*, 153–159. [[CrossRef](#)]
29. Liu, Q.; Lu, H.; Ma, S. Improving kernel Fisher discriminant analysis for face recognition. *IEEE Press* **2004**, *14*, 42–49. [[CrossRef](#)]
30. Fang, Z.; Wang, Q.; Wei, H. Functional analysis model for selecting leading industry under grey information. *Kybernetes Int. J. Syst. Cybern.* **2013**, *41*, 851–859. [[CrossRef](#)]
31. Javanmardi, E.; Liu, S. Exploring grey systems theory-based methods and applications in analyzing socio-economic systems. *Sustainability* **2019**, *11*, 4192. [[CrossRef](#)]
32. Tsai, M.S.; Hsu, F.Y. Application of grey correlation analysis in evolutionary programming for distribution system feeder reconfiguration. *IEEE Trans. Power Syst.* **2010**, *25*, 1126–1133. [[CrossRef](#)]
33. Liu, S.; Guan, Y.; Song, D. Correlation analysis of bearing track using grey system theory. *Kybernetes* **2012**, *41*, 945–952.
34. Yang, L.J.; Xiong, X.F.; Zhang, Y. Research on condition-based maintenance policy of electric power equipment based on grey correlation degree and TOPSIS. *Power Syst. Prot. Control* **2009**, *18*, 74–78.
35. Yuan, Z.; Sun, C.; Li, A. Assessment on condition based maintenance policy of transformer using fuzzy multiple attribute decision making. *High Volt. Eng.* **2004**, *30*, 33–35.

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