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Machine Learning Enabled Cluster Grouping of Varistors in Parallel-Structured DC Circuit Breakers

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ABSTRACT This letter presents the first ever trial of machine learning enabled cluster grouping of varistors for DC circuit breakers (DCCBs). It reveals that the manufacturing discrepancy of varistors is a main challenge in their parallel connection. The proposed cluster grouping concept is introduced to classify varistors according to the interruption characteristic, in which the *K*-means algorithm is adopted to learn the clamping voltage curves. 70 420 V/50 A V420LA20 varistors are measured in a 120 A transient current interruption platform individually to acquire 70 sets of testing data to train the machine learning engine. Then, 28 new varistors are further tested to verify the trained algorithm, which are classified into 7 clusters using the proposed machine learning method. A 500 V/520 A solid-state circuit breaker (SSCB) is implemented with four parallel varistors in the same cluster. Experiments validate that the current is evenly distributed in varistors, and the difference is limited to 3.1%, which improves parallel varistors lifetime significantly.

INDEX TERMS DC circuit breakers, solid-state circuit breakers, varistors, machine learning.

I. INTRODUCTION

Direct current (DC) power systems are becoming popular due to their renewable energy penetration, high efficiency, and low cost [1]. However, they also have concerns such as nonexistence of zero current crossings and low system impedance, which induce risks in fault conditions. DC circuit breakers (DCCBs) are effective solutions to isolate faults. Hybrid circuit breakers (HCBs) and solid-state circuit breakers (SSCBs) are emerging technologies that present advantages of arc-free fault interruption and fast response speed.

Metal oxide varistors (MOVs) are usually used to absorb fault energy [2]. Imposing excessive transient energy on varistors significantly impacts their lifetime [3]. To safely handle high fault current, it is common to utilize multiple varistors in parallel [4], [5], [6]. Nevertheless, varistors are not originally designed for parallel connections. Considering their non-linear characteristic, it is difficult to achieve consistency due to manufacturing discrepancy. Overcoming this intrinsic drawback of parallel varistors has become a significant technical gap for a safe and reliable DCCB design.

This letter presents a novel machine learning based design method for the parallel connection of varistors. The procedure of varistor clustering is introduced, including 1) varistor data acquisition, 2) data preprocessing, 3) parameter optimization and model training, and 4) varistor cluster prediction. Parallel consistency of clustered varistors is validated by groups of fault interruption experiments on a 500 V/520 A SSCB prototype. The risk of unbalanced

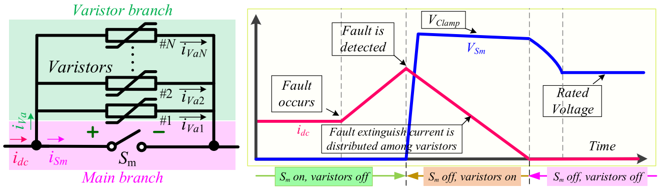

FIGURE 1. Typical configuration of varistor clamping based DC circuit breakers, indicating main branch and varistors branch and critical waveforms.

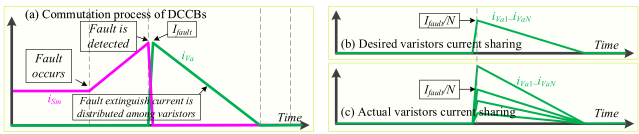

FIGURE 2. Currents of fault interruption: (a) Commutation process. (b) Evenly distributed varistors current. (c) Practical unbalance current distribution.

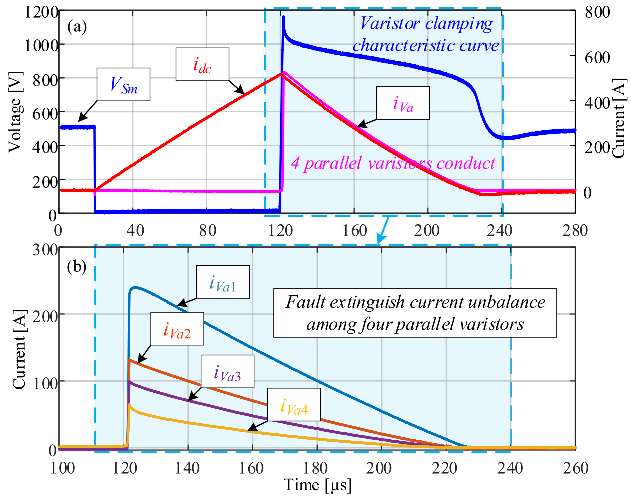

FIGURE 3. Experimental validation of unbalanced current distribution in a 500 V/520 A SSCB with four randomly selected parallel varistors.

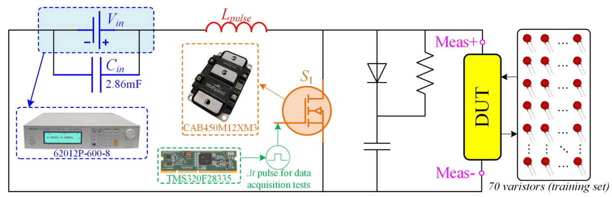

FIGURE 4. 120 A Pulse current generator platform to obtain clamping characteristic curve of varistors at similar inductive interruption scenarios as DCCB.

current is significantly reduced. The presented machine learning clustering design method is suitable for low, medium, and high voltage varistors parallel optimization in DCCB applications.

The rest of this letter is organized as follows. Section II reveals the severe fault current unbalancing issue in typical multi-varistor parallel structured DC circuit breakers. Section III introduces the proposed machine learning design concept and demonstrates practical engineering process of the proposed clustering design method for exemplary varistors. Section IV shows a SSCB prototype design guideline and experimentally compares the varistors current sharing performance before and after applying the proposed method. Section IV also provides varistor lifetime enhancement analysis with the clustering design. Section V concludes this letter.

II. MOTIVATION: UNBALANCED FAULT CURRENT DISTRIBUTION

Fig. 1 indicates a typical configuration of varistor clamping based circuit breaker, which consists of a main switch branch and a parallel varistors branch. When a fault is detected, the main switch turns off, and varistors conduct. The fault current i_{dc} is extinguished by the clamping voltage overshot V_{Clmap} provided by varistors.

Fig. 2(a) shows the commutation process. The fault extinguishing current is distributed among parallel varistors. Fig. 2(b) shows balanced current sharing among varistors, where i_{Va1}~$i_{VaN} \approx I_{fault}/N$. However, the practical fault extinguishing currents are not evenly distributed as shown in Fig. 2(c).

Fig. 3 shows experimental validation of unbalanced current distribution. The testing condition is explained in Section IV-A. Four V420LA20 varistors are randomly selected and connected in parallel in a 500 V/520 A SSCB. It indicates a huge difference in MOV currents. 46% of the fault current is extinguished by a single varistor. This severe unbalancing issue puts the long-term reliability of an SSCB at a high risk.

III. CLUSTER ANALYSIS BASED MACHINE LEARNING CONCEPT

A. VARISTORS DATA ACQUISITION

In Fig. 3, the trapezoidal clamping voltage curve (blue color) contains key information of a varistor that affects its current extinguishing property. To obtain sufficient data for machine learning model training, a pulse current generator platform is established as shown in Fig. 4.

The device under test (DUT) represents V420LA20 samples. The target is to use a limited number of tests to obtain the clamping data of varistors. The current magnitude is tuned by a high-precision DC source V_{in} (62012P-600-8) and the switch S_1 turn on duration Δt based on the equation below.

$$I_{Test} = V_{in} \times \Delta t / L_{pulse} \tag{1}$$

The data acquisition tests are conducted at $I_{Test} = 120$ A for 70 samples with $V_{in} = 50$ V, $L_{pulse} = 62$ μH and $\Delta t = 150$ μs. Fig. 5 shows the distribution of all 70 varistor clamping characteristic curves, indicating a significant discrepancy.

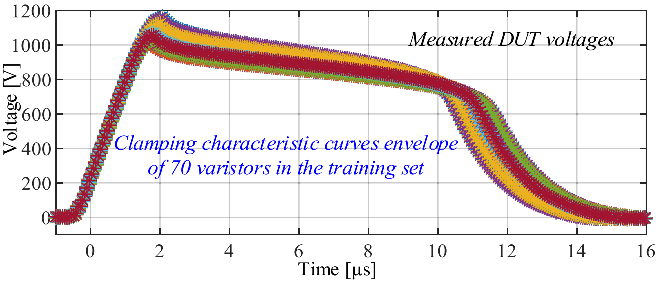

FIGURE 5. Distribution of 70 clamping characteristic curves in the training set, indicating a significant discrepancy among varistors.

B. DATA PREPROCESSING AND TRAINING SET ESTABLISHMENT

Each varistor's curve can be nondimensionalized and described as a time array feature vector:

$$\boldsymbol{x}_{sample} = \left[x_1, x_2, x_3, \cdots, x_{N-1}, x_N\right] \tag{2}$$

where, N depends on the measurement precision and time duration. It can be reduced by step sampling processing to decrease the calculation complexity while keeping key physical information of the varistor sample.

By obtaining all 70 feature vectors, a $M \times N$ data matrix of the training set is formed as below, where M represents the number of varistor samples.

$$X_{training} = \begin{bmatrix} \boldsymbol{x}_{samp1} \\ \boldsymbol{x}_{samp2} \\ \vdots \\ \boldsymbol{x}_{sampM} \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1,N-1} & x_{1,N} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2,N-1} & x_{2,N} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & x_{M,3} & \cdots & x_{M,N-1} & x_{M,N-1} \end{bmatrix} \tag{3}$$

In the specific task demonstrated in this paper, M and N are 70 and 266 respectively.

C. MODEL TRAINING BASED ON K-MEANS CLUSTERING ALGORITHM

The K-means method is a classical clustering algorithm in unsupervised learning. It classifies M varistor samples into K clusters. The distance between within-cluster feature vectors is low, while inter-cluster feature vectors distance is high. Table 1 provides the pseudocode of a K-means algorithm based varistor clustering task, which is summarized below.

Step I: Randomly select K feature vectors from the training set $X_{training}$ as the initial centroid vectors.

Step II: The Euclidean distances between M varistor feature vectors and K centroid vectors are calculated. Each varistor is then assigned to the closest cluster.

Step III: Update the K centroid vectors based on the mean value of all contained varistor vectors in each cluster.

TABLE 1 Pseudocode of K-Means Algorithm Based Varistor Clustering Task

Randomly initiate K varistor feature vectors from $\{\boldsymbol{x}_{samp1}, \boldsymbol{x}_{samp2}, \ldots, \boldsymbol{x}_{sampM}\}$ as centroids vectors $\{\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_K\}$
repeat
for $j = 1, 2, \ldots, M$ **do**
Calculate Euclidean distance between varistor feature vector $\boldsymbol{x}_j$ and each centroid vector $\boldsymbol{\mu}_i$ $(1 \le i \le K)$: $d_{ji} = \left\Vert \boldsymbol{x}_j - \boldsymbol{\mu}_i \right\Vert_2$;
Determine cluster label of $\boldsymbol{x}_j$ based on its closest centroid vector: $\lambda_j = \arg\min_{i \in \{1,2,\cdots,K\}} d_{ji}$;
Assign cluster membership to varistor $\boldsymbol{x}_j$: $C_{\lambda_j} = C_{\lambda_j} \bigcup \{\boldsymbol{x}_j\}$;
end for
for $i = 1, 2, \ldots, K$ **do**
Calculate new centroid vectors: $\boldsymbol{\mu}_i' = (1/\lvert C_i \rvert) \cdot \sum_{\boldsymbol{x} \in C_i} \boldsymbol{x}$
if $\boldsymbol{\mu}_i' \neq \boldsymbol{\mu}_i$ **then**
Update current centroid vector $\boldsymbol{\mu}_i$ as $\boldsymbol{\mu}_i'$ '
else
Fix current centroid vector $\boldsymbol{\mu}_i$
end if
end for
until convergence: none of current centroid vectors is updated
Return clusters $\{C_1, C_2, \ldots, C_K\}$ and centroids $\{\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_K\}$

Step IV: Repeat *Steps II* and *III* until none of centroid vectors is updated.

As one of the classical clustering algorithms, computational complexity of K-means method is usually depicted by big O notation. The computational complexity of model training process is $O(t{\cdot}k{\cdot}n{\cdot}d)$ while that of the prediction process is $O(k{\cdot}d)$, where t represents number of iterations during clustering, k is the number of centroids (clusters), n is the number of datapoints that need to be clustered, and d is the dimension of each datapoint.

The selection of the cluster number K is significant for the K-means algorithm. The Elbow method is commonly used to obtain an optimal K value based on sum of vector distances in all clusters, which is depicted below.

By clustering all varistor vectors in the training set $\{\boldsymbol{x}_{samp1}, \boldsymbol{x}_{samp2}, \ldots, \boldsymbol{x}_{sampM}\}$ through the above K-means algorithm, returned results include cluster labels $\{C_1, C_2, \ldots, C_K\}$ of each varistor vector $\boldsymbol{x}_j$ and their centroids $\{\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_K\}$. The sum of distances in the k^{th} cluster is defined as below.

$$D_k = \sum_{\boldsymbol{x}_j \in C_k} \sum_{\boldsymbol{x}_i \in C_k} \left\Vert \boldsymbol{x}_j - \boldsymbol{x}_i \right\Vert^2 = 2n_k \sum_{\boldsymbol{x}_j \in C_k} \left\Vert \boldsymbol{x}_j - \boldsymbol{\mu}_k \right\Vert^2 \tag{4}$$

Where n_k is the number of varistors in the k^{th} cluster C_k. When the number of clusters is K, a within-cluster sum of squares (WSS) is defined as below.

$$W_K = \sum_{k=1}^{K} (1/2n_k) \cdot D_k = \sum_{k=1}^{K} \sum_{\mathrm{x}_j \in C_k} \left\Vert \boldsymbol{x}_j - \boldsymbol{\mu}_k \right\Vert^2 \tag{5}$$

For all 70 varistor feature vectors in the training set, clustering with different K values would return different clusters and centroids results. Fig. 6 shows calculated WSS variation regarding K varying in a wide span from 1 to 20. W_K is a pure numerical parameter devised for comparison. The absolute value of W_K does not contain any physical information. A

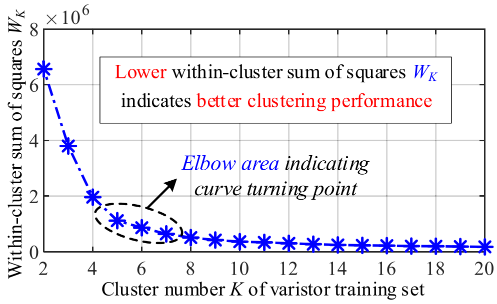

FIGURE 6. Calculated WSS variation regarding K value varying from 1 to 20.

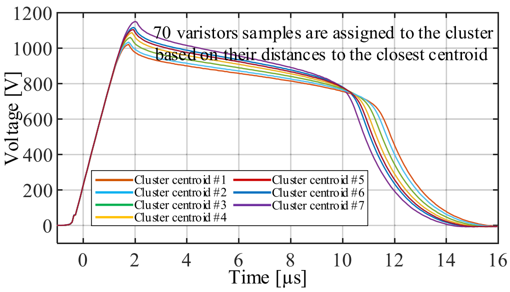

FIGURE 7. Clamping characteristic curves of returned 7 centroids after clustering of the 70 varistors training set.

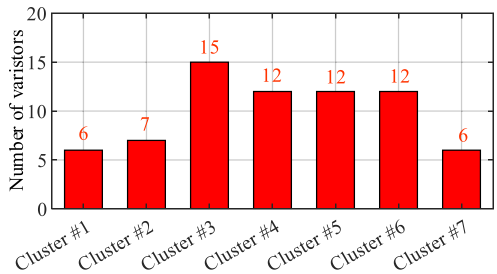

FIGURE 8. Distribution of 70 varistor samples in each cluster.

lower W_K value is always desired since it indicates better clustering performance.

Fig. 6 shows that W_K decreases dramatically first. After $K > 7$, the decrement of W_K tends to be stable. The elbow area of the curve indicates that $K = 7$ is a turning point which is selected for the following varistors clustering process.

The clustering analysis is performed using K-means algorithm in MATLAB based on the training set of 70 varistor vectors, which follows the procedure in Table 1. Fig. 7 shows clamping characteristic curves of the returned 7 centroid vectors, indicating apparent differences between various clusters. Fig. 8 further shows distribution of 70 varistor samples in each cluster. The clusters #1 and #7 have the farthest distances with other clusters, which receives less within-cluster membership. Meanwhile, more varistors are assigned to intermediate clusters #3∼#6, which basically follow a Gaussian distribution.

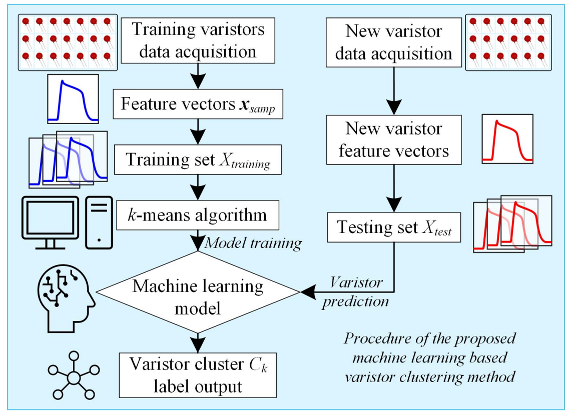

FIGURE 9. Proposed machine learning clustering design procedure.

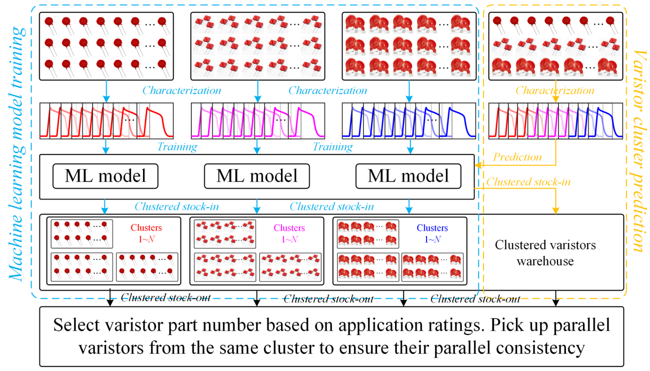

FIGURE 10. Practical engineering process of the proposed machine learning based clustering method for different types of varistors.

D. MODEL TESTING AND VARISTORS CLUSTERING PREDICT

The established machine learning model needs to be validated by new data. Therefore, 28 new V420LA20 varistors are tested on the same platform in Fig. 4. Their clamping characteristic curves are measured, data are preprocessed in the same procedure, and a testing dataset is then established as X_{test} which has dimensions of 28×266.

Finding the nearest centroid from each test feature vector, the new varistors in the testing set can be classified using the existing clusters. It means that the derived machine learning model can be used to predict new varistor's cluster label. Fig. 9 summarizes the proposed machine learning clustering design procedure.

E. PARALLEL VARISTORS SELECTION PROCESS

Fig. 10 shows the practical engineering process of the proposed machine learning based clustering method for varistor parallel utilization. All varistors including training samples and testing parts are eventually stocked in a clustered varistor warehouse. In any DC circuit breaker or other application case where multiple varistors are needed in parallel, the part number can be selected first based on the oriented ratings.

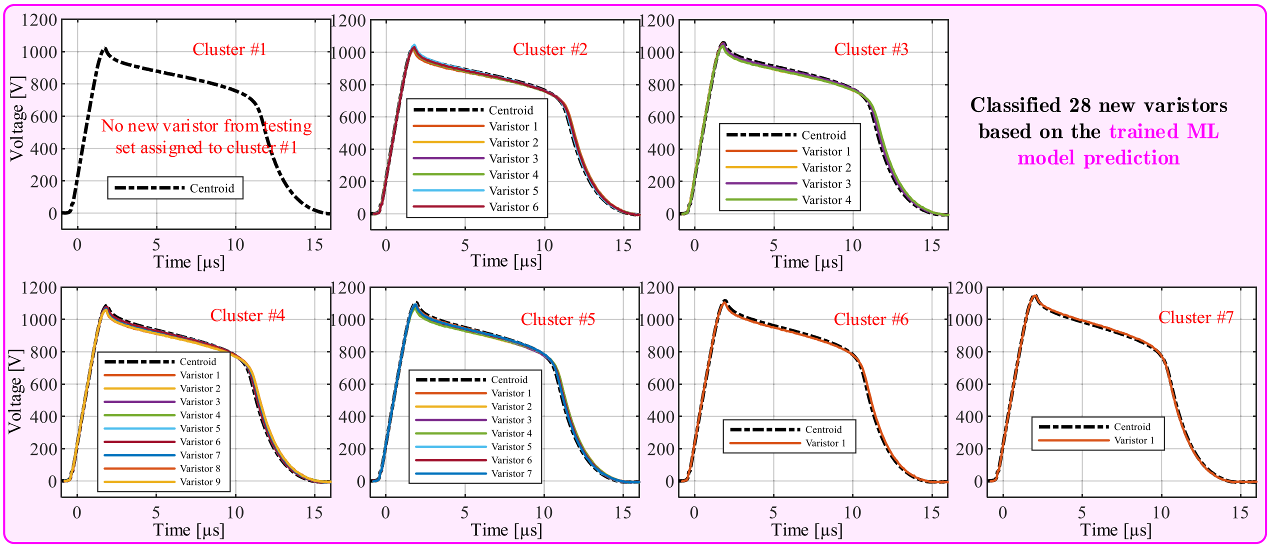

FIGURE 11. Classified new varistors based on the trained machine learning model, showing their clamping characteristic curves with corresponding centroid curve.

Then specific varistor parts will be selected from the same cluster to enhance their parallel consistency.

It should be noted that although characterization of the varistors is still needed in the data acquisition process, it does not take a lot of time and resource. For example, only a low voltage pulse generator platform is needed instead of the rated dc platform, which greatly simplifies this process.

Besides, individual machine learning models will be trained for each type of varistor. A clustered varistor warehouse/pool can be established based on the machine learning method. Each type of varistors will be clustered into various groups. Clustered varistors can be stocked out per requisition and meanwhile new varistors can be stocked in with their cluster label by the trained machine learning model. In this case, it will be very convenient for not only the ongoing design but also any future DC circuit breaker designs to select consistent varistors for parallel utilization.

Using the testing set of 28 new varistors' feature vectors, Fig. 11 classifies their clamping characteristic curves by cluster memberships based on the procedures shown in Figs. 9 and 10. Intermediate clusters #2∼#5 have more varistors than farther clusters #1, #6 and #7. It must be noted here that all the original and processed data of training and testing varistors in the clustering operation process are included throughout Figs. 5–8 and 11 in this section.

IV. EXPERIMENTAL VALIDATION

A. HARDWARE DESCRIPTION

Parallel consistency of varistors in each cluster needs to be experimentally validated. Fig. 12 shows an SSCB prototype for varistor parallel testing, and parameters are listed in Table 2. For S_m, four SiC MOSFETs are connected in parallel, where each switch has an individual clamping unit. Four varistors are paralleled to handle faults. All main switches, clamping

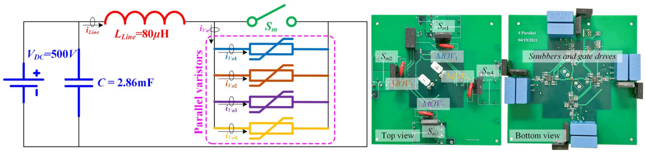

FIGURE 12. Varistor parallel testbench based on a symmetrical SSCB prototype [7].

TABLE 2 SSCB Prototype Parameters for Varistor Parallel Test

Parameter	Value	Parameter	Value
V_{DC}	500V	S_m	C3M0016120D
L_{line}	80μH	Varistors (MOV)	V420LA20
I_{fault}	520A	$n_{parallel}$	4

units, and varistors are symmetrically placed to prevent parallel current unbalancing resulting from layout inconsistency [7]. Elaborations regarding the design guidelines of the major components of the SSCB are presented below.

The SSCB in this paper adopts pure varistors as the voltage clamping solution. Usually, varistors feature a clamping overvoltage ratio OVR roughly equal to 2 as defined below [8].

$$OVR_{MOV} = V_{Clamp}/V_{M(DC)} \approx 2 \tag{6}$$

Where V_{Clamp} refers to varistor maximum clamping voltage, and $V_{M(DC)}$ means the DC voltage rating of the varistor. When applied voltage stress exceeds $V_{M(DC)}$, varistor gradually loses its off state high impedance, and starts entering non-linear region where resistance drops significantly with voltage increasing. To avoid any significant leakage current, $V_{M(DC)}$ of varistor should be no lower than the system voltage rating V_{DC}, meaning $V_{M(DC)} \geq V_{DC}$ to ensure varistor works in strict off region when the SSCB is at opening state.

Since the presented SSCB design targets a $V_{DC} = 500$V DC power system, it can be derived from (6) that the maximum clamping voltage of the varistor should be no lower than two times that of V_{DC}, meaning that $V_{Clamp} \geq 1000$ V should be satisfied. Specifically, the varistor V420LA20 from Littelfuse discussed in previous sections is a suitable selection which has a clamping voltage $V_{clamp} = 1120$ V at 50 A peak current, leaving sufficient safety margin. The main switches S_m voltage rating should be higher than V_{Clamp} to avoid overvoltage breakdown during the opening transients. Therefore, 1200 V SiC discrete MOSFETs C3M0016120D are used, which also feature an ultralow on-state resistance of 16 mΩ to reduce the conduction losses when the SSCB is at normal closing state.

The selection of varistor size (disc diameter) is also of great significance for SSCB design. It determines the varistor surge current capability, which limits the total breaker lifetime. The varistor surge current capability is up to both the pulse current magnitude I_{pk} and pulse width τ. As indicated by Fig. 3, the varistor current in DC breakers are in triangular shape, whose pulse width can be approximately estimated by the following equation.

$$\tau_{triangular} \approx L_{line} I_{fault} / (V_{Clamp} - V_{DC}) \tag{7}$$

Where L_{line} refers to system line inductance, and I_{fault} means system fault current magnitude. However, the actual pulse width $\tau_{triangular}$ cannot be directly used. It must be converted to a standard 8/20 μs exponential waveform on the basis of equivalent energy [9], which is depicted by the following equations.

$$\begin{cases} E_{triangular} = K_{triangular} I_{pk} V_{Clamp} \tau_{triangular} \\ E_{\exp} = K_{\exp} I_{pk} V_{Clamp} \tau_{\exp} \end{cases}$$

$$E_{triangular} = E_{\exp} \Rightarrow \tau_{\exp} = \frac{K_{triangular} \tau_{triangular}}{K_{\exp}} \tag{8}$$

Where K is a constant whose value varies for different types of waveshapes. For triangular and exponential waveshapes discussed in this paper, $K_{triangular} = 0.5$ and $K_{exp} = 1.4$ are provided respectively.

The converted pulse width τ_{exp} can then be used to find the estimated varistor lifetime based on the surge current capability data provided by manufacturer [10].

With regards to the demonstrated design point in this paper, a $\tau_{exp} \approx 39$ μs is calculated by converting the $\tau_{triangular}$ measured in Fig. 3. Assuming current among four parallel varistors are evenly distributed, $I_{pk} = I_{fault}/n_{parallel} = 130$A is obtained.

The lifetime of the selected 14 mm disc varistor is thence estimated up to 5000 times of operations based on the manufacturer data [10], which is acceptable considering that fault opening is a relatively rare scenario for a breaker that is supposed to work in normal conduction status in most of its lifecycle.

It should be noted that this varistor lifetime estimation is an upper limit in ideal cases. In practice, I_{pk} of certain varistor might be much higher than $I_{fault}/n_{parallel}$ as presented in Fig. 3, which significantly affects varistors and total SSCB lifetime. It justifies the motivation of this work to render the actual operating point of parallel varistors in SSCBs close to the abovementioned ideal design point by the proposed machine learning based varistor clustering method. More details of the varistor lifetime estimation before and after the clustering design compared to the ideal design point will be illustrated in Section IV-C.

B. VARISTOR CURRENT SHARING TESTS WITH DIFFERENT CLUSTERS

During tests, A 2.86 mF capacitor is charged to 500V for fault interruption as defined in [7]. The load side is directly shorted to emulate a short circuit fault. S_m turns on for 100 μs to generate a 520 A pulse current. For each test, four parallel varistors are selected from the same cluster. Four tests are conducted with regards to clusters #2, #3, #4 and #5 respectively. Clusters #1, #6 and #7 are not tested due to insufficient within-cluster varistor quantity.

Fig. 13 shows experimental results of 500 V/520 A fault current interruption tests, demonstrating varistor currents distribution comparison. Fig. 13(a) shows the waveforms of breaker voltage, line current and total clamping branch current in the complete testing timescale, in which the fault current extinguishing details are illustrated in Fig. 13(b) and (c) with regards to scenarios before and after applying the machine learning based varistor clustering method.

It is noted that the results in Fig. 13(c) are obtained upon four randomly selected varistors in cluster #2. The maximum currents of i_{Va1}~i_{Va4} are 132.9 A, 132.6 A, 130.6 A, and 130.5 A. Maximum deviation from the average current is only 0.95%, which indicates that a significant improvement of current balance is achieved for parallel varistors compared to the non-clustered condition in Fig. 13(b).

Varistor current sharing testing results of other clusters #3, #4, and #5 are also demonstrated to validate the comprehensive effectiveness of the proposed clustering method.

Fig. 14(a) shows the testing result of cluster #3, where there are collectively four varistors available based on Fig. 11. Since there is no room for random testing, all the four varistors in stock are used for the current interruption test. The maximum currents of four parallel varistors are 129.4 A, 135.9 A, 128.2 A, and 135.6 A respectively. Maximum deviation from the average current is calculated as 3.1%.

For the testing of the following clusters #4 and #5, four varistors are randomly selected since there are excessive amount of varistors, which is similar to cluster #2 testing. The testing result of cluster #4 is presented in Fig. 14(b). Similarly, the maximum currents of parallel varistors are measured as 133.0 A, 134.4 A, 132.2 A, and 138.8 A, implying a 3.1% deviation from the average current.

Fig. 14(c) demonstrates the testing result of cluster #5. The maximum currents of parallel varistors are measured as 132.2 A, 132.5 A, 130.3 A, and 132.3 A. Maximum deviation from the average current is only 1.2%.

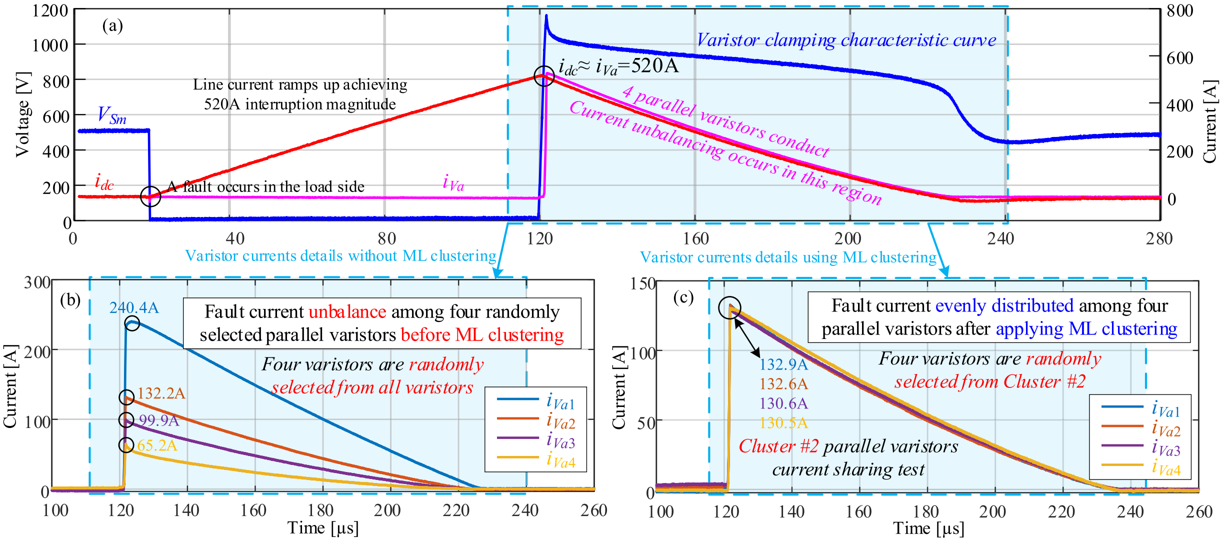

FIGURE 13. Experimental results of 500 V/520 A fault current interruption tests, showing varistor currents distribution comparison. (a) Breaker voltage, line current and clamping branch current in the complete testing timescale, (b) four varistors current unbalancing details without ML clustering, (c) improved current distribution of four randomly selected varistors from cluster #2.

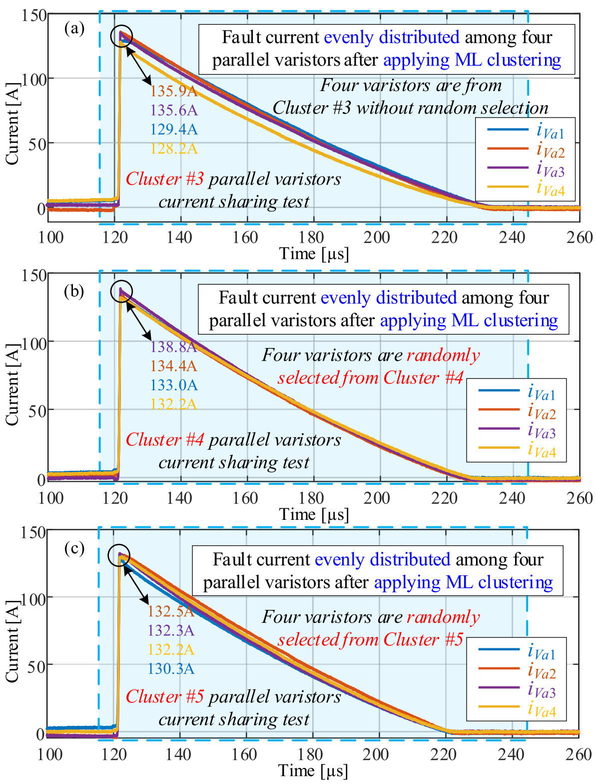

FIGURE 14. Experimental results of improved varistors current sharing. Four varistors are selected from (a) cluster #3, (b) cluster #4, and (c) cluster #5. The varistors selection in cluster #3 is not random while that of clusters #4 and #5 are random.

To summarize, random data selection based experimental results of four varistor clusters successfully validate the effectiveness of the proposed machine learning based varistor parallel design method. Compared to the scenario before the clustering design, the current sharing of parallel varistors in all clusters is significantly improved.

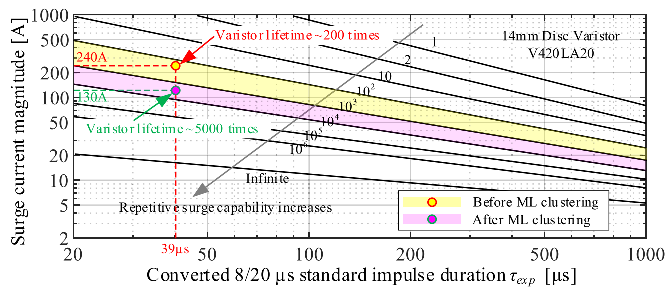

FIGURE 15. Comparison of varistor lifetime (repetitive surge capability [10]) before and after the machine learning based clustering design.

C. EFFECT OF MACHINE LEARNING BASED CLUSTERING ON IMPROVING VARISTOR LIFETIME

The unbalanced current distribution is a challenging issue as it affects the reliability and lifetime of the varistor and total breaker. As indicated by Fig. 13(b), in a 500V/520 A SSCB with four randomly selected parallel varistors without clustering (same part number), 46% of the fault current (240A) is extinguished by a single varistor. Fig. 15 indicates that the lifetime of the specific varistor consuming the highest current (240A) is only ∼200 times, which is very limited. For varistors in parallel in a SSCB, any single varistor breakdown will lead to a direct short circuit across the main switches, which means the system will lose protection. Therefore, the current unbalance between paralleled varistors significantly affects the lifetime and reliability of the total SSCB, which is not desired.

The proposed machine learning based varistors clustering method is then motivated to address the challenging current sharing issue. As shown in Figs. 13(c) and 14, by applying machine learning concept in varistors parallel design, the total 520 A fault current is evenly distributed among four paralleled varistors, meaning that each varistor current is reduced to around 130A. In this case, the varistors lifetime is significantly enhanced to ∼5000 times as indicated in Fig 15, which is 25 times higher than the original case before the clustering design. It proves that involving machine learning concept in parallel varistors design can effectively enhance the lifetime and reliability of the total SSCB.

V. CONCLUSION

A cluster analysis-based machine learning design method for paralleling varistors in DCCBs is presented in this letter. Varistors current unbalance caused by intrinsic manufacturing discrepancy is revealed. Procedure of the varistor clustering design is presented, including data acquisition, preprocessing, K-means model training, and new varistors cluster prediction. A 500 V/520 A SSCB prototype with a symmetrical layout is used to validate the proposed method for paralleling four varistors. The results show that the maximum current deviation is only 3.1%. Effects of the machine learning clustering method on improving parallel varistors lifetime are quantified. The proposed varistor clustering method is a promising solution to improve multi-varistor parallel based circuit breaker design.

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