IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 15 February 2024, accepted 10 April 2024, date of publication 15 April 2024, date of current version 26 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3389031

RESEARCH ARTICLE

Intelligence Detection of DC Parallel Arc Failure With Featuring From Different Domains

HOANG-LONG DANG[1], SANGSHIN KWAK[1], (Member, IEEE), AND SEUNGDEOG CHOI[2], (Senior Member, IEEE)

[1]School of Electrical and Electronics Engineering, Chung-Ang University, Seoul 06974, South Korea
[2]Department of Electrical and Computer Engineering, Mississippi State University, Starkville, MS 39762, USA

Corresponding author: Sangshin Kwak (sskwak@cau.ac.kr)

This work was supported in part by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) under Grant 2020R1A2C1013413, and in part by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea under Grant 20214000000280.

ABSTRACT DC microgrids are increasingly becoming the backbone of renewable energy integration. Their ability to efficiently manage intermittent sources like solar and wind power is transforming the energy landscape. However, a critical challenge remains in the form of DC arc faults, which can significantly compromise the reliability and safety of these systems. Parallel arc faults represent a particularly challenging scenario due to their unique electrical behavior. Unlike series arc faults, which cause a decrease in system current, parallel arcs can lead to a significant increase in current due to the low resistance path they create. This research delves into the electrical behavior of DC systems during parallel arc faults. By analyzing the source current signals in different domains, the authors aim to identify specific characteristic features of the source current that can serve as reliable indicators combined with artificial learning models for arc fault diagnosis. The findings of this research can have significant implications for the improvement of advanced arc failure recognition systems. This research represents a valuable step towards safe and reliable DC systems by addressing the challenge of parallel arc fault detection.

INDEX TERMS DC parallel arc fault, feature characteristics, artificial learning models.

I. INTRODUCTION

The world's insatiable appetite for fossil fuels has triggered a two-fold crisis: dwindling resources and global warming. In response, distributed renewable energy sources like solar and wind power are rapidly taking root across the globe [1]. As reliance on these alternatives grows, ensuring their reliability and safety becomes paramount [2]. Unlike traditional AC systems, renewable energy systems rely on DC transmissions, introducing a new vulnerability: DC arc faults. These persistent electrical discharges can occur due to improper installation, vibrations, or aging connections, posing a serious fire hazard within PV systems and other DC microgrids [3]. DC microgrids, with their intricate network of cables and connections, are vulnerable to a silent threat: DC arc faults. These persistent electrical discharges, unlike their AC counterparts, have no natural off switch, making them a ticking time bomb. A single spark from a damaged cable or loose joint can ignite an inferno, as evidenced by the devastating fire incidents in PV systems [4], [5], [6]. No zero crossing in DC systems allows these arcs to burn uninhibited, posing a constant threat to safety and stability. Unlike AC's flickering dance, DC arcs burn with unwavering rage, a silent threat fueled by the absence of a current "reset." These persistent demons manifest in two forms: series and parallel. Series arcs, slinking through loose connections or fleeting shorts, sip current from connected loads, masking their presence [7]. But exceed safety limits by two to five times, and they erupt into a scorching inferno, consuming cables and wires before stumbling protection devices can intervene. Parallel arcs, however, are a different beast. Born from damaged insulation, they amplify the current, stoking an inferno that melts and vaporizes conductors, leaving naught but smoldering ghosts, far worse than their series counterparts [8]. This characteristic allows them to burn at an arc current below the threshold for most protective devices, making them a hidden threat. Unlike

The associate editor coordinating the review of this manuscript and approving it for publication was Kai Song.

their series counterparts, parallel arc faults don't just persist, they can actually amplify the system's current, leading to an intensifying heat signature and a progressively larger, scorching flare-up. This inferno has the potential to melt and vanish conductors and wiring, causing even greater physical damage than the malfunctions associated with series faults [9]. The exploration of parallel failure in DC systems is currently in its early stages, lacking a comprehensive protection scheme. However, existing literature offers insights into detecting arc failure events. A comparison between series and parallel arcs in DC systems is detailed in [10], providing a foundational understanding. Additionally, [11] delves into the different domain characteristics of arc failures in DC systems, contributing to the knowledge base in this area. Notably, [12] employs the detection of significant current fluctuations as a method to identify parallel arc events, showcasing one approach to enhance detection capabilities in these systems. Conversely, artificial learning models (ALMs) have been successfully applied in detecting arc failures, yielding promising outcomes, as evidenced by studies such as [13], [14], [15], and [16]. However, it's noteworthy that these investigations primarily focus on series arc faults, leaving a gap in the thorough exploration of ALM applications for parallel arcs. Recognizing this, there is a compelling necessity for a comprehensive study encompassing diverse operational situations specific to parallel arc faults. Recent research into parallel arc faults reveals a crucial correlation between the source current in different domains and the superior performing of artificial learning models [17]. In realistic applications, measuring the arc current during a parallel arc fault is challenging due to the unknown location of the arc event. Consequently, the source current emerges as the most suitable signal for effective fault diagnosis in this study. This recognition underscores the importance of considering the source current for robust diagnostic processes in the context of parallel arc faults.

This study intricately explores the electrical dynamics associated with parallel arc faults. Through a detailed analysis of source current signals in different domains, the objective is to pinpoint distinctive features within the source current. These identified features are intended to serve as robust indicators when integrated with artificial learning models for the purpose of arc fault diagnosis. The outcomes of this research carry substantial implications for the advancement of sophisticated arc fault detection systems. By addressing the complexities of parallel arc fault detection, this research contributes significantly to heightening the protection and reliability of DC organizations, marking a crucial stride in the domain of electrical system security. The proposed method offers several novel contributions. By recognizing the distinct characteristics and hazards posed by parallel arcs, the proposed method fills a significant gap in existing literature, which primarily focuses on series arc faults. Through an intricate analysis of source current signals in different domains, the proposed method aims to identify robust indicators for fault diagnosis. This approach offers a deeper understanding of the electrical dynamics associated with parallel arc faults, facilitating more accurate detection and diagnosis. The study leverages ALMs as powerful tools for identifying elusive faults. By integrating ALMs with effective feature extraction techniques, the proposed method enhances fault diagnosis accuracy, thereby improving the safety and reliability of DC systems. This paper lays out a clear roadmap to understanding and detecting arc faults. Section II meticulously constructs the configuration setup, providing a detailed canvas for analyzing current behavior. Section III empowers you with knowledge of ALMs, powerful tools for identifying these elusive faults. We delve into effective feature extracting techniques. Section IV delivers the scientific results, unveiling the secrets of current behavior across various operating conditions. Finally, Section V distills the wisdom gained from ALMs, offering valuable insights and paving the way for future advancements in arc fault detection.

II. DC PARALLEL ARC FAULT GENERATION AND CHARACTERISTICS IN DIFFERENT DOMAINS

The experimental setup, designed in accordance with the UL1699B standard [18], incorporates an arc creator and associated electronics elements to gather arc data, as illustrated in Figure 1. The KEYSIGHT N8741A, a versatile power supply capable of delivering up to 300V, 11A, and 3.3kW of power, plays a crucial role in this experiment. It serves as the heart of the DC source, providing the steady 300V voltage that fuels the arc generation process. The arc current, denoted as i_{arc}, flows through specially designed arc rods held in place by a meticulous step motor. This motor ensures safe and controlled separation of the rods, allowing for precise arc gap adjustments crucial for analyzing arc behavior at different distances. The gap itself is meticulously monitored by an electric ruler, its precise measurements feeding into the data acquisition system for detailed analysis. Finally, the three-phase inverter, burdened by a 10Ω resistor and 10mH inductor, serves as the simulated load representing real-world electrical systems. To ensure safety during the generation of a parallel arc, a resistor R_{limit} is serially inserted into the arc generator. This resistor serves the crucial role of limiting the arc current, especially given the rapid increase in source current (i_s) associated with the initiation of a parallel arc. Table 1 provides detailed specifications for the parallel arc fault, offering comprehensive insights into the experimental parameters and conditions. Initiating the experiment, a controlled surge of DC voltage energizes the three-phase inverter load. Simultaneously, the meticulously calibrated step motor meticulously pulls the arc rods apart at a precise rate of 2.5mm/s, replicating the gradual increase in distance that can occur during system faults. In this controlled separation, an oscilloscope, operating at a 250kHz sampling frequency specifically chosen to capture the dynamic nuances of arc current, meticulously records the electrical behavior both before and after the rods part ways. The initiation of the arc introduces significant fluctuations, contributing to arc current noise. The diagnostic process, executed using MATLAB, utilizes the collected data for accurate fault

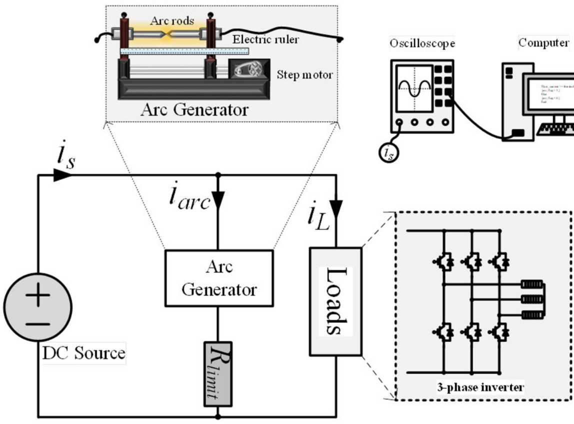

FIGURE 1. DC parallel arc failure generation.

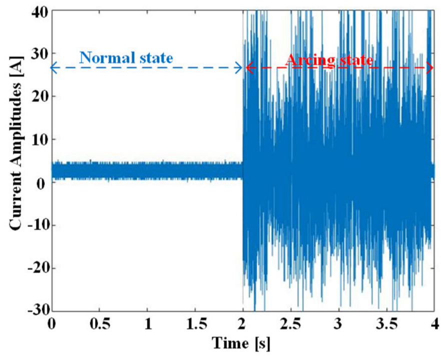

FIGURE 2. The source current waveforms under the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz.

TABLE 1. Specifications of experimental arc fault generation.

Load type	Three-phase DC-AC converter							
Control method	SVPWM							
Load current (A)	3				5			
Limit resistor (Ω)	600		300		600		300	
Arc current (A)	0.5		1		0.5		1	
Switching rate (kHz)	5	15	5	15	5	15	5	15

detection. The acquired signals are systematically divided into sets representing 0.8 ms periods, facilitating testing and training processes through ALMs. To precisely control the three-phase inverter and generate realistic arc scenarios, the experiment leverages the advanced technique of Space Vector Pulse Width Modulation (SVPWM). The core of SVPWM lies in the concept of "space vectors," which combine the instantaneous voltages of all three phases into a single point in a two-dimensional space. By strategically manipulating these vectors and calculating the corresponding switching patterns for the inverter's power transistors, SVPWM synthesize three-phase waveforms with near-perfect sinusoidal fidelity. This precise control over the inverter output waveform replicates realistic operating conditions and generate controlled arc events for detailed analysis. This comprehensive approach ensures meticulous control and analysis throughout the experimental setup.

Figure 2 visually presents the signals during both experimental arcing and normal states, specifically under conditions of load current 3 A, 5 kHz switching frequency, and 0.5 A arc current. The presented figures unmistakably depict waveform shapes that remain stable and analogous before the commencement of any arcing. However, upon the initiation of a fault event, a cascade of abnormal behaviors becomes evident in the signals. The current waveform, formerly a smooth sine wave, becomes riddled with harmonic components, a spectral chorus whose frequencies whisper tales of the arcing plasma's chaotic nature. These aberrations in the signal behavior during fault events present valuable cues that could prove instrumental in diagnosing the occurrence of a fault event. This in-depth analysis of the signal characteristics during both normal and arcing states is crucial for developing a robust diagnostic framework for failure diagnosis.

In Figure 3, the FFT investigation of the source current is presented under conditions of 3 A load current, 0.5 A arc current, and a 5 kHz switching frequency. The manifestation of a parallel arc is evident in the notable increase in current during its occurrence. This results in significantly larger harmonics during the arcing state compared to the normal state. High-order harmonics are visibly introduced to the signals after initiating the arc fault. While frequency-domain analyses like FFT provide valuable insights, they come with certain drawbacks. The computation-intensive nature and demand for high sampling rates could potentially compromise execution time and precision in real-world applications, particularly during fault events. Conversely, time-domain signals allow for processing with lower sampling rates, ensuring faster computational efficiency. This investigation leverages different domain inputs for the diagnosis of parallel arc faults. Initially sampled at a frequency of 250 kHz, the signals undergo segmentation into discrete sets, each lasting 0.8 ms, facilitating subsequent testing and training procedures. Employing the FFT procedure on each dataset facilitates the extraction of frequency-domain features. These features, derived from different domains, are subsequently utilized as inputs for ALMs to effectively diagnose parallel arc events. This integrative approach aims to leverage the powers of both domains, ensuring an all-inclusive and accurate diagnostic model for parallel arc fault detection.

III. FEATURE EXTRACTIONS FROM DIFFERENT DOMAINS AND ARTIFICIAL LEARNING PROTOTYPES

A. CHARACTERISTIC EXTRACTIONS IN TIME DOMAINS

The role of features in machine learning implementations is pivotal. Features, essentially subsets of input data, provide a representation of the original data. While a richer set of features contributes to the effectiveness of ALMs, an excessively high number may lead to reduced classification performance or the risk of overfitting. Striking the right balance in feature

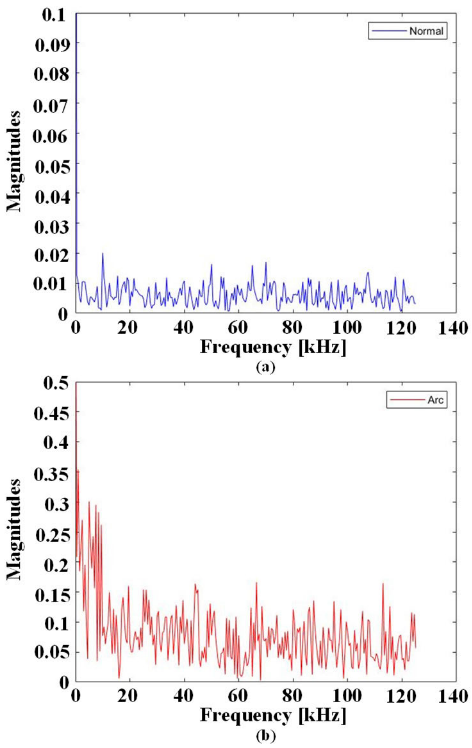

FIGURE 3. The FFT analysis of source current under the load current of 3 A with the arc current of 0.5 A and switching frequency of 5 kHz. (a) Normal state. (b) Arcing state.

selection is crucial for optimal ALM functionality. To develop a robust model, data sampled at a frequency of 250 kHz is subjected to careful processing. The recorded data undergoes segmentation into smaller datasets, each spanning 0.8 ms intervals. These segmented datasets serve the dual purpose of training and testing ALM algorithms. For each dataset, a range of features is extracted, encompassing metrics such as average (avr), median (med), variance (var), root mean square (rms), integral (int), kurtosis (kur), entropy (ent), and the distance between the maximum and minimum currents (ptp). This comprehensive suite of features aims to provide a nuanced and detailed input for ALMs, fostering a balanced and effective model for accurate fault diagnosis. These features are expressed as:

$$avr = \frac{1}{K}\sum\nolimits_{n=1}^{K} i_n \tag{1}$$

$$med = \frac{i_{(K/2)} + i_{\left(\left(\frac{K}{2}\right)+1\right)}}{2} \text{ if K is even} \tag{2}$$

$$med = i_{(K+1)/2} \text{ if K is odd} \tag{3}$$

$$rms = \sqrt{\frac{1}{K}\sum\nolimits_{n=1}^{K} |i_n|^2} \tag{4}$$

$$var = \frac{\sum_{n=1}^{K} |i_n|^2 - \frac{\left|\sum_{n=1}^{K} i_n\right|^2}{K}}{K-1} \tag{5}$$

$$int = \sum\nolimits_{n=1}^{K} |i_n| \cdot \frac{1}{K} \tag{6}$$

$$kur = \frac{1}{K-1}\sum\nolimits_{n=1}^{K} (i_n - avr)^2 \tag{7}$$

$$ent = -\sum\nolimits_{n=1}^{K} (i_n)^2 \cdot lg\left(i_n^2\right) \tag{8}$$

$$ptp = \max(i_1, i_2, \ldots, i_K) - \min(i_1, i_2, \ldots, i_K) \tag{9}$$

here i_n represents the data component at n^{th} position within separately information array and K is the quantity of components inside separately interval. Figures 4 and 5 provide a visual representation of the feature values extracted from time domain signals with load current amplitudes set at 3 A and 0.5 A arc current, maintaining a switching frequency of 5 kHz. The computation of the average involves summing all components inside an information array and distributing by the entire components. Notably, average values exhibit steady shapes across ordinary and fault conditions. The ordinary state shows a relatively constant value, whereas the arcing period possesses fluctuations. Median values, representing the middle value of a dataset. Comparable with the average, the medians display big differences among various working states. The steadiness of the median in the ordinary condition dissimilarities with the oscillating character in the fault condition. The root mean square (rms) derived from time data are also presented. rms values contribute additional insights into signal characteristics, aiding in the classification process. Similar to average, median, and rms, the peak-to-peak (ptp) exhibit discernible differences among various working states. Additionally, the fluctuations of ptp and kurtosis are more pronounced than other features, leading to more reliable index. Detailed analysis underscores the significance of these time domain features in capturing the nuances of signals during normal and arcing states, laying the foundation for effective classification in arc fault detection scenarios.

B. FEATURE EXTRACTION IN FREQUENCY DOMAIN

In each distinct sample interval, the signal undergoes meticulous separation, followed by FFT examination to extract frequency domain features using equations (1 - 9) for frequency components. Figures 6 and 7 vividly illustrate the frequency domain features with current amplitudes set at 3 A and 0.5 A arc current, maintaining a switching frequency of 5 kHz. Average values within the frequency domain exhibit steady shapes across ordinary and fault conditions. The ordinary condition demonstrations a moderately steady mean, whereas the fault condition initiates oscillations. The median robustly captures the middle point of a dataset. Root mean square (rms) values showcase patterns akin to peak-to-peak (ptp) and variance, representing steadiness in the ordinary situation and changeability in the fault condition. Notably, the fluctuations of kurtosis are more pronounced than other features, although the difference gap between normal and arcing states is not as clear as in rms, ptp, and variance. Entropy reveals distinctions between states, but overlapping regions could pose challenges for classification. This nuanced analysis delves into the intricate details of frequency domain features, emphasizing their role in effective signal

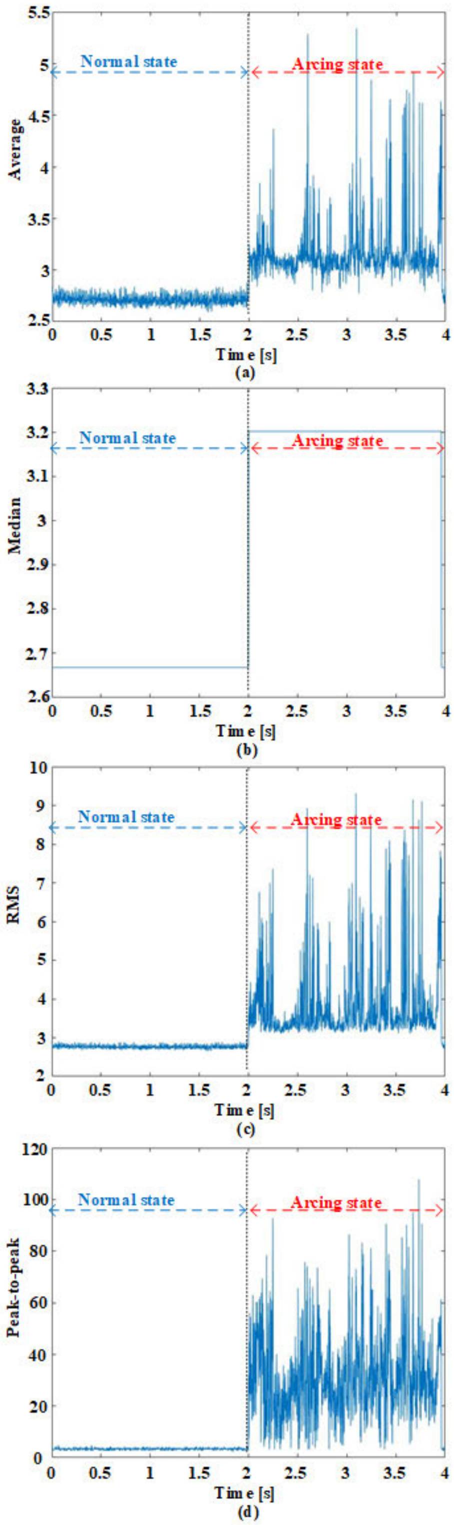

FIGURE 4. The time domain features for the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz. (a) Average. (b) Median. (c) rms. (d) ptp.

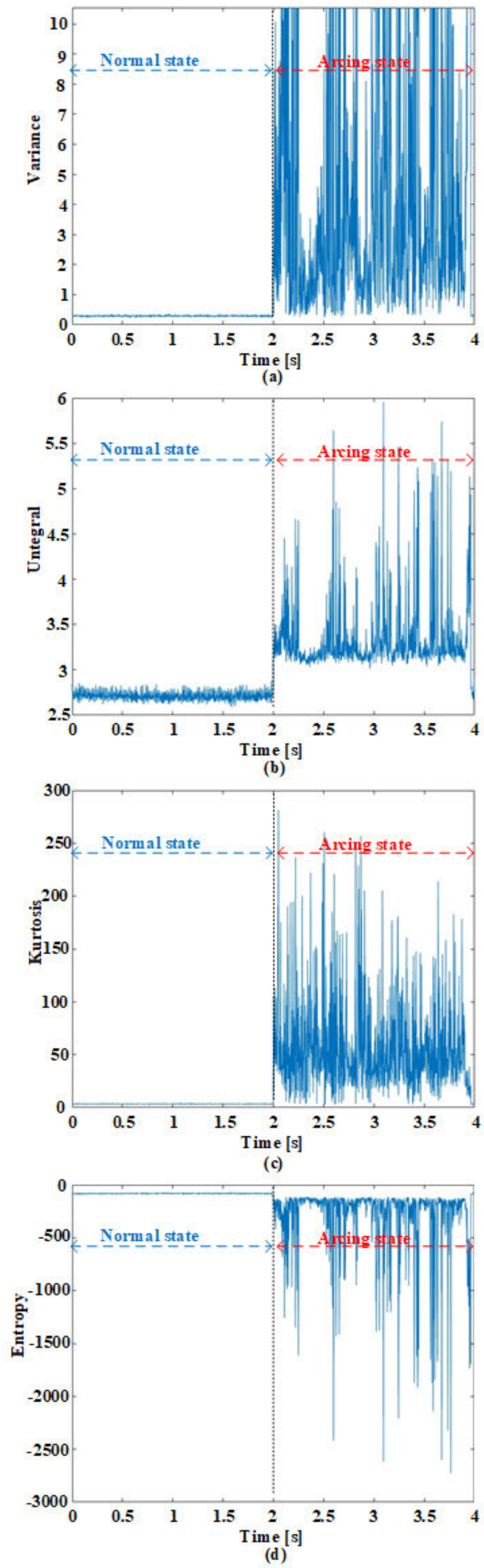

FIGURE 5. The time domain features for the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz. (a) Variance. (b) Integral. (c) Kurtosis. (d) Entropy.

classification and providing a foundation for advanced arc fault detection systems.

The analysis of time and frequency domain features provides valuable insights into the characteristics of signals

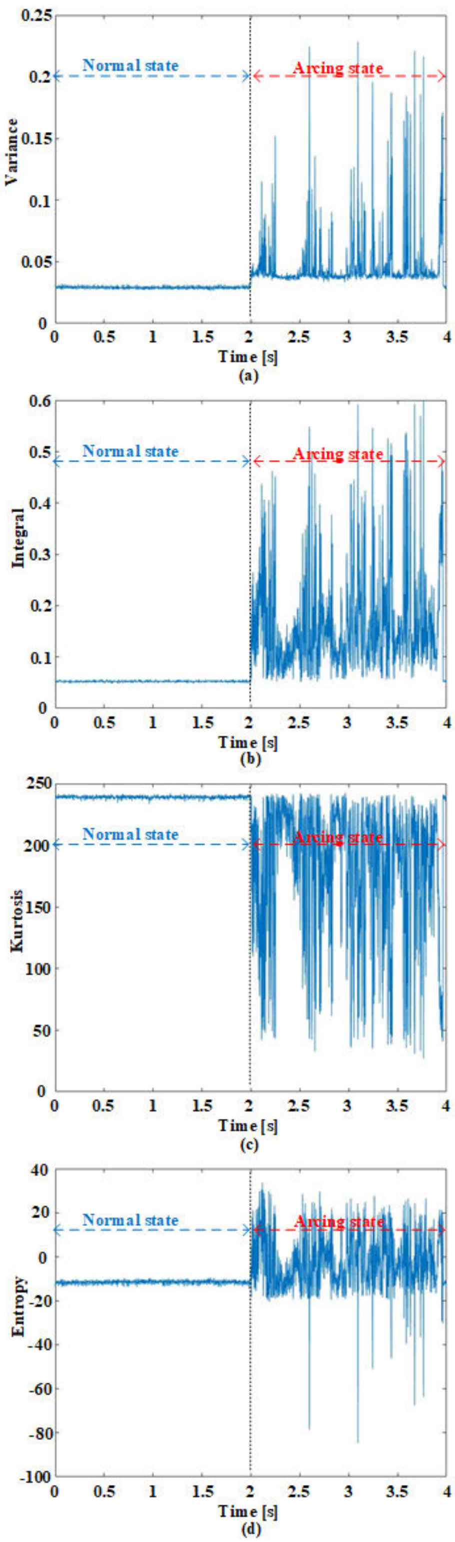

FIGURE 6. The frequency domain features for the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz. (a) Variance. (b) Integral. (c) Kurtosis. (d) Entropy.

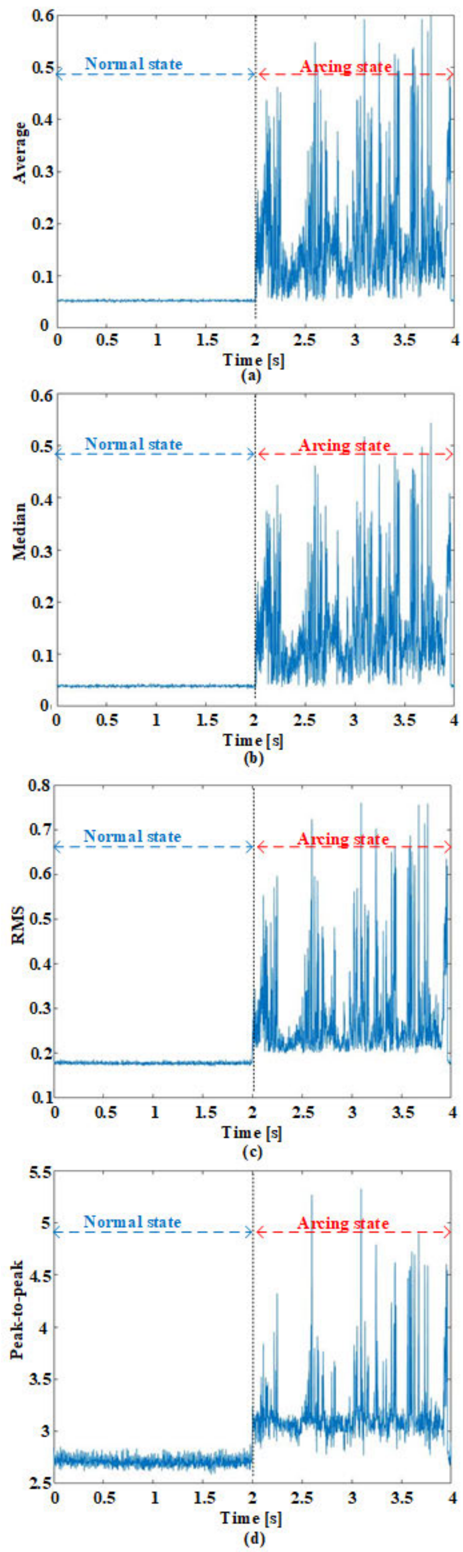

FIGURE 7. The frequency domain features the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz. (a) Average. (b) Median. (c) rms. (d) ptp.

during normal and arcing states, laying the groundwork for effective classification in arc fault detection scenarios. Figures 8 and 9 provide the distribution of time- and frequency-domain features for the load current of 3 A with the arc current of 0.5 A at the switching rate of 5 kHz, respectively. In the time domain, several key features, including

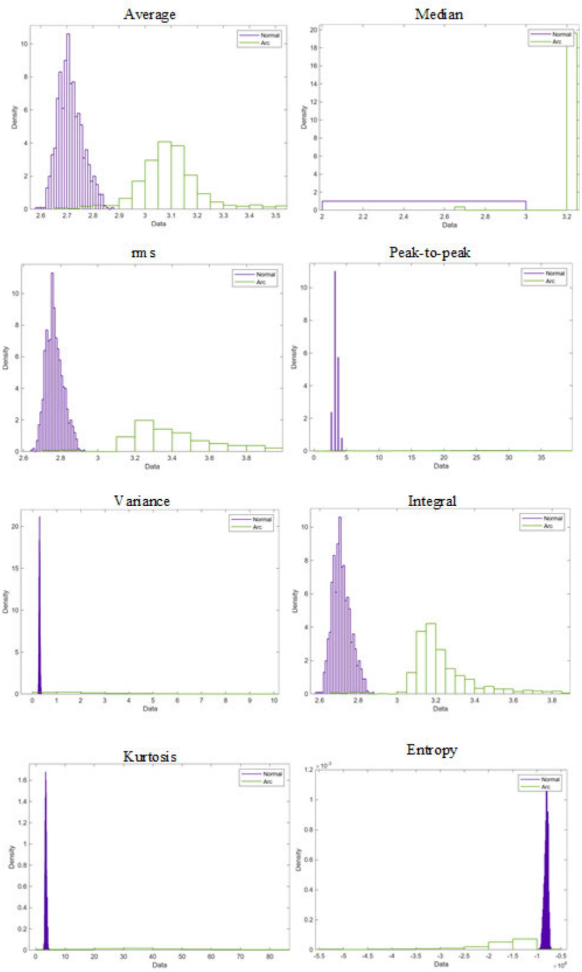

FIGURE 8. **The distribution of time domain features for the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz.**

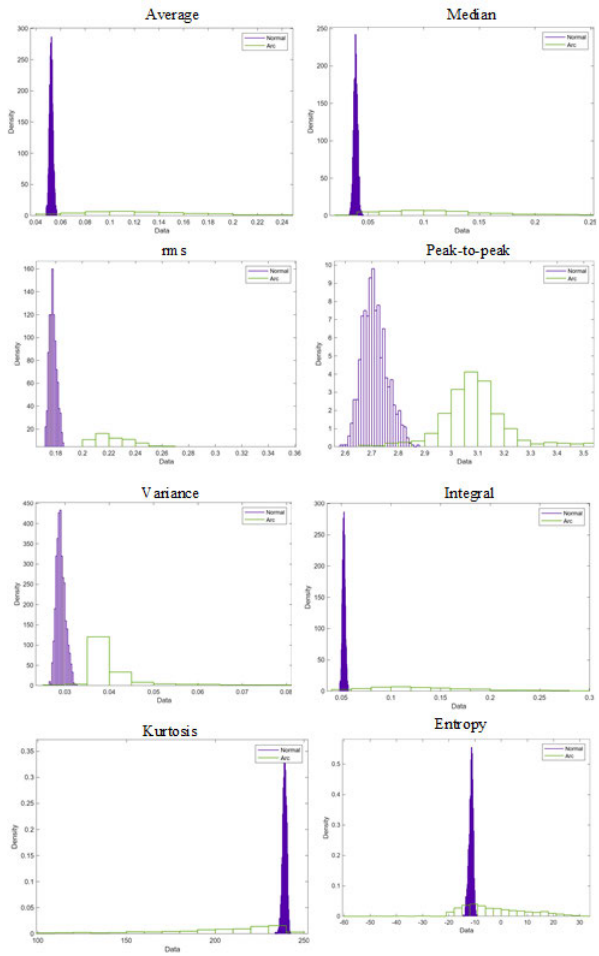

FIGURE 9. **The distribution of frequency domain features for the load current of 3 A with the arc current of 0.5 A at switching frequency of 5 kHz.**

average, median, rms, and integral values, exhibit distinct distributions among different operation states. Whereas, rms, ptp, and variance exhibit distinct distributions between normal and arcing states in frequency domain. Overall, the analysis highlights the significance of both time and frequency domain features in capturing the nuances of signals during different operation states. These features play a crucial role in effective signal classification and provide a foundation for the development of advanced arc fault detection systems.

To conduct experiments to verify the theoretical analysis, a systematic approach should be followed. Set up a laboratory environment or simulation platform that emulates DC parallel arc fault conditions. Ensure that the setup accurately represents real-world scenarios to make the results applicable. Collect a sufficient amount of data representing both normal and fault conditions. This data should include source current signals captured during various fault scenarios. Extract time-domain features and FFT features from the collected data. Ensure that the features are computed accurately and consistently. Implement algorithms for fault detection using both time-domain and FFT features. This may involve training machine learning models or developing rule-based algorithms. Conduct experiments by applying the implemented algorithms to the collected data. Evaluate the performance of each algorithm in terms of fault detection accuracy, and other relevant metrics. Perform statistical analysis to compare the performance of algorithms utilizing time-domain features, FFT features, and their combination.

C. ARTIFICIAL LEARNING MODELS

Support Vector Machines (SVMs) stand out as robust and versatile algorithms extensively utilized in machine learning for diverse tasks, spanning classification to regression. SVM operate on the core principle of delineating data points into separate categories by identifying a hyperplane. This hyperplane serves as a clear boundary. SVMs effectively segregate data while maximizing the distance between different classes. This distance, known as the margin, is vital for optimum sorting functioning, as it ensures robust segregation between classes [19]. In the arena of arc fault detection, a potent implementable algorithm often takes center stage: K-Nearest Neighbors (KNN). Imagine placing a new signal, suspected of harboring an arc fault, amongst a multitude of previously analyzed signals. KNN would then meticulously calculate the distances between this newcomer and all its neighbors, leveraging metrics like Euclidean or Manhattan distances to measure their closeness. But not all neighbors hold equal weight. KNN identifies the k closest companions, those whispering the most similar stories, and ultimately assigns the newcomer the class label most prevalent among this intimate circle. The simplicity and interpretability of this logic make KNN a compelling choice, especially when dealing with complex, non-linear relationships like those often found in arc fault diagnostics. Subsequently, the algorithm evaluates the group categorizations of these data and appoints the most prevalent group classification to the data input. This distinctive procedure fundamentally signifies that the classification of the data input is contingent on the collective ‘‘vote’’ of its nearest labels [20]. Decision Trees (DTs) takes the form of a tree organization, separately node denotes a judgment with a particular aspect, and separately subdivision indicates a potential conclusion. The construction of a DT begins with a particular foundation point containing the intact data inputs. This particular foundation point is divided into numerous sub-nodes using the most explanatory characteristic. The selection of the most informative feature is guided by data factor, which determines the decline in indecision about the classification markers. At individually intersection, a judgement regulation is formulated using the selected characteristic and a divided spot that amplifies data factor. This decision law partitions the information into subdivisions based on the characteristic rate. The procedure of recursive separating endures till a specified interrupting condition is crossed. The terminal points at the end of the structure, known as end-nodes, represent definitive classification or regression predictions [21]. Ensemble learning methodologies (ELM) diverge from single models by leveraging the cooperative knowledge of numerous prototypes to attain high-class functioning. This collaborative approach involves uniting the prognostications of various particularized prototypes, ensuing the outcomes that are more precise and consistent than those of some single prototype. Among the multitude of ELM, Random Forest (RF) emerges as one of the most widely adopted, stemming from the foundational principles of DTs. The mechanics of Random Forest involve constructing a collaborative comprising numerous DTs, individually focused on a distinct subdivision of the fundamental information. A critical hyperparameter in RF is the number of trees, which affects the algorithm's performance and can be adjusted accordingly. While a larger forest generally leads to improved accuracy, it also increases computational demands. Typically, the number of trees chosen falls inside the scale of several hundreds to thousands, achieving a delicate equilibrium between precision and computational productivity [22]. Naive Bayes (NB) utilizes Bayes' statement principles to assemble prognostications. In this framework, the possibility of a components fitting to a particular category is processed with observed features and aforementioned knowledge of the problem domain. The NB algorithm begins by establishing the prior probability for each class. Subsequently, it calculates the provisional possibility of examining the characteristics for each class, assessing the evaluate between characteristic assessments and the particular category. By means of Bayes' theorem, it then computes the subsequent possibility of individually category with the former possibility and the provisional possibilities. This decider possibility represents the category involvement of the information aspect once studying all monitored characteristics. The predicted category is determined by selecting the group with the top subsequent possibility [23].

IV. DIAGNOSIS OF DC PARALLEL ARC FAULT WITH FEATURING FROM DIFFERENT DOMAINS

In the framework of diagnosing DC parallel arc faults, our method strategically leverages the features extracted from the source current, as delineated in Figure 8. This study strategically leverages features extracted from the source current signal, focusing on both time and frequency domains. In the time domain, we meticulously employ eight features, capturing various aspects of the current behavior. Additionally, eight features are extracted in the frequency domain, providing insights into the spectral characteristics of the current signal. Notably, this innovative approach involves combining these features, pairing time averages with frequency averages to generate unique inputs. This comprehensive strategy results in a total of 24 distinct inputs, each contributing to a nuanced understanding of arc behavior. The refined approach underscores the critical importance of feature combinations for achieving enhanced diagnostic accuracy. By combining features from both time and frequency domains, this research captures a broader range of information, enabling more precise fault detection. In each domain - time, frequency, and the combination of both - there are 8,000 data sets for training purpose and 6,400 data set for testing. Therefore, a total of 24,000 datasets are employed for training purposes, while 19,200 datasets are allocated for testing. To ensure a comprehensive evaluation of algorithmic performance, this research maintains a balanced ratio of arcing to normal sets

(1:1) across all cases. This balanced dataset allows to assess the effectiveness of our diagnostic method under both fault and normal operating conditions. The chosen evaluation metric for gauging the efficacy of the ALMs is accuracy. The accuracy rate, representing the ratio of correctly predicted datasets and the total test datasets, stands as a robust measure of algorithmic performance. It is stated as:

$$Accuracy\ rate = \frac{number\ of\ dataset\ correctly\ classified}{all\ the\ dataset\ in\ test\ set} \tag{10}$$

The identification of the best-performing algorithm is grounded in achieving the highest accuracy, underscoring the algorithm's exceptional ability to discern between arcing and normal states with precision. This approach ensures a rigorous assessment and selection of the most effective algorithm for DC parallel arc fault diagnosis.

In the assessment of DC parallel arc fault diagnosis utilizing SVM models, as depicted in Figure 11, the role of input features emerges as a critical determinant of performance. Across various scenarios, certain features prove to be exceptionally effective, with time average, time rms, time median, time integral, and combinations of time and frequency features (average, median, rms, ptp) consistently achieving high accuracy percentages. Additionally, FFT ptp, time ptp, and time kurtosis exhibit reliable performance, contributing significantly to robust fault detection. Conversely, features such as FFT median, FFT rms, FFT kurtosis, and FFT average, while generally reliable, demonstrate slightly lower accuracy when compared to the top-performing features. Particularly, FFT median exhibits less consistent performance across different scenarios, suggesting a potential decrease in reliability for fault detection. This nuanced analysis underscores the crucial importance of selecting appropriate features for DC parallel arc fault diagnosis, with time average, time rms, time median, time integral, and certain feature combinations emerging as the most dependable inputs for accurate and reliable fault detection.

In the diagnostic evaluation of DC parallel arc faults utilizing RF models, presented in Figure 12, a diverse set of input features reveals varying levels of performance. Notably, time average, time median, time rms, and time integral consistently exhibit robust fault detection capabilities across diverse fault scenarios, showcasing high accuracy percentages. These features emerge as reliable indicators, particularly in scenarios involving 0.5A arcs at both 5kHz and 15kHz, as well as 1A arcs at 5kHz. On the other hand, time ptp and time variance, while generally reliable, demonstrate slightly lower accuracy when compared to the top-performing time features. Shifting the focus to frequency domain features, FFT rms, FFT ptp, and FFT variance display commendable performance, contributing to accurate fault detection. However, other FFT features show comparatively lower accuracy in specific scenarios. Interestingly, combining time and FFT features yields the most promising results. These hybrid features demonstrate a balanced performance across fault conditions, mitigating the shortcomings observed in individual time or frequency domain features. This nuanced analysis underscores the importance of selecting and combining features judiciously for effective DC parallel arc fault diagnosis using RF models.

In the diagnostic assessment of DC parallel arc faults utilizing K-Nearest Neighbors (KNN) models, as depicted in Figure 13, the method consistently demonstrates robust performance across diverse fault scenarios. Time average, time median, time integral, time entropy, and time rms emerge as stalwart features, consistently showcasing robust fault detection capabilities and achieving high accuracy percentages. Notably, their performance remains impressive in scenarios involving 0.5A arcs at both 5kHz and 15kHz, as well as 1A arcs at 5kHz, with accuracy consistently reaching or nearing 100%. Time ptp and time variance also display commendable performance, albeit slightly lower than the top-performing time features. Shifting to the frequency domain, FFT ptp, FFT variance, and FFT rms exhibit reliability, contributing to accurate fault detection. While FFT average and FFT median show slightly lower accuracy, their overall performance remains commendable. Similar to the RF model, combining time and FFT features enhances the overall performance, offering a balanced approach to fault detection. This detailed analysis emphasizes the effectiveness of KNN in DC parallel arc fault diagnosis and the significance of selecting and combining features judiciously for optimal performance.

NB emerges as a powerful diagnostic tool for DC parallel arc faults, as illustrated in Figure 14, especially when capitalizing on a synergistic combination of time and frequency domain features. Time features, encompassing average, median, integral, entropy, and rms, effectively capture crucial aspects of signal dynamics over time. These features offer valuable insights into the overall behavior and patterns exhibited during the occurrence of arc faults. The reliability of time features is evident in NB's consistently high accuracy percentages across various fault scenarios, such as 0.5A arcs at both 5kHz and 15kHz, as well as 1A arcs at 5kHz. In the frequency domain, NB strategically utilizes FFT features, including ptp, variance, and rms, to analyze the spectral characteristics of the signal. This domain provides information about the frequency components present in the signal, offering a complementary perspective to time-domain analysis. The efficacy of NB in leveraging frequency features is demonstrated by its robust fault detection capabilities, even in scenarios with challenging conditions. The combination of time and FFT features harnesses the strengths of both domains, capturing nuanced information about the signal. This synergistic integration enhances fault detection accuracy by providing a more comprehensive view of the underlying signal features. The amalgamation of time and FFT features compensates for potential limitations in each domain, resulting in a more robust diagnostic model.

Figure 15 illustrates the diagnostic prowess of DT in detecting DC parallel arc faults, revealing consistent high accuracy across various fault scenarios. When scrutinizing a 3A load and 0.5A arc, whether at 5kHz or 15kHz, DT excels in capturing distinctive features from both time and frequency domains. The robust performance of DT across individual features, such as time average, time median, time rms, time integral, FFT ptp, FFT variance, and the combinations of time and frequency features, underscores its capability to discern complex fault patterns. Expanding the analysis to a 5A load with 0.5A and 1A arcs, time average, time median, FFT ptp, FFT variance, and the combinations of time and frequency features continue to demonstrate reliability in fault detection. Notably, these diagnostic results are evident in scenarios with varying fault intensities, emphasizing its adaptability to different fault conditions. The amalgamation of time and FFT features further elevates DT's performance, showcasing a harmonized approach to fault diagnosis.

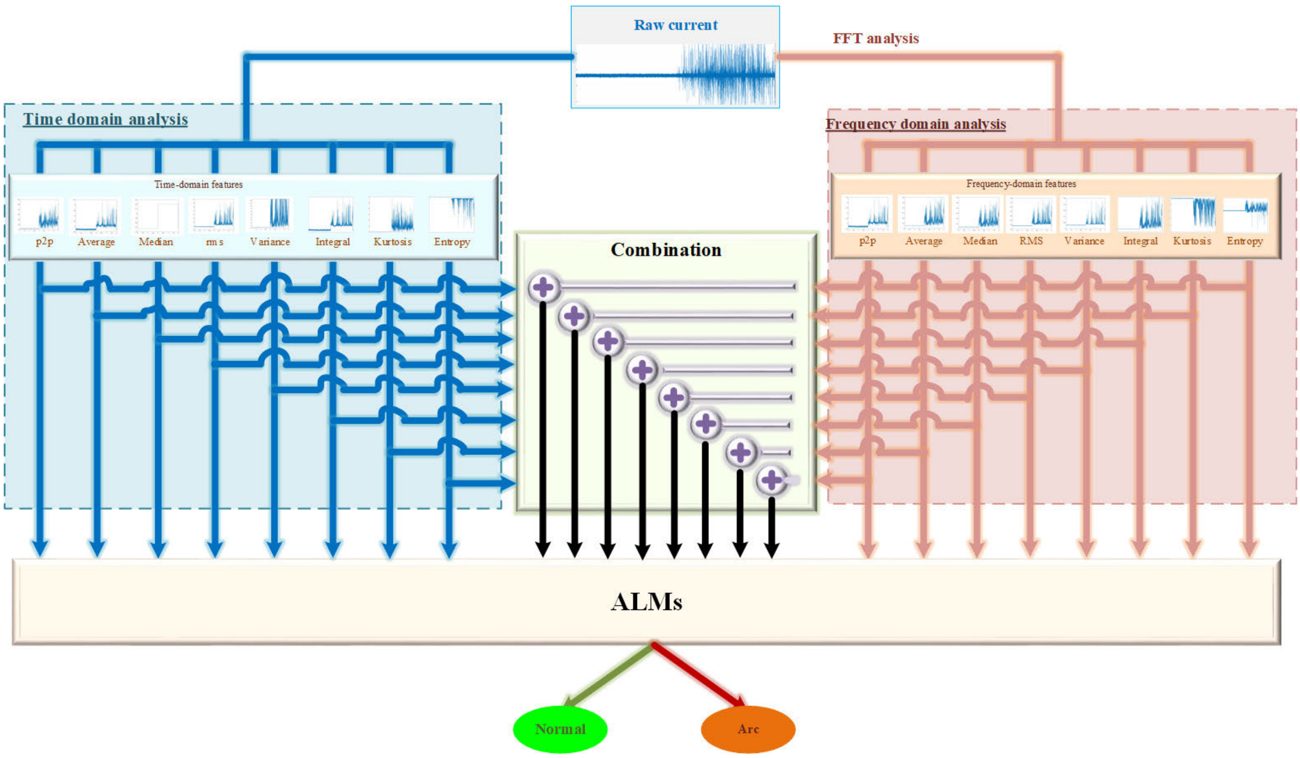

FIGURE 10. The diagnosis scheme for DC parallel arc faults with featuring from time and frequency domain.

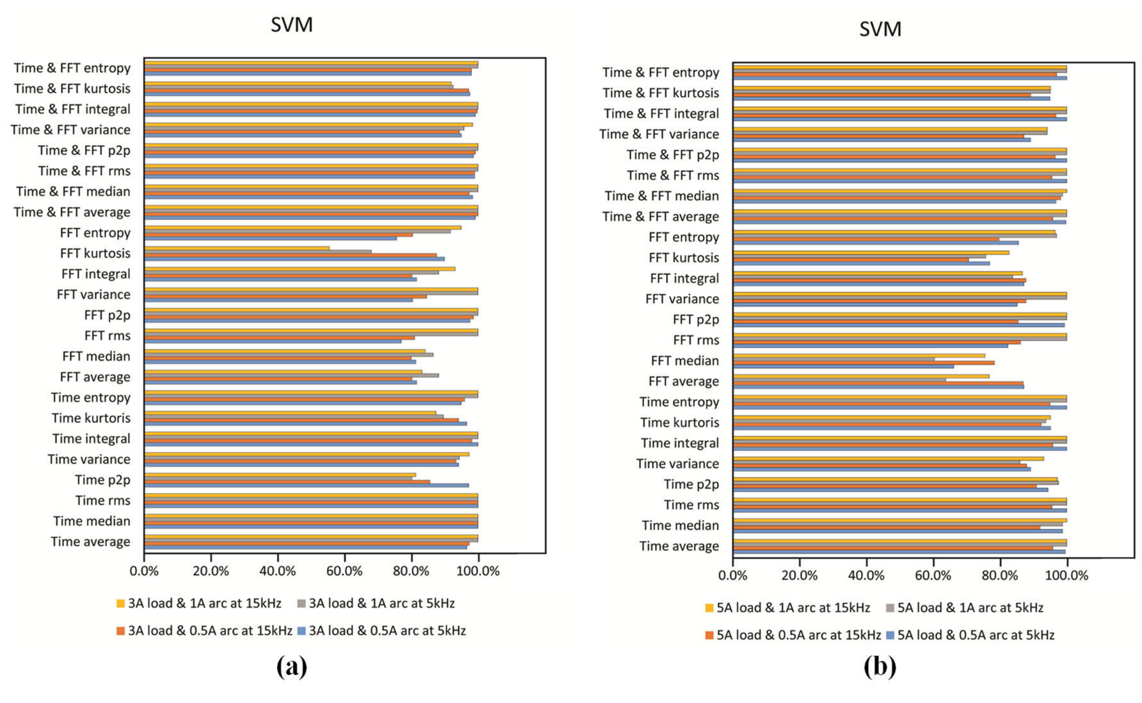

FIGURE 11. Detecting accuracy of SVM (a) 3 A load current amplitude. (b) 5 A load current amplitude.

Figure 16 presents a comprehensive overview of the diagnostic performance of various input features under different Artificial Learning Models (ALMs) for detecting DC parallel arc faults. Time-domain features, encompassing metrics such as average, median, integral, and rms, consistently exhibit superior performance across different fault scenarios. These

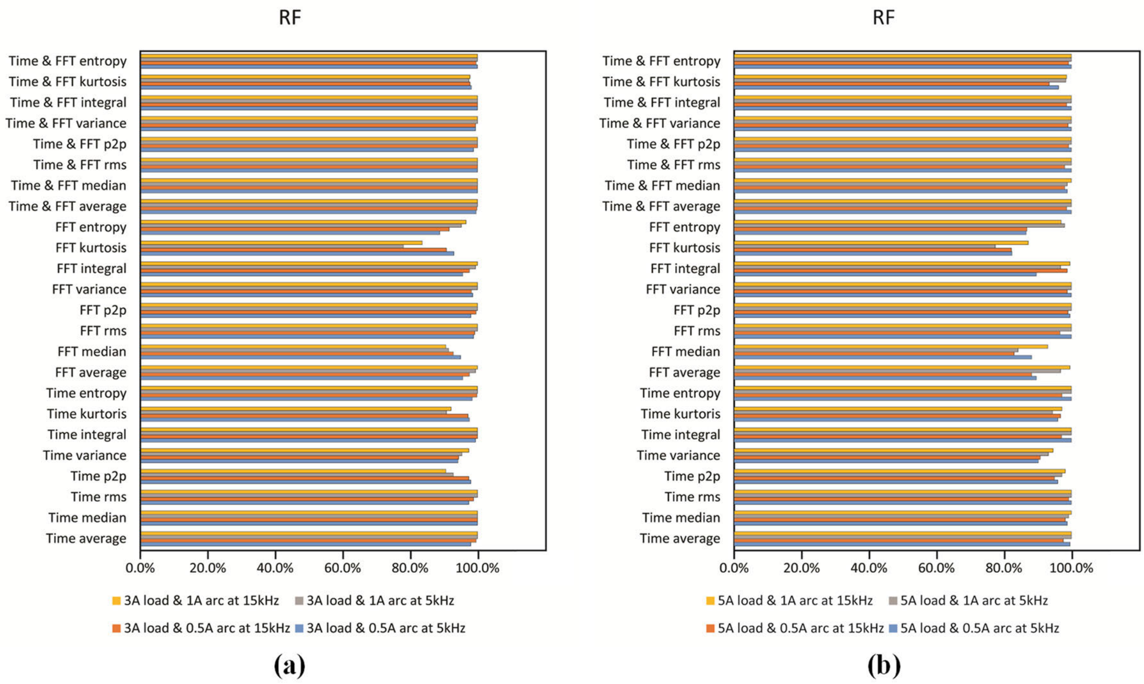

FIGURE 12. Detecting accuracy of RF (a) 3 A load current amplitude. (b) 5 A load current amplitude.

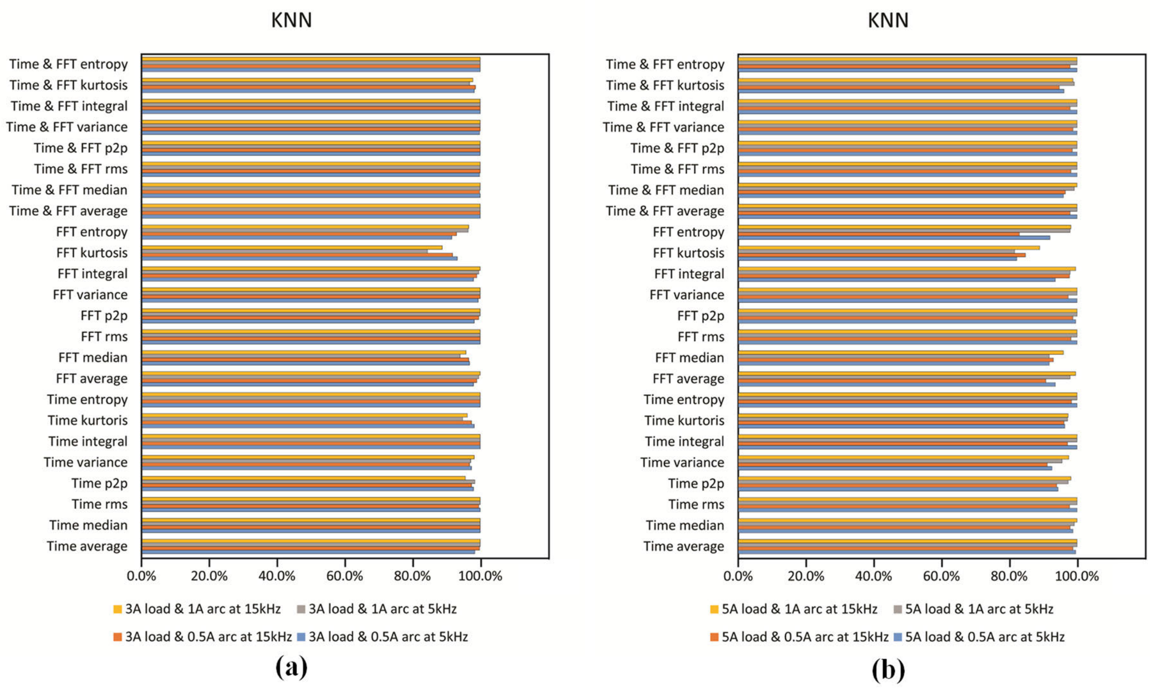

FIGURE 13. Detecting accuracy of KNN (a) 3 A load current amplitude. (b) 5 A load current amplitude.

features effectively capture the temporal characteristics of signals, providing valuable insights into the dynamic behavior during arc faults. The reliability of time-domain features is evident in their robustness across different fault magnitudes and frequencies, showcasing their adaptability to diverse conditions. On the other hand, FFT features, including average, median, and rms, demonstrate slightly lower accuracy compared to time-domain features. While FFT features offer

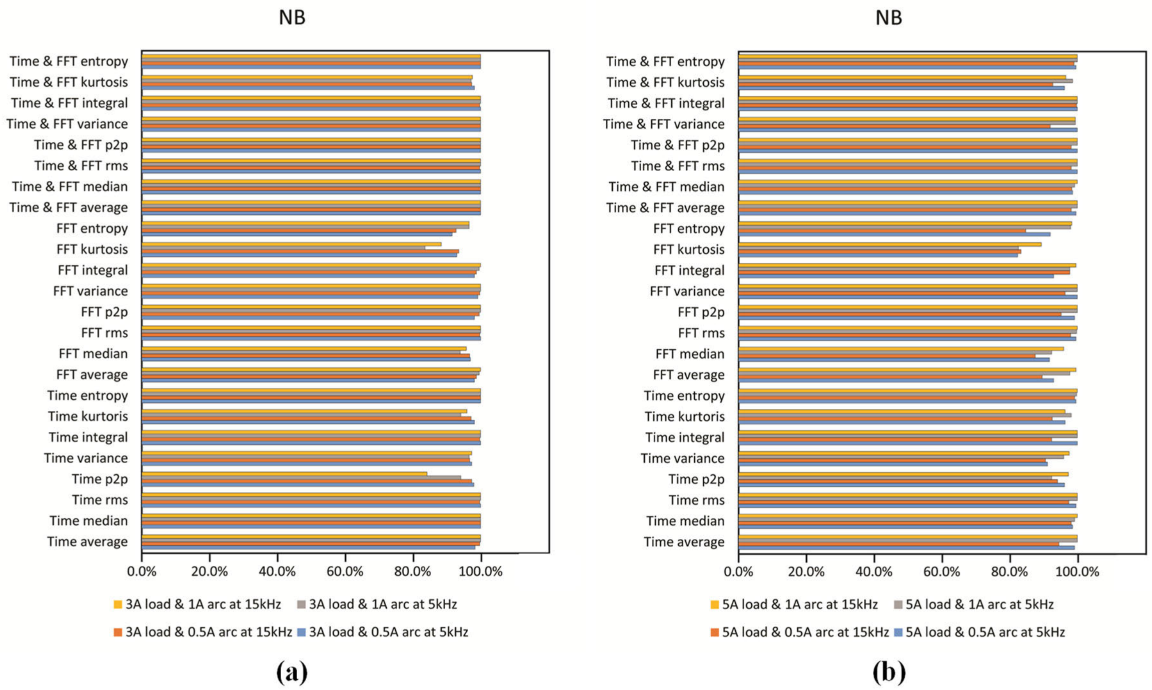

FIGURE 14. Detecting accuracy of NB (a) 3 A load current amplitude. (b) 5 A load current amplitude.

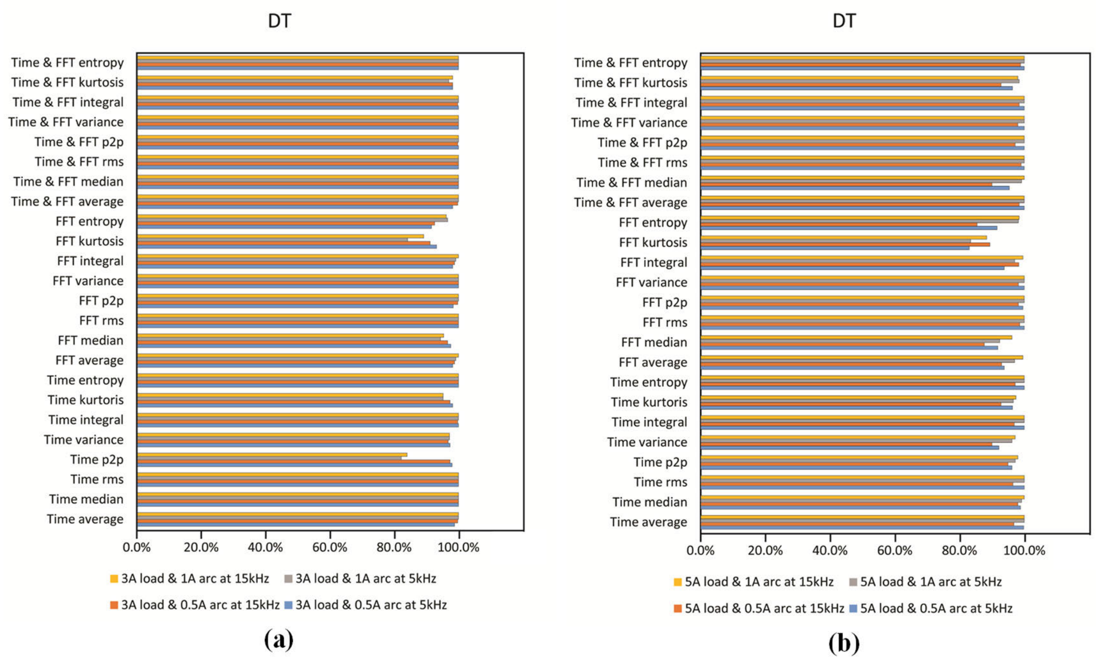

FIGURE 15. Detecting accuracy of KNN (a) 3 A load current amplitude. (b) 5 A load current amplitude.

insights into the spectral components of the signal, they might face challenges in capturing nuanced temporal dynamics. The limitations of FFT features are particularly noticeable in certain fault scenarios, where their performance is surpassed by time-domain counterparts. The combination of time and FFT features presents a compelling approach to fault detection. This fusion leverages the strengths of both domains, compensating for the limitations inherent in each. The synergistic

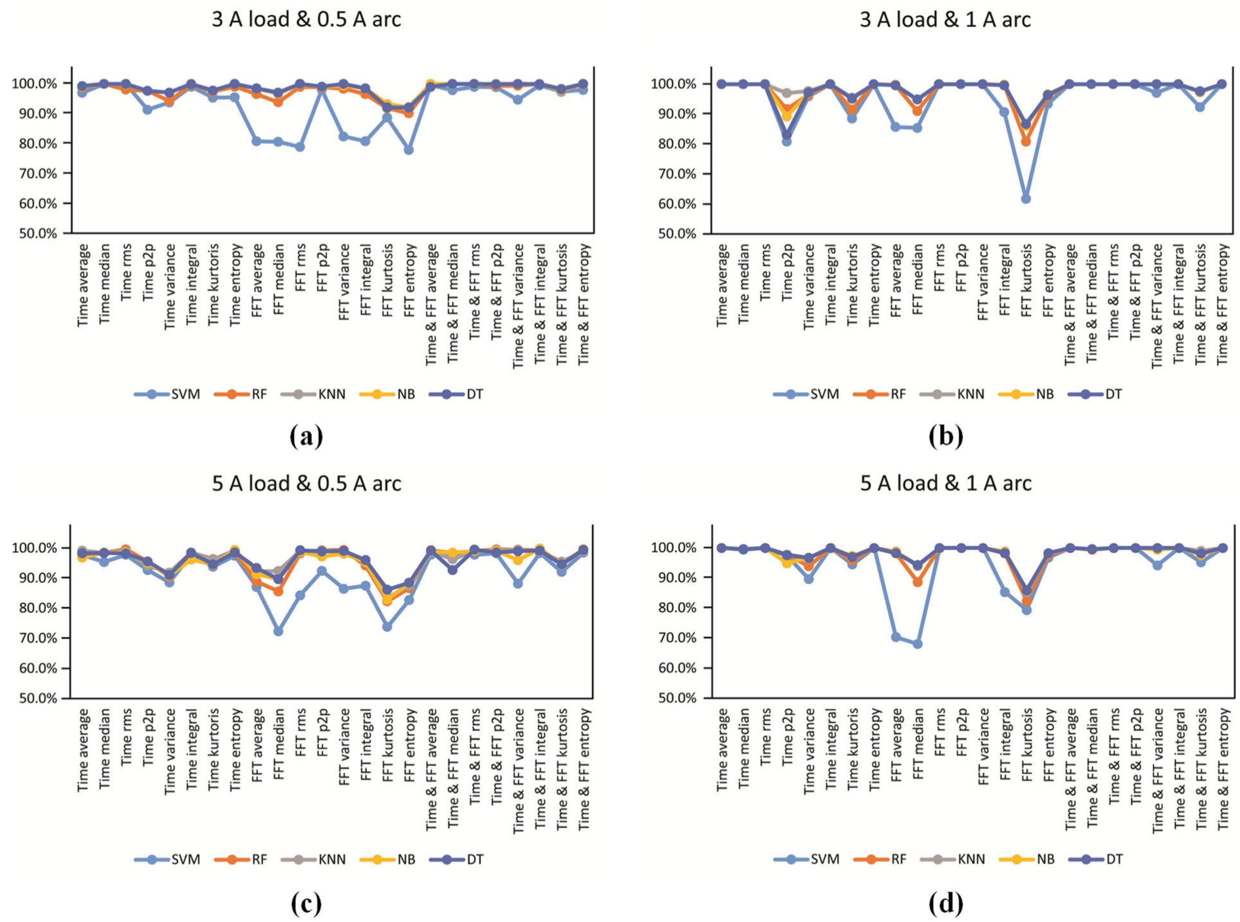

FIGURE 16. Overall detecting accuracy of AIL models (a) 3 A load current amplitude and 0.5 A arc current. (b) 3 A load current amplitude and 1 A arc current. (c) 5 A load current amplitude and 0.5 A arc current. (d) 5 A load current amplitude and 1 A arc current.

TABLE 2. Comparisons of different arc fault diagnosis approaches.

Approaches	Input	Features	Techniques
Approach 1 [24]	Time-domain current	Current spike and arc energy	Signal processing
Approach 2 [25]	Frequency-domain current	Sum of frequency spectrum	Signal processing
Approach 3 [17]	Time- and frequency-domain signals	Raw data time- and frequency-domain current	Intelligence learning techniques
Proposed approach	Time- and frequency-domain source current	Featuring from time and frequency domains	Intelligence learning techniques

effect enhances the overall diagnostic accuracy, providing a more comprehensive understanding of the signal characteristics. This combination proves beneficial in scenarios where fault patterns are complex and multifaceted. In summary, while time-domain features outperform FFT features in DC parallel arc fault detection, the combination of both domains emerges as a powerful strategy. Time features offer robust insights into the temporal dynamics of signals, whereas FFT features contribute spectral information.

Table 2 provides a comprehensive summary of the detection accuracies achieved by different approaches, including approaches 1 [24], 2 [25], and 3 [17], all of which achieved 100% accuracy. The comparison among these approaches sheds light on their methodologies and techniques in achieving high detection accuracies for DC parallel arc faults. Approach 1 showcases the efficacy of utilizing specific features extracted from time-domain signals for accurate fault detection. However, its reliance on manually engineered features such as current spike and arc energy may limit its adaptability to diverse operating conditions and fault scenarios, potentially overlooking certain arc behaviors. Approach 2 emphasizes the potential of frequency-domain analysis in identifying arc faults, particularly through the examination of spectral components. Nonetheless, the simplicity of summing the frequency spectrum may oversimplify the nuanced characteristics of arc signatures, potentially compromising detection robustness. Approach 3 harnesses the power of artificial intelligence to analyze complex data from multiple domains, resulting in accurate fault detection. However, its drawback lies in using raw data from both domains without extensive feature engineering, potentially hindering its ability to extract relevant information effectively. In contrast, the proposed approach combines the strengths of both time and frequency domains by utilizing time- and frequency-domain source current signals. This approach integrates features from both domains and employs intelligence learning techniques for fault detection, demonstrating the effectiveness of integrating diverse features for enhanced fault detection.

Considering the complexity and nuances associated with diagnosing DC parallel arc faults, leveraging deep learning techniques could indeed be a promising approach. Deep learning models, particularly neural networks, have demonstrated remarkable capabilities in handling intricate patterns and relationships within data. By training deep learning models on a diverse dataset comprising both normal and fault conditions, it's possible to extract intricate features and patterns that may not be easily discernible using traditional methods. However, the decision to adopt deep learning should be carefully considered based on quality of data, computational resources and so on. In general, deep learning models need a lot of labeled data for training, which may pose challenges in certain scenarios where data collection is limited or expensive. Moreover, the implementation of deep learning models necessitates significant computational resources, including powerful hardware and potentially lengthy training times. Additionally, the interpretability of deep learning models can sometimes be a concern, as they operate as black boxes, making it challenging to understand the underlying mechanisms driving their decisions. Despite these challenges, the potential benefits of employing deep learning for DC parallel arc fault diagnosis are substantial. Deep learning models have the capacity to automatically learn complex representations from data, potentially leading to more accurate and robust diagnostic systems. Therefore, while careful consideration of the associated challenges is warranted, exploring the application of deep learning in this context could offer valuable insights and advancements in arc fault detection technology.

V. CONCLUSION

In conclusion, the investigation into DC parallel arc fault diagnosis presents notable findings that significantly contribute to the understanding and enhancement of diagnostic accuracy in electrical systems. The source current emerges as a key signal that encapsulates critical information about the system's behavior during fault conditions. Its significance suggests that focusing on this parameter can lead to more effective fault detection strategies. Further investigation into the source current involves a detailed analysis of time-domain features, FFT features, and their combinations. It is observed that time-domain features consistently exhibit superior performance across different fault scenarios compared to FFT features. Time-domain features, such as average, median, integral, and rms, effectively capture the temporal characteristics of signals and provide valuable insights into the dynamic behavior during arc faults. FFT features, offering a spectral perspective of the signal, complement the time-domain features. While slightly trailing in accuracy compared to time-domain features, FFT features contribute valuable frequency-related information. However, the combination of time and FFT features presents a compelling approach to fault detection. This fusion leverages the strengths of both domains, compensating for the limitations inherent in each. The synergistic effect enhances the overall diagnostic accuracy, providing a more comprehensive understanding of the signal characteristics. This combination proves beneficial in scenarios where fault patterns are complex and multifaceted. However, it's essential to recognize the trade-offs between time and frequency domains. Time-domain features might excel in capturing temporal dynamics but could be less effective in representing frequency-related characteristics. Conversely, FFT features may provide spectral insights but might struggle with nuanced temporal patterns. The choice between the two should be driven by the specific diagnostic requirements and the nature of the fault conditions. In essence, the investigation into DC parallel arc fault diagnosis not only highlights the impact of switching frequency and the significance of source current but also underscores the effectiveness of a multi-faceted approach. Integrating time-domain and FFT features offers a robust strategy for fault detection, balancing the strengths and weaknesses of each domain. This nuanced understanding contributes to the development of more reliable and adaptable fault detection systems in electrical systems.

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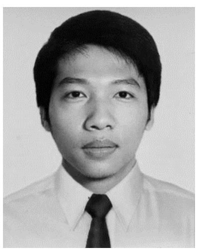
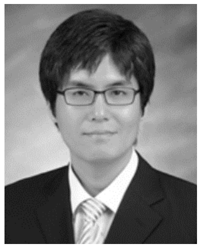
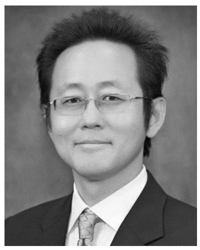


HOANG-LONG DANG received the B.S. degree in electrical and electronics engineering from the Ho Chi Minh City University of Technology, Vietnam, in 2015. He is currently pursuing the combined M.S. and Ph.D. degree in electrical and electronics engineering with Chung-Ang University, Seoul, South Korea. His research interests include matrix converters, fault detections, and artificial intelligence.



SANGSHIN KWAK (Member, IEEE) received the Ph.D. degree in electrical engineering from Texas A&M University, College Station, TX, USA, in 2005. From 2007 to 2010, he was an Assistant Professor with Daegu University, Gyeongsan, South Korea. Since 2010, he has been with Chung-Ang University, Seoul, South Korea, where he is currently a Professor. His current research interests include the design, modeling, control, and analysis of power converters for electric vehicles and renewable energy systems as well as the prognosis and fault-tolerant control of power electronics systems.



SEUNGDEOG CHOI (Senior Member, IEEE) received the B.S. degree in electrical and computer engineering from Chung-Ang University, Seoul, South Korea, in 2004, the M.S. degree in electrical and computer engineering from Seoul National University, Seoul, in 2006, and the Ph.D. degree in electric power and power electronics from Texas A&M University, College Station, TX, USA, in 2010. From 2006 to 2007, he was a Research Engineer with LG Electronics, Seoul. From 2009 to 2012, he was a Research Engineer with Toshiba International Corporation, Houston, TX, USA. From 2012 to 2018, he was an Assistant Professor with The University of Akron, Akron, OH, USA. Since 2018, he has been an Associate Professor with Mississippi State University, Starkville, MS, USA. His current research interests include degradation modeling, fault-tolerant control, and fault-tolerant design of electric machines, power electronics, batteries, solar panels, and wider vehicular/aircraft microgrid systems.