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THE CLASSIFICATION TECHNIQUE USNIG A NEURAL NETWORK

The multilevel carrier-based sinusoidal PWM is used for controlling gate drive signals for the cascaded MLID as shown in Figure 1. It should be noted that other modulation strategies can be used to control a cascaded MLID as well; one unique method to balance a switching loss of other levels, particularly at low modulation index, has been proposed in manuscript [1].

The modulation index (m_a) is the ratio between an amplitude modulation waveform and an amplitude combination of carrier bands; for instance, the 0.8 out of 1.0 m_a is represented in Figure 2. The number of carrier bands depends upon the number of separate dc source (SDCS); the two SDCS cascaded MLID requires two carrier bands on positive side and two carrier bands on negative side and each band has equal amplitude.

The selection of diagnostic signals is very important because the neural network could learn from unrelated data to classify faults which would result in improper classification. Simulation results of input motor current waveforms during an open circuit fault at different locations of a MLID (shown in Figure 5) are illustrated in Figure 3 and Figure 4.

The simulation model is illustrated in Figure 5; Power simulation (PSIM) from Power sim Inc is used as power circuit of a MLID and Matlab-Simulink from Matworks is used to generate gate drive signals. As can be seen in Figure 3 and 4, the input motor currents can classify open circuit faults at the same power cell by tracking current polarity (see Figure 4); however, it is difficult to classify the faults at different power cells; the current waveform for a fault of S_{A+} in H-bridge 2 (Figure 3) looks identical to that for a fault of S_{A+} in H-bridge 1 (Figure 4 (a)). As a result, the detection of fault locations could not be achieved with only using input motor current signals.
Also, the current signal is load dependent; the load variation may lead to misclassification; for instance, light load operation as reported in a central interruptible demand (CID) case in [1]. Auspiciously, Figure 2 indicates that an output phase PWM voltage is related to turn-on and turn-off time of associated switches; hence, a faulty switch can not generate a desired output voltage; The output voltage for a particular switch is zero if the switch has a short circuit fault, whereas the output voltage is about V_{dc} of SDCS if the switch has an open circuit fault. For this reason, the
output phase voltage can convey valuable information to diagnose the faults and their locations.

The simulation results of output voltages are shown for an MLID with open circuit faults and short circuit faults in Figure 6. One can see that all fault features in both open circuit and short circuit cases could be visually distinguished [2]. Also, experimental results of output voltage signals of open circuit faults in each location of two 12 V separate dc source (SDCS) MLID as shown in Figure 5 with multilevel carrier-based sinusoidal PWM gate drive signals are shown in Figure 7 and Figure 8.

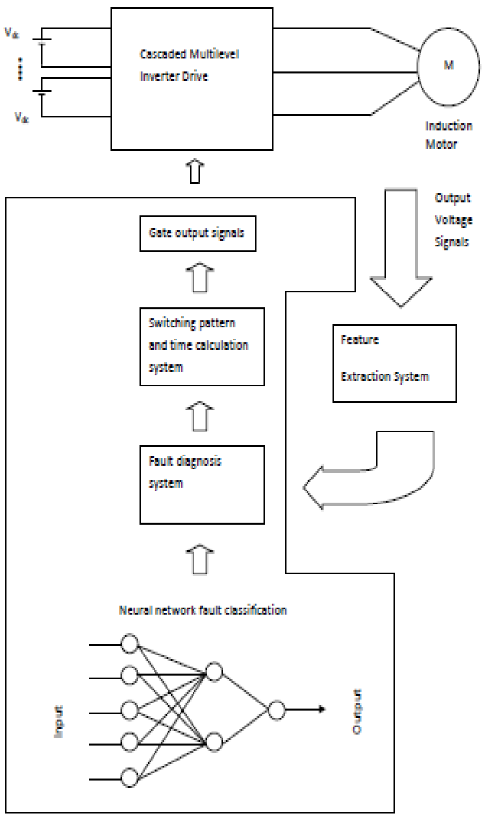


Fig. 1. Structure of fault diagnosis system

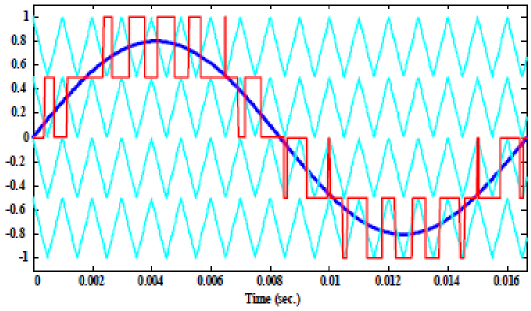


Fig. 2. Multilevel carrier-based sinusoidal PWM showing carrier bands, modulation waveform, and inverter output waveform (m_a = 0.8/1.0)

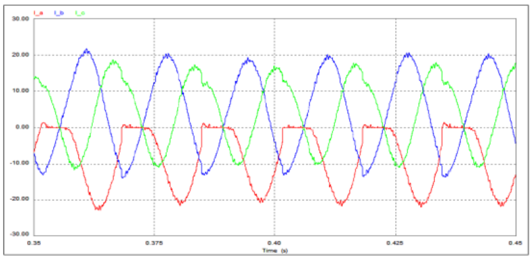
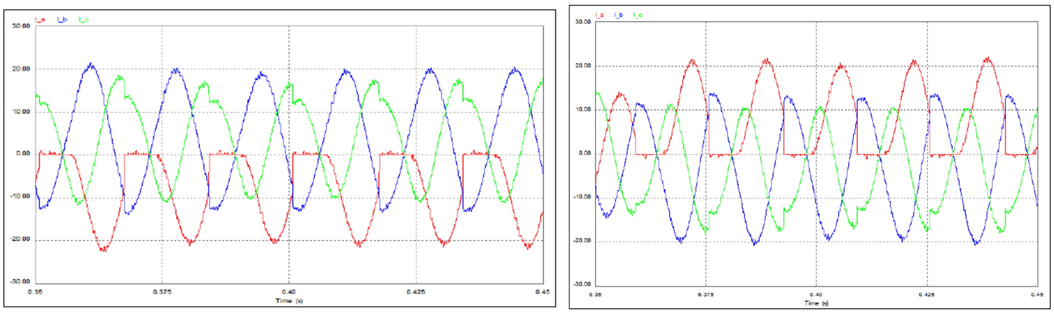


Fig. 3. Input motor currents during open circuit fault at switch S_{A+} of H-bridge 2



a) b)

Fig. 4. Input motor currents during open circuit fault at H-bridge 1:
a) switch S_{A+} , b) switch S_{B+}

Obviously, the results show that the output phase voltage signals are related to the fault locations and fault types (open circuit and short circuit) [3, 4]. One can see that all fault features can be visually distinguished in both fault types and fault locations via the output phase voltage signals; however, the computation unit cannot directly visualize as a human does.

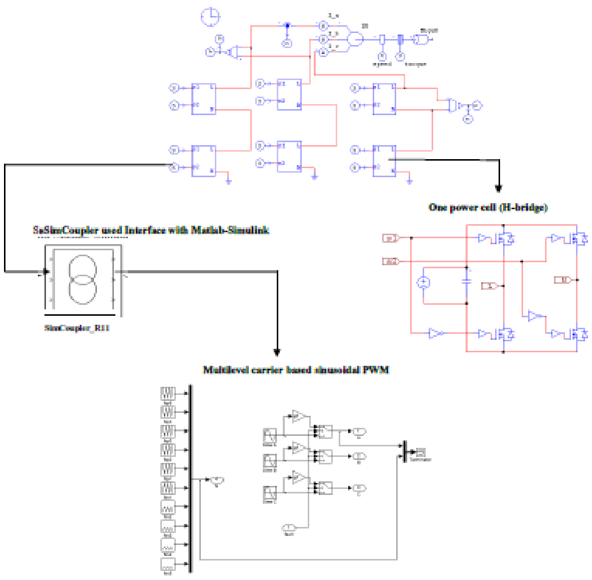
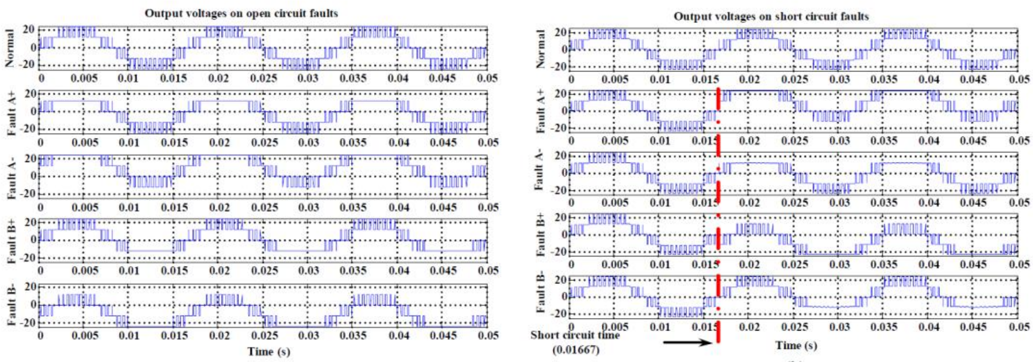


Fig. 5. Simulation model using Psim and Matlab-Simulink



a) b)

Fig. 6. Simulation of output voltages signals showing fault features at S_{A+}, S_{A-}, S_{B+}, and S_{B-} of H-bridge 2 with modulation index = 0.8 out of 1.0: a) open circuit faults, b) short circuit faults

A neural network is one suitable AI-based technique which can be applied to classify the fault features. Besides, a classification technique using a neural network offers an extra degree of freedom to solve a nonlinear problem; the failure of a single neuron will only partially degrade performance. If an input neuron fails, the network can still make a decision by using the remaining neurons.

In contrast, if only a single input, for instance the dc offset of signals, is used as the input data to classify the faults, the diagnosis system may not perform classification when the input data has drifted or the single sensor has failed [5]. Furthermore, a neural network also permits parallel configuration and seasonal changes. Additional H-bridges and fault features (short circuit) can be conveniently extended into the system with more training data and parallel configuration. Therefore, the fault types and fault locations in a cascaded MLID will be attempted to diagnose from its output voltage waveform.

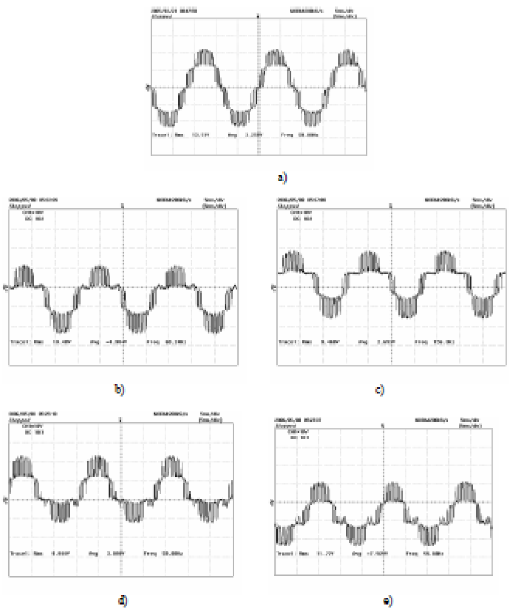


Fig. 7. Experiment of open circuit fault of H-bridge 1 with modulation index = 0.8 out of 1.0: a) normal, b) S_{A+} fault, c) S_{A-} fault, d) S_{B+} fault, e) S_{B-} fault

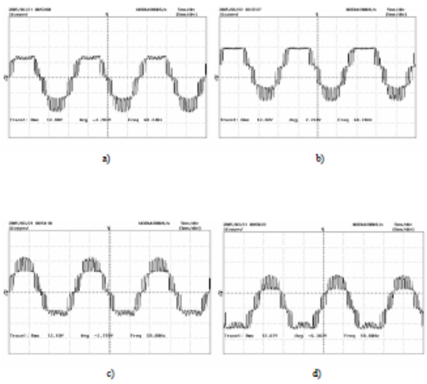


Fig. 8. Experiment of open circuit fault of H-bridge 2 with modulation index = 0.8 out of 1.0: a) S_{A+} fault, b) S_{A-} fault, c) S_{B+} fault, d) S_{B-} fault

Diagnostics the fault types and fault locations in a cascaded MLID from its output voltage waveform.

REFERENCES

1. Shapkenov B. K., Kaliev B. Z., Kaidar A. B. The Theory and Practice of energy converters. Saarbrucken, Germany: Publishing house «LAP Lambert Academic Publishing». 2014. 461 p.

2. Kaidar A. B., Kopyrin V. S., Shapkenov B. K., Markowski V. P. Experi-mental studies inverter with pulse width modulation for power supply systems with renewable energy sources // YI reading Sh Shokina: Materials Interna-native scientific and technical conference. October 10. 2014. P. 134–140.

3. Кайдар А. Б., Шапкенов Б. К., Марковский В. П. Экспериментальные исследования инвертора с широтно-импульсной модуляцией для систем электроснабжения с возобновляемыми источниками энергии // Вестник ПГУ. 2014. № 3. С.137–143.

4. Кайдар А. Б., Шапкенов Б. К., Марковский В. П. Оценка средних и действующих значений тока, мощности статических потерь на этапах коммутации инвертора с широтно-импульсной модуляцией для систем электроснабжения с возобновляемыми источниками энергии // Вестник ПГУ. 2014. № 3. С. 129-136.

5. Шапкенов Б. К., Иванова Е. В., Кайдар А. Б., Вахитов А. Е. Нейросетевое моделирование электрических нагрузок для оперативного прогнозирования и управления режимами электроэнергетических систем. Энергетическое обследование как первый этап реализации концепции энергосбережения: материалы междун. молодеж. конф. Томск: Изд-во ООО «СПБ Графикс», 2012. С. 341-345.