# CuES: Conditional Uncorrelation-based Characteristic Enhancement and Fusion of Electrical Signals

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***Abstract*—The lifespan of a generator greatly depends on the quality and aging of its stator bar insulation material. Aging of insulation materials can lead to premature equipment failure and significant material loss, resulting in substantial economic losses. However, existing methods for predicting the lifespan of electronic wire bars have several drawbacks, such as slow training speed, the need for a large amount of training data, and a tendency to overfit. To address this issue, we propose a characteristic enhancement algorithm based on conditional uncorrelation. This algorithm leverages characteristic enhancement to generate an extensive dataset and utilizes subset selection to identify relevant electrical parameters for predicting the remaining life span of the stator bar's main insulation configurations. Experimental results demonstrate the advantages of our research compared to deep learning models. Our approach offers a promising solution for accurately predicting the remaining life of stator bar insulation, thereby facilitating effective maintenance planning and minimizing economic losses.**

***Index Terms*—stator bar, conditional uncorrelation, characteristic enhancement, life span**

## I. Introduction

Factories, mines, and enterprises heavily rely on electricity to power their mechanical equipment, lighting, and heating systems [1]. Additionally, large generator sets provide a stable source of electricity for both social and industrial production. The smooth operation of generator sets is crucial to ensure the uninterrupted functioning of production lines, promote industrial growth, and improve efficiency, which are vital for economic development. A malfunction in the generator not only poses a risk to the equipment but also disrupts the power supply, resulting in substantial economic losses.Among the various components of a generator, stator bars play a pivotal role in maintaining the stability of the entire unit [2]. The condition of their insulation material significantly impacts the generator's service life. Over time, during the usage and storage of generators, insulation materials undergo irreversible degradation in their mechanical and dielectric properties due to a combination of stress factors like electricity, heat, mechanical vibration, and the surrounding environment. This phenomenon is commonly known as insulation material aging.The aging of insulation materials can lead to premature equipment failure, substantial material loss, significant economic setbacks, and even environmental pollution and safety concerns [3]. Statistical data [4] indicates that damage to insulation materials is one of the primary causes of generator failures. Consequently, recognizing the significance of aging insulation materials is paramount and cannot be overlooked.

By closely monitoring the changes in electrical parameters and thermal diagrams throughout the aging process of stator bar insulation, it becomes possible to detect the level of insulation material aging promptly. This enables workers to be alerted and take timely measures to address any aging issues that arise.Currently, the conventional approach to predicting the lifespan of stator bars involves the construction of aging enclosed chambers [5] and meticulous control of environmental conditions [6]. While these methods can accurately forecast the service life, they come with drawbacks such as high costs, limited flexibility, the necessity for specialized staff training, and significant energy consumption.Although machine learning-based methods have made strides in reducing costs and improving efficiency, certain shortcomings persist in the training process. These include slow training speeds, vulnerability to local optima, sensitivity to initial weights and biases, the requirement for substantial amounts of training data, and the potential for overfitting [7]. Addressing these limitations is crucial for further advancements in the field. Efforts are being made to enhance the training speed, develop robust optimization algorithms, reduce the dependence on initial weights and biases, and explore techniques for training with smaller datasets while avoiding overfitting. Overcoming these challenges will contribute to the development of more efficient and reliable methods for predicting the lifespan of stator bars [8], [9].

The objective of this study is to build upon previous research efforts in order to enhance work efficiency, improve prediction accuracy, and reduce prediction costs. To achieve these goals, this study introduces an innovative electrical signal fusion algorithm that leverages the conditional uncorrelation

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Fig. 1. Picture of an aging stator bar.

characteristic enhancement. By establishing a robust relationship between non-destructive electrical parameters and the lifespan of wire rods, this algorithm demonstrates exceptional capabilities, superior performance, and resistance to interference and fluctuations in data. Consequently, it enables more accurate and reliable predictions of insulation material aging. By employing this approach, the study seeks to improve the comprehension and prediction of insulation material aging, ultimately leading to enhanced operational efficiency and cost-effectiveness.

The second section of this article will focus on presenting the research conducted by previous scholars in the field. It will provide a comprehensive overview of their work and contributions.Moving on to the third section, a thorough explanation of the aggregation principle underlying the electrical parameter fusion algorithm based on conditional uncorrelation characteristic enhancement will be provided. This section will delve into the intricate details of how the algorithm combines and integrates electrical parameters to enhance the prediction accuracy of insulation material aging.In the subsequent fourth section, the accuracy of our proposed algorithm will be rigorously evaluated and assessed against other existing algorithms using a dedicated test set. This comparative analysis will shed light on the strengths and weaknesses of different approaches and highlight the superior performance of our proposed algorithm.Finally, in the fifth and final section, a comprehensive summary of the entire article will be presented. This summary will encapsulate the key findings, contributions, and implications discussed throughout the article, providing readers with a cohesive understanding of the research and its potential impact in the field of insulation material aging prediction.

## II. Related Works

**Characteristic Enhancement:** Structured characteristic enhancement is aimed at improving the quality and diversity of structured datasets in order to enhance the performance of machine learning models [10]. It can be broadly categorized into two mainstream approaches.The first approach is characteristic augmentation [11], [12], which involves generating new samples by applying a series of transformations or operations to the original data. In the context of structured data, operations such as random sorting, permutation and combination, and the addition of noise can be performed to create augmented samples with increased variability.The second approach is feature engineering [13]–[16], which involves transforming or combining the original data to generate new features. For instance, in the case of timestamp data, features such as year, season, and workday can be extracted. Similarly, in the case of text data, features such as word frequency, part of speech, and sentence length can be derived through appropriate transformations [17]. By employing these approaches, structured characteristic enhancement enables the incorporation of additional relevant information and patterns into the dataset, thereby empowering machine learning models to make more accurate predictions and achieve better performance in various tasks [18].

Due to the potential risk of overfitting in the feature engineering process and the considerable time and computational resources required for managing large datasets, we have opted to employ data augmentation as a technique to enhance the characteristics of the data.

**Subset Selection:** Subset selection is a technique used to identify the most relevant or significant characteristic subset from the original set of characteristics, with the aim of improving the performance and efficiency of machine learning models. Several methods are commonly used for subset selection:The first method is based on filtering [19], which involves evaluating the statistical relationships between characteristics and ranking them according to a specific metric. Characteristics are then selected based on their rankings, with the top-ranked characteristics forming the desired subset.The second method is based on wrapper methods [20], which use a greedy search strategy to explore different characteristic subsets. These subsets are evaluated using cross-validation or other evaluation methods to determine the optimal characteristic subset.The third method is based on embedding methods [21], where the model training process incorporates a complexity constraint through regularization or penalty terms. This leads to the automatic selection of relevant characteristics during the training phase.By utilizing these subset selection methods, machine learning models can focus on the most informative characteristics, leading to improved model performance, reduced computational complexity, and enhanced efficiency.

Nevertheless, conventional subset selection methods [22] face challenges when dealing with large-scale characteristic spaces, as they exhibit exponential computational complexity when searching for all possible subset combinations [23]. This limitation places a burden on computational resources and time. Furthermore, these methods may prioritize individual characteristics while disregarding other relevant characteristics, leading to information loss or the inclusion of redundant characteristics.To tackle these challenges, we propose a subset selection strategy grounded in conditional uncorrelation. This innovative approach aims to address the aforementioned problems. By assessing the conditional uncorrelation among

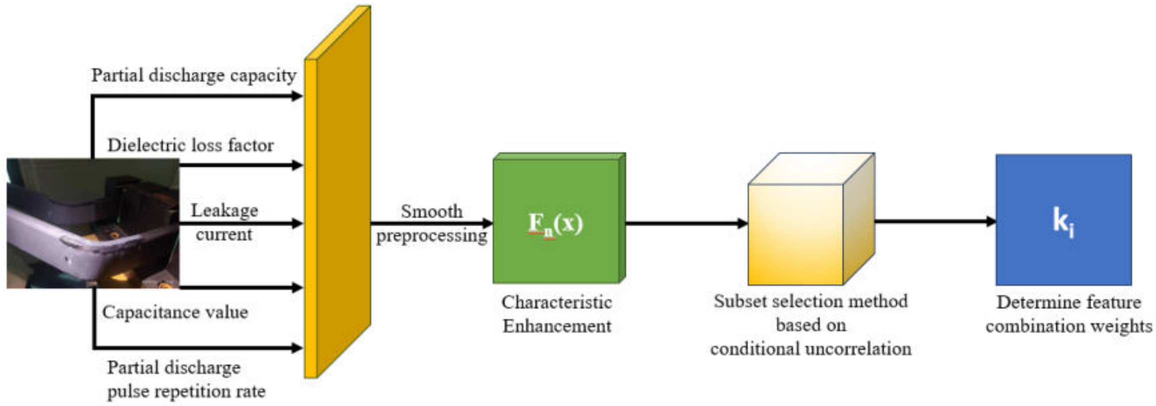



Fig. 2. The overall architecture of conditional uncorrelation-based characteristic enhancement and fusion of electrical signals. First, we consider the inherent correlation of the data and enhance the features of 5 sets of electrical parameter data. Finally, We use a subset selection method based on conditional uncorrelation to select 7 parameters from the feature enhancement parameters to determine the parameters of the lifespan prediction model.

characteristics, we can identify subsets of characteristics that exhibit minimal correlation with each other, thus diminishing redundancy and information loss.

**Convolutional Neural Network:**Convolutional neural networks [24] can automatically learn and extract characteristics from images, offering benefits like translation invariance and local connectivity [25]. In this article's experimental section, we performed comparative experiments using four sets of regression models based on convolutional neural networks [26], [27] to showcase the effectiveness of our proposed algorithm.

## III. Method

By analyzing the trend of changes in a given sequence of electrical parameters, we utilize the conditional uncorrelation-based characteristic enhancement [28], [29]. This approach allows us to determine the combination weight of characteristic indicators based on the principle of minimum deviation. This helps us in estimating the function and building a model to predict the lifespan of the main insulation.

In this process, we take into account the correlation between different characteristic indicators and consider their respective contributions to the overall prediction. By assigning appropriate weights to these indicators, we can effectively capture the key factors that influence the lifespan of the main insulation.The resulting model not only provides valuable insights into the estimation of main insulation life but also serves as a predictive tool for determining the expected lifespan based on the given electrical parameter sequence. This approach contributes to a more accurate and reliable prediction of the main insulation's lifespan, which is crucial for maintenance planning and ensuring the optimal performance of electrical systems.

### A. Characteristic Enhancement

Given the intrinsic correlation among electrical parameters, we leverage characteristic enhancement methods to broaden the dataset and create more training samples. Specifically, we utilize eight fundamental functions: $(x, x^2, \sqrt{x}, x^3, \sqrt[3]{x}, log(x), 2^x, e^x)$ to individually enhance the data for each electrical parameter. Through the application of these functions, we modify the original data, thereby introducing variations and capturing more intricate relationships within the dataset. This strategy allows us to enrich the dataset and boost its representational capacity, ultimately resulting in improved model performance and a more comprehensive understanding of the underlying patterns present in the electrical parameters.

In our characteristic enhancement process, the parameter that serves as the base for enhancement is a first-order nonlinear term. By applying the function $f(x) = x$, we maintain the original first-order linear term of the parameter while introducing nonlinearity. This approach allows us to preserve the linear relationship present in the data while also capturing higher-order nonlinear patterns. By incorporating both linear and nonlinear components in the characteristic enhancement, we can effectively uncover more intricate and nuanced information within the dataset, leading to improved modeling and analysis capabilities.

In industrial settings, electrical parameters frequently interact with each other. To tackle this issue, we introduce a method where we multiply the parameters in pairs and utilize eight fundamental functions to improve the results. This multiplication generates a nonlinear term of second order, which effectively captures the collective impacts of these interactions.

Furthermore, when enhancing the parameter using the function $f(x) = x$ , we preserve the second-order linear term of the parameter. This means that while introducing nonlinearity through characteristic enhancement, we still preserve the underlying linear relationship between the parameter and its interactions with other parameters.By incorporating both second-order nonlinear terms and second-order linear terms through pairwise multiplication and characteristic enhancement, our

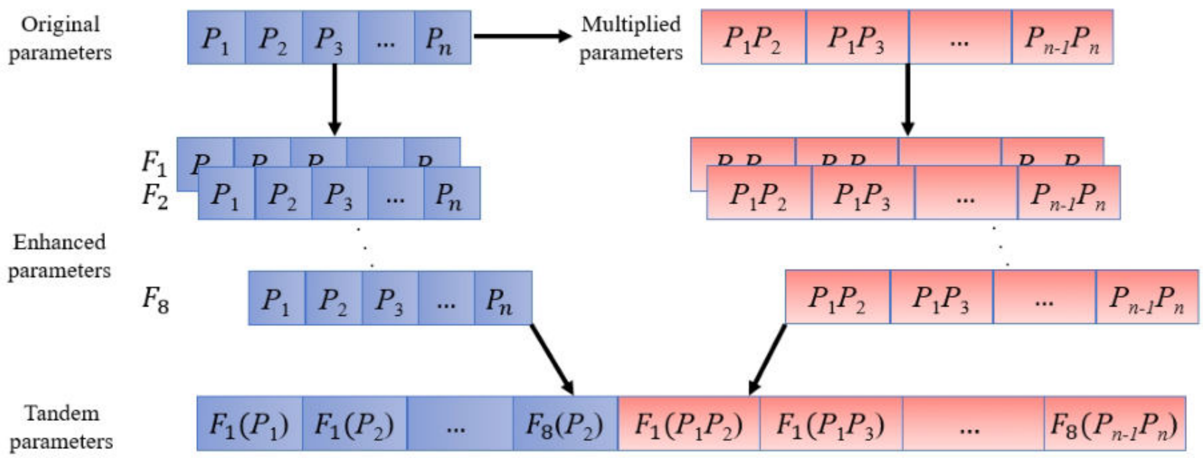



Fig. 3. Specific process of characteristic enhancement. First, we apply 8 basic functions to individually enhance the characteristics. Than, we further enhance the data by incorporating pairwise products of electrical parameters. Next, using the same set of 8 basic functions, we apply them to the pairwise products of the electrical parameters. Finally, by combining these two steps of feature enhancement, we create a dataset of enriched features that capture both individual and pairwise interactions between the electrical parameters.

approach effectively captures the complex interactions and nonlinear dynamics present in industrial scenarios. This allows us to gain deeper insights and achieve more accurate modeling of electrical systems.

The specific process of characteristic enhancement is shown in the figure:

### B. Subset Selection Method for Conditional Uncorrelation

Mathematically, the health level of the main insulation can be used as the target variable $\boldsymbol{y}$, and the variables that may affect the health level of the main insulation can be used as the predictive variable $\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_n}$. A multiple regression equation can be established as the evaluation model for health level:

$$\hat{\boldsymbol{y}} = \beta_0 + \beta_1 \boldsymbol{x_1} + \beta_2 \boldsymbol{x_2} + ... + \beta_n \boldsymbol{x_n} \tag{1}$$

where $\hat{\boldsymbol{y}}$ is the predicted value of the target variable, $\beta_0$ is a constant, and $\beta_i (i = 1, 2, ..., n)$ is the regression weight.

Considering the large dimension of electrical parameter data, it is difficult to use the least squares method. Therefore, we adopt sparse regression and select $k$ parameters $\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}$ from all $\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_n}$ obtained through characteristic enhancement to determine the parameters of the life prediction model.In sparse regression, the objective function we need is to minimize the mean square error(MSE) between the objective variable $\boldsymbol{y}$ and its estimated value $\hat{\boldsymbol{y}}$:

$$MSE(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{1}{d} ||\boldsymbol{y} - (\beta_0 \mathbf{1} + \beta_1 \boldsymbol{x_1} + \beta_2 \boldsymbol{x_2} + ... + \beta_k \boldsymbol{x_k})||_2^2 \tag{2}$$

Where $d$ is the dimension of the predictor variable and the target variable, and $\hat{\boldsymbol{y}} = \beta_1 \boldsymbol{x_1} + \beta_2 \boldsymbol{x_2} + ... + \beta_k \boldsymbol{x_k}$ is the optimal linear combination of $\boldsymbol{y}$. The essence of this problem is the multivariate correlation between the predictor variable $\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}$ and the target variable $\boldsymbol{y_1}, \boldsymbol{y_2}, ..., \boldsymbol{y_k}$.

We can use mathematical methods to rewrite the objective function.If $\boldsymbol{a_1}, \boldsymbol{a_2}, ..., \boldsymbol{a_m}$ is m n-dimensional non-zero variance variables, and $1 < m < n$, and $\rho_{\boldsymbol{a_i a_j}} (i, j = 1, 2, ..., m)$ represents their Pearson correlation coefficients, then their correlation matrix $R$can be expressed as:

$$R = \begin{bmatrix} \rho_{\boldsymbol{a_1 a_1}} & \rho_{\boldsymbol{a_1 a_2}} & \cdots & \rho_{\boldsymbol{a_1 a_m}} \\ \rho_{\boldsymbol{a_2 a_1}} & \rho_{\boldsymbol{a_2 a_2}} & \cdots & \rho_{\boldsymbol{a_2 a_m}} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{\boldsymbol{a_m a_1}} & \rho_{\boldsymbol{a_m a_2}} & \cdots & \rho_{\boldsymbol{a_m a_m}} \end{bmatrix} \tag{3}$$

The square of the unsigned correlation coefficient between them is [30], [31]:

$$r^2_{\boldsymbol{a_1}, \boldsymbol{a_2}, ..., \boldsymbol{a_m}} = 1 - det(R) \tag{4}$$

The square of the unsigned uncorrelated coefficient is:

$$\omega^2_{\boldsymbol{a_1}, \boldsymbol{a_2}, ..., \boldsymbol{a_m}} = det(R) \tag{5}$$

By incorporating the above mathematical derivation into formula(2), we can obtain [32]:

$$\begin{aligned} MSE(\boldsymbol{y}, \hat{\boldsymbol{y}}) &= \sigma^2_{\boldsymbol{y}} - \sigma_{\boldsymbol{y}\hat{\boldsymbol{y}}} \\ &= \frac{det \begin{bmatrix} \sigma & \sigma_{iy} \\ \sigma^T_{iy} & \sigma^2_y \end{bmatrix}}{det(\sigma)} \Leftrightarrow \sigma^2_y \frac{\omega^2(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}, \boldsymbol{y})}{\omega^2(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k})} \end{aligned} \tag{6}$$

where $\sigma_y$ is the standard deviations of $y$,$\sigma_{iy}$ is the covariance of $x_i$ and $y$.Therefore, based on the definition of the unsigned uncorrelation coefficient, we can obtain:

$$\omega(\boldsymbol{y}, \hat{\boldsymbol{y}}) = \frac{\omega(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}, \boldsymbol{y})}{\omega(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k})} \tag{7}$$

$\omega(\boldsymbol{y}, \hat{\boldsymbol{y}})$ measures the linear uncorrelation between $\boldsymbol{y}$ and $\hat{\boldsymbol{y}}$. Due to the similarity between the form of formula(7) and the form of conditional probability, and the range of values for each term in the formula is (0,1), $\omega(\boldsymbol{y}|\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k})$ is used to represent $\omega(\boldsymbol{y}, \hat{\boldsymbol{y}})$, i.e:

$$\omega(\boldsymbol{y}|\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}) = \frac{\omega(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}, \boldsymbol{y})}{\omega(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k})} \tag{8}$$

We will refer to $\omega(\boldsymbol{y}|\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k})$ as conditional uncorrelation.The conditional uncorrelation formula provides a calculation method for the uncorrelation relationship between the target variable $\boldsymbol{y}$ and its estimated value $\hat{\boldsymbol{y}}$. Solve the optimal sparse regression objective function in formula(2) [33], which includes:

$$\min_{\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}} MSE(\boldsymbol{y}, \hat{\boldsymbol{y}}) \Leftrightarrow \min_{\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}} \frac{\omega^2(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k}, \boldsymbol{y})}{\omega^2(\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_k})} \quad (9)$$

The above equation provides the objective function for selecting the target variable in sparse regression problems based on conditional uncorrelation. The smaller the value of conditional uncorrelation, the stronger the correlation between variables. By solving for the minimum conditional uncorrelation of $\boldsymbol{y}$ and $\hat{\boldsymbol{y}}$, the optimal subset with only $k$ predictive variables can be selected for $\boldsymbol{y}$, that is, the $k$ most relevant factor variables.

## IV. Experiments

### A. Dataset

Our training and evaluation process extensively utilizes a dataset that we have developed in-house. This dataset is specifically curated to encompass the primary insulation electrical parameters associated with stator windings. It comprises a comprehensive collection of 11 distinct electrical parameter sets, including partial discharge quantity, interference discharge quantity, partial discharge pulse repetition rate, interference pulse repetition rate, wire rod temperature 1, wire rod temperature 2, dielectric loss factor, leakage current, capacitance value, high-voltage terminal current, and high-voltage terminal frequency. These parameters are meticulously measured and recorded over time, allowing for an in-depth analysis of their behavior. Moreover, to enhance the dataset's value, we have also incorporated lifespan parameters that pertain to five different insulated wire rods. This rich and diverse dataset empowers our training process and facilitates the evaluation of our model's performance and accuracy.

### B. Data Preprocessing

To address the challenges posed by outliers and fluctuating noise in our collected data, we devoted careful attention to the preprocessing stage. Considering various filtering methods, we ultimately opted for smoothing filtering to enhance the quality of the electrical data. This filtering technique effectively mitigates the impact of outliers and noise, resulting in cleaner and smoother data.

In comparison to alternative filtering methods, smooth filtering offers distinct advantages. It minimizes alterations to the overall shape and important characteristics of the signal, preserving the underlying trend and key characteristics. By doing so, it ensures that the overall structure and relevant information of the signal are retained.Importantly, smooth filtering allows us to effectively reduce the influence of outliers on signal analysis and processing. Outliers, which are often caused by measurement errors or anomalous data points, can distort the analysis and interpretation of the signal. By smoothing the data, we mitigate the impact of these outliers, enabling more reliable and accurate signal analysis.

By selecting smooth filtering as our pre-processing technique, we ensure a more robust and accurate analysis of the electrical data. This step is crucial for extracting meaningful insights and identifying patterns within the data, ultimately enhancing our understanding of the key electrical insulation parameters for stator windings.

### C. Implementation Details

In our study, we used a characteristic enhancement algorithm based on subset selection, along with four sets of convolutional neural networks, to establish the relationship between stator bar life and electrical parameters. Our objective was to develop a predictive model that accurately captures this relationship.

To assess the performance and correlation strength of our model, we utilized evaluation metrics including SROCC, KROCC, and PLCC. These metrics serve as reliable indicators of prediction accuracy and the strength of correlation between the model's predictions and the actual lifespan of the stator bars.By utilizing these evaluation metrics, we obtained valuable information about the predictive ability of our model and its correlation with the lifespan of the stator bars. These metrics serve as quantitative measures of the model's performance, allowing us to assess its accuracy and reliability in predicting the life of the stator bars.The specific data are shown in Table I. Group LCNN and TCNN used convolutional neural networks (CNN) with different numbers of layers as their models. Group VGG-16 used the VGG-16 model, while group VGG-19 used the VGG-19 model. Finally, in group CuES, we introduced our proposed model.

TABLE I
Comparison of Evaluation between Deep Learning Models and Subset Selection Models with Conditional Incorrelation.

| **Model** | ***SROCC*** | ***KROCC*** | ***PLCC*** | ***Average Error***(%) |
|---|---|---|---|---|
| LCNN | 0.72 | 0.45 | 0.79 | 15.39 |
| TCNN | 0.80 | 0.59 | 0.73 | 20.09 |
| VGG-16 [34] | 0.79 | 0.57 | 0.76 | 24.66 |
| VGG-19 [34] | 0.78 | 0.56 | 0.81 | 21.73 |
| **CuES** | **0.99** | **0.95** | **0.91** | **10.76** |

We compared the experimental results with those of a non-destructive electrical parameter evaluation model based on condition uncorrelation. Even for the CNN1 model with the lowest average error rate in deep learning models, SROCC was 0.27 lower than the subset selection method based on condition uncorrelation, KROCC was 0.50 lower than the subset selection method based on condition uncorrelation, and PLCC was 0.12 lower than the subset selection method based on condition uncorrelation, However, the average error rate decreased by nearly 5 percentage points. Although the other deep models improved SROCC, KROCC, and PLCC, the improved ones greatly increased the error, and the performance was still not as good as the subset selection method with conditional uncorrelation.Furthermore, in Figure 2, it can be

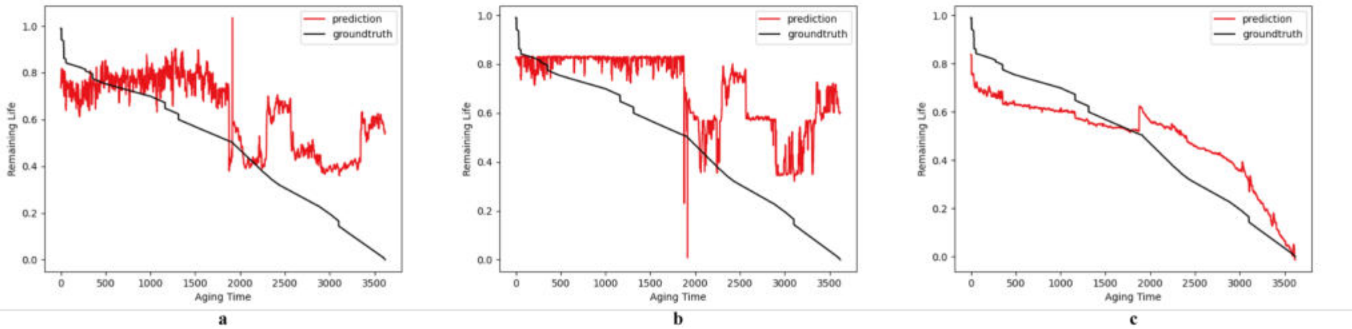



Fig. 4. Comparison of Lifespan Prediction and Ground Truth across Different Models: a) A comparison chart of the life curves of a convolutional neural network model, b) A comparison chart of the life curves of the VGG-19 model, c) A comparison chart of the life curves of our proposed model. It can be seen that the life prediction curve of our proposed model is more in line with the real life curve and has more practical application value.

seen that the life prediction curve of our proposed model is more closely aligned with the actual life curve.A comparison demonstrates this:

- Our evaluation model, which is based on the conditional uncorrelation subset selection method, surpasses deep learning models in terms of the three widely used correlation indicators: SROCC, KROCC, and PLCC. Our model's performance in these indicators is exceptional, positioning it at the forefront of current advancements in the field. This achievement establishes our model as state-of-the-art and demonstrates its superiority over deep learning approaches.
- Our model boasts a significant advantage over other approaches due to its reduced parameter count, resulting in a more streamlined architecture. This efficiency translates into a faster running speed during large-scale inference processes. By minimizing the number of parameters while maintaining high performance, our model optimizes computational resources and expedites the analysis of extensive datasets. Our model's accelerated processing capability enables users to obtain results swiftly and effectively, making it particularly well-suited for time-critical tasks and scenarios that involve processing vast amounts of data.
- Our model is proficient in capturing higher-order data characteristics, which enables it to reveal intricate patterns and uncover underlying rules within the dataset with enhanced precision. By leveraging its advanced architecture, the model goes beyond analyzing individual data points and delves into the complex relationships and interactions among them. This capability allows it to discern subtle dependencies and extract latent information that might be missed by traditional methods. Our model enables users to gain a deeper understanding of the data and make more informed decisions by providing accurate insights and revealing previously undiscovered associations.

### D. Ablation Study

In order to assess the importance of data augmentation, we conducted ablation experiments by using different sets of basic functions to enhance the data. Specifically, we compared the performance of four sets and six sets of basic functions with the original eight sets of functions.

The results of the ablation experiments in table II indicate that the performance of the models using four or six sets of basic functions is inferior to that of the model using all eight sets. In Group FourFusion, we used four sets of basic functions $(x, x^2, \sqrt{x}, x^3)$ to enhance the data. In Group SixFusion, we used six sets of basic functions $(x, x^2, \sqrt{x}, x^3, \sqrt[3]{x}, log(x))$ to enhance the data. In group Allfusion, we used all basic functions $(x, x^2, \sqrt{x}, x^3, \sqrt[3]{x}, log(x), 2^x, e^x)$ to enhance the data. The SROCC, KROCC, PLCC, and mean error values obtained from the model with eight sets of basic functions demonstrate its effectiveness in accurately predicting the lifespan.The visualisation results are shown in Figure 3.

These experimental findings highlight the significance of utilizing all eight basic functions for characteristic enhancement. By incorporating a comprehensive set of functions, we can effectively capture the underlying patterns and relationships within the data, resulting in improved lifespan prediction accuracy.

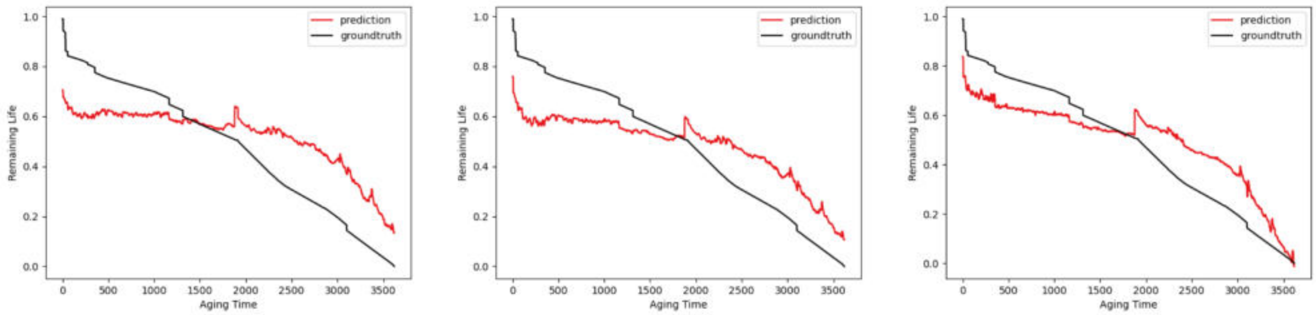
TABLE II

ABLATION STUDY: IMPACT OF DIFFERENT NUMBERS OF BASIC FUNCTIONS ON LIFESPAN PREDICTION.

| **Model** | ***SROCC*** | ***KROCC*** | ***PLCC*** | ***Average Error(%)*** |
|---|---|---|---|---|
| FourFusion | 0.95 | 0.84 | 0.89 | 14.87 |
| SixFusion | 0.97 | 0.91 | 0.92 | 13.60 |
| **Allfusion** | **0.99** | **0.95** | **0.91** | **10.76** |

## V. CONCLUSION

In order to accurately assess the aging degree of the insulation layer in stator bars, we propose a combination of a subset selection method based on conditional uncorrelation and a deep learning prediction approach. By establishing the




a b c

Fig. 5. Subjective Results of Ablation Experiments on Feature Enhancement. We ran three groups in our ablative feature enhancement experiments: a) The data was enhanced using four sets of basic functions $(x, x^2, \sqrt{x}, x^3)$, b) The data was enhanced using six sets of basic functions $(x, x^2, \sqrt{x}, x^3, \sqrt[3]{x}, log(x))$, c) The data was enhanced using eight sets of basic functions $(x, x^2, \sqrt{x}, x^3, \sqrt[3]{x}, log(x), 2^x, e^x)$. The results of these experiments showed that using eight sets of basic functions to enhance the data resulted in lifetime predictions that were close to the true values.

relationship between multiple parameters and the lifespan of stator bars, we aim to achieve accurate predictions. Through extensive testing, our proposed subset selection method with conditional uncorrelation has demonstrated superior performance compared to deep learning models when applied to the given data.This research endeavor is expected to greatly assist maintenance personnel of hydroelectric generators in developing more effective maintenance plans and making informed decisions. By extending the lifespan of generator units, mitigating the risk of faults and accidents caused by thermal insulation aging, and avoiding economic losses resulting from unit failures, the proposed method can have a significant positive impact.

However, it is important to acknowledge that our method still has certain limitations. Although our proposed approach yields promising results, there may still be discrepancies between the predicted and actual values. Additionally, due to hardware constraints, we have only considered the case where electrical parameters are multiplied pairwise during characteristic enhancement. More complex scenarios have not been thoroughly explored in this context.Further research and improvements are warranted to address these limitations and enhance the accuracy and comprehensiveness of our method.

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