11th International Conference on Power Electronics-ECCE Asia
May 22 - 25, 2023 / ICC Jeju, Jeju, Korea

SVM-based series arc detection algorithm for photovoltaic system

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***Abstract*-- In this paper, we present a SVM-based series arc detection algorithm for photovoltaic system. SVM is a technique of extracting a hyperplane that maximizes the margin between series arc fault samples and normal state samples from training dataset and arc noise can be effectively classified using the extracted hyperplane. As input parameters for SVM, various DWT-based feature parameters are used. The hyperplane for determining the class is obtained on initial step, and this is applied to the arc detection algorithm for SVM testing. The real-time arc detection test is performed through TMS320f28335 DSP. It is verified that not only the series arc can be successfully detected with SVM-based algorithm, but also the detection time is satisfied the required detection time of the UL1699B safety standards.**

***Index Terms*—** Machine learning, Series arc detection, Support vector machine

I. Introduction

Arcs generated in photovoltaic power generation systems include series arcs, parallel arcs, and ground fault arcs. Parallel arc has a high probability of arc detection because a current close to the short-circuit current is instantaneously generated. However, in the case of a series arc, the amplitude of the current does not change significantly because it acts the same as adding a series impedance between contacts, and it is broken by the load and the size of the current is limited [1]. In addition, there is a problem in that the PV module, which is a DC current source, is not extinguished by itself during the daytime when solar radiation exists. Therefore, various studies for detecting series arcs are being conducted. The important points are detection accuracy, detection time, and applicability. The series arc detection device can be applied in the form of an AFCI that cuts off power when detected, or can be applied to control an operating point by transmitting a trip signal to a PV inverter. Therefore, the accuracy of the detection can affect the power output, i.e. the economics of the PV plant. Also, according to the UL1699B standard, in order to prevent a fire caused by a DC series arc, it must be detected and extinguished within 2 seconds from the moment of occurrence of the arc [2]-[4]. Also, the detection criteria of the arc detection device may vary depending on the system, and should be universally applied to most systems through the flexibility of the detection criteria.

In general, a frequency analysis technique such as FFT or DWT is used as an arc detection technique, and a detection technique through noise pattern analysis has also been studied [5]-[11]. However, there is a difficulty in tuning the detection criteria.

Recently, various machine learning techniques have been studied, and regression problems, classification problems, and clustering problems are being solved through data learning. Support vector machine (SVM) is a representative technique that can derive an optimal solution for classification problems. It can model a hyperplane that separates samples corresponding to different classes with the maximum margin.

Therefore, it can also be applied to the problem of classifying normal current and arc current. In addition, SVM can propose adaptive classification criteria for system operating conditions through training and proper normalization.

We propose an SVM-based arc detection algorithm that classifies the series arc fault and normal state with the extracted hyperplane, which maximizes the margin between series arc fault samples and normal state samples from training dataset. In chapter 3, feature parameters for series arc detection are proposed, and in chapter 4, the application of the arc detection algorithm to a microprocessor-based series arc detection device is covered.

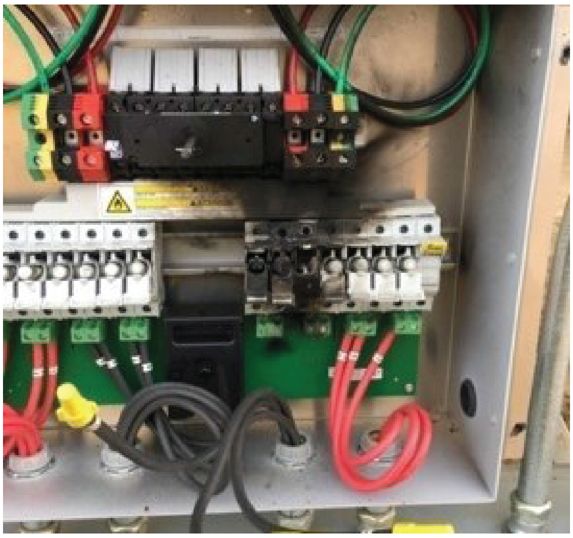


Fig. 1. Picture of series arc fire hazard

Also, in Chapter 5, data acquisition from various systems, and arc detection accuracy according to combination of datasets and normalization are presented. This algorithm is applied into TMS320F28335 DSP for performance of real-time arc detection tests and the performance of SVM-based arc detection algorithms is verified.

II. SVM-BASED ARC DETECTION

SVM is a machine-learning technique that extract optimal threshold distinguishing the classes based on training samples. SVM mathematically calculates a hyperplane that can separate classes in the training data with the largest margin in the training data as shown in Fig. 1. When the new data comes, series arc detection can be achieved by comparing with the pre-modeled hyperplane as shown in the Fig. 3. The hyperplane that maximizes the margin between the arc fault samples and the normal samples is derived.

$$w^T x + b = 0 \tag{1}$$

Here, W is normal vector of hyperplane and b is the bias. The extracted hyperplane is applied as a criterion for determining the occurrence of DC series arc in real-time.

In the case of series arc detection, it is binary classification because it can be classified into two classes, i.e., normal current and arc current. Since the distribution of extraction parameters between normal current and arc current shows a similar tendency for each PV system, the hyperplane kernel is selected as a polynomial kernel.

$$\text{Polynomial kernel :}\ K\langle x_1, x_2\rangle = \left(\alpha\langle x_1, x_2\rangle + \beta\right)^d = 0 \tag{2}$$

When hyperplanes are modeled, classifiers are modeled with hard margins or soft margins depending on how much training error is tolerated.

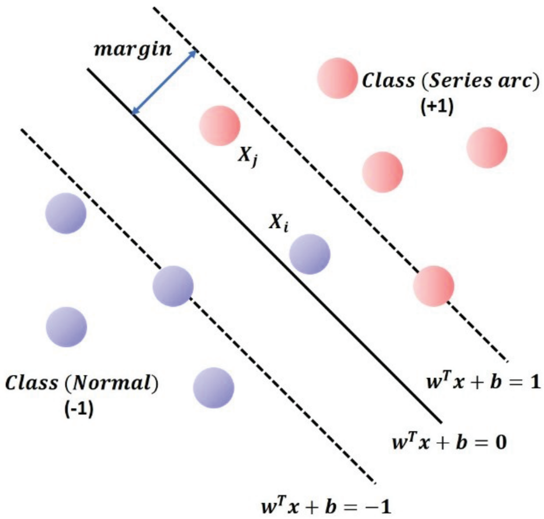


Fig. 2. SVM training conceptual diagram

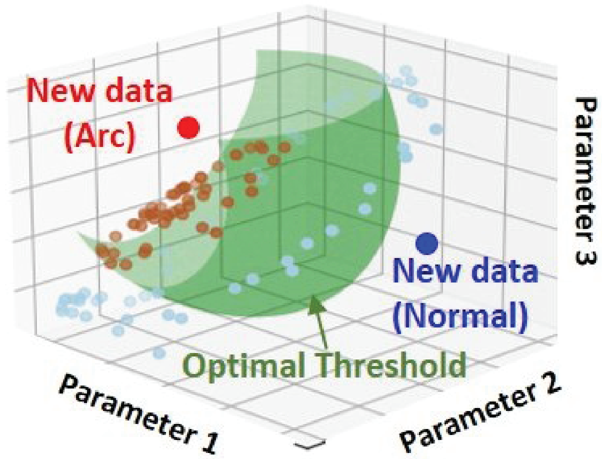


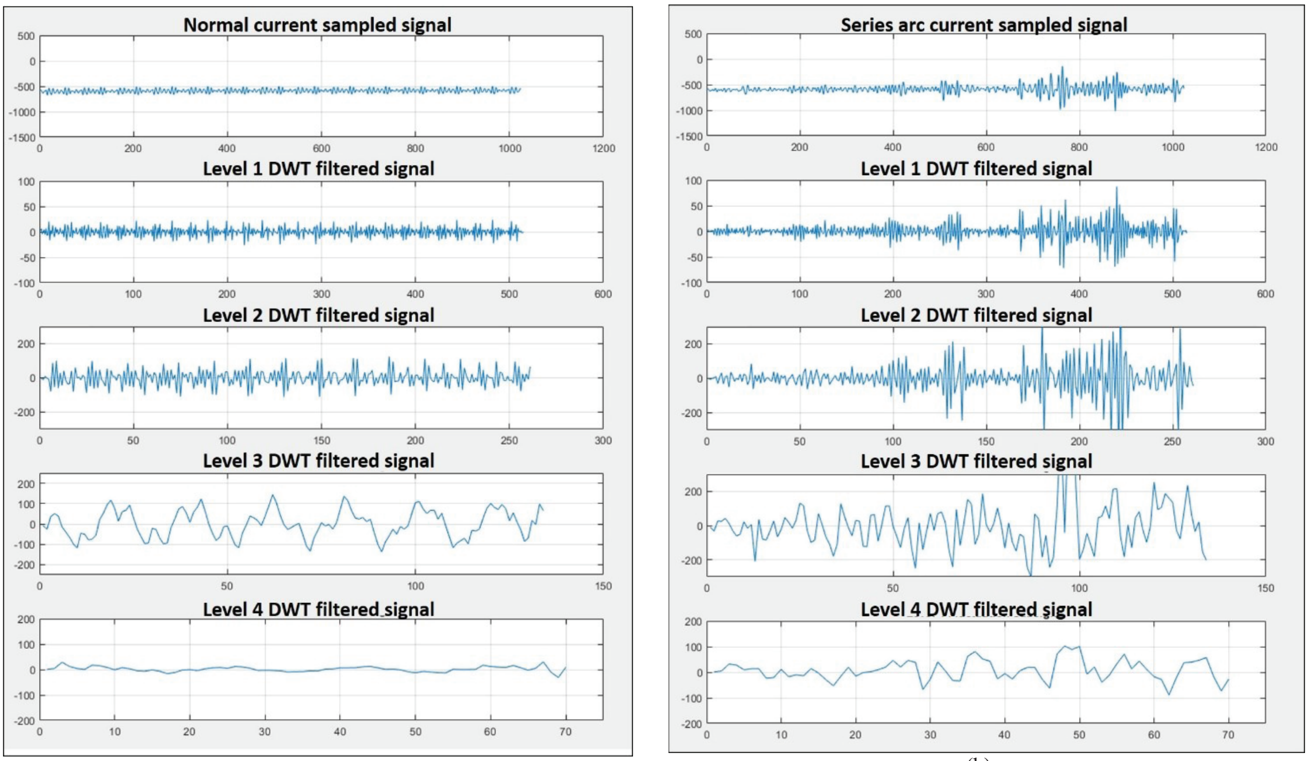
Fig. 3. SVM testing conceptual diagram

The cost parameter determines the trade off between the margin of the classifier and the training error. The larger the cost, the less training error is allowed, but the lower the margin, the more it is modeled as an overfit classifier. Conversely, the smaller the cost, the more training error is allowed, but the margin can be increased by that much. In this study, the cost was selected to lower the training error rather than increase the margin.

III. FEATURE PARAMETERS FOR CLASSIFICATION

In this study, the arc detection method detects the noise component of the series arc by sensing the string current. A current transformer (CT) or a Rogowski coil can be used for current sensing. When a series arc occurs, the frequency component of the series arc noise has a Gaussian distribution, but a method of detecting the series arc noise in a high frequency region by applying an analog filter is used to distinguish it from system noise such as inverter switching noise. In addition, the acquired current information filters low-frequency signals through a DWT-based signal processing process and analyzes only high-frequency signals to effectively determine the presence or absence of a series arc. The input parameters were selected in consideration of the detection accuracy. The input parameter dataset obtained in advance through the DWT analysis method is used for SVM training.

Figure 4 shows the analysis of the current sample data obtained during normal current and arc current by the DWT technique. Through DWT, only signals with high frequency components can be extracted based on the frequency corresponding to the sampling rate/2 of the existing signal. Signals extracted from level 1 to level 4 through DWT decomposition have different frequency bands [12]. The noise component shown in Fig. 4 (a) represents the noise component due to the PV inverter's switching and current ripple. The noise component due to the PV inverter and the series arc noise component are overlapped in Fig. 4 (b).



(a) (b)

Fig. 4. DWT analysis of normal current and series arc current (a) Normal current (b) Series arc current

Various statistics-based characteristic parameters such as Average, RMS, and Deviation can be utilized for series arc detection from the analyzed DWT signal. In this paper, when a series arc occurs, the high-frequency noise is larger than the normal current, and parameters for detecting the series arc are applied by analyzing these characteristics. In addition, parameters that can be analyzed relatively easily in the time domain through a stand-alone type embedded-based DSP were selected.

The first parameter is a parameter representing the density of current samples in a specific range from zero of high-frequency noise for current data sampled in the time domain. In order to extract the corresponding parameter, selection of an appropriate range is required, which is selected in the range of about 50% to 80% of the entire sample. This parameter represents a characteristic in which the density of current samples within a specific range decreases due to high-frequency noise when a series arc occurs.

Range_count = countif (-range < sample[i] < +range) (3)

Figure 5 shows an example of extracting the range count parameter value from about 30 dwt sample signals, and 12, the number of samples within the range, is derived. The second parameter is a parameter for extracting the degree to which the rate of change of the current sample is greater than the average rate of change of the current sample at the time of normal current, by using the high-frequency characteristics of the series arc noise. In order to extract this parameter, the average rate of change of the current sample should be periodically updated every cycle.

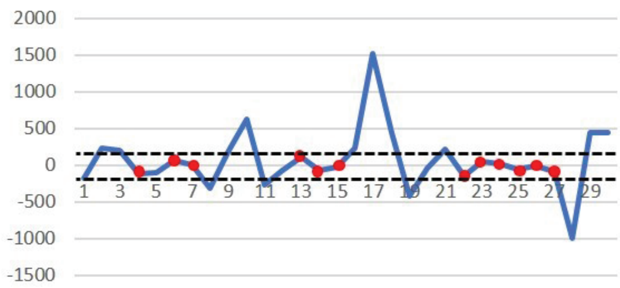


Fig. 5. Extraction of range count parameter

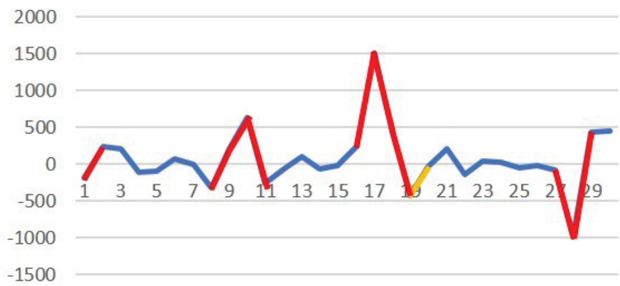


Fig. 6. Extraction of displacement count parameter

Displacement_count = countif (sample[i]-sample[i-1] > average_displacement) (4)

Figure 6 shows an example of extracting the displacement count parameter value from about 30 dwt sample signals. When the displacement between the 19th sample and the 20th sample is the average displacement, 8, which is the number of sections representing the displacement exceeding the average displacement, is extracted.

The third parameter is an absolute mean parameter to determine the amplitude of the high-frequency component of the series arc. Since low-frequency signals are filtered by applying an advanced analog filter and a DWT-based digital filter, there is an advantage in that only the amplitude of high-frequency arc noise excluding system noise can be extracted with a simple parameter.

$$Absolute\_mean = \frac{\sum_{i=1}^{n} \left| sample[i] \right|}{n} \tag{5}$$

IV. Implementation of SVM-based Arc Detection Algorithm

The SVM-based arc detection algorithm is applied to a stand-alone series arc detection board, and the flowchart of the algorithm is shown in Figure 7. The current sample data obtained in advance by the offline method is trained to model a hyper plane that distinguishes samples in the case of normal current and samples in the case of series arc current based on the selected cost, gamma, and kernel. The feature parameters presented in Chapter 3 are used as input parameters for SVM training. Figure 8 shows the declaration of dataset including class number, and the value of feature parameters.

The TMS320F28335 DSP was used for data acquisition and algorithm execution. There is a memory limit to store enough training data, therefore it is important to model a hyperplane that can accurately distinguish between normal current and arc current with a small amount of data. This is related to the normalization of SVM input data, and a technique was applied to store the rate of change of each parameter extracted from the current sample and use it as input data for efficient memory utilization and arc detection accuracy improvement. Figure 9 shows the transmitted information from TI DSP that the training error achieved 0% with only 82 input data.

After training is completed in the initial stage, the algorithm loop starts. Current sensor senses the string current and the analog signal is filtered and amplified. Here, the band width of analogue filter is designed having the cutoff frequency above inverter switching frequency. Next, current sampling through ADC are performed every loop. For analysis of high frequency component, ADC sampling speed is selected as 800 kHz.

A DWT analysis technique is performed to detect the sampled current sample using the high-frequency characteristics of the series arc noise. DWT extracts low-frequency component signals and high-frequency component signals using Daubechies 4 wavelet filter, and extracts feature parameters using only high-frequency component signals.

Feature parameters are extracted for each DWT level's signal and the normalization is conducted. SVM testing is performed using the extracted normalized parameters and the hyperplane modeled in the initial training. Through testing step, the class of testing data is determined, and if the class of testing data is determined as a fault class, the series arc fault is detected.

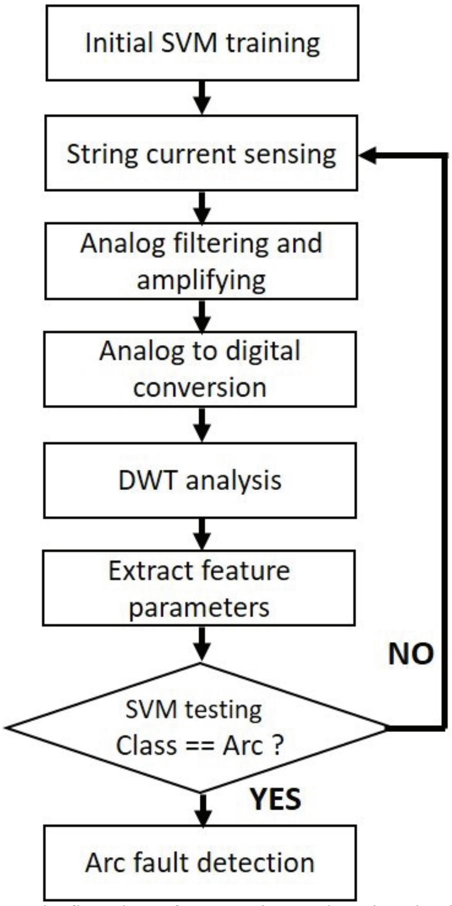


Fig. 7. The flow chart of SVM series arc detection algorithm.

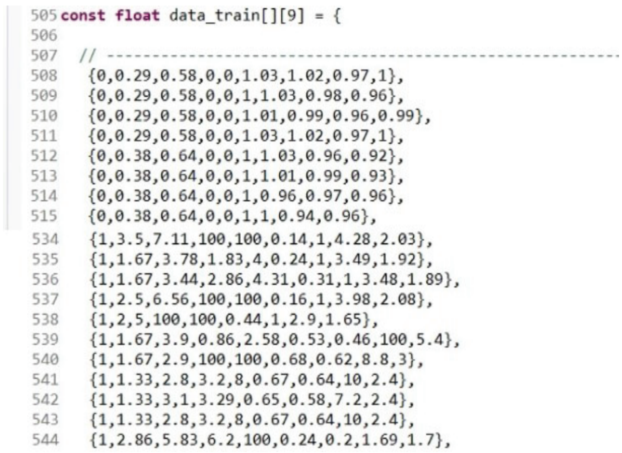


Fig. 8. Sample of SVM Training input dataset

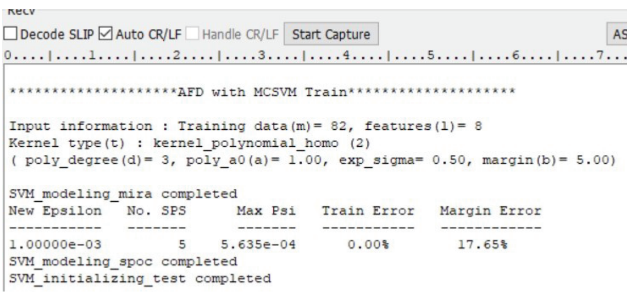


Fig. 9. SVM Training result on TI DSP

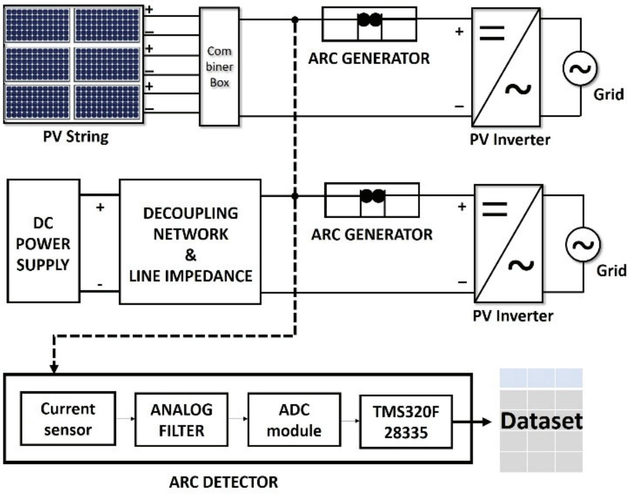


Fig. 10. Series arc test circuit

V. EXPERIMENTAL RESULTS

Series arc generation and training data collection were conducted. First, the collection was performed in a real PV system including PV modules and PV inverters, and second, in a test facility simulating a PV system according to the UL1699B standard using a DC power supply, line impedance, and decoupling network. A Rogowski coil and current transformer were used as current sensors for sample acquisition. A series arc was generated using a motorized arc generator including copper electrodes.

The arc detection time including ADC sampling time, DWT decomposition and SVM classification is presented. The series arc detection test with real-time DSP is conducted on the UL1699B test circuit as shown in Fig. 3. DC power supply, decoupling network and line impedance simulate the PV panel and cable. Also, arc generator generates the series arc on the input string of PV inverter. The performance of distinguishing the series arc and normal state is verified through the training accuracy and arc detection time.

In the system of figure 10, current samples were acquired using current sensors, and feature parameters were extracted and datasets were collected using DSP. Table 1 shows the classification accuracy according to the combination of collected datasets. Testing accuracy is greatly affected by the type of current sensor, tested system, and training of testing data. That is, the arc detection algorithm requires prior training under the corresponding experimental conditions for high classification accuracy. However, by applying normalization, the classification accuracy were improved by more than 98% even when testing data were not included in the training. Figure 11 shows the waveforms for detecting series arc by applying the normalization when series arcs occur in an untrained system condition. When the arc fault is detected, the AFD signal changes to high. The series arc was successfully detected within one cycle, and it took about 5 milliseconds from the occurrence of the arc to the detection. It is verified that it satisfies the required detection time of the UL1699B safety standards.

Figure 12 shows the example of distribution for dataset of normal current and series arc current. X-axis is value of range_count parameter and y-axis is displacement_count parameter. These samples can be divided into separated classes without error samples even by linear hyperplane. Also, since the SVM input dataset have eight feature parameter, the classifier modeling can be easily achieved without any error sample.

TABLE I
CLASSIFICATION ACCURACY ACCORDING TO DATASET AND TESTING CONDITION

Variety of current sensor	Variety of system	Numbers of training and testing data	Testing data included in training data	Classification Accuracy without normalization	Classification Accuracy with normalization
2	1	122	Included	70.8%	100%
1	1	50	Included	100%	100%
1	2	98	Included	100%	100%
2	3	148	Included	96.7%	99.3%
3	4	270	Included	94.4%	100%
2	1	75	Not Included	72.3%	100%
2	1	122	Not Included	53.3%	100%
2	3	148	Not Included	62%	98.64%
3	4	270	Not Included	60.1%	98.88%

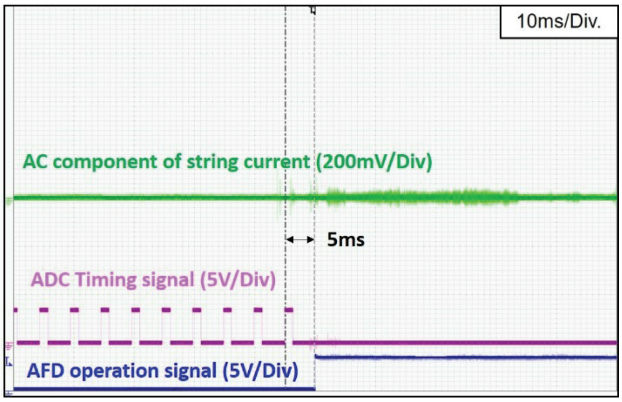


Fig. 11. Waveform of series arc detection

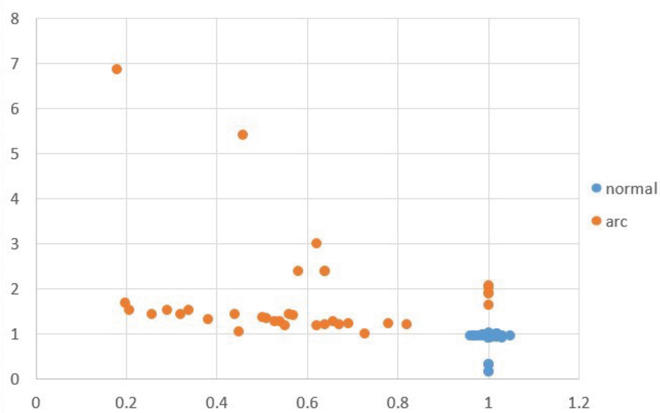


Fig. 12. Normalized dataset of normal current and series arc current

VI. CONCLUSIONS

In this paper, a SVM-based arc detection algorithm is proposed for detection accuracy and high applicability of series arc detector. Considering the high frequency characteristics of series arc noise, DWT analysis were applied for extracting feature parameters. Also normalization of feature parameter was performed and achieved high detection accuracy by more than 98% even for untrained data. SVM based algorithm was applied to a real-time DSP, resulted in the arc detection performance complying with the UL1699B standard. In the future, the trained SVM model will be tested in various actual PV systems.

ACKNOWLEDGMENT

This work was supported by the project titled as Development of DC Arc Interruption Technology and Performance Evaluation Facility for Medium and Large PV System Development (NO. 20192910100090) granted by Korea Institute of Energy Technology Evaluation and Planning (KETEP), Ministry of Trade, Industry and Energy, Korea.

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