A Concept of Condition Monitoring for AC-DC Converter Output Capacitors via Discriminative Features

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Abstract

This paper discusses recent research on the condition monitoring (CM) approach for aluminium electrolytic capacitors (AEC) used in power electronics equipment such as switched-mode power supplies (SMPS). Capacitors are identified as the most critical component with the highest percentage of failure in AEC. CM offers a better paradigm for AEC due to its long-lasting ability (endurance). This study proposes accelerated life testing through electrical stress and long-term frequency testing for the AEC component. An experiment test bench was set up to monitor the critical electrical parameters such as dissipation factor (D), equivalent series resistance (ESR), capacitance (Cp), and impedance (Z), which serve as health indicators (HI) for the evaluation of the AECs. Time-domain features were extracted from the measured data, and the best features were selected using the correlation-based technique. This research contributes to developing a cost-effective CM approach for AECs used in power electronics equipment, which can reduce downtime and maintenance costs.

1. Introduction

Prognostics and Health Management (PHM) is a rapidly growing field that has recently gained significant attention, particularly for power electronic devices. PHM is the process of monitoring a system's health, identifying any faults, predicting its remaining useful life, and making recommendations for maintenance or replacement before the system fails. PHM has become an essential tool for condition-based monitoring (CBM), predictive maintenance, and the diagnosis of power electronic devices in the power electronics industry (Achouch et al., 2022; Fei, Bin, Jun, & Shunhua, 2020; Cachada et al., 2018; Zonta et al., 2020).

Power electronic devices are critical in many industries, including aerospace, automotive, renewable energy, and electric power systems. The reliability and availability of these devices are of utmost importance for the safe and efficient operation of these systems. However, power electronic devices are susceptible to failure owing to various factors such as thermal stress, electrical stress, and ageing. The loss of power to electronic devices can result in significant downtime, costly repairs, and catastrophic consequences (Wang & Blaabjerg, 2021).

To overcome these challenges, PHM techniques have been developed to monitor the health of power electronic devices, identify anomalies, and predict their remaining useful life. PHM techniques involve the use of various sensors, data acquisition systems, and analytical tools to gather data on a device's operational state. The collected data were then analyzed using feature-engineering processes to extract meaningful features that could accurately diagnose the health status of the device. CBM is a critical application of PHM that allows for real-time monitoring of the device's health and performance, enabling maintenance actions to be taken before any failure occurs. Predictive maintenance, on the other hand, involves using statistical models to predict when maintenance should be performed based on the device's usage history and current health status. Diagnosis, another crucial application of PHM, involves identifying the cause of failure and determining the necessary corrective actions.

This paper presents a comprehensive review of PHM techniques for power electronic devices, with particular emphasis on CBM, Predictive Maintenance, and Diagnosis. We also discuss the feature engineering process used to extract meaningful features from the collected data and the analytical tools used to analyze the data. This paper aims to provide an overview of the current state-of-the-art in PHM for power electronic devices and identify future research directions.

Using filter-based statistical approaches to extract discriminative features can be beneficial for improving the performance of a machine learning model. These approaches work by analyzing and ranking the relevance of features in a dataset based on their statistical characteristics, such as correlation with the target variable or variance (Kushwaha, Buckchash, & Raman, 2017; Urbanowicz, Meeker, La Cava, Olson, & Moore, 2018).

By selecting the most informative features and removing irrelevant ones, these methods can reduce the data's dimensionality, improving the learning process's efficiency and preventing overfitting. Additionally, they can enhance the interpretability and generalizability of the model by focusing on features that are more likely to have a meaningful relationship with the outcome.

However, it is essential to note that filter-based approaches are not a one-size-fits-all solution. Their effectiveness may vary depending on the specific dataset and the learning task. Moreover, they may not capture complex interactions and nonlinear relationships among the features, which could be better handled by more sophisticated techniques such as wrapper or embedded feature selection methods. Overall, filter-based statistical approaches can be a valuable tool for feature selection in machine learning, providing a simple and fast way to improve performance and interpretability, especially in cases where the number of features is large, or the data is noisy (Kareem A.B., 2022; Bayo & Jang-Wook, 2022).

2. Research Motivation and Literature

Electrolytic capacitors are one of the most commonly used components in power electronics circuits, including AC/DC converters. However, they are also one of the most fault-prone components, with a high failure rate compared to other components. Therefore, understanding how to diagnose faults in these capacitors is critical to ensure the reliability and longevity of AC/DC converter systems (Jami Torki, 2023; Shahraki, Al-Dahidi, Taleqani, & Yadav, 2023). Faulty electrolytic capacitors can lead to safety hazards such as electric shock, fire, and explosions. Therefore, diagnosing and addressing faults in these capacitors is essential to prevent accidents and ensure the safety of personnel working with AC/DC converters. Repairing or replacing faulty electrolytic capacitors can be expensive, especially in large-scale AC/DC converter systems. By diagnosing faults in these capacitors early on, maintenance personnel can take corrective action before the problem escalates, reducing repair costs and minimizing downtime. Faulty electrolytic capacitors can also impact the energy efficiency of AC/DC converters, leading to increased energy consumption and reduced performance. Diagnosing and addressing faults in these capacitors can help maintain the energy efficiency of AC/DC converters, reducing operating costs and minimizing environmental impact (Duan & Chen, 2023). The papers provide different methods for studying and monitoring the condition of aluminium electrolytic capacitors. It presents a methodology for studying the impact of thermal cycling on the wear-out of aluminium electrolytic capacitors used in automotive cases (R. Cousseau & Idkhajine, 2013). It proposes a new method for condition monitoring of aluminium electrolytic capacitors using accelerated life testing, which has a higher accuracy level than existing methods (Bhargava C. & Y., 2018). It presents an experimental offline technique for estimating the condition of aluminium electrolytic capacitors based on estimating equivalent series resistance and capacitance values (Amaral & Cardoso, 2007). It proposes a method for hotspot temperature estimation of aluminium electrolytic capacitors based on the linear dependence between capacitance and temperature (Jedtberg H., 2017). These papers collectively suggest that various methods are available for studying and monitoring the condition of aluminium electrolytic capacitors, which can predict their lifetime and ensure their reliability.

3. Proposed Method

3.1. Feature Extraction and Feature Selection

The correlation coefficient is a widely used filter-based technique for feature extraction and selection. It measures the linear relationship between a feature and the class labels, providing insights into how much the feature's values change as the class labels change. By considering the correlation coefficient, we can identify the most discriminative features that exhibit a strong association with the class labels.

Mathematical Expression: Let's consider a capacitor dataset with features denoted as X = $X_1, X_2, ..., X_n$, and a corresponding class label Y. The correlation coefficient between a feature X_i and the class label Y can be calculated using a measure such as Pearson's correlation coefficient:

$$Corr(Xi, Y) = Cov(X_i, Y)/(std(X_i) * std(Y)) \qquad (1)$$

Here, $Cov(Xi, Y)$ represents the covariance between X_i and Y, while std(X_i) and $std(Y)$ represent the standard deviations of X_i and Y, respectively.

The correlation coefficient ranges from -1 to 1, indicating the strength and direction of the relationship. A positive correlation coefficient indicates a direct relationship, where higher values of X_i tend to be associated with higher values of Y. Conversely, a negative correlation coefficient suggests an inverse relationship, where higher values of X_i are associated with lower values of Y. A correlation coefficient close to 0 indicates a weak or no linear relationship.

To extract discriminative features using the correlation coefficient, you can calculate the correlation coefficient for each feature and the class label and then rank the features based on the absolute value of their correlation coefficients. Features with higher absolute correlation coefficients are considered more strongly associated with the class labels and, therefore, more discriminative.

By applying the correlation coefficient-based feature selection, you can identify the most relevant features from the capacitor dataset, which can subsequently be used for machine learning tasks or further analysis. Table 1 shows the statistical features extracted from the capacitor dataset for condition monitoring. These would help in engineering the best features for training and testing artificial neural networks.

Table 1. The time-domain statistical features extracted from the multi-capacitor dataset

Feature Description	**Definition**
Root Mean Square	$X_{rms} = \sqrt{\frac{\sum_{i=1}^{n}(x_i)^2}{n}}$
Mean	$\bar{x} = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)$
Kurtosis	$X_{kurt} = \frac{1}{N}\Sigma\left(\frac{(x_i-\mu)^3}{\sigma}\right)$
Interquartile range	$upperquarterQ_3 - lowerquarterQ_1$
Median abs deviation	$X_{mad} = \frac{1}{n}\sum_{i=1}^{n}\lvert x_i - m\rvert$
Skewness	$X_{\text{skew}} = E\left[\left(\frac{(x_i-\mu)^3}{\sigma}\right)\right]$
Max	$X_{\max} = \max(x_i)$
Min	$X_{\max} = \min(x_i)$
Crest Factor	$X_{CF} = \frac{x_{\max}}{x_{rms}}$
Peak factor	$x_{PF} = \frac{x_{\max}}{\sqrt{x_s}}$
Wave Factor	$x_{WF} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert^2}}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert}$
Standard error mean	$X_{sem} = \frac{standarddeviation}{\sqrt{n}}$
Standard deviation	$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$
Variance	$VAR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$

3.2. Artificial Neural Networks

ANN stands for Artificial Neural Network, which is a computational model inspired by the structure and functioning of biological neural networks. It consists of interconnected nodes called neurons that process and transmit information. ANNs are widely used in machine learning and have proven to be effective in various tasks such as classification, regression, and pattern recognition.

The mathematical expression of an Artificial Neural Network can be broken down into several components:

Neurons and Activation Function: Each neuron in the network receives inputs, performs a computation, and produces an output. The output is determined by applying an activation function to the weighted sum of the inputs. The activation function introduces non-linearity into the network, enabling it to learn complex patterns and relationships. Mathematically, for a neuron i in a given layer, the output can be represented as:

$$Output(i) = Act.Function(WeightedSum(i)) \tag{2}$$

Weighted Sum: The weighted sum is computed by multiplying each input by its corresponding weight and summing them together with an optional bias term. The weights represent the strength of the connections between neurons and are adjusted during the training process to optimize the network's performance. Mathematically, for a neuron i in a given layer, the weighted sum can be expressed as:

$$WeightedSum(i) = (Input(j) * Weight(i,j)) + Bias(i) \tag{3}$$

where $Input(j)$ represents the j th input to neuron i, $Weight(i,j)$ represents the weight connecting input j to neuron i, and Bias(i) represents the bias term for neuron i.

An Artificial Neural Network typically consists of multiple layers of neurons, including an input layer, one or more hidden layers, and an output layer. The number of layers and the number of neurons in each layer depend on the specific problem and network design. The neurons in each layer are connected to the neurons in the subsequent layer, forming a forward propagation of information. The learning process in an ANN involves adjusting the weights and biases to minimize the difference between the network's predicted output and the desired output. This is typically achieved using a process called backpropagation, which utilizes an optimization algorithm such as gradient descent. The objective is to find the optimal set of weights that minimizes a predefined loss or error function. The mathematical expression for the training process involves calculating the error between the predicted output and the desired output, propagating the error back through the network, and updating the weights and biases based on the computed gradients. Table 2 shows the ANN classifier architecture for this study.

Table 2. ANN-classifier design architecture

Parameters	Description
Learning Rate	0.001
Hidden Layer	25
Max-Iter	50
Activation	reLU
Solver	Adam
Early Stopping	True
Random State	1

4. Experimental Test Bench

LCR (Inductance, Capacitance, and Resistance) meters are commonly used for data collection of electrical signals. These meters provide a convenient and accurate means of measuring the impedance characteristics of electronic components, such as resistors, capacitors, and inductors. LCR meters can accurately measure parameters like capacitance, inductance, resistance, quality factor (Q-factor), and equivalent series resistance (ESR). Connecting the electrical signal source or device under test to the LCR meter can measure and record the impedance response across a range of frequencies. In the experimental process, a capacitor is subjected to a temperature range of 80 to 120 degrees Celsius using a controlled environmental setup. A HIOKI LCR meter is connected to the capacitor to perform measurements at varying voltages and frequencies up to 8MHz. The LCR meter is configured to use a slow measurement speed for high accuracy. The experiment involves gradually increasing the temperature while taking LCR measurements at specific intervals to monitor changes in dissipation factor, capacitance, resistance, and reactance properties. The data collected will provide insights into the capacitor's performance under different temperature, voltage, and frequency conditions. This data collection process enables comprehensive analysis and characterization of the electrical properties of components and circuits, facilitating design, troubleshooting, and quality control in various electronic applications. Figure 1 shows the experimental test bed for the data collection process for the electrolytic capacitor condition monitoring. Table 3 shows the test conditions manually set using the LCR software for the data collection process. The highest and lowest values that can be precisely measured depend on the meter's measuring range. To maintain accuracy and prevent overloading the instrument, it is necessary to choose a measurement range. It is appropriate for the component's predicted values is crucial. Using the Speed option, you can regulate the LCR meter's measuring speed or rate. Fast measurements may be necessary for some applications to boost throughput, whereas longer, more accurate measurements may be required where accuracy is a higher priority. To accommodate diverse testing needs, the Speed function often provides numerous speed settings or measurement modes (for example, rapid, medium, and slow). Use the "LowZ" (Low Impedance) mode to test components with low impedance values. Standard LCR measurements can not be reliable or precise enough when working with components like low-value capacitors or inductors. When measuring AEC with low impedance values, the LCR meter's sensitivity and accuracy are improved by the LowZ mode. The LCR meter can reliably measure components with very low impedance by minimizing its internal parasitic impedance by turning on the LowZ mode. It is constructive for measuring tiny SMD (surface mount device) components or other gadgets with low parasitic resistance. Table 4 shows the electrical parameters captured during the data collection. They were manually inputted into the LCR software as shown in Figure 2. Analyzing and characterizing the electrical properties of aluminium electrolytic capacitors used in SMPS output filters is vital for optimizing the power supply's performance, efficiency, stability, and reliability. It also aids in ensuring safety, compliance, and the longevity of the overall system. Designers and engineers must consider these factors when selecting capacitors and designing SMPS circuits to achieve the desired performance and reliability. Table 5 shows the fault classification for the ANN classifier.

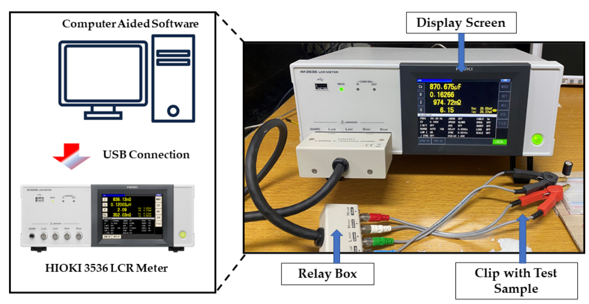

Figure 1. The experimental test bed of the electrolytic capacitor under varying load conditions

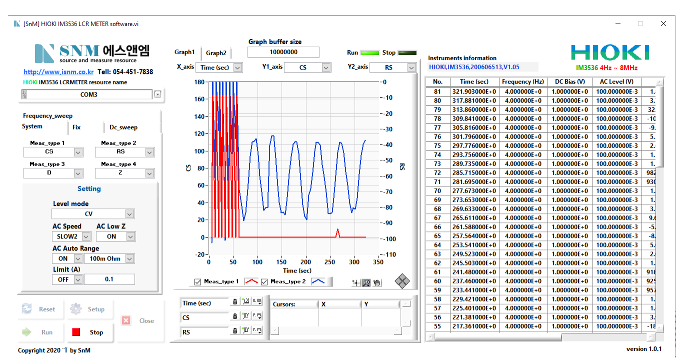

Figure 2. A screenshot into the data collection framework for the electrolytic capacitor

Table 3. The experimental test conditions for the electrolytic capacitor

Functions	Description
Electrical Parameters	Cs–Rs–D–Z
Frequency/Freq-Step	8 MHz/1000 Hz/10 Hz
DC Bias	ON 1.0 volts
Signal Level	0.5 Vrms
Measurement Range	Auto
Speed	SLOW2
LowZ mode	ON

Table 4. The electrical parameters assigned for the experiment procedure

Parameters	Description	Expression
Rs	Equivalent Series Resistance	$ESR = \|Z\| Cos\theta$
Cs	Capacitance	$Cs = \frac{D}{\omega R}$
Z	Impedance	$Z = \frac{\|X_c\|}{Sin\theta}$
D	Dissipation Factor	$tan\delta = \frac{ESR}{X_c}$

5. Result Analysis and Discussion

The proposed method can be summarised into two steps, namely the feature extraction and selection stage and the deep learning-based diagnostic framework. The concept of this research is ensuring the right features from the electrolytic capacitors are fed to the deep learning algorithm. The Pearson correlation technique was used as a filter-based method to identify features that have a strong linear relationship with the target variable or class labels. Setting a threshold, such as 0.8, allows us to select features that have a correlation coefficient above this threshold, indicating a relatively strong correlation. Figure 3 shows the feature selection visualization using the Pearson correlation techniques. The number of features selected was reduced from 14 to 9 based on the threshold set. The selected features are as follows: Mean, root mean square, interquartile range, max, min, kurtosis, skewness, peak factor, and wave factor. The labels for the ANN classifier were set with respect to the temperature variance of 80, 90, 100, 110, and 120 degrees which correspond to the label on the confusion matrix as 0, 1, 2, 3, and 4, respectively. A total number of 7000 samples were set aside for the training, while 3000

Table 5. Fault classification for the experimental setup

Cases (Label)	Temperature (° C)
Case A (0)	80
Case B (1)	90
Case C (2)	100
Case D (3)	110
Case E (4)	120

samples were set aside for testing the ANN model.

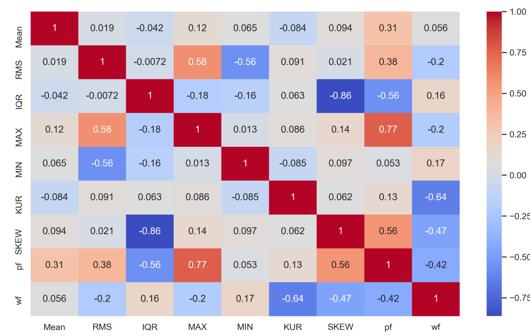

Figure 3. Visualization plot from the features selected

Table 6 shows the global performance assessment for the ANN classifier model comprising of the accuracy, precision, recall and f1 score. The mathematical expression for these metrics is highlighted below:

$$\text{Accuracy} = \frac{TP}{TP + FP + TN + FN} \tag{4}$$

$$\text{Recall/Sensitivity} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{F1- Score} = \frac{2 * \text{Sensitivity} * \text{Precision}}{\text{Precision} + \text{sensitivity}} \tag{7}$$

where TP = True positive, FP - False positive, TN = True negative, and FN = False negative. Figure 4 shows the validation and loss score plot from the artificial neural network after being fed the discriminative features from the dataset. The loss score represents a measure of error for the ANN model between predicted outputs and the actual target values during each iteration of the training process. The validation score of the ANN model represents the assessment or metrics whereby a portion of the data is set aside as a validation set. The ANN model performance is later evaluated on this validation set after the training process. The validation score helped in detecting overfitting, and hence a k-fold technique was deployed to ensure the assessment of the ANN model. Further work will be done in the aspect of increasing the data sample for training and testing and optimization techniques for the algorithm. Figure 5 shows the confusion matrix for the ANN algorithm between the true label and the predicted label.

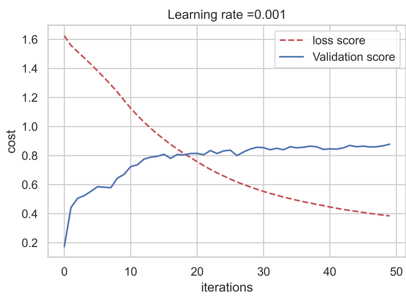

Figure 4. The loss score against the validation score for the ANN algorithm

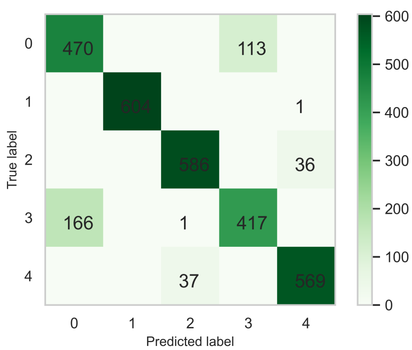

Figure 5. The confusion matrix for the ANN algorithm

Table 6. Global performance assessment of the ANN classifier model

Accuracy	Precision	Recall	F1 Score	Cost (secs)
88.57%	88.53%	86.83%	86.32%	27.7833

6. Conclusion

In conclusion, this conference paper presented a comprehensive framework for fault diagnostics of electrolytic capacitors using a feature extraction and selection approach coupled with an Artificial Neural Network (ANN) model. The data acquisition process involves a setup of capacitors exposed to varying temperatures of 80 to 120 degrees in a chamber acting as a fault sample for the capacitors. The focus was on utilizing the Pearson correlation as a filter-based feature extraction method, with a threshold of 0.8, to identify the most relevant features for fault diagnosis. The results obtained from the ANN model demonstrated promising performance. The initial attempt yielded an accuracy of 88.57% for the training dataset and 88.20% for the testing dataset. These results indicate that the selected features, obtained through the Pearson correlation technique, contained valuable information for accurately classifying and diagnosing faults in electrolytic capacitors. However, further optimization of the ANN algorithms is still necessary to improve the accuracy of the fault diagnostics system. These can involve fine-tuning the model's hyperparameters, adjusting the network architecture, or exploring advanced training techniques such as regularization or ensemble methods. By optimizing the ANN algorithms, it is anticipated that the accuracy of the fault diagnostics system can be further enhanced. This paper's feature extraction and selection framework lays a solid foundation for future research in fault diagnostics for electrolytic capacitors. Using the Pearson correlation as a filter-based method allowed for the identification of meaningful features, reducing the complexity of the dataset and improving the efficiency of the ANN model. In conclusion, this research provides valuable insights into developing accurate fault diagnosis systems for electrolytic capacitors. By leveraging filter-based feature extraction and selection techniques, coupled with ANN models, the diagnostic accuracy can be significantly improved, leading to more efficient maintenance strategies and enhanced reliability of electrical systems. Further research and optimization efforts on the ANN algorithms will contribute to achieving even higher levels of accuracy in fault diagnosis for electrolytic capacitors.

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Biographies

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