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A restoration-clustering-decomposition learning framework for aging-related failure rate estimation of distribution transformers

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ABSTRACT

Distribution transformers (DTs) are critical components used in power distribution networks, and they are vulnerable to aging failures due to irreversible insulation degradation. Therefore, the accurate estimation of the aging-related failure rates (AFRs) is necessary for the reliability-centered maintenance and replacement strategies needed for ensuring service reliability and safety. Various data-intensive models have been proposed for AFR evaluation of power equipment. However, these models cannot be used for AFR evaluation of DTs due to the limitation of the available data. This paper tackles this important problem in an unconventional way by it develops a novel Restoration-Clustering-Decomposition learning framework to model the AFRs of individual DTs and improve evaluation accuracy. The proposed approach requires only the non-intrusive data that can be directly extracted from existing available databases, making it feasible to be applying to numerous DTs. First, the analysis of the degree of polymerization (DP) degradation and the Latin Hypercube sampling (LHS) technique are combined to reproduce aging failure data. Then, an optimal Entropy-weighted K-means (EW-K-means) clustering method and the classic 2-parameter Weibull model are used to evaluate the average AFRs of different DT groups through failure data analysis. Then, a DP-based decomposition function is introduced to quantify the relative aging degree of in-group individuals and to derive the probabilistic AFRs of each DT in the group. Application examples of a scrapped DT population in Chongqing Electric Power Company of China are presented and discussed in detail. The results show that the proposed learning framework has a promising capability for AFR evaluation of individual DTs and bears great practicality in the real world.

Acronyms

DT	Distribution Transformer
AFR	Aging-Related Failure Rate
DP	Degree of Polymerization
LHS	Latin Hypercube Sampling
EW-K-means	Entropy-Weighted K-means
HST	Hottest-Spot Temperature
EWM	Entropy Weight Method
MLE	Maximum Likelihood Estimate
KDE	Kernel Density Estimation

1. Introduction

Distribution transformers (DTs) are the most important components used in power distribution networks, considering their designed capability to transform the medium voltage to the low voltage level used for households and commercial customers [1,2]. For a medium-sized city, there may be hundreds or even thousands of DTs [3,4]. The status of DTs plays a crucial role in ensuring the secure and reliable operation of distribution networks [5]. Hence, dynamically monitoring and evaluating the performance and the reliability level of DTs is necessary for the reliability-centered maintenance and replacement strategies for distribution networks [6,7].

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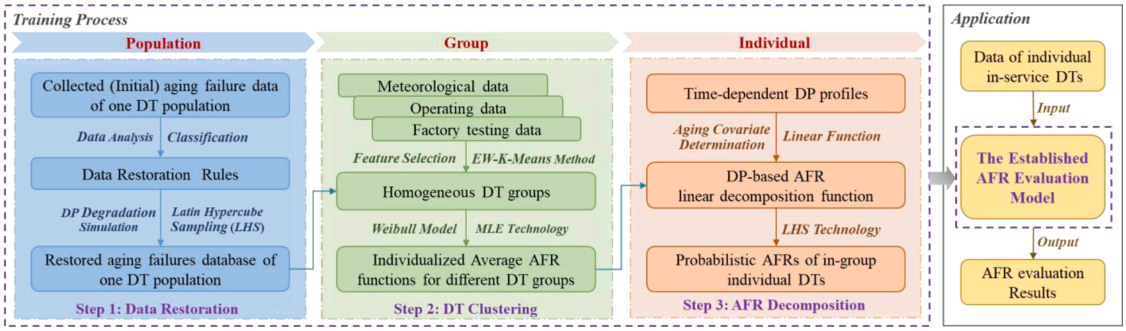

Fig. 1. Structure diagram for the proposed Restoration-Clustering-Decomposition Learning Framework.

In this context, the failure rate is an important reliability parameter of DTs, which is defined as the state transition rate of a DT from normal operation to failure at a special time [8,9]. As far as DTs are concerned, their failures can be classified into two categories: repairable random failures and non-repairable aging failures [10]. Generally, modeling the random failure rate is relatively easy because it can be assumed as a constant irrelative to operating time in most cases [11]. Aging failures of DTs gradually occur because of stressed conditions, including oil leakages, overloading, and unbalanced loadings in the long term, which renders the aging-related failure rate (AFR) of DTs uncertain and time-variant [12].

Because of the significant population of DTs on feeders, it is almost impossible to equip all DTs with the advanced sensors for collecting the diagnostic data associated with the aging degree, such as oil chromatographic, dielectric loss, partial discharge, and frequency response data [13–15]. In other words, it is difficult to apply the data-intensive methods, including Proportional Hazards Models [16,17], Hidden Markov Models [18], and Health Index (HI) based Models [19,20], for the AFR evaluation of individual DTs due to their population.

The asset-age-based Weibull distribution models have been widely used in the DT's AFR evaluation for a long time [21,22]. Existing studies proved that the 2-parameter Weibull model could well describe the aging processes and AFRs of a DT population. Nevertheless, this model only uses age as a single input variable, and other factors causing aging are ignored [2]. This results in a difficult situation where DTs with differentiated aging degrees have the same AFR at the same age. Such a result may significantly deviate from reality in some cases [5].

Consequently, it is absolutely necessary to develop an evaluation method to accurately quantify and distinguish the aging degrees of individual DTs only relying on non-intrusive data (e.g., loading data, meteorological data, etc.), which can be directly extracted from existing databases.

There is another issue in the AFR modeling process. In many databases of electric utilities, the scrapping ages of scrapped DTs (i.e., the span from commission to scrap) are recorded [23]. Using these scrapping age data would lead to a pessimistic AFR evaluation result [24,25]. Therefore, it is necessary to convert the collected scrapping age data of scrapped DTs into their technical lifetimes, which are defined as the time intervals from commission to expected aging failures that occur in this paper. This data problem is seldom investigated systematically.

To tackle the above challenges, this paper proposes a Restoration-Clustering-Decomposition learning framework to estimate the AFRs of individual DTs. In this framework, aging failure data restoration (processing & conversion), DT clustering, in-group AFR decomposition, and uncertainty modeling are all integrated to improve the credibility and accuracy of DT's AFR evaluation. To the best of our knowledge, this is the first attempt to construct such a framework for the AFR estimation of DTs. The proposed approach can be easily applied for numerous DTs even without installing monitoring equipment since it only requires the available non-intrusive data but does not require other data from intrusive health monitoring devices. In addition, the proposed approach can also be used for the AFR evaluation of other power distribution assets by modifying the established modules that are special for DTs.

The work extends prior art by adding the following contributions:

- A long-existing problem that did not gain enough attention but has a significant impact in modeling, namely aging failure data restoration, is raised and analyzed. This problem is then solved through the proposed DP degradation analysis and Latin Hypercube sampling (LHS) techniques.
- A comprehensive DT clustering feature system and an efficient Entropy-weighted K-means (EW-K-means) clustering algorithm are developed for grouping DTs, improving the estimation accuracy of average AFRs for different DT groups.
- A DP-based decomposition function is established to quantify the relative aging degrees of individual in-group DTs. It can be used to derive the probabilistic AFRs of individual DTs considering the data uncertainty.

This paper is organized as follows: Section 2 overviews the proposed framework. Section 3 introduces the approach for reproducing the collected aging failure data (i.e., scrapping age data). Section 4 describes how to derive the average AFR of each DT group based on DT clustering and the 2-parameter Weibull model. Section 5 discusses how to compute the AFRs of individual in-group DTs through a decomposition function. Section 6 demonstrates the applicability of the proposed method by applying it to a real DT population. Discussion is given in Section 7, and the last section concludes the work.

2. Overview of the proposed framework

As mentioned in Section 1 above, in this paper, we develop a novel Restoration-Clustering-Decomposition learning framework for AFR estimation of individual DTs. The diagram of the proposed framework is shown in Fig. 1 below.

As Fig. 1 shows, the proposed learning framework contains two processes: the training process and the application process. The training process mainly includes three steps as follows:

Step 1: Restoration. Aging failure data are the basic input data required by the proposed framework, and these data will be used to fit the AFR curves of DT groups. This step focuses on restoring the collected scrapping age data of scrapped DTs into their technical lifetimes to construct a reasonable and credible aging failure dataset. Specifically, the degree of polymerization (DP) analysis and Latin Hypercube sampling (LHS) techniques are jointly adopted to restore the collected scrapping age data of historical scrapped DTs. It is worth noting that the proposed restoration method is derived from several widely accepted physical-based and data-driven models.

Step 2: Clustering. Generally, the average AFR of the DT group can be derived by fitting the in-group aging failure data. Since the collected scrapped DTs are run under different operating and

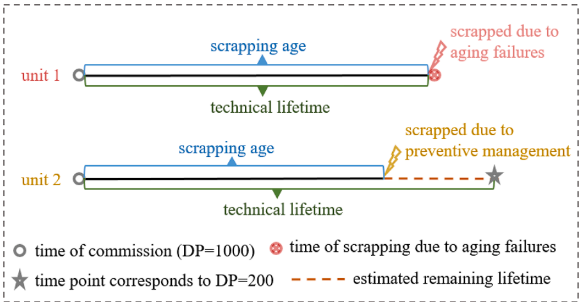

Fig. 2. Graphical representation of the aging failure data restoration rules.

environmental conditions, it is necessary to stratify them into different homogenous DT groups to obtain accurate average AFRs. Inspired by this, an EW-K-means clustering method is applied in this step to group the scrapped DT population into some homogenous groups according to the constructed clustering feature system. Then, the classic 2-parameter Weibull model is used for modeling the average AFR of each DT group. It should be emphasized that the 2-parameter Weibull model has been proved suitable for the simulated dataset according to the hypothesis testing results.

Step 3: Decomposition. To address the heterogeneity of in-group DTs, the average AFRs of DT groups can be set as a reference value, and the AFRs of individual in-group DTs can be estimated based on their actual aging behavior. On this basis, a DP-based decomposition function is adopted in this step to quantify the relative aging degrees of individual in-group DTs. It will then be used for deriving the individual AFRs of in-group DTs from the average AFR.

After these steps are completed, the established model can be applied to evaluate the real-time AFRs of individual in-service DTs. Considering the uncertainty resulting from the data restoration operation, the LHS-based calculation step is undertaken for AFR probabilistic assessment.

The above processes will be explained in detail in Sections 3-6.

3. Aging failure data restoration

This section illustrates the approach for restoring the collected scrapping age data of scrapped DTs to their technical lifetimes based on the DP degradation analysis and LHS techniques.

3.1. Aging failure data restoration

In general, the reasons for DT being scrapped can be classified into two categories: aging failures and preventive management [9]. As is shown in Fig. 2, for a DT that is scrapped due to aging failures (e.g., unit 1), its technical lifetime can be directly set equal to its scrapping age. In practice situations, however, most aged DTs are scrapped due to preventive management [20]. In this case, the technical lifetime of a preventively scrapped DT (e.g., unit 2) will be longer than its recorded scrapping age. As discussed in Section 1, the technical lifetime of a preventively scrapped DT can be assumed to be the aging-related lifetime when expected aging failures occur. Accordingly, the key to aging failure data restoration is to accurately estimate the aging-related lifetimes of the preventively scrapped DTs. Since the non-repairable deterioration of insulation paper is the dominant factor that causes limitation in DT's aging-related lifetime, the lifetime of insulation paper is generally considered as the DT's aging-related life span [26]. The insulation papers of DTs are composed of long chains of glucose rings that build the cellulose polymer molecule. The average length of these chains is termed degree of polymerization (DP) [27]. As the best indicator to evaluate the aging condition of the DT's insulation paper, the DP-value will decrease over time as the paper's irreversible aging process under the combination of thermal, electrical, and chemical stresses. Based on previous studies, an end-of-life criterion for DTs is usually defined as the time point when DP drops to 200 [27,28]. Accordingly, the technical lifetime of a preventively scrapped DT equals the expected operation years when its DP-value decreases to 200 [29]. Based on the above discussion, Fig. 2 gives the graphical representation of the proposed aging failure data restoration rules in detail. It is worth noting that these proposed restoration rules are suitable for numerous DTs in existing distribution networks.

However, in practical engineering, direct measuring the DP-values of insulation papers is impossible because this operation implies an invasive manipulation of the insulation system of DTs. Therefore, this paper developed a computation-based DP estimation method that combines several widely-accepted physical models and data-driven models, allowing indirect and non-invasive estimation of the DTs' time-varying DP-values. Details of the proposed approach are given in the following sub-sections.

3.2. Degradation simulation of Degree of Polymerization

A wide-accepted physical model (the Arrhenius-Kinetic equation), which has been recommended by serval industry standards such as CIGRE-323, is adopted here to calculate the change in DP-value over a specific time [28,30]:

$$\frac{1}{DP_t} - \frac{1}{DP_0} = A \times e^{\frac{-Ea}{RT}} \times t \tag{1}$$

Eq. (1) assumes that the degradation process of DP is controlled by a dynamic reaction rate, exp(-Ea/RT). Ea is the activation energy of the aging reaction that equals 111KJ mol^{-1}. R is the universal gas constant equal to 8.314 J mol^{-1} K^{-1}. A is a time-varying pre-exponential factor for describing the chemical environment in h^{-1}. T is the time-varying hottest-spot temperature (HST) of the DT's winding in K (Kelvins). t is the operating time in hour (h). DP_0 and DP_t denote the initial DP-value and the DP-value after an operating time t, respectively.

To accurately calculate the time-varying DP-values, a recursive form of (1) can be derived as:

$$\frac{1}{DP_{(k)}} - \frac{1}{DP_{(k-1)}} = A_{(k-1)} \times e^{\frac{-Ea}{R\left(T_{(k-1)}+273\right)}} \times \left(t_{(k)} - t_{(k-1)}\right) \tag{2}$$

where index k represents the iteration stage, and the period of each iteration can be discretized into one hour. According to (2), the DP-value in each iteration can be calculated as long as the A-value and T-value in that iteration are obtained.

Previous studies have proved that the A-value depends on the moisture content in insulation paper and the oxygen level in the transformer tank, whereas the T-value is determined by the load ratio and ambient temperature [31,32]. In view of this, the following sub-sections are devoted to presenting the method applied for obtaining these two time-varying parameters of (2) to clarify how the practical concern can be considered in the model.

3.2.1. A-value

Enough thermal aging test for DT's paper insulation has proven that the A-value can be defined as a polynomial function of moisture content and oxygen level, which is given by:

$$A_k = \xi_1 \cdot \omega_{k,paper}^3 + \xi_2 \cdot \omega_{k,paper}^2 + \xi_3 \cdot \omega_{k,paper} + \xi_4 \tag{3}$$

where $\omega_{k,paper}$ represents the moisture content in the insulation papers in iteration k. The values of ξ_1, ξ_2, ξ_3, and ξ_4, are determined by the oxygen levels and paper types, and their recommended values for different oxygen levels and paper types can be found in [31–33]. Since the oxygen level of oil-immersed DTs is generally kept at a low level regardless of the operating time, and the type of insulation paper is determined before the commission, A_k can be directly calculated by (3) when inputting $\omega_{k,}$

Algorithm 1
Generation method of future load ratio data.

Input: S # the total simulation times;
ϑ # the simulation duration (in yr);
$LF = [LF_1, LF_2, \ldots, LF_{23}, LF_{24}]$ # daily mean load ratio for the DT calculated from the historical data;
$\psi = [\psi_1, \psi_2, \ldots, \psi_{\vartheta-1}, \psi_\vartheta]$ # the expected cumulative annual growth rate of the DT's load in future ϑ years obtained from the electrical utility;
$SD\%$ # the standard deviations of hourly means.
Output: the simulating load ratio profile of future ϑ years in each simulation;
1: Set the iteration index of simulation times q=0.
2: Let q=q +1. Set the iteration index of simulation year in q^{th} simulation, j =0.
3: Let j=j+1. Generate the normal distribution of load ratio in w^{th} hour of a day in year q, i.e., $N(LF_w\cdot(1+\psi_q), LF_w\cdot(1+\psi_q)\cdot SD\%)$ (w=1,2,…,24).
4: Randomly sample the load ratio of every hour in year q based on area-partition and inverse transformation of the corresponding normal distributions [37].
5: If $j > \vartheta$, GOTO **Step-6**. Otherwise, GOTO **Step-3**.
6: If $q > S$, then **STOP**. Otherwise, GOTO **Step-2**.
7: Print the simulating load ratio profile in each simulation.

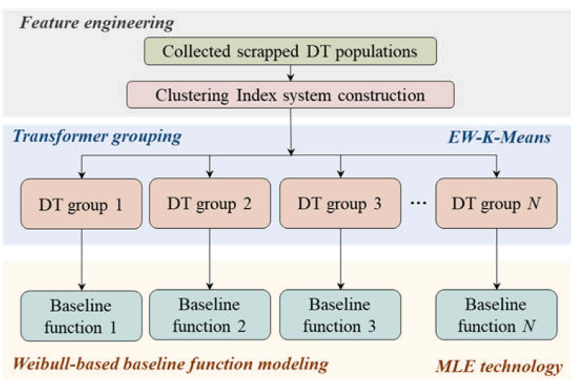

Fig. 3. Structure of the clustering-based average AFR model.

paper·

Nevertheless, directly measuring the moisture content in the insulation paper at each iteration is impossible for many utilities because the measurement kit is not cost-effective. As an alternative, a practical method for calculating moisture content in insulation papers, i.e., the ABB model [30], is adopted here, which is given by:

$$\omega_{k,paper} = 2.069\cdot\exp\left(-0.030\cdot\theta_{tu,k}\right) \times \omega_{k,oil}{}^{\chi\left(\theta_{tu,k}\right)} \tag{4}$$

$$\omega_{k,oil} = 10^{\left(7.420-\frac{1670}{\theta_{tu,k}}\right)} \times RH_k \tag{5}$$

$$\chi(k) = 0.405\cdot\theta_{tu,k}{}^{0.097} \tag{6}$$

where $\omega_{k,oil}$, $\theta_{tu,k}$, and RH_k are the moisture content in the insulation oil (μg/g), top-oil temperature (°C), and environmental relative humidity (%) in iteration k, respectively. In practice, $\theta_{tu,k}$ can be derived from the ambient temperature data, and relative humidity data can be exported from the local meteorological centers. Accordingly, the A-value in each iteration can be obtained by substituting (4)-(6) into (3).

3.2.2. T-value

IEEE standard C57.91-2011 has presented a well-known dynamic thermal model that explains how DT's dynamic HST (T-value) can be affected by loading and ambient temperatures. In this model, the variable T-value is a function of loading and ambient temperature in each iteration, which is given by:

$$T_k = \theta_{tu,k} + \Delta\theta_{h,k} = \theta_{ae,k} + \Delta\theta_{tu,k} + \Delta\theta_{h,k} \tag{7}$$

where $\theta_{tu,k}$ and $\theta_{ae,k}$ are the HST, top-oil temperature, and ambient temperature in iteration k, respectively. $\Delta\theta_{tu,k}$ and $\Delta\theta_{h,k}$ are the top-oil and hottest-spot temperature rise over ambient and top-oil temperature, respectively, which are given by the following equations [34]:

$$\Delta\theta_{tu,k} = \Delta\theta_{tu,r}\cdot\left(\frac{LF_k^2 R + 1}{R+1}\right)^{\sigma_1} \tag{8}$$

$$\Delta\theta_{h,k} = \Delta\theta_{h,r}\cdot\left(LF_k\right)^{2\sigma_2} \tag{9}$$

where LF_k is the load ratio in iteration k. R is the ratio of load loss at rated loads to lose at zero loads. $\Delta\theta_{tu,r}$ and $\Delta\theta_{h,r}$are the top-oil and hottest-spot temperature rise at rated load, respectively. σ_1 and σ_2 are the constant transformer parameters determined through a lookup table depending on the cooling system of DTs [1]. Based on (7)-(9), the T-value in each iteration can be obtained.

Following the above procedures, the sequential DP-values of any preventively scrapped DTs from commission to scrap can be obtained. The technical lifetimes of these scrapped DTs can be determined by matching the degrading-over-time DP profiles and the corresponding criteria (i.e., DP=200). In practice situations, however, the DP-values of these preventively scrapped DTs have not yet dropped to 200 when they got replaced. In this case, it is necessary to generate artificial data about these preventively scrapped DTs' future loading, ambient temperature, and relative humidity to simulate their future operational and environmental conditions for forecasting the subsequent DP-values. Detailed modeling procedures are given in the following part.

3.3. Restoration of the technical lifetime of DTs based on the Latin Hypercube Sampling technique

The preventively scrapped DT's future load ratio, ambient temperature, and relative humidity data can be simulated by exploiting the distribution rules from their historical data [35,36]. Considering the inherent uncertainties (i.e. stochastic nature) associated with their future operational and environmental conditions, the Latin Hypercube sampling (LHS) technique is adopted in this paper to generate multiple sets of future data for determining the technical lifetime distributions of these preventively scrapped DTs.

LHS is an integration of stratified and random sampling, which can be used for generating a random sample of parameter values from the established distribution. Previous studies have proved that LHS is more stable and precise than Monte Carlo simulation for a given sample size [37]. By repeated sampling, it can account for the uncertainty in environmental and operational conditions that power equipment may experience in the future. This calculation uses simulation to generate future load ratio data to illustrate the proposed data generation method. Note that the generation of hourly ambient temperature and relative humidity follows the same procedures. The procedures for generating future load ratio data are described by Algorithm 1:

Following Algorithm 1, the merged data that includes the real historical data and simulated future data can be made long enough, enabling us to capture the time point when the DP-value decreases to 200 (i.e., determine the technical lifetimes of preventively scrapped DTs). The restored technical lifetime in each simulation can be used to fit the technical lifetime distributions of the preventively scrapped DTs through kernel density estimation.

Since this proposed data restoration method integrates several physical-based models and data-driven models that are all derived from thermal aging tests, it can construct a more reasonable and credible aging failure dataset (technical lifetime dataset) of preventively scrapped DTs. The constructed dataset will then be used as the input data in the subsequent AFR modeling.

4. Clustering-based average AFR model for DT groups

In previous studies, the DTs of the same type will form a DT

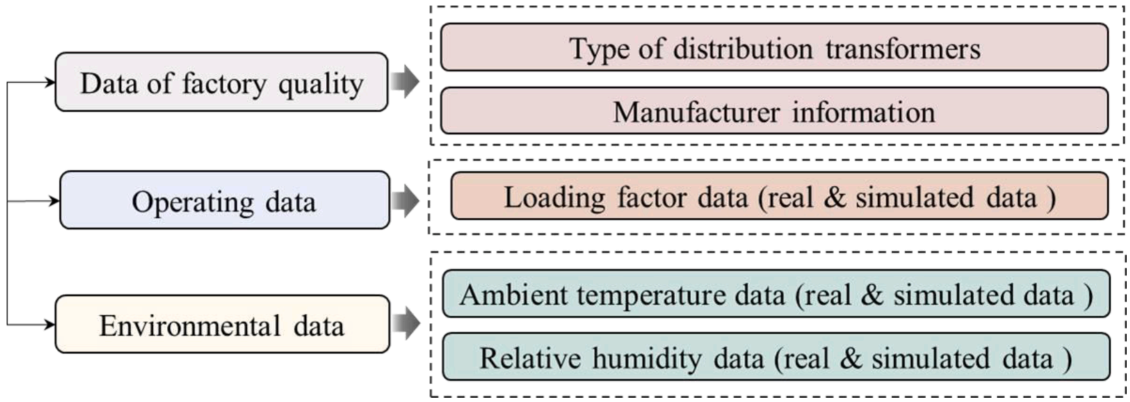

Fig. 4. Comprehensive data structure for DTs.

population and are assumed to have the same aging process and average AFR. In practice, however, these DTs are installed in different calendar years and run at different operating and environmental conditions [38]. In this case, a mixed DT population exists, and using the same average AFR would lead to a biased evaluation [39]. Thus, the DT populations with the same type should be stratified into different homogenous DT groups, and the in-group DTs follow a similar aging process and can have the same average AFR.

Based on the above discussion, this section developed a novel clustering-based approach for modeling the average AFRs of different DT groups combined with the 2-parameter Weibull model. The structure of the approach is shown in Fig. 3.

It can be seen from Fig. 3 that the proposed clustering-based average AFR modeling approach mainly includes the following three procedures:

1) Feature engineering: building a comprehensive clustering feature system that can describe and distinguish individualized characteristics of different DTs.
2) Transformer grouping: stratifying the collected scrapped DT population into relatively homogeneous groups using the proposed EW-K-means clustering method based on the clustering features.
3) Weibull parameters estimation: estimating the Weibull distribution parameters in the average AFR functions of different DT groups using the Maximum Likelihood Estimate (MLE) technique.

Details about these three procedures are illustrated in the following sub-sections. Before this, the 2-Parameter-Weibull-based average AFR function is briefly reviewed.

4.1. 2-Parameter-Weibull-based average AFR model

The 2-parameter Weibull distribution model has been widely used for in-group asset reliability studies, and it can efficiently describe the average AFR of in-group DTs [40,41]. For this reason, this work uses the 2-parameter Weibull model as the basic function to model the average AFR of each DT group, given by:

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{P(t < T < t + \Delta t | T > t)}{\Delta t} = \frac{f(t)}{R(t)} \tag{10}$$

where $\lambda(t)$ denotes the average AFR for a DT group at time t. $R(t)$ and $f(t)$ are the reliability function and probability density function corresponding to the 2-parameter Weibull model, respectively. $R(t)$ and $f(t)$ are expressed as follows:

$$R(t;\alpha,\beta) = 1 - F(t;\alpha,\beta) \tag{11}$$

$$F(t;\alpha,\beta) = 1 - \exp\left[-(t/\alpha)^{\beta}\right] \tag{12}$$

$$f(t;\alpha,\beta) = \left(\frac{\beta}{\alpha}\right)\left(\frac{t}{\alpha}\right)^{\beta}\cdot\exp\left[-(t/\alpha)^{\beta}\right] \tag{13}$$

where α and β are the Weibull scale and shape parameters, respectively, and they can be estimated through MLE analysis of the collected in-group aging failure data [25]. Incorporating (11)-(13) to (10), the specific expression of the average AFR function is given by:

$$\lambda(t;\alpha,\beta) == \frac{f(t;\alpha,\beta)}{R(t;\alpha,\beta)} = \left(\frac{\beta}{\alpha}\right)\left(\frac{t}{\alpha}\right)^{\beta} \tag{14}$$

It is worth noting that the DTs in the same group share the same Weibull scale and shape parameters, whereas the values of the two Weibull parameters are different for different DT groups. In other words, different DT groups have different average AFRs.

The following sub-sections will detail introduce the methods for DT grouping and each group's Weibull parameters estimation. Once these tasks are completed, the average AFR function of each DT group can be obtained.

4.2. Construction of clustering feature system

The selection of clustering features has a great influence on the results of the DT grouping. The feature engineering step aims to extract and establish a comprehensive system of features for describing the asset conditions and degradation processes of individual DTs.

Generally, the performance of DTs mainly depends on their factory quality, operating conditions, and environmental conditions where they are located [42,43]. Accordingly, the following three categories of data are selected to form the clustering feature system, as shown in Fig. 4 below.

In the first data category, the type of DTs refers to their technical parameters in terms of voltage classes (Vc), available capacity (Ac), and cooling systems (Cs). The manufacturer information includes the evaluation scores of electric utilities to the suppliers' product quality (Es). The factory electric test results include the no-load current/loss (I_{nl}/P_0), short-circuit impedance/loss (Z_{si}/P_d), and ground resistance (Ω_{gr}) before DT commission. These nine extracted indicators can be derived from the Power Grid Equipment Ledger or Maintenance Management Systems.

Since the degradation of DTs has also been traced back to the three time-varying factors in Section 3, i.e., load ratio, ambient temperature, and relative humidity, these three corresponding data types are selected as the source of the second and third categories. To describe the time-space characteristic and the uncertainty (resulting from simulated future data) of these factors during the actual life spans of scrapped DTs, the following three indicators are defined (taking load ratio data as examples) [44]:

Define 1. : The Absolute Quantity Feature of load ratio:

$$AQF_{LF} = \frac{1}{S}\sum_{s=1}^{S}\left(\frac{1}{Ws}\sum_{w=1}^{Ws} LF_{s,w}\right) \quad (15)$$

where S is the simulation times and Ws is the restored lifetime (in hr) in the s^{th} simulation of a scrapped DT. $LF_{s,w}$ is the load ratio in w^{th} hour in the s^{th} simulation. This feature can reflect the average absolute degree of the load ratio during a DT's life span.

Define 2. : The Variance Feature of load ratio:

$$VA_{LF} = \frac{\frac{1}{S}\sum_{s=1}^{S}\left(\sqrt{\frac{1}{Ws}\sum_{w=1}^{Ws}\left(LF_{s,w} - \frac{1}{Ws}\sum_{w=1}^{Ws} LF_{s,w}\right)}\right)}{AQF_{LF}} \quad (16)$$

This feature is interpreted as the degree of load ratio dispersion during the life span of a scrapped DT. The larger VA_{LF} is, the higher the fluctuation degree of the load ratio is.

Define 3. : The Trend Feature of load ratio:

$$TF_{LF} = \frac{1}{S}\sum_{s=1}^{S}\frac{\sum_{w=1}^{Ws}\left(LF_{s,w} - \frac{1}{Ws}\sum_{w=1}^{Ws} LF_{s,w}\right)\left(w - \frac{Ws}{2}\right)}{\sum_{w=1}^{Ws}\left(w - \frac{Ws}{2}\right)^2} \quad (17)$$

This feature is used to describe the long-term variety trend of the load ratio. A bigger and positive TF_{LF} implies that the trend of DT's load ratio is getting larger over time, and this situation is probably due to the increase in the user's power load.

Similarly, the other six features corresponding to the ambient temperature and relative humidity data, AQF_{AT}, VA_{AT}, TF_{AT}, AQF_{RH}, VA_{RH}, and TF_{RH} can be obtained. These nine features can be used to describe the heterogeneity in the individual DTs' operating and environmental conditions.

An example of a clustering feature vector (FV) for an individual DT T_m can be given below:

$$FV = [V_c, A_c, C_s, E_s, I_{nl}, P_0, Z_{si}, P_d, \Omega_{gr}, AQF_{LF}, VA_{LF}, TF_{LF}, AQF_{AT}, VA_{AT}, TF_{AT}, AQF_{RH}, VA_{RH}, TF_{RH}] \quad (18)$$

The feature vectors of these collected scrapped DTs will then be used as the input data in the following DT grouping.

4.3. DT grouping based on EW-K-means method

This sub-section describes the addopted EW-K-means clustering method that is used for DT grouping. Firstly, assuming that the collected scrapped DT population contains M individual DTs, then the feature matrix can be described as:

$$\mathbf{x} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,N} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,N} \end{bmatrix} \quad (19)$$

In matrix $\mathbf{x}$, element $x_{m,n}$ is the initial value of the n^{th} feature of the m^{th} DT. In practice, each feature type has a different unit, and the difference between the feature magnitudes can be quite large. Therefore, it is necessary to normalize the numerical values. The Min-Max normalization is adopted here [45]:

$$X_{m,n} = \frac{x_{m,n} - \min(x_{1,n}x_{2,n}\ldots x_{M,n})}{\max(x_{1,n}x_{2,n}\ldots x_{M,n}) - \min(x_{1,n}x_{2,n}\ldots x_{M,n})} \quad (20)$$

where $X_{m,n}$ represents the normalized value of the n^{th} feature of the m^{th} DT (n=1,2,…,19).

Furthermore, considering the different importance of the various features for the DT's performance description, the Entropy Weight Method (EWM) is adopted to adaptively determine the weights of different features. Compared with various subjective weighting models, the biggest advantage of the EWM is the avoidance of the interference of human factors on the weight of features [46]. The detailed process is given as follows:

1) Calculate the entropy value of the n^{th} feature (h_n) [47]

$$h_n = -\frac{1}{\mathrm{In}M}\sum_{m=1}^{M} f_{m,n}\cdot \mathrm{In} f_{m,n} \quad (21)$$

$$f_{m,n} = \frac{X_{m,n}}{\sum_{m=1}^{M} X_{m,n}} \quad (22)$$

where $f_{m,n}$ is the contribution of the m^{th} evaluated DT under the n^{th} feature (n=1,2,…,19).

1) Calculate the entropy weight of the n^{th} feature (ew_n)

$$ew_n = \frac{1 - h_n}{M - \sum_{N=1}^{N} h_n} \quad (23)$$

where 1-h_n is the entropy redundancy of the n^{th} feature, and the sum of ew_n (n=1,2,…,19) is equal to 1.

Then, the classic K-means clustering algorithm is used for DT adaptive grouping analysis based on the entropy-weighted Euclidean distance. The K-Means method is a very popular unsupervised clustering method for dealing with large datasets with great efficiency and low computational complexity [25]. It only requires one input parameter, i.e., the expected number of clusters (the C-value), making it more suitable for industrial applications compared with other clustering methods [48]. The mathematical description of the improved K-Means method based on entropy-weighted Euclidean distance (i.e., the EW-K-means method proposed in this paper) is discussed as follows.

1) Initialization. Let the number of DT groups be C, and randomly select C samples in the dataset as the initial group centers.
2) DT grouping. Associate all the collected DTs to their nearest group center $\boldsymbol{X}_c$= [$X_{c,1}$, $X_{c,2}$,…,$X_{c,n}$] based on entropy-weighted Euclidean distance (c=1,2,…,C). The weighted distance from DT m to the c^{th} group center is calculated by:

$$Dis(m,c) = \sqrt{\sum_{n=1}^{N} ew_n\left(X_{m,n} - X_{c,n}\right)} \quad (24)$$

3) Group center update. According to the result of step 2), the average value for each group is calculated as the new group center.

$$\widehat{X}_{c,n} = \frac{1}{|Gc|}\sum_{X_m \in Gc} X_{m,n} \tag{25}$$

where Gc and $|G_c|$ represent the c^{th} DT group and the number of DT in group c, respectively. m=1,2, …, $|G_c|$ and n=1,2,…,19.

1) Error calculation. Calculate the squared error E under the new group centers:

$$E = \sum_{c=1}^{C}\sum_{X_m \in Gc}\sum_{n=1}^{N} ew_n\left(X_{m,n} - \widehat{X}_{c,n}\right)^2 \tag{26}$$

2) Iterative calculation. Repeat steps 2) to 4) until the location of the group centers and the minimum E-value no longer change.

In practice, to optimize the performance, different C-values can be tested, and the clustering quality evaluation metrics, the elbow criterion, can be applied to identify the best C-value [49]. In addition, a minimum number of 20 DTs is required for each group because this is the qualifying criterion for Weibull function modeling [39].

Following the above procedures, the collected scrapped DT population can be grouped, which is the basis for each group's average AFR modeling. Note that different state-of-art clustering algorithms can also be used for DT grouping.

4.4. Weibull parameters estimation for each DT group

After completing the DT grouping, the restored in-group aging failure data (i.e., technical lifetimes) can be used to fit each group's Weibull-based average AFR. The MLE is adopted here for the Weibull parameters estimation for each DT group.

Suppose the c^{th} DT group has $|G_c|$ scrapped DTs. Thus, the likelihood function of the Weibull-based average AFR function corresponding to the c^{th} group can be written as [50]:

$$\begin{aligned} &L_c(\alpha_c, \beta_c) \\ &= L_c\left(\underbrace{t_{1,1}, \ldots, t_{1,S_r}}_{\mathrm{DTT}_1}, \underbrace{t_{2,1}, \ldots, t_{2,S_r}}_{\mathrm{DTT}_2}, \cdots, \underbrace{t_{|G_c|,1}, \ldots, t_{|G_c|,S_r}}_{\mathrm{DTT}_{|G_c|}} \middle| \alpha_c, \beta_c\right) \\ &= \prod_{i=1}^{|G_c|}\prod_{s_r=1}^{S_r} f_c\left(t_{i,s}\middle|\alpha_c, \beta_c\right) \\ &= \prod_{i=1}^{|G_c|}\prod_{s_r=1}^{S_r}\left(\frac{\beta_c}{\alpha_c}\right)\left(\frac{t_{i,s_r}}{\alpha_c}\right)^{\beta_c}\exp\left(-\left(\frac{t_{i,s_r}}{\alpha_c}\right)^{\beta_c}\right) \end{aligned} \tag{27}$$

where α_c and β_c are the scale and shape parameters to be estimated for the c^{th} DT group. $f_c(\cdot)$ is the probability density function of the Weibull model for group c. Since the restored failure time of a preventively scrapped DT is not a definite value but a probability distribution, its failure time set obtained from the S_r sampling is included in the likelihood function (Sr is set as 200 here). t_{i,s_r} denotes the restored failure time of DT T_i in the s_r^{th} sampling.

To simplify computation, we take the logarithm of $L_c(\alpha_c, \beta_c)$, and the optimal parameter estimators $(\widehat{\alpha}_c, \widehat{\beta}_c)$ should satisfy:

$$(\widehat{\alpha}_c, \widehat{\beta}_c) = \mathrm{argmax}L_c(\alpha_c, \beta_c) = \mathrm{argmax}In(L_c(\alpha_c, \beta_c)) \tag{28}$$

Some numerical methods, such as Newton–Raphson have been used for solving (28) [51]. In this paper, the default function 'wblfit' in MATLAB software is adopted to estimate the confidence intervals of the two parameters at 95% confidence, and the corresponding mean values are selected as the $\widehat{\alpha}_c$.and $\widehat{\beta}_c$

Incorporating (27) to (14), the time-dependent average AFR function for the c^{th} DT group can be expressed as:

$$\lambda_c(t; \widehat{\alpha}_c, \widehat{\beta}_c) = \left(\frac{\widehat{\beta}_c}{\widehat{\alpha}_c}\right)\left(\frac{t}{\widehat{\alpha}_c}\right)^{\widehat{\beta}_c} \tag{29}$$

where t is the asset age (i.e., operating years) of the DTs within group c (c=1, 2, …, C). It is worth noting that the confidence intervals of the average AFR can also be calculated by considering the confidence intervals of estimated Weibull parameters.

5. Individual AFR modeling of in-group DTs based on the decomposition function

This section presents the method for modeling the individual AFRs of in-group DTs based on a decomposition function, which quantifies the relative aging degree of an individual DT with respect to the whole group. Details are introduced in the following sub-sections.

5.1. Brief introduction of in-group decomposition

As mentioned above, the average AFR model established in Section 4 can more finely reflect the aging-related aggregated features of the whole DT group. Nevertheless, different DTs within the same group should have different individual AFRs at the same time point due to their heterogeneous aging processes.

To consider this in this paper, we have developed a novel decomposition function to link the individual aging degrees with the average AFR and to derive the heterogeneous FRs of in-group DTs. Take an individual DT T_m in group c for example, given the group's average AFR $\lambda_c(t)$and T_m's real-time aging covariate $Q_{c,m}$, its AFR at time t can be expressed as:

$$\lambda_{c,m}(t) = \lambda_c(t)\cdot\mathbb{R}\left(t; Q^t_{c,m}\right) = \left(\frac{\widehat{\beta}_c}{\widehat{\alpha}_c}\right)\left(\frac{t}{\widehat{\alpha}_c}\right)^{\widehat{\beta}_c}\cdot\mathbb{R}\left(t; Q^t_{c,m}\right) \tag{30}$$

where $Q^t_{c,m}$is the covariate that describes the aging degrees of T_m at time t. $\mathbb{R}(\cdot)$ is the decomposition function that is used to quantify the relative aging degree of T_m towards the whole group c. $\mathbb{R}(t; Q_{c,m}) = 1$ represents that the individual aging degree of T_m is the same as the average aging degree of group c, and then the individual AFR of T_m equal to $\lambda_c(t)$. When $\mathbb{R}(t; Q_{c,m}) > 1$, the individual AFR of T_m is large than $\lambda_c(t)$, and if $\mathbb{R}(t; Q_{c,m}) < 1$ it is less than $\lambda_c(t)$.

To build such a decomposition function, the following tasks need to be solved: 1) Selection of the time-dependent aging covariate of individual DTs. 2) Determination of the specific form of eq. (30). The solutions proposed in this paper are as follows.

5.2. Selection of the time-dependent aging covariate

The aging covariate is generally derived from the aging-related measurements of DTs [8]. In practice, the selection of aging covariates depends on the availability, variation, and sensitivity of the measurement data. More importantly, the aging covariate should be able to significantly distinguish the heterogeneous aging degrees of individual DTs.

As well known, the DTs will be aging gradually under the combination of thermal, electrical, and chemical stresses resulting from dynamic operating and environmental conditions. Based on this, previous studies [8,15] used various measurements such as the temperature or gas and oil results to construct a complex aging covariate vector and then derived a weighted index to distinguish the individual aging degrees. However, the following limitations make difficult the application to the in-service aged DTs:

Table 1
Basic information of the two illustrative scrapped DTs.

ID	Commissioning time	Scrapping time	Scrapping age (yrs)
T_1	April 1998	May 2021	23.12
T_2	December 2000	July 2021	20.61

1) Various DT health or aging monitoring devices are required to obtain these measurements, which is impossible for the in-service aged DTs since most of them do not install the devices due to cost limits.
2) Determination of the weights of different covariates highly depends on expert knowledge and lacks explicit physical meanings, making its application even more difficult for electric utility engineers.
3) The aging covariate vector contains many operating and environmental features, and these features may be highly correlated, which will bring potential errors in aging degree evaluation.

For these issues, in this way, we select a widely accepted aging index, the time-varying DP-value (Degree of Polymerization) of DT, as the single aging covariate to distinguish the aging degrees of individual DTs, and the reasons are as follows:

1) The DP-value has been regarded worldwide as the best indicator to quantify the aging degree of DTs [52]. It can accurately reflect the coupling impact of operating and environmental factors through prior aging mechanism analysis.
2) The real-time DP-value can be obtained through the computation-based method (introduced in Section 3) without any additional measurements, which is more convenient for aged DTs in industrial applications.

Therefore, the observed aging covariate vector of $|G_c|$ DTs in group c at time t can be expressed as:

$$\mathbb{Q}_c^t = \left[\mathrm{Q}_{c,1}^t, \mathrm{Q}_{c,2}^t, \cdots, \mathrm{Q}_{c,|G_c|}^t\right] \tag{31}$$

where $|G_c|$ is the number of DT in group c and $\mathrm{Q}_{c,|G_c|}^t$ is the value of aging covariate (i.e., DP-value) of $|G_c|^{th}$ DT at time t. Vector $\mathbb{Q}_c^t$ is used to calculate the relative aging degree of individual DTs through the decomposition function established in the following sub-section.

5.3. Determination of the decomposition function

Several functions have been proposed to describe the relationship between asset conditions and measurement information. Among them, the linear function is a rather general approach and applicable for a wide range of measurements, and it assumes that the relationship between the relative aging degree and aging covariate is linear [8]. Therefore, this paper adopts a negative-linear decomposition function to calculate the relative aging degree of an individual DT T_m, which is defined as:

$$\mathbb{R}(t; Q_{c,m}) = \frac{\mathrm{Q}_{c,per} - \mathrm{Q}_{c,m}^t}{\mathrm{Q}_{c,per} - \overline{\mathbb{Q}}_c^t} \tag{32}$$

where $\mathbb{R}(t; Q_{c,m})$ is the relative aging degree of T_m towards group c at time t. $\mathrm{Q}_{c,per}$ is defined as the value that describes the perfect condition (non-aging condition) of DTs, and it generally equals 1000 [26]. $\overline{\mathbb{Q}}_c^t$ is the average DP-value of all obtained values $\mathrm{Q}_{c,i}^t$in group c at time t, which is calculated as:

$$\overline{\mathbb{Q}}_c^t = \frac{1}{|G_c|}\sum_{i=1}^{|G_c|}\mathrm{Q}_{c,i}^t \tag{33}$$

It can be seen from (32) that the value of $\mathbb{R}(t; Q_{c,m})$ increases with the decrease $\mathrm{Q}_{c,m}^t$. Incorporating (32) into (30), the individual AFRs of DTs with the same group can be evaluated.

In practice application, the DP-values of the scrapped DTs may not be determined values but the probability distributions resulting from the data restoration operation. In this case, the AFR evaluation result is also probabilistic. To quantity the uncertainty, the Latin Hypercube Sampling (LHS) method is adopted. Take a new in-service DT T_{new} that belongs to group c as an example, the evaluated AFR of T_{new} in the s^{th} simulation at time t can be expressed as:

$$\lambda_{new}^s(t) = \left(\frac{\widehat{\beta}_c}{\widehat{\alpha}_c}\right)\left(\frac{t}{\widehat{\alpha}_c}\right)^{\widehat{\beta}_c}\cdot\left(\frac{\mathrm{Q}_{c,per} - \mathrm{Q}_{c,m}^t}{\mathrm{Q}_{c,per} - \overline{\mathbb{Q}}_c^{t,s}}\right) \tag{34}$$

where $\overline{\mathbb{Q}}_c^{t,s}$ is the average DP-value of group c in the s^{th} simulation. The above steps should be performed sufficient times to obtain the probability density distribution of the individual AFR of T_{new} at time t using nonparametric estimation methods [53]. Here, an effective nonparametric estimation method, i.e., the Nonparametric Kernel Density Estimation (KDE) method, is adopted for probability density distribution estimation, and the technical details of the KDE method can be found in [54].

6. Empirical analysis

6.1. Dataset description & Preliminary assumptions

In this section, 207 oil-immersed DTs (mode: S9-30kVA/10/0.4kV) that were scrapped between 2017 and 2021 years in Chongqing Electric Power Company of China are selected and employed to verify the usefulness of the proposed approach. A practical value for the initial DP-value of these DTs is set as 1000 [55]. The cooling system's parameters of these DTs can refer to [56]. The historical meteorological data can be derived from the Greenhouse Data Analysis Platform of China [57]. The SD% used for generating these DTs' future condition data is set as 10% [58]. The simulation times S and simulation duration ϑ are set as 10000 times and 80 years, respectively. All simulations are implemented in the MATLAB 2017b platform on a personal computer with a 3.0 GHz Intel (R) Core (TM) i5 CPU and 8 GB RAM.

6.2. Empirical results

This section is devoted to demonstrating the empirical results using the proposed Restoration-Clustering-Decomposition learning approach. Detailed processes and analysis are also presented in the following part.

6.2.1. Results of aging failure data restoration

This case focuses on applying the proposed data restoration approach to the 207 preventively scrapped DTs for constructing a credible aging failure dataset.

By inputting the historical operating and environmental data of these DTs into the process, their heterogeneous DP degradation curves can be simulated. According to the restoration rules given in Section 3, the restored technical lifetimes (i.e., aging-related lifetimes) of these DTs in each simulation corresponds to the time points when their time-varying DP-values drop to 200. To better illustrate the usability of the proposed restoration approach, two illustrative scrapped DTs are selected for discussion. Basic information about these two illustrative scrapped DTs is provided in Table 1 below.

As listed in Table 1, the scrapping ages of T_1 and T_2 are 23.12 and 20.61 years, respectively. For comparison, their restored technical lifetimes obtained from 10000 times sampling are shown in Fig. 5-(a) and (b).

Based on the datasets, the probability density distributions of the restored technical lifetime of T_1 and T_2 can be fitted using the KDE method. Detailed results are shown in Fig. 5-(c) and (d), respectively. Specifically, the following observations can be made from Fig. 5 and

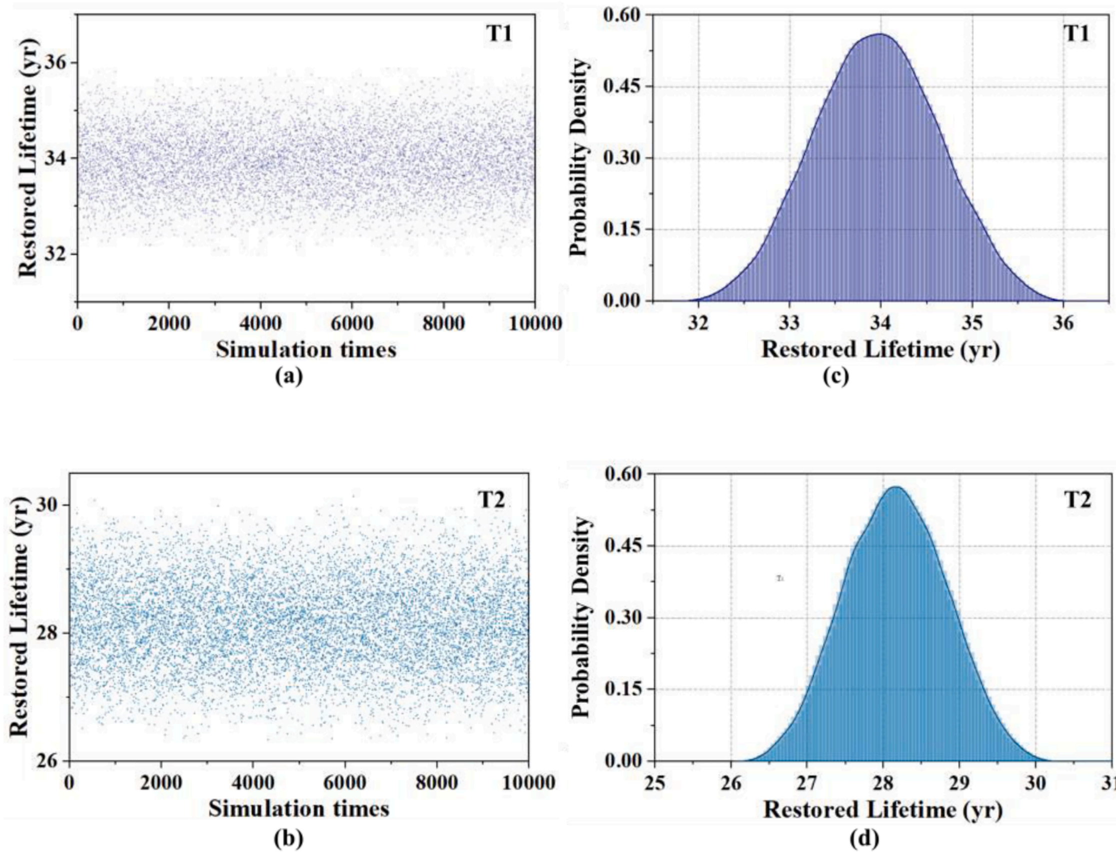

Fig. 5. Dataset and corresponding probability density distributions of the restored technical lifetime of T_1 and T_2.

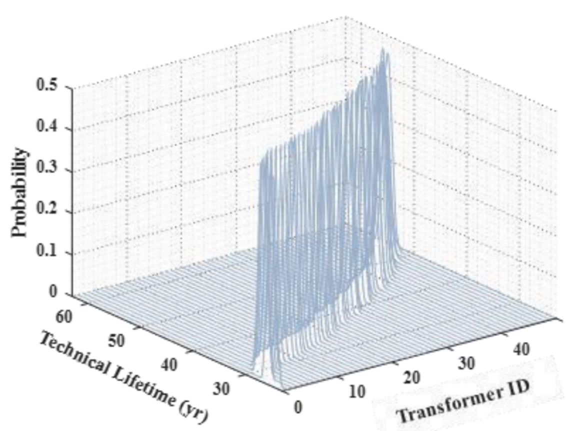

Fig. 6. Restored technical lifetimes of the 50 DTs.

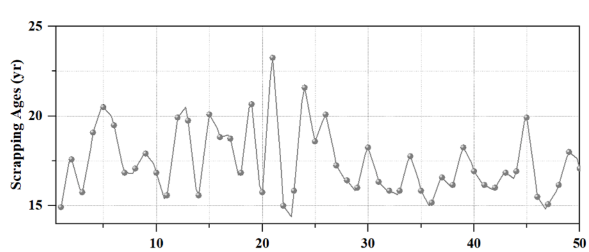

Fig. 7. Scrapping ages of the 50 individual DTs.

Table 1:

- The restored technical lifetime of T1 is between 31.99 and 35.87 years, whereas that of T2 is between 26.34 and 30.16 years. The restored lifetimes of these two DTs are longer than their scrapping ages and the designed usage years (20 years in China). This is because these two DTs do not always operate under the rating load rate and rating environmental temperature (40 °C) during their entire service life.
- The restored technical lifetimes of T1 and T2 are not fixed values under different simulations. This is because the uncertainty of their future environmental and operating conditions are fully considered in the data restoration process. The intervals of restored results imply that the uncertainty of DTs' future environmental and operating conditions indeed has a significant influence on the restoration results.
- The restored lifetimes of T2 are smaller than that of T1, although they are put into operation and scrapped in the same periods. To cite an instance, the maximum difference between their restored lifetime can be up to 9.53 years. This is because T2 has a higher loading factor during its service life compared with T1, making it has a faster aging process. This finding indicates that taking the scrapping ages as the aging failure dataset for the AFR modeling and evaluation is inaccurate.

Similarly, the probability distributions of the restored technical lifetimes of the other 205 scrapped DTs can be obtained. For illustration, the restored results of 50 randomly selected DTs are shown in Fig. 6 below. For comparison, their statistically scrapping ages are given in Fig. 7.

As can be seen from Figs. 6 and 7, the restored lifetimes of these 50 scrapped DTs are generally larger than their scrapping ages, which

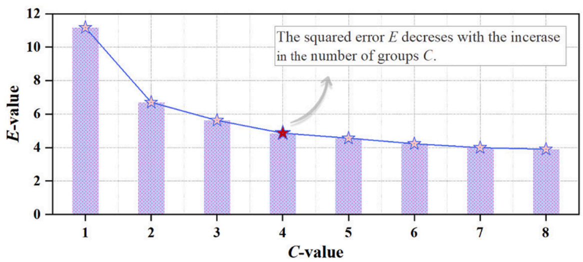

Fig. 8. Relationship between the number of groups C-value and squared error E-value.

Table 2
Detailed information about different DT groups.

	DT Group ID	Number of DTs	$\widehat{\alpha}_c$	$\widehat{\beta}_c$
Case 1	1	55	42.08	5.35
	2	82	43.44	5.18
	3	47	45.72	5.51
	4	23	48.35	5.97
Case 2	UD	207	44.19	5.27

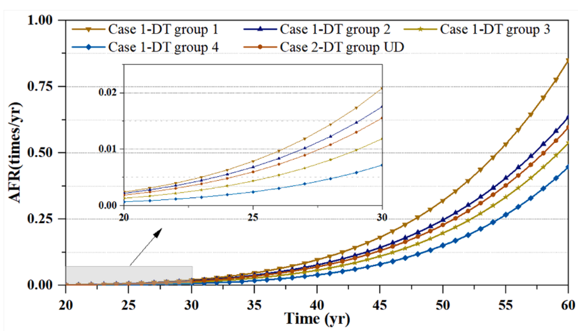

Fig. 9. Comparison of average AFR results.

further illustrates the importance of the aging failure data restoration process. Noteworthy is that the proposed data restoration approach enables us to involve multiple aging factors in the aging process analysis for a credible restoration of the scrapped DTs' aging-related lifetimes. The industrial experts also confirm that the restored aging failures data are reasonable and acceptable. Moreover, this approach is feasible for other types of scrapped DTs as the input data required can be made available from the existing databases in utilities.

6.2.2. *Results of DT's AFR evaluation*

Having restored the aging failure data, this case is devoted to grouping the 207 preventively scrapped DTs and evaluating the average AFRs of different DT groups through the clustering process introduced in Section 4.

Firstly, the 207 scrapped DTs are divided into some homogenous groups using the proposed EW-K-means method. The relationship between the number of groups (i.e., C-value) and the corresponding squared error E-value is shown in Fig. 8 below.

It can be seen from Fig. 8 that the E-value will decrease when the C-value increases. Specifically, the E-value decreases dramatically when the C-value is smaller than 4, whereas it decreases slowly when the C-value is larger than 4. When the C-value is equal to 4, the E-value has decreased by 56.71% compared to that of the C-value equals 1. As a result, the optimal number of groups is determined as 4 in this paper according to the classic elbow method [49].

Based on the above grouping results, each group's Weibull distribution parameters, i.e., scale parameter $\widehat{\alpha}_c$ and shape parameters$\widehat{\beta}_c$, can be estimated using the default function 'wblfit' in MATLAB software. Detailed results about each DT group, including the number of contained DTs and the estimators of Weibull parameters, are summarized in ***Case 1*** of Table 2. For comparison, the results that treat all 207 DTs as one group (i.e., group UD) are also provided in ***Case 2*** of this Table. Moreover, the results of the goodness of fit tests regarding the four built Weibull distributions are given in Appendix B.

It can be seen from Table 2 that there are quite some differences in the estimation values of the Weibull parameters between the four DT groups in ***Case 1***, indicating that these four DT groups indeed have non-negligible differential aging processes. Specifically, group 1 has the fastest degradation speed, whereas group 4 has the slowest degradation. Furthermore, the estimators of group UD in ***Case 2*** are at the average level of ***Case 1.*** For quantitative analysis purposes, the time-varying average AFR curves corresponding to each DT group are shown in Fig. 9 below.

From Fig. 9 and the enlarged subgraph, the following quantitative observations can be summarized:

- The average AFRs of all groups in Case 1 and Case 2 gradually increase after 20 years. This observation indicates that the irreparable aging failures will become an unavoidable factor of DT populations' unreliability after 20 years, which agrees with the practical findings in engineering.
- The average AFRs in the four groups in Case 1 have significant differences in both growth trends and numerical values. The AFR curve of group 1 has the fastest growth rate whereas while group 4 has the lowest. In the 45th year, the AFR of group 1 reaches 0.182 times/year, 27.27%, 65.08%, and 126.64% larger than that of groups 2-4 in Case 1, respectively.

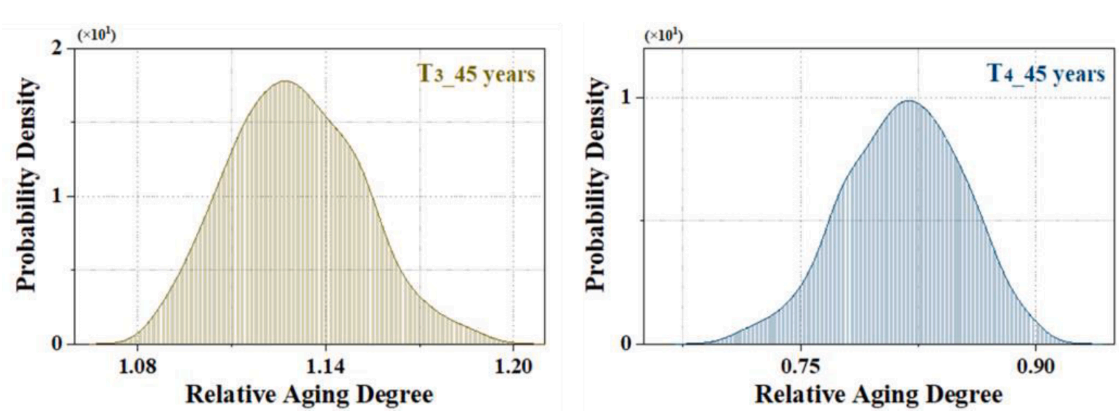

Fig. 10. Comparison of the relative aging degrees at the age of 45 years.

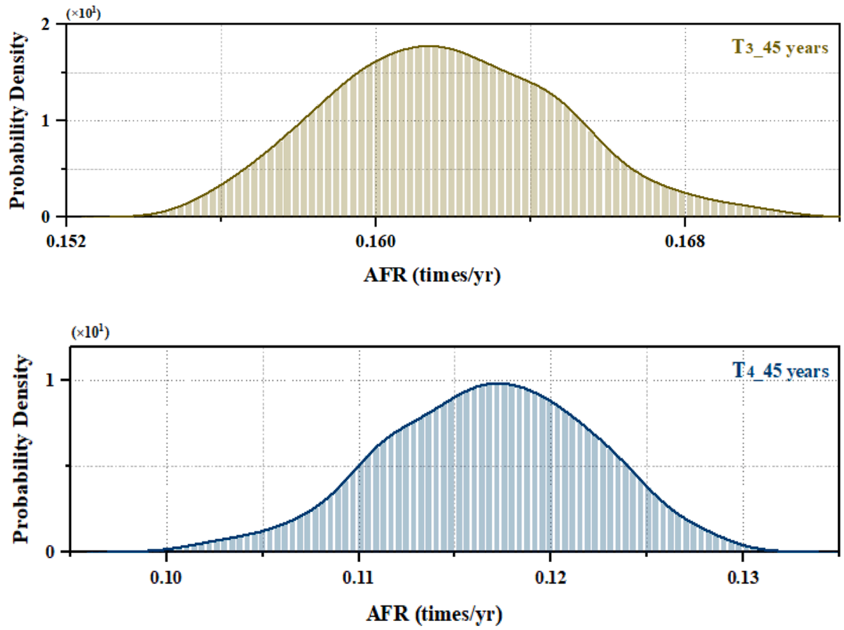

Fig. 11. Probabilistic AFRs of T3 and T4 at the age of 45 years.

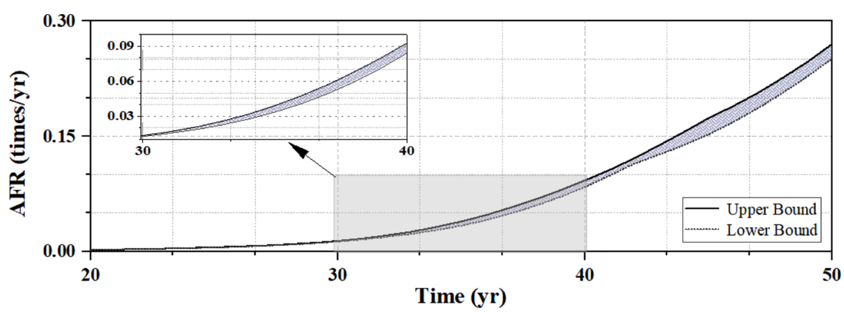

Fig. 12. Probabilistic AFRs of T_3 from 0–50 years.

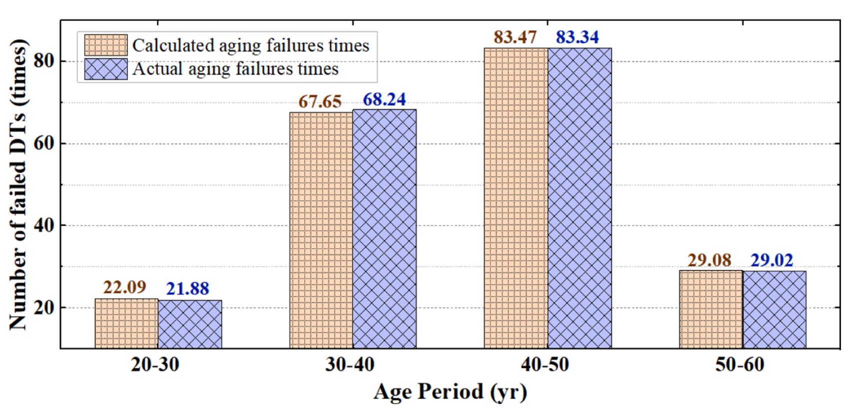

Fig. 13. Inversion results at different age periods.

- The AFR curve of group UD in Case 2 has a larger growth rate and values than groups 3-4 of Case 1 but is smaller than the other two groups. In the 45th year, the AFR of group UD is 0.131 times/year, 28.01%, 8.37% smaller than groups 1-2, and 18.86%, 63.18% larger than group 3-4, respectively.

The above observations demonstrate the importance of the DT grouping process on AFR evaluation. Based on the evaluated average AFR results, the individual AFRs of in-group DTs can be assessed using the proposed decomposition function method. For demonstration, two DTs that belong to group 2, namely T_3 and T_4, are selected for comparison and discussion. For better illustration, the KDE method is also adopted here to calculate the probability density distributions of relative aging degree and AFRs of T_3 and T_4 at the age of 45 years. Details about the used KDE method have been discussed in Section 5 above.

The relative aging degrees of T_3 and T_4 towards group 2 at a representative age (45 years) are shown in Fig. 10 below.

According to Fig. 10, the AFRs of T_3 and T_4 at the age of 45 years can

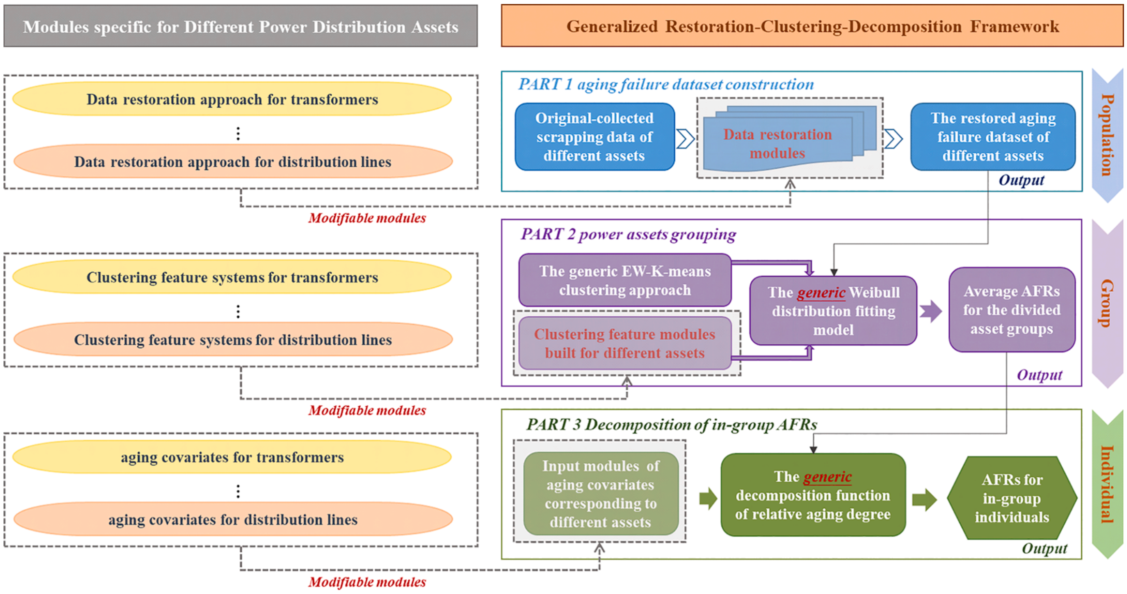

Fig A1. The generalized Restoration-Clustering-Decomposition framework.

Table B1
Results of the goodness of fit tests.

	K-S statistic	*Critical value*
DT group 1	0.0091	0.0130
DT group 2	0.0066	0.0106
DT group 3	0.0056	0.0140
DT group 4	0.0110	0.0201

*The significance level α is set as 0.05.

be calculated using (34) in Section 6. Detailed results are shown in Fig. 11.

From Figs. 10 and 11, the following several observations can be drawn.

- The relative aging degrees of T3 and T4 at the age of 45 years are not fixed values but are described by probability distributions. Fig. 11 shows that the relative aging degree of T3 is between 1.065 and 1.212 at the age of 45 years, whereas that of T4 is around 0.670 to 0.942. The reason for these uncertainties is that the DP-values of some DTs in group 2 at 45 years are not fixed values but others, and they are described by the probability distributions obtained from the data restoration process.
- The probabilistic AFR of T3 is larger than the average AFRs of group 2 at the age of 45 years. The reason lies in that the relative aging degree of T3 is higher than the average aging degree at this age, and therefore it would have higher AFRs. In comparison, the probabilistic AFR of T4 is smaller than the average AFR. Specifically, at the age of 45 years, the AFRs of T3 and T4 are between 0.153 and 0.173, 0.096 and 0.135 times/year, respectively. These two results are significantly different from the average AFR (i.e., 0.143 times/year).

The above discussions indicate that considering the individual aging degrees of DTs in the AFR evaluation is of great importance. Comparatively, using the conventional age-based 2-parameter Weibull model cannot distinguish the individuals, and it would lead to a less accurate AFR evaluation. Additionally, Fig. 12 provides the area of the probabilistic AFR of the T_3 age range (0–50 years).

It can be concluded from the shaded area of Fig. 12 that the uncertainty in the AFR evaluation results is non-ignorable, especially when the DT is greater than 20 years old. Furthermore, this observation shows another superiority of the proposed AFR evaluation approach, i.e., it can generate probabilistic descriptions of AFRs, allowing the operators to grasp the lower and upper limits of DT's operational risks and to make proper maintenance and retirement decisions.

6.3. Accuracy analysis

An inversion analysis method proposed in [38] is adopted in this case to test the accuracy of the above AFR evaluation results. This method compares the number of failed DTs calculated from the proposed approach with the actual statistical results at different age periods. The Mean Relative Error (*MRE*) is used to quantitative the error between the calculation results and the actual results:

$$MRE_h = \frac{1}{C}\sum_{i=1}^{C}\frac{\left|NF_{c,h}^{cal} - NF_{c,h}^{act}\right|}{NF_{c,h}^{act}} \times 100\%, h = 1, \dots, H \tag{35}$$

where $NF_{c,h}^{cal}$ and $NF_{c,h}^{act}$ denote the number of failed DTs during age period h that is calculated from the proposed approach and actual statistics, respectively. It is worth noting that a lower *MRE* indicates higher AFR evaluation accuracy.

The inversion results at four representative age periods (20-30 years, 30-40 years, 40-50 years, 50-60 years) using the above inversion method are provided in Fig. 13.

It is evident from Fig. 13 that the calculated numbers of failed DTs are very closer to the actual statistics at the four representative age periods. Specifically, the average *MRE*-value is 0.516%, indicating that the proposed Restoration-Clustering-Decomposition learning approach is a superior and promising approach for accurately evaluating the AFRs of individual DTs.

7. Discussion

This section focuses on discussing the practical applications of the proposed AFR estimation framework and the potential research directions.

7.1. Practical applications

The regulation reform of the electric power industry has created an important challenge for the ongoing maintenance of the aging DT assets.

Power utilities need to make the most cost-effective maintenance strategy to maintain the safe operation of these aging DTs [59]. One important and challenging task in developing such a strategy is prioritizing maintenance activities for different DTs. To compute better results, the reliability level of the individual DTs and the impact of their maintenance interruption on the system's reliability are required to be considered in the maintenance priority assignment decision-making. The failure rate has been regarded worldwide as the preferred reliability measure of power equipment, and therefore the AFR evaluation results will be directly used as the essential input data for a maintenance priority assignment algorithm [8]. Another essential issue in optimal maintenance strategy-making is determining the optimal inspection interval of DTs to minimize the maintenance and failure loss costs [60]. The maintenance cost mainly depends on the implemented maintenance strategies (major or minor maintenance), which are determined based on the real AFRs of DTs. Meanwhile, the failure loss cost mainly depends on the loss of load resulting from DT failure, while the AFRs of DTs determine the expected loss of load. Therefore, It can be said that the aforementioned works (maintenance priority assignment and maintenance interval scheduling) all need accurate AFR evaluation results to gain the best results.

7.2. Future research

In the clustering step of the proposed framework, an EW-K-Means clustering method is adopted for DT grouping, whose effectiveness has been demonstrated through numerical analysis. In our future study, more advanced clustering algorithms can be developed and embedded in the proposed framework to promise the robustness of the proposed approach when applied to the AFR estimation of other power distribution assets. Recently, some novel neural-network-based clustering algorithms (e.g., the Learning Vector Quantization method) have been proposed, which are suitable for clustering large and complex datasets [61]. Inspired by this, a feasible research direction in the future is developing a neural network-based clustering method that can be specially used for power distribution asset grouping. The chief challenge for this work will be to design an efficient neural network model that can achieve an optimal trade-off between network topology simplification and clustering ability improvement. For this optimization problem, a potential solution is integrating advanced optimization algorithms into the neural network construction.

In fact, there are many different domains where advanced optimization algorithms have been applied as solution approaches, such as track schedules, traffic resource allocation, vehicle routing planning, etc. [62]. For example, [63] proposed a novel adaptive polyploid memetic algorithm for the cross-docking terminal truck scheduling problem that can assist CDT operators with proper operations planning from the truck scheduling perspective. To minimize the total cost associated with traversing the edges of the network and the total cost associated with visiting the nodes of the network in vehicle routing, a customized nature-inspired evolutionary algorithm is designed in [64]. Furthermore, A multi-objective heuristic model is also proposed in [65] for resource allocation among level crossings, which can minimize not only the total hazard severity due to potential accidents but the associated traffic delays as well. In addition to the above studies, much effort has also been devoted to improving the generalization ability & scalability of these optimization algorithms [66–68]. In conclusion, these efficient optimization algorithms have played an important role in solving optimization & decision problems in various engineering fields. We believe these algorithms can also be applied to neural network optimization in our future research.

8. Conclusion

This paper proposes a novel and comprehensive Restoration-Clustering-Decomposition learning framework for AFR evaluation of DTs. Compared to previous works, this framework has the following advantages:

1) It can distinguish and evaluate the AFRs of individual DTs under different aging degrees with higher credibility and accuracy compared to the conventional Weibull model.
2) It can effectively promise the data quality of AFR modeling by using a proposed hybrid-driven approach in which physical-based and data-driven models are integrated to reproduce aging failure data.
3) It can significantly improve the evaluation accuracy of average AFRs by establishing an unsupervised learning method, i.e., the EW-K-means method for DT grouping.
4) It can help provide credible results in the subsequent reliability assessment by utilizing a practical decomposition function to distinguish the aging degrees of in-group DTs and to calculate the probabilistic AFRs.

The paper has established the theoretical framework for AFR evaluation and proved its feasibility and benefits. This approach can also subsequently be used for distribution network reliability evaluation and transformer asset management (e.g., maintenance and investment decision-making). It is our belief that the proposed approach can be further verified by more cases of other utilities. A feasible extension of the current work is to extend the proposed framework to a generic framework that is also suitable for the AFR evaluation of other power distribution assets. Some advanced forecasting algorithms can also be embedded in this framework for predicting the AFR within a predefined horizon.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Some data used during the study were provided by a third party.

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Appendix A

This manuscript constructed a novel Restoration-Clustering-Decomposition framework and developed feasible modules that are specific for distribution transformers (DTs) for the AFR evaluation. The proposed framework can be used in a general way upon the substitution of the modules specific for transformers are modified (in replacement of the modules that are specific for other types of power assets). The generalized framework is provided in the Figure below.

As shown in Fig. A1 above, the generalized Restoration-Clustering-Decomposition framework mainly includes three parts:

1) Aging failure dataset construction: this step aims to restore the collected scrapping data of different power assets into their technical lifetimes to construct a reasonable and credible aging failure dataset. Due to the differential degradation mechanism in different power equipment, different data approaches should be devised for each type of power equipment and then embedded in part 1 of the proposed framework. In this manuscript, the data restoration approach of distribution transformers (DTs) is proposed. When it comes to other types of power assets, the corresponding data restoration modules should be developed and embedded into part 1 of the framework.
2) Power asset group: this step aims to group the power asset populations of the same type into some homogenous groups based on their individualized clustering feature systems. In this manuscript, the clustering feature system suitable for DTs has been devised. Furthermore, this manuscript proposed a universal EW-K-means clustering method for the DT grouping, which can also be directly used for the grouping of any type of power asset. In summary, when it comes to other types of power assets, the corresponding clustering feature systems should be developed and embedded into part 2 of the framework. On this basis, the power assets can be grouped by using the universal EW-K-means method.
3) AFR decomposition: this step aims to derive the individual AFRs of in-group power assets according to their individualized relative aging degrees. For the DTs studied in this manuscript, the DP indicator is selected as the aging covariate, and a universal decomposition function is used to quantify the relative aging degrees of individual in-group DTs. When it comes to other types of power assets, the correspondingly aging covariates should be explored and embedded into part 3 of the framework. On this basis, the universal decomposition function can be directly used for the quantification of the relative aging degree of other types of power assets.

Appendix B

In order to prove that the Weibull model can well fit the constructed aging failure dataset, the built Weibull distributions corresponding to each transformer group (a total of 4 groups) have been tested using the Kolmogorov-Smirnov goodness of fit method. Test results are given as follows.

It can be observed from Table B1 that the values of the test statistic are all greater than the critical values at a significance level of 0.05 (α=0.05), indicating that the Weibull distribution is suitable for the used aging failure dataset.

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