Fault Diagnosis of Capacitance Aging in DC Link Capacitors of Voltage Source Inverters Using Evidence Reasoning Rule

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Capacitance aging of DC link capacitors in voltage source inverters (VSIs) is a common fault which can lead to instability of the DC voltage. In such a failure state, although the VSI can still work, its performance gradually deteriorates, resulting in a shorter service life of the equipment. Here, an online monitoring and fault diagnosis method for capacitance aging based on evidence reasoning (ER) rule is presented. Features from the DC link voltage data with different levels of capacitance aging are extracted, and data features are generated as pieces of diagnostic evidence, which are then combined according to the ER rule. Finally, capacitance aging fault levels were estimated using the combined results. This method has better diagnostic performance compared to a backpropagation (BP) neural network approach and can be used to flexibly define the relative weighting of each evidence parameter depending on the application. This approach can therefore be widely used for fault diagnosis of an array of different devices.

1. Introduction

Voltage source inverters (VSIs) are generally reliable, accurate, and effective and have become the most common inverter type used in industry [1]. A capacitor is a key component of VSIs, as they supply the input current to the inverter, compensate for the difference between the power requirement of the inverter and the output power of the rectifier, suppress the current harmonics, absorb feedback energy, meet instantaneous power demand, and stabilize voltage fluctuations [2]. There are three main types of capacitor: electrolytic, ceramic, and film capacitors. Of these, the electrolytic capacitor is most commonly used in VSIs. Electrolytic capacitors generally have a much shorter life expectancy compared with the service life of the inverter. Capacitor faults generally include short circuits, electric leakages, and capacitance attenuation. As inverter operation proceeds, evaporation of electrolyte will cause gradual capacitance attenuation. And although the inverter can still function as capacitance aging increases, overcurrent and under voltage situations increasingly arise when the inverter runs under load, increasing potential safety hazards [3]. This fault is classified as an incipient fault and does not generally trigger the protection system. However, if left undetected and untreated, this situation can significantly reduce the service life of the equipment. It is therefore increasingly important to diagnose capacitance aging in order to evaluate and carry out preventative maintenance in advance.

Historically, equivalent series resistance (ESR) and capacitance C are two important parameters used to evaluate capacitance aging. A fault situation is defined if the ESR is more than the double of its initial value. When capacitance attenuation exceeds 20% of the initial value, the capacitor is classified as failed [4]. The majority of methods used to detect capacitor faults are based on monitoring the ESR value, including offline and online modes. Offline detection
methods are gradually becoming obsolete as they do not allow dynamic management [5]. On the other hand, for online detection methods, the most direct and effective method is to estimate the ESR value using the correlation between current and voltage values [6, 7]. The ratio of capacitor voltage to supply voltage can also be used to calculate the ESR by reference resistor [8]. However, the accuracy of the technique depends largely on the difference of the reference resistors. The influence of temperature on ESR has also been widely investigated [9, 10]. Improvements in the measuring terminal have been used to obtain more accurate ESR values [11]. In addition, a built-in self-test (BIST) method was used to monitor the attenuation of capacitance C [12]. However, there are few research studies which consider the capacitor fault state jointly determined by ESR value and capacitance C. Oukaou et al. [13] monitored both parameters, and the aging index was estimated using the least squares method, which is proved to be effective.

However, all above methods are based on the principle of using formulae to fit the relationship between the acquisition signal source and the capacitor ESR value and capacitance C which is not ideal. The monitoring parameters are various and complex. Moreover, it is difficult to identify incipient faults and predict serious faults using this approach. At present, data-driven fault monitoring and identification methods are increasingly used due to their broad applicability and high diagnostic accuracy [14, 15]. Data-driven methods using artificial neural networks (ANNs) have been used to estimate capacitance capacity [16]; however, the accuracy of ANN method is limited by the quantity of training samples. Extended neural network (ENN) algorithms and chaotic synchronization detection methods have also been used to identify capacitor faults [17]. An online track circuit compensation capacitor fault diagnosis method based on K- fault diagnosis method was reported [18]. Unfortunately, these methods only consider the identification of serious faults that have occurred and do not carry out further subdivision on the degree of capacitor faults which would allow much earlier intervention and fault correction.

Here, we propose a fault diagnosis method for capacitance aging in DC link capacitors used in inverters which is based on the evidence reasoning (ER) rule [19]. Based on the principle of data-driven decision making, this method does not assume any relationship between capacitance and other parameters [20, 21], but only generates types of diagnostic evidence and combines them by measuring the DC link voltage value under different capacitance attenuation degrees and then estimates the fault level of capacitance aging based on the combined results. The advantage of using the ER rule method is that it has the ability to deal with the variable information provided by incipient fault situations and it can also define the relative reliability of different information sources. Moreover, for multiple types of evidence, the relative weighting or importance between different types of evidences can be allocated. This weighted information can then be considered comprehensively to provide more correct data for final decision making. Different fault thresholds can be set according to expert user experience in different practical applications. The method also has the advantages of using fewer parameters but providing higher monitoring sensitivity.

2. Simulation Model and Experiment

2.1. A Simulation Model for a Marine Electric Propulsion System. In marine electric propulsion systems, the propeller is driven by an electric motor. This propulsion method abandons the traditional way in which the shaft system and propeller are driven by the prime mover and is efficient and energy saving and allows excellent maneuverability and flexible arrangements [22, 23]. The most common electric propulsion system is generally powered by diesel generator sets, which provide electric power to propulsion motors through switchboard and frequency converters and which then drives the propellers to generate thrust. The ship “Jiangsu ferry 3011” was used in this work as a case study and is a ferry ship which is in use and which runs across the Yangtze River between Zhenjiang and Yangzhou in Jiangsu province in China (Figure 1). The ship is 90 meters long and 15.4 meters wide and has a tonnage of 720 tons and is the first civil ship adopting an electric propulsion system (Figure 2) using DC power in China.

A DC power system is used on board, which means the electric power is generated from an alternating current (AC) generator and transformed into DC power by a rectifier to feed the DC bus. Power is then transmitted to inverters to drive propulsion motors and other auxiliary loads. The basic parameters of this marine power system are shown in Table 1.

The overall life cycle of electric propulsion ships is characterized by working in highly variable environments with multiple types of interference, strong maneuvering requirements, and complex river conditions for 24 hours per day, always accompanied by potential incipient faults in the electrical system. The inverter is the core component of the ship’s electric propulsion system. The failure of the DC link capacitor is one of the most common faults of the inverter [24]. Due to the different operating environments and different types of electric propulsion systems, the degree and characteristics of capacitor attenuation are irregular and uncertain. In addition, with current monitoring technology, it is difficult to track, collect, and extract data which can identify fault features. The accumulated data are often incomplete and invalid, which frustrates careful research-based and data-driven solutions. However, by building a computer model of this system, we can simulate the life cycle characteristics of the ship’s electric propulsion system and track the fault characteristics of the capacitor with time, laying the foundations for a new and rigorous research-based approach to incipient fault diagnosis which can be developed for use on board these electric ferries.

Based on the main parameters in Table 1, we developed a simulation model of this marine electric propulsion system using a Matlab/Simulink environment [25] as shown in Figure 3.

In the simulation model, the Jiangsu ferry 3011’s electric propulsion system consists of generator, rectifier, inverter, and propulsion motors. The DC link capacitor is made up of
two identical capacitors in series, and N is the midpoint between the two capacitors. The propulsion system consists of two propulsion motors of the same type. Tm1 and Tm2 are the load torques of the two propulsion motors.

2.2. Fault Simulation. In this paper, the most frequent working condition was selected for research, and the load torque was set at 2228Nm. In the DC link, three different levels of capacitance attenuation were set in the simulation model. The initial capacitance $C_1$ is $7500e^{-6}$ F, and 90–100% of the initial capacitance is classified as normal. With the gradual deterioration of capacitance, if the capacitance is set to $C_2$ (80–90% of initial capacitance), it is defined as an incipient fault. If the capacitance value is set to $C_3$ (less than 80% of initial capacitance), it is no longer an incipient fault, but a serious fault. At the same time, the data sampling frequency was set to 50kHz to collect the instantaneous DC link voltage $V_{DC}$ for 24 seconds, including three levels of capacitance with 1.2 million data points. Among them, the data of $C_1$ are generated in the 1–8th second, the data of $C_2$ are generated in the 8–16th second,
and the data of C3 are generated in the 16–24th second. In order to make the diagnosis process closer to the actual situation, the measured $V_{DC}$ is added with noise, and the $awgn$ function in Matlab was used to add 30 dB white Gaussian noise to $V_{DC}$ as shown in Figure 4.

In this figure, The fluctuation range of the upper and lower limits of the DC voltage under the capacitance $C_1$ is from $-0.79\%$ to $+0.49\%$; for capacitance $C_2$, the fluctuation range is from $-0.87\%$ to $+0.56\%$, and for capacitance $C_3$, the fluctuation range is from $-1.09\%$ to $+0.65\%$. So, the instantaneous value of the DC bus voltage under different fault levels has no obvious feature distinction, and it is difficult to effectively diagnose using the general threshold method.

We further propose an inference model based on an ER rule to estimate the fault level of capacitance attenuation by collecting and analyzing instantaneous voltage data $V_{DC}$ from the DC link. The definition of fault levels and their thresholds can be set according to different capacitor types and different application systems. This method does not need to make assumptions about the relationship between ESR values, capacitance values, and voltage values from the DC link as it directly learns the fault characteristics and can then be used to diagnose a predetermined fault level using a data-driven approach.

3. Fault Diagnosis Based on Evidence Reasoning Rule

3.1. Outline of ER Rule. The evidence reasoning (ER) rule has been proposed by Yang et al. [26, 27], and the evidence can be defined here as follows:

$$e_j = \left\{ (\theta, p_{\theta,j}) | \forall \theta \subseteq \Theta, \sum_{\theta \in \Theta} p_{\theta,j} = 1 \right\}.$$  

(1)

Here, define $\Theta = \{h_1, h_2, \ldots, h_N\}$ as a frame of discernment; it contains mutually exclusive and collectively exhaustive hypotheses. $P(\Theta)$ and $2^\Theta$ represent all the subsets of the power set $\Theta$. $(\theta, p_{\theta,j})$ is an element of evidence $e_j$ which indicates the degree of $e_j$ approaching $\theta$ (not an empty set) is $p_{\theta,j}$, when $p_{\theta,j} > 0$, $(\theta, p_{\theta,j})$ is the focal element of $e_j$.

The concepts of reliability $r_j$ and weight $w_j$ of $e_j$ are introduced in the ER rule. $r_j$ is the ability of the information source, which characterizes credibility of this $e_j$ for the fault diagnosis system. On the other hand, for $w_j$, it is different from $r_j$, which can be defined by the person who uses this diagnostic method according to subjective conditions such as different equipment or different environments. $w_j$ represents the importance degree of different types of evidence. The weighted belief distribution with reliability factor and weight factor is defined as follows:

$$m_j = \left\{ (\theta, m_{\theta,j}) | \forall \theta \subseteq \Theta, \left\{ P(\Theta), \bar{m}_{P(\Theta)}, j \right\} \right\},$$  

(2)

where $m_{\theta,j}$ represents the degree of $e_j$ approaching $\theta$ after combining $r_j$ and $w_j$, which is defined as follows:

$$m_{\theta,j} = \left\{ \begin{array}{ll}
0, & \theta = \emptyset, \\
0, & \theta \subseteq \Theta, \theta \neq \emptyset, \\
c_{\theta,j} (1 - r_j), & \theta = P(\Theta),
\end{array} \right.$$  

(3)

where $m_{\theta,j} = w_j P_{\theta,j} C_{\theta,j} = 1/(1 + w_j - r_j)$ are normalization factors; it makes $\sum_{\theta \in \Theta} m_{\theta,j} + m_{\theta,j} = 1$, wherein $\sum_{\theta \in \Theta} P_{\theta,j} = 1$.

If the two pieces of evidence are independent of each other, they can be combined with the ER rule as follows:
where $P_{θ,ε(2)}$ represents the degree of how the two pieces of evidence jointly support $θ$, and the fusion process includes the bounded sum and the orthogonal sum. The bounded sum is reflected in $(1 − r_j)$ ($i = 1, 2$), which means the sum of the two sets of evidence $ε_1$ and $ε_2$ independently approaches $θ$, and it includes the interaction between $ε_1$ and $ε_2$. For example, when $ε_1$ is considered to be completely reliable $(1 − r_1) = 0$, then $(1 − r_j)m_{θ,2} = 0$, which means that $ε_2$ has no effect on the combined results. Conversely, $ε_1$ has no effect on the combined results. In addition, the orthogonal sum indicates the degree of all evidence jointly approaching $θ$. This method can also combine multiple pieces of evidence without order restriction while satisfying the exchange law and the combination law [28, 29].

3.2. Diagnostic Process. Figure 5 outlines the fault diagnosis process using the ER rule.

First, the instantaneous DC voltage value $V_{DC}$ is obtained as shown in Section 2.2 so that the peak-to-peak voltage value $V_{PP}$ can be calculated from $V_{DC}$. Here, 0.02 seconds, including 1000 data points, is taken as a window length to obtain the average value of $V_{PP}$ of 400 data windows named as $V_P(t)$. $V_P(t)$ is obtained by calculating the root mean square value of the $V_{DC}$ with same window length, and then by normalization. $V_P(t) ∈ [s_1, s_2]$ and $V_R(t) ∈ [s_1, s_2]$, where $s_1$ and $s_2$ are, respectively, the minimum and maximum values of the input characteristic signals $V_P(t)$ and $V_R(t)$. The capacitor aging fault level is then defined as $C(t)$, $C(t) = [1, 2, 3]$. And $V_P(t)$, $V_R(t)$, and $C(t)$ are denoted together as $T = \{[V_P(t), V_R(t), C(t)] | t = 1, 2, \ldots, T_S\}$, $T_S = 1200$, where $[V_P(t), V_R(t), C(t)]$ is a sample vector.

Secondly, the data $[V_P(t), V_R(t), C(t)]$ in $T$ are converted to the form of similarity degree to the reference value. The reference value set of the capacitor fault level is $D = \{D_n | n = 1, \ldots, N\}$, where $N$ is the number of reference values of the capacitor fault level. The input reference values set of the voltage signal $V_i$ is $A_i = \{A_{ij} | i = 1, \ldots, j, i = P, R\}$, where $j_i$ is the number of reference values of $V_i$. The similarity distribution of $V_i(t)$ to reference values $A_{ij}$ is calculated as follows:

$$T_i(V_i(t)) = \{A_{ij} | j = 1, \ldots, j_i; i = 1, 2\},$$

where $\alpha_{ij}$ represents the similarity of $V_i(t)$ to the reference value $A_{ij}$.

Similarly, the calculation process for the similarity distribution of the fault level $C(t)$ to the reference value $D_n$ is as follows:

$$T_O(C(t)) = \{(D_n, y_n) | n = 1, \ldots, N\},$$

where $y_n$ denotes the similarity of $C(t)$ to $D_n$.

The parameter form similar to $(α_{ij}Y_{PP}α_{ij+1}Y_{PP}α_{ij}Y_{PP}α_{ij+1}Y_{PP}α_{ij}Y_{PP}α_{ij+1}Y_{PP})$ can be obtained after completing the calculation of all the sample sets in $T$, where $α_{ij}$ denotes the comprehensive similarity of the input value in sample pair $(V_i(t), C(t))$ matching the reference value $A_{ij}$, $D_n$. Table 2 shows the cast statistics result of all sample pairs in $T$, and $\sum_{n=1}^{N}δ_n = \sum_{j=1}^{j_i}η_j = T_S$.

According to the casting statistics shown in Table 2, the degree of belief $β_{n,j}$ of $ε_j$ can be calculated as follows:

$$\beta_{n,j} = \frac{α_{n,j}δ_n}{\sum_{k=1}^{N}(α_{k,j}δ_k)},$$

where $\sum_{n=1}^{N}β_{n,j} = 1$. Then, the evidence corresponding to the reference value can be defined as follows:

$$e_j = [β_{1,j}^g, β_{2,j}^g, \ldots, β_{N,j}^g].$$

Therefore, an evidence matrix, as shown in Table 3 can be constructed to describe the relationship between $V_i(t)$ and $C(t)$.

Now we define reliability $r_j$ and weight $w_i$ of evidence $ε_j$ after obtaining the evidence of the input $V_i$, $r_j$ defined in this paper is determined by the Spearman rank correlation coefficient for ranked data [30]. The Spearman rank correlation coefficient expresses the closeness of the relationship between the two sets of variables and it is suitable for describing the reliability between $V_i(t)$ and $C(t)$ in this case. The calculation procedures are as follows:

$$d_j = V_i(t) − C(t),$$

$$r_j = 1 − \frac{6\sum_{i=1}^{N}d_i^2}{T_S(T_S^2 − 1)},$$

where $d_i$ is the difference between $V_i(t)$ and $C(t)$ and $r_j$ is the reliability of the evidence.

For all of the input values $V_i(t)$, they must be within the interval $[A_{ij}, A_{ij+1}]$ formed by the two adjacent reference
values, and evidence $e_i$ and $e_{i+1}$ corresponding to the two reference values will be activated. The final evidence of the input values $V_i(t)$ can be weighted by $e_i$ and $e_{i+1}$ with the calculated reliability $r_i$.

$$e_i = \left\{ \left( D_n, p_{n,i} \right) \right\}, \quad n = 1, \ldots, N,$$

$$p_{n,i} = \alpha_{i,j} P_{n,j} + \alpha_{i,j+1} P_{n,j+1}.$$  

The initial evidence weight is set as $w = r_i$, and $e_1$ and $e_2$ are combined by ER rule. The fusion process is as follows:

$$p_{n,e}(2) = \frac{m_{n,e}(2)}{\sum_{k \in D} m_{k,e}(2)},$$

$$m_{n,e}(2) = \left( (1 - r_2) \frac{n_{i,1}}{n} \right) + \left( (1 - r_1) \frac{n_{i,2}}{n} \right) + \sum_{B \cap C = n} m_{B,1} m_{C,2},$$

$$O(V(t)) = \left\{ \left( D_n, p_{n,e}(2) \right) \right\}, \quad n = 1, \ldots, N.$$

After the fusion process is completed, the combined result is obtained. Furthermore, the fault level of the capacitor can then be estimated based on the combined results.

$$C(t) = \left\{ \left. D_n \right| \max P_{n,e}(2) \right\}.$$

### 4. Analysis of Simulation Examples

#### 4.1. Training Model

In the experiment, 80% of the total sample set $T$ (sample size $T_s = 1200$) was randomly selected.
including 3 reference values in total. The training sample set is as shown in Table 14. In this figure, the ordinate value of 1 indicates that the capacitance is normal, the value 2 indicates that the capacitance is in serious fault. On the time axis of the abscissa, the true level of the capacitance at different level capacitance attenuation in test set to 100. The diagnostic results of $T_R$ are shown in Table 14 and Figures 6 and 7.

The difference between the true and estimated levels of capacitance at different level capacitance attenuation in test set is as shown in Figure 7. In this figure, the ordinate value of 1 indicates that the capacitance is normal, the value 2 indicates that the capacitance is in incipient fault, and the value 3 indicates that the capacitance is in serious fault. On the time axis of the abscissa, the true level of the capacitance is normal for 0 to 8 seconds, an incipient fault for 8 to 16, and a serious fault for 16 to 24.

Figure 8 shows the estimated levels of the test set calculated by the trained ER and BP neural network, respectively.

### 4.3. Analysis of Diagnostic Results

As can be seen from Tables 4–13, the optimized diagnostic results are more accurate. Especially for capacitor fault levels 2 and 3, the judgment is more accurate, and misjudgment is greatly reduced. In order to further verify the reliability of the ER fault diagnosis model, test set $T_E$ was used for diagnosis. In the meanwhile, a classical three-layer BP neural network approach was selected for comparison. The learning rate was set as $\eta = 0.05$, and the maximum number of iterations was set to 100. The diagnostic results of $T_E$ are shown in Table 14 and Figures 6 and 7.

Table 4: Casting result tables of sample pairs ($V_P(t), C(t)$).

| $C$ | $A_1^P$ | $A_2^P$ | $A_3^P$ | $A_4^P$ | $A_5^P$ | $A_6^P$ | $A_7^P$ | $A_8^P$ | $A_9^P$ | $A_{10}^P$ | Total |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|----------|-------|
| $D_1$ | 6.7877  | 7.8030  | 8.1517  | 8.4575  | 8.8254  | 9.1441  | 9.5400  | 9.9043  | 10.3445 | 10.7758  | 320.0000 |
| $D_2$ | 0.4224  | 0.5122  | 0.6417  | 0.7847  | 0.9223  | 1.0756  | 1.2347  | 1.4038  | 1.5829  | 1.7720  | 320.0000 |
| $D_3$ | 0.1070  | 0.4748  | 3.1453  | 5.8447  | 8.6086  | 13.9508 | 320.0000 |
| Total | 25.8775 | 111.9654| 97.3063 | 98.6772 | 98.5623 | 88.7160 | 95.6765 | 99.1500 | 100.5757 | 135.9027 | 960.0000 |

Table 5: Casting result tables of sample pairs ($V_R(t), C(t)$).

| $C$ | $A_1^R$ | $A_2^R$ | $A_3^R$ | $A_4^R$ | $A_5^R$ | $A_6^R$ | $A_7^R$ | $A_8^R$ | $A_9^R$ | $A_{10}^R$ | Total |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|----------|-------|
| $D_1$ | 43.7841 | 58.7483 | 39.0959 | 29.8323 | 25.1073 | 28.5133 | 29.5964 | 28.3416 | 27.0418 | 9.9390  | 320.0000 |
| $D_2$ | 5.3529  | 35.4618 | 43.8672 | 31.0040 | 37.8508 | 34.7105 | 39.9841 | 30.3652 | 34.8532 | 36.5502 | 320.0000 |
| $D_3$ | 0.0679  | 0.1245  | 0.1733  | 0.2177  | 0.2759  | 0.3375  | 0.4244  | 0.5122  | 0.6417  | 0.1070  | 320.0000 |
| Total | 49.1370 | 95.5613 | 93.3047 | 90.1617 | 96.8907 | 99.1500 | 100.3356 | 100.5757 | 135.9027 | 320.0000 |

as the training sample $T_R = \{ [V_P(t), V_R(t), C(t)] \mid t = 1, 2, \ldots, T_{SE}\}$, sample size $T_{SR} = 960$, and the remaining 20% was selected as the test sample $T_R = \{ [V_P(t), V_R(t), C(t)] \mid t = 1, 2, \ldots, T_{SE}\}$, sample size $T_{SE} = 240$. Based on experience, the reference value set for the initial parameter $V_R(t)$ is $A_1 = \{6.7877, 7.8030, 8.1517, 8.4575, 8.8254, 9.1441, 9.5400, 9.9043, 10.3445, 10.7758\}$, including 10 reference values in total. The reference value set for the initial parameter $V_R(t)$ is $A_2 = \{0, 0.0679, 0.1245, 0.1733, 0.2177, 0.2759, 0.3375, 0.4244, 0.5122, 0.6417\}$, including 10 reference values in total. The reference value set $D$ of $C(t)$ is $D = \{1, 2, 3\}$, including 3 reference values in total. The training sample set $T_R$ is processed through the steps described in Section 4 to obtain casting result tables of sample pairs ($V_P(t), C(t)$), which are presented in Tables 4 and 5.

After obtaining the casting result tables, the evidence matrix table of $V_I$ is obtained by normalization of likelihoods as shown in Tables 6 and 7.

After obtaining the evidence matrix tables, the reliability factors $r_1 = 0.8897$ and $r_2 = 0.4117$ of the evidence parameters $e_1$ and $e_2$ are calculated with the sample dataset $T$. The initial fault diagnosis result on the sample training set $T_R$ can be obtained by using the ER rule, and the results are presented in the form of a confusion matrix as shown in Table 8.

It can be seen from the initial diagnostic results that the accuracy is not satisfactory because the initial set of reference values $A_r$, reliability factor $r_2$, and weight $w_j$ are not the optimal ER rule parameters, so the ideal diagnostic accuracy cannot be achieved. Therefore, it is necessary to establish a parameter optimization model for the ER rule process.

### 4.2. Parameter Optimization

The mean square error between the estimated value and the real value of the capacitor fault level is set as the objective function, and the set of optimization parameters $P$ is determined at the same time.

$$P = \{ A_i^r, w_j \mid i = P; r; j = 2, \ldots, J_i - 1\},$$

where $w_j$ represents the weight of the evidence, and the other parameters are set to $A_1^r = s_1^r$, $A_2^r = s_2^r$, $A_3^r = s_1^r$, $A_4^r = s_2^r$.

The objective function is optimized by using the fmincon function in Matlab, and the optimal parameter set $P$ is obtained after training. At the same time, the optimized casting result tables, optimized evidence matrix table, and optimized capacitance aging fault diagnosis results can be obtained.

The optimization procedure is as follows: the training samples $T_R$ are used to train the ER rule model, and the optimal parameter set $P$ is obtained after training. The training samples $T_R$ are used to train the ER rule model, and the optimal parameter set $P$ is obtained after training. The obtained optimal parameter set $P$ is used to test the test samples $T_E$, and the diagnostic results are obtained.
Table 6: Evidence matrix table for input $V_P$.

| Capacitor fault level | $V_P$ | Total |
|-----------------------|-------|-------|
| $C_1$                 |       | 267   |
| $C_2$                 | 47    | 238   |
| $C_3$                 | 0     | 45    |

Table 7: Evidence matrix table for input $V_R$.

| Capacitor fault level | $V_R$ | Total |
|-----------------------|-------|-------|
| $C_1$                 |       | 427   |
| $C_2$                 | 47    | 238   |
| $C_3$                 | 0     | 45    |

Table 8: Initial diagnostic results of ER.

| Capacitor fault level | $C_1$ | $C_2$ | $C_3$ | Total |
|-----------------------|-------|-------|-------|-------|
| $C_1$                 | 267   | 53    | 0     | 320   |
| $C_2$                 | 47    | 238   | 35    | 320   |
| $C_3$                 | 0     | 45    | 179   | 320   |

Table 9: Optimized casting result table of sample pairs ($V_P(t)$, $C(t)$).

| Capacitor fault level | $V_P$ | Total |
|-----------------------|-------|-------|
| $C_1$                 |       | 14.7558 |
| $C_2$                 | 47    | 238   |
| $C_3$                 | 0     | 45    |

Table 10: Optimized casting result table of sample pairs ($V_R(t)$, $C(t)$).

| Capacitor fault level | $V_R$ | Total |
|-----------------------|-------|-------|
| $C_1$                 |       | 51.2310 |
| $C_2$                 | 47    | 238   |
| $C_3$                 | 0     | 45    |

Table 11: Optimized evidence matrix table for input $V_P$.

| Capacitor fault level | $V_P$ |
|-----------------------|-------|
| $C_1$                 |       |
| $C_2$                 | 47    |
| $C_3$                 | 0     |

Table 12: Optimized evidence matrix table for input $V_R$.

| Capacitor fault level | $V_R$ |
|-----------------------|-------|
| $C_1$                 |       |
| $C_2$                 | 47    |
| $C_3$                 | 0     |
From the results presented, the diagnostic accuracy of the BP neural network approach is lower than that obtained using the ER rule model, which is mainly seen in the diagnosis of capacitor fault level 2. This fault level 2 represents an incipient fault. For the case of \( C_2 \), the change of DC bus voltage is not as obvious as case of \( C_3 \), which is a very small change. Therefore, it is difficult to distinguish the change from \( C_1 \) to \( C_2 \) in the specific diagnosis process. In this case, there are two reasons for the low accuracy of BP neural network. Firstly, BP neural network is sensitive to initial weights and bias, and these two values are randomly selected in each BP training, so every time, the training tends to converge to different local minimum, resulting in low diagnostic accuracy in some diagnosis experiments. Secondly, the choice of structure of BP neural network has not a unified and complete theoretical guidance, normally only selected by experience. The selected structure may not the most suitable, and there may be a better network structure, but it takes more time to select and adjust. However, the above problem does not exist in ER; its initial reliability and weights are derived from sample data, and their calculating method has clear physical meanings. The evidences

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### Table 12: Optimized evidence matrix table for input \( V_R \).

| \( C \) | \( e_1^R \) | \( e_2^R \) | \( e_3^R \) | \( e_4^R \) | \( e_5^R \) | \( e_6^R \) | \( e_7^R \) | \( e_8^R \) | \( e_9^R \) | \( e_{10}^R \) |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| \( A_1 \) | 0 | 0.0679 | 0.1245 | 0.1733 | 0.2177 | 0.2759 | 0.3375 | 0.4244 | 0.5122 | 0.6417 |
| \( D_1 \) | 1 | 0.8293 | 0.5643 | 0.3361 | 0.2836 | 0.2882 | 0.2591 | 0.0816 | 0.0019 | 0 |
| \( D_2 \) | 2 | 0.1675 | 0.4052 | 0.3729 | 0.3404 | 0.3137 | 0.3615 | 0.3651 | 0.3339 | 0.0339 | 0 |
| \( D_3 \) | 3 | 0.0032 | 0.0305 | 0.2910 | 0.3760 | 0.3981 | 0.3793 | 0.5533 | 0.6642 | 0.9661 | 1 |

### Table 13: ER optimized diagnosis results.

| Capacitor fault level | \( C_1 \) | \( C_2 \) | \( C_3 \) | Total | Accuracy (%) |
| --- | --- | --- | --- | --- | --- |
| \( C_1 \) | 256 | 64 | 0 | 320 | 80.00 |
| \( C_2 \) | 31 | 254 | 35 | 320 | 79.38 |
| \( C_3 \) | 0 | 40 | 280 | 320 | 87.50 |

### Table 14: Diagnostic results of the ER/BP test set.

| Capacitor fault level | \( C_1 \) | \( C_2 \) | \( C_3 \) | Total | Accuracy (%) |
| --- | --- | --- | --- | --- | --- |
| \( C_1 \) | 65/75 | 15/5 | 0 | 80 | 81.25/93.75 |
| \( C_2 \) | 6/30 | 70/45 | 4/5 | 80 | 87.50/56.25 |
| \( C_3 \) | 0 | 5/14 | 75/66 | 80 | 93.75/82.50 |

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**Figure 6: Results comparison between ER (blue) and BP (red).**
generated method is based on data statistics and likelihood normalization method. It is strictly based on the principle of sample statistical reasoning, thus reducing the randomness and uncertainty in process of diagnosis.

In the process of actual dynamic monitoring, fault trend prediction is of great importance to marine electric propulsion systems. Nowadays, what the marine electric propulsion system operators need urgently is to be able to predict the state of the equipment before faults occur to allow the faults to be corrected prior to more serious damage or economic loss. Therefore, the ER rule method is a flexible and applicable approach which serves as an early warning and management assistance system for fault diagnosis in marine electric propulsion systems.

5. Conclusions

In this paper, an online monitoring and fault diagnosis method for capacitance aging of DC link capacitors of VSI based on ER rule is proposed. Diagnostic evidence is generated from information sources, and then reliability factors and weighting of each parameter are determined by evaluating the correlation between fault features and fault levels. The ER rule was then used to combine the evidence, and each fault level was estimated based on the combined results. Finally, we defined the objective function to optimize the ER rule parameters to make the diagnostic results more accurate. Compared with most classical data-driven method, BP neural networks, the ER rule method also has higher diagnostic accuracy and applicability in the field of incipient fault diagnosis. Unlike other types of fault diagnosis methods, this data-driven method has the advantage that it does not need to assume any mapping relationships between fault features and fault models. In addition, this method can be extended not only to serious fault diagnosis but also incipient fault diagnosis due to its ability to redefine different weighting to each evidence parameter depending on the application field. When using this method on ships, it is
flexible enough to allow changes to the parameters in the ER rule to meet the needs of the different electric propulsion systems in use on board diverse types of vessel. The Jiangsu ferry 3011 is a new ship. However, the aging process of capacitor will take years. Therefore, the actual aging data cannot be obtained for research. The method described in this paper will be a promising diagnostic method to detect incipient fault for Jiangsu ferry 3011; further analysis and discussion will be carried out after collecting overall life cycle’s physical data.

Data Availability
The data used to support the findings of this study were supplied by [The 711th Research Institute of China Shipbuilding Industry Corporation] under license and so cannot be made freely available. Requests for access to these data should be made to [Yelan He, email:heylj99@163.com].

Conflicts of Interest
The authors declare that they have no conflicts of interest.

Authors’ Contributions
Linhao Liao and Haibo Gao contributed equally to modeling, calculation, and writing. Yelan He, Xiaobin Xu, Zhiguo Lin, Yajie Chen, and Fubing You gave useful advice and suggestions and contributed to the discussion and preparation of the manuscript.

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