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Broad Learning Based Fault Detection and Diagnosis Method for Three-Phase Six Switch Converter

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***Abstract*—Since the last few decades, research on power converters has been critical of the power electronics field. In recent years, the two level converter has gained a lot of attention due to its simple structure and control for various applications. From the design phase to manufacturing, converter reliability is a key performance indicator that must be considered. Due to the vast number of interdependent components and subassemblies that constitute the $2L$ converter, it is vulnerable to a wide variety of failure modes and processes. Fault-tolerant ability of the topologies is very crucial for the reliable operation of the overall system. This paper provides an analytical study of the fault-tolerant ability of the $2L$ converter with open-circuit fault (OCF). This analysis has been used for the detection and identification of faulty components using less computational complex broad learning system. The superior fault recognition capability of the proposed work proves the robustness of the proposed method for the fault diagnosis of $2L$ power converter.**

***Index Terms*—Broad learning system, fault recognition, open-circuit fault, Power converter.**

I. INTRODUCTION

In recent years, the building and industrial sectors have shown a greater emphasis on renewable energy sources (RES) [1], [2]. By the end of 2021, the renewable energy generation capacity was 3064GW, out of which 40% of the generation capacity comes from hydro. The share of solar and wind energy was 849GW and 825GW, respectively. With the renewable energy, the role of power converters increases, thus creating reliability issues of the overall system. Fig. 1 shows the distribution of the faults in a power converters [3].

Excessive voltage, excessive current, and excessive temperature are three major causes of premature failure of capacitors used in power converters. An excessive voltage could be the result of transitory events, or it could be the result of prolonged swells and over-voltages. Every one of these things could reduce the lifespan of the capacitor. The lifespan of a capacitor can be significantly shortened by exposure to overcurrent in either a transient or constant condition. Each of these factors has the potential to expedite the dielectric ageing process, which in turn would decrease its expected lifespan. It is also well knowledge that high temperatures can shorten the lifespan of electrical components. This is also a major factor that contributes to the failure of capacitors. When a capacitor is subjected to excessive voltage or current, the result is an

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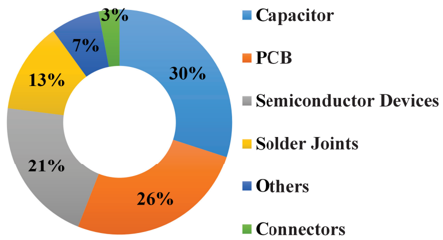


Fig. 1. Distribution of fault in power converters [3].

increase in the capacitor's internal temperature, which in turn shortens the capacitor's lifespan [4].

Capacitor is considered to have OCF when the end connections get unplugged [5], [6]. PCBs, while their high level of functionality, are also known for their susceptibility to damage. The PCB or its components can not sustain physical damage if they are dropped, hit by an object, subjected to heat, or even exposed to elements such as dust, or water [7]. Power semiconductor devices are vital to power electronic systems however, the fault in these devices can lead to OCF or SCF. Since power electronic converters are used in increasingly vital processes, characteristics such as reliability, durability, health monitoring, and predictive maintenance become increasingly significant. Also, such application frequently experiences stress due to high ambient temperatures and significant temperature variations. Both overheating and overcurrent can produce open circuit faults (OCFs) or short circuit faults (SCFs) in semiconductor devices [8], [9]. The $2L$ power converter consists of six switches, their associated gate driver circuits, PCB, filters, etc. Therefore, this converter is very much prone to the OCF or SCF.

Recently, several signal processing methods such as fast Fourier transform [10], wavelet transform [11], principal component analysis [12] are proposed to extract the most distinguish coefficient for the fault diagnosis of power converter. The extracted efficacious coefficients are further fed to very popular machine learning algorithm for the identification of fault types over rule based conventional fault detection methods. The machine learning algorithms such as support vector regression [13], extreme learning machine [14] and random vector functional link network [15] are used to recognize the power converter faults efficiently. Also, very time consuming and large memory dependent deep learning methods such as deep sparse autoencoder [16] and deep feedforward network [17] are proposed to obtain maximum recognition accuracy. In this paper, we have proposed a very less computational complex

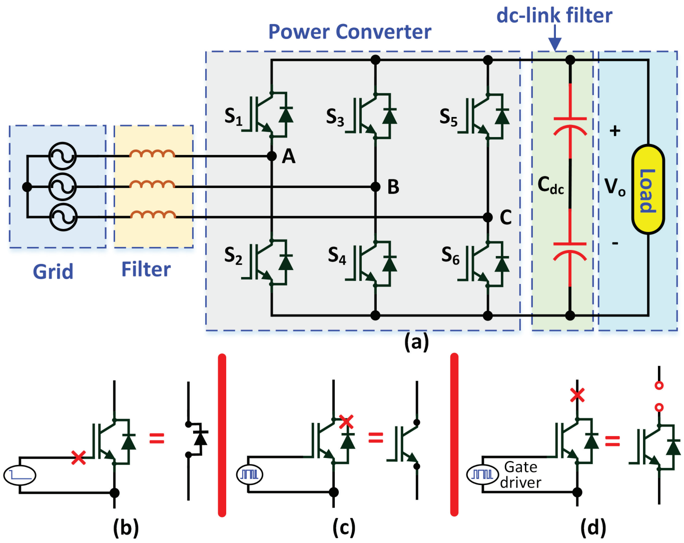


Fig. 2. Open circuit faults (a) Schematic of the three-phase converter, (b) Failure of the gate driver circuit, (c) Failure of the antiparallel diode and (d) Wire or PCB connection breaks down.

with excellent performance based broad learning system [18], [19] to detect and recognize the OCF for different conditions of the $2L$ power converter. Also, the proposed work has not adopted any extra advance signal processing algorithm for the extraction of suitable data input for the machine learning algorithm to obtain maximum fault recognition accuracy.

II. OCF IN THREE-PHASE 2L PFC PWM RECTIFIER

Fig. 2 (a) shows the schematic of the three-phase rectifier. It consists of six switches and a DC link capacitor. The grid is connected to the converter via a filter. Each switch is associated with the three different types of open circuit faults and these have also been shown in Fig. 2. The open circuit fault in the converter can be developed by three different means. Fig. 2(b) shows the failure of the gate driver circuit which causes the OCF. This failure results in only an antiparallel diode connected to the converter as the gate pulse becomes zero which prevents the switch to perform necessary switching. In another case of OCF, the wire or PCB connection breaks which results in the complete isolation of the switch from the converter. This scenario has been shown in Fig. 2(c).

III. BROAD LEARNING SYSTEM

The architecture of the broad learning system (BLS) is twofold, such as the generation of the feature node, and the generation of the enhancement node. From the input fault signals the mapped features are determined to form the feature nodes and later randomly generated weights are assigned to the mapped features to form enhancement nodes. Finally, the feature nodes and enhancement nodes are connected to the output node by performing matrix inversion to determine the weights of the links between the hidden layer and the output layer. For a set of input fault current data, I with M rows and N columns, the network develops the future nodes by using a mapped feature f_z. The i^{th} group of mapped feature nodes can be represented as,

$$Z_i = f_z(IW_i + b_i), \quad i = 1, 2, 3, \cdots, n \tag{1}$$

Where, W_i and b_i are the randomly generated weight and bias for the i^{th} group of mapped feature nodes. f_z is the mapping function and n is the total number of groups of mapped feature nodes. n number of groups of Z are obtained and concatenated form Z^n as given in equation (2).

$$Z^n = [Z_1, Z_2, Z_3, \cdots, Z_n] \tag{2}$$

The enhancement nodes are established by considering Z^n as input dataset and another activation function f_h is used to generate enhancement nodes can be presented as,

$$H_j = f_h(Z^n W_{h_m} + b_{h_m}) \tag{3}$$

Where $W_(h_m)$ and $b_(h_m)$ are the randomly generated weight and bias of enhancement nodes. m number of groups of H are obtained and concatenated to form H^m, as given in equation (4).

$$H^m = [H_1, H_2, H_3, \cdots, H_m] \tag{4}$$

Furthermore, the BLS model is created by concatenating both the Z^n and H^m and the output node Y is defined with connecting weights (W_o) of the model as below.

$$\begin{aligned} Y &= [Z_1, Z_2, Z_3, \cdots, Z_n | H_1, H_2, H_3, \cdots, H_m] W_o \\ &= [Z^n, H^m] W_o \end{aligned} \tag{5}$$

The recorded three-phase windowed fault signals are concatenated to create the original highly nonlinear and nostationary signal to feed into the BLS algorithm as an input by setting appropriate target of the seven class classification model. Finally, 40% of three-phase current fault data is used to train the BLS, 20% of data is used for validation of the developed model and the remaining 40% of data is used for testing the proposed model to test, examine and validate the robustness of the proposed method.

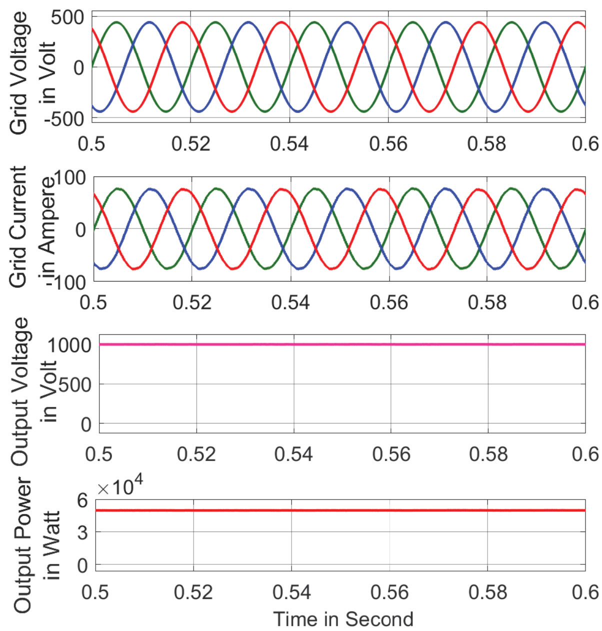


Fig. 3. Grid phase voltage, grid current, output voltage, and output power at normal operating condition.

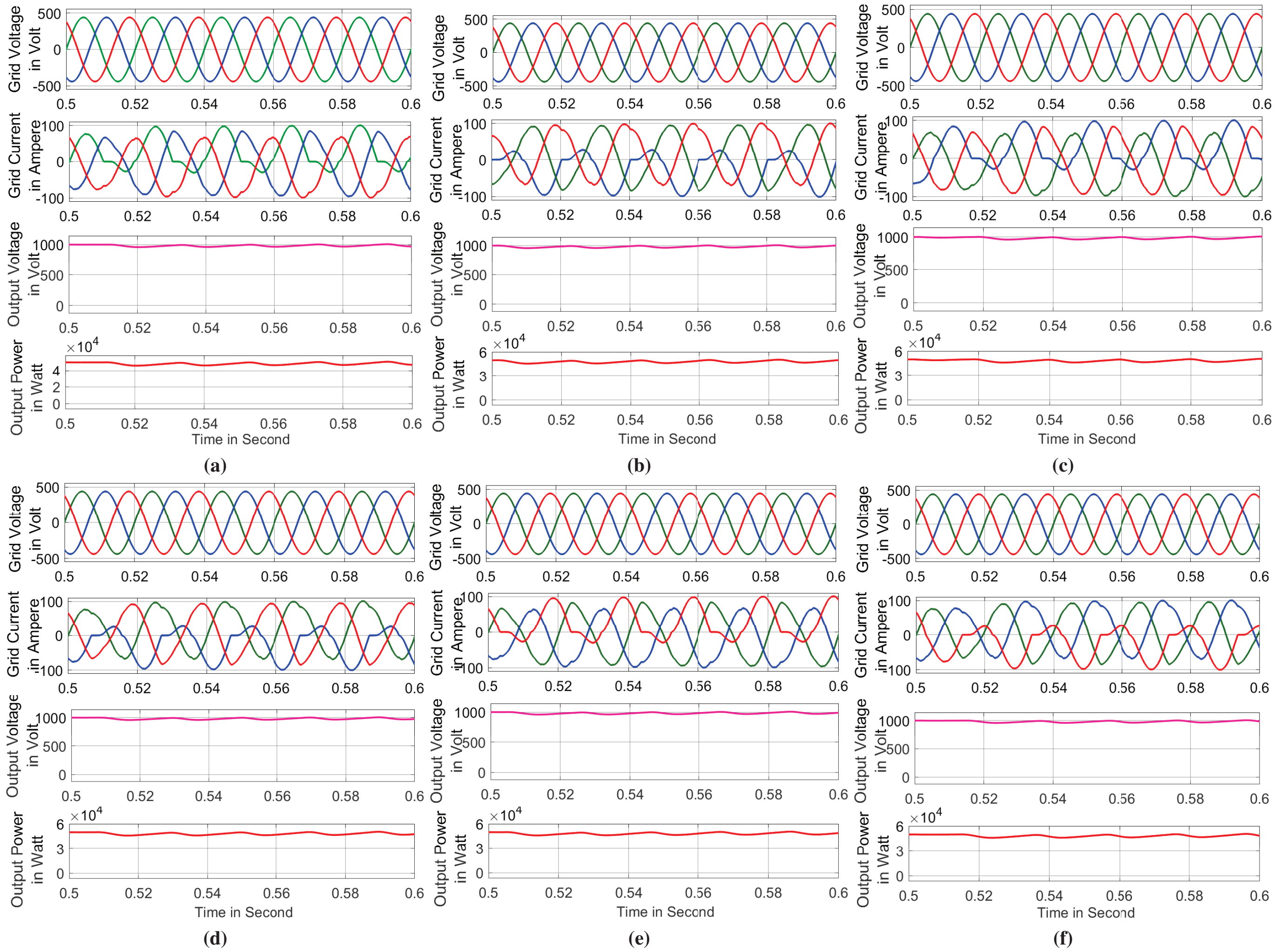
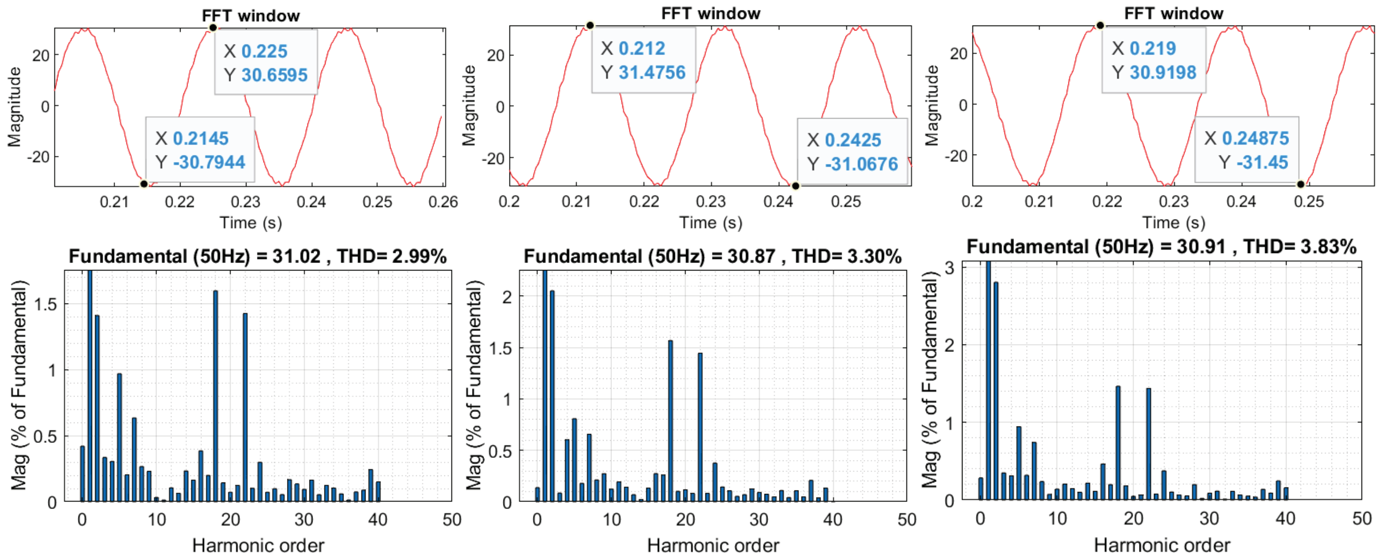
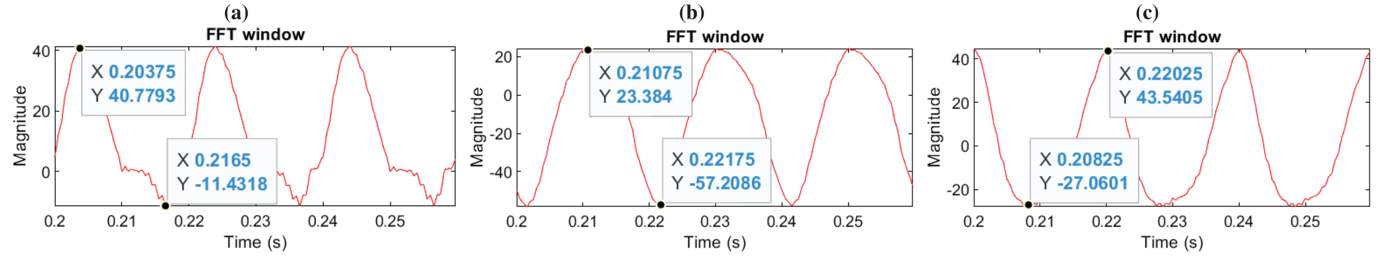


Fig. 4. Fault waveforms of (a) switch S_1, (b) switch S_2, (c) switch S_3, (d) switch S_4, (e) switch S_5, and (f) switch S_6.



(a) (b) (c)



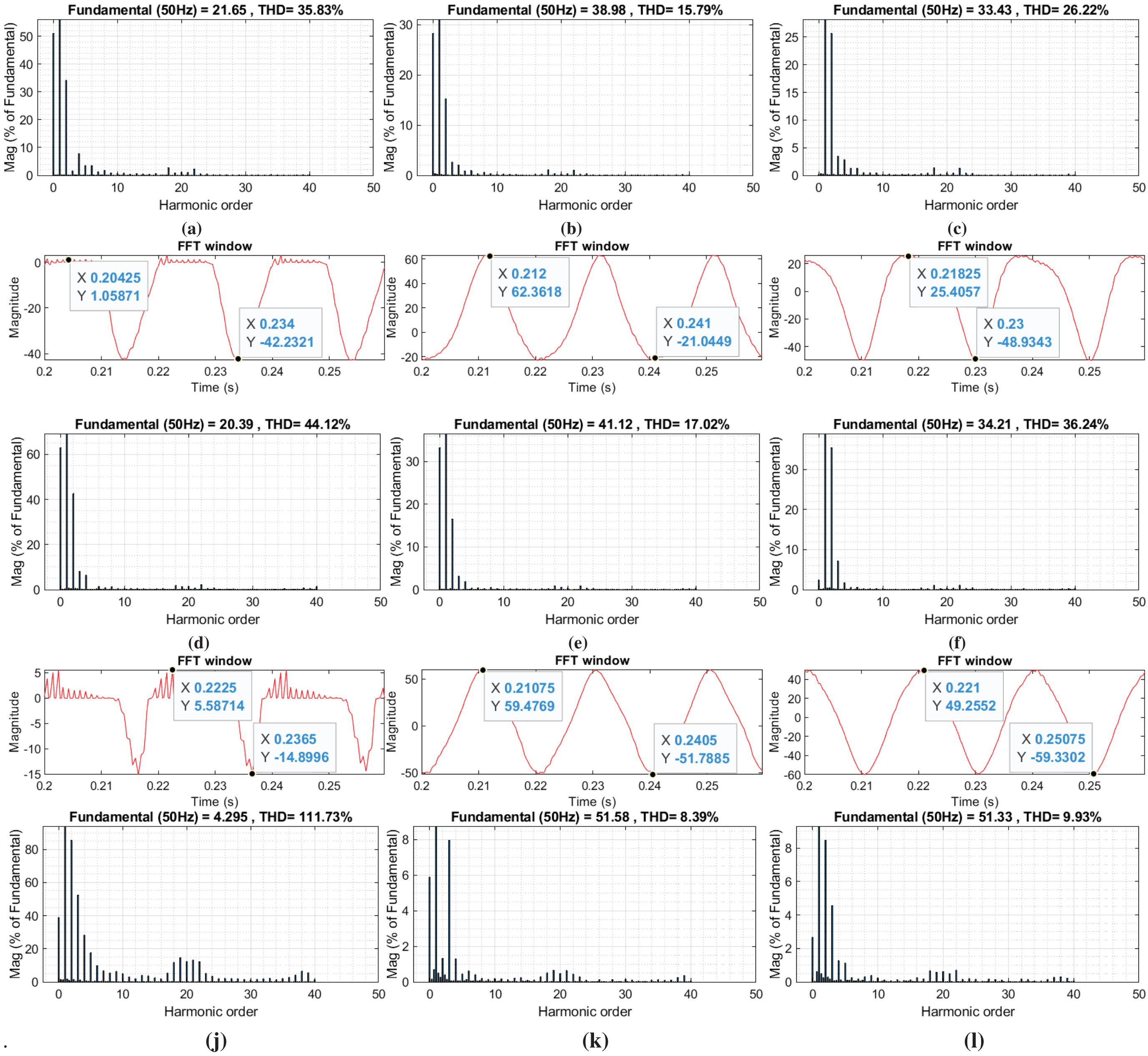


Fig. 5. Phase A, B, and C current with respective harmonics for (a)-(c) Healthy condition, (d)-(f) Gate driver failure, (g)-(i) Diode failure and (j)-(l) Wire breakdown, respectively.

TABLE I. OCF ANALYSIS FOR SWITCH S_1

Fault	Phase A					Phase B					Phase C				
Types	0	2	3	P+ (A)	P- (A)	0	2	3	P+ (A)	P- (A)	0	2	3	P+ (A)	P- (A)
Healthy	0.42	1.40	0.33	30.65	30.79	0.11	2.06	0.09	31.47	30.07	0.24	3.0	0.36	30.92	31.45
GDF	51.6	34.7	1.9	40.78	11.43	28.2	15.3	2.3	23.38	57.21	0.8	20.7	3.3	43.54	27.056
DF	63.2	42.9	8.5	1.06	43.23	33.7	16.3	3.4	62.36	21.05	2.2	35.6	7.3	25.40	48.93
WB	39	85	53	5.58	14.90	5.8	1.4	8.0	59.48	51.79	2.6	8.5	4.5	49.26	59.33

*GDF: gate driver fault, DF: diode fault, WB: wire breakdown. 0: DC components, 2: 2nd harmonics, 3rd: third harmonics, P+: positive peak, P- : negative peak.

IV. SIMULATION RESULTS FOR DIFFERENT SCENARIOS

The three-phase two-level power converter has been simulated and the results are presented in Fig. 3. The input grid voltage is set to 540V (rms) and the DC output voltage is selected as 1000V. A load of 20Ω is connected at the output which results in 50kW output power. The filter inductor of $5mH$ has been used. A UPF has been achieved using the PWM control with carrier frequency being 5kHz. Fig. 3 shows the normal operating condition with the grid phase voltage, grid current, output voltage, and output power. The grid current and voltage are in phase which ensures the UPF operation of the

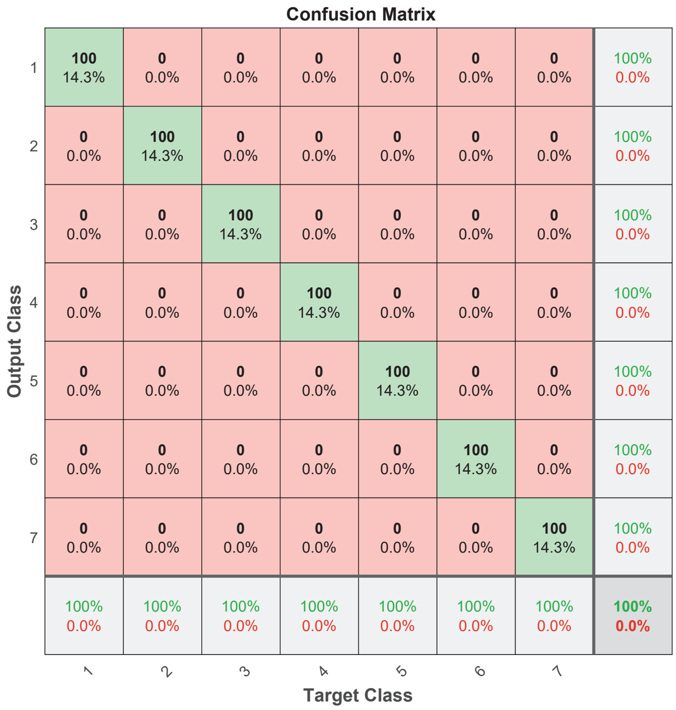


Fig. 6. Classification accuracy of the proposed method.

converter. Fig. 4 (a)-(f) show the operation of the converter in case of gate failure which results in zero gate voltage of switch S_1 to S_6.

Fig. 5 shows the output current for each phase with their harmonic spectrum in the case of OCF in switch S_1. The results have been summarized in Table I. In normal operating conditions, all the phase currents are sinusoidal with THD in the range of 3%. All the lower-order harmonics have very small magnitude. In the case of the fault in switch S_1, the currents are no longer sinusoidal and their peaks get changed as the output power remains almost equal to 50kW. This is because the share of the other two health phases increases due to the fault in one phase. From Table I, it can be observed that there is a significant increase in the DC component, 2^{nd} and 3^{rd} harmonic components of the phase current as a percentage of fundamental. Further, the change in the positive and negative peaks is significant in all other phases. All these values are only for the OCF in switch S_1 which is connected to the top switch of phase A. A similar pattern has been observed in the case of OCF in the bottom switch S_2 or in the switches of other phases. Therefore, based on these values, a fault detection and localization technique has been developed which can identify the fault type as well as the fault location.

Furthermore, the recorded six class fault and normal three-phase current signal of window size of two cycles i.e. before as well as after fault one cycle with the sampling frequency of 25kHz of 50Hz network are imported to the proposed BLS model as inputs. The corresponding feature and enhancement nodes are computed using the tangent hyperbolic and sigmoid activation function respectively by assigning random weight and bias. Both feature node, as well as enhancement node outputs, are mapped to the output nodes to compute the output weight matrix at the training stage of multiclass classification of the different six switch faults of the power converter. Two hundred fifty signals of each fault as well as normal operating conditions are recorded and 100 signals are imported as input at the training stage and 20% of total signals are used to validate the developed network. The obtained accuracy in both the training, as well as validation stages, is 100%. Finally, the trained network is tested using 100 signals of each class, and the obtained 100% classification accuracy is presented in the form of a confusion matrix in Fig. 6. The outstanding performance of the proposed method proves the robustness for the recognition of switch fault of the power converter.

V. CONCLUSION

In this work, an idea of OCF detection and recognition has been discussed which is based on the broad learning system. The $2L$ converter working as a PFC rectifier has been analyzed for the OCF in one switch for six different fault scenarios. Based on the lower-order harmonics and the change in the peak value of the grid current, a novel threshold-based method is proposed for the detection and classification of seven different classes. The $2L$ converter is analyzed and compared with the healthy conditions. Furthermore, the machine learning-based method is proposed to obtain maximum recognition accuracy for the classification of power converter open circuit faults.

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