Multilayer Neural Network with Multivalued Neurons MLMVN based CLASS E Resonant Inverter Fault Detection

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Abstract

This paper aims at proposing an effective approach, based on neural networks, to the fault diagnosis of Class-E DC-AC resonant inverters. A MultiLayer artificial Neural Network based on MultiValued Neuron (MLMVN) with a complex QR-decomposition is used to identify parameter value changing (i.e. fault detection) on a Class-E resonant inverter through steady state measurements of voltages and currents.

1 Introduction

Modern power converters are utilized in several applications and in many of them, such as hybrid automotive power systems, artificial heart power supply systems, underwater vehicles power systems, are safety critical. In these kinds of applications a fault can lead to fatal consequences. Therefore, fault identification is crucial to prevent fault propagation and avoid catastrophic failures of the converter, which affect proper operation [1-9]. Among the components utilized in both PWM and resonant converters circuits [10, 11], inductors and capacitors have the greatest impact on the converter operation because faults and aging manifest as changes in the value of the parameters out of tolerances. Moreover, parasitic inductances and capacitance are exploited inside resonant converter to achieve proper operation. Unfortunately, parasitic component variations are large and, therefore, they can easily result in improper operation of the converter circuit.

Artificial Neural Networks (ANN) can be effectively utilized to detect parameter variations in a generic structure, and in particular faults inside a converter circuit. They need a database containing information about system characteristics, normal working conditions, past experiences on fault diagnosis obtained from measurements or simulations [12, 13].

In this paper two different and innovative tools are combined together in order to achieve the desired objective: a software which allows to perform in a very simple way the parametric repeated simulation of a DC-DC converter, and a complex-valued neural network that performs the identification of the fault elements. After a short description of these tools, the overall method is presented and, finally, its application to a class-E DC-AC resonant inverter will be shown.

2 SapwinPE and the Complex-valued Neural Network

The data utilized to train the neural network have been achieved by running time-domain simulations of the converter circuit with SapWinPE, a software which performs time-domain simulations of switching converters. SapWinPE is a switching circuit simulator based on the simulator developed by the authors SapWin [14, 15] and using a symbolic approach to evaluate the time domain response of the converter starting from a symbolic transfer function of the circuit. This represents something totally innovative and it is essential for this work. Actually, both PWM and resonant power converters switch voltages and currents in very short times; this results in strong convergence problems and frequent simulation abortions when using conventional tools. Consequently, the currently available tools are strongly limited in this kind of applications, especially when repeated multi-parametric simulations are needed as it is in the fault diagnosis investigation. On the contrary, SapWinPE is based on a numerical solution of symbolic functions rather than numerical approximations of circuit waveforms and, therefore, it results in fast and accurate simulations with no convergence problems. In Fig. 1 a screenshot of SapWinPE is shown, with a steady-state parametric response of a Class E resonant inverter.

The selected neural network is based on the Multi-Valued Neuron (MVN) presented in [16, 17]. This is a neural element based on the principles of multiple-valued threshold logic in the field of complex numbers. The MVN continuous version used in this work maps n inputs to a single output. This mapping is described by a multi-valued (k-valued) function with n variables $f(x_1,\ldots,x_n)$, that has its inputs and output located on the unit circle. Then, the MVN activation function is:

$$P(z) = e^{i\mathrm{Arg}\, z} = z / |z| \tag{1}$$

where $z=w_0+w_1x_1+\ldots w_nx_n$ is the weighted sum, and Arg(z) is the main value of the argument (phase) of the complex number z. Thus, in the case of continuous MVN, the output is the projection of the weighted sum on the unit circle, as shown in Fig. 2.

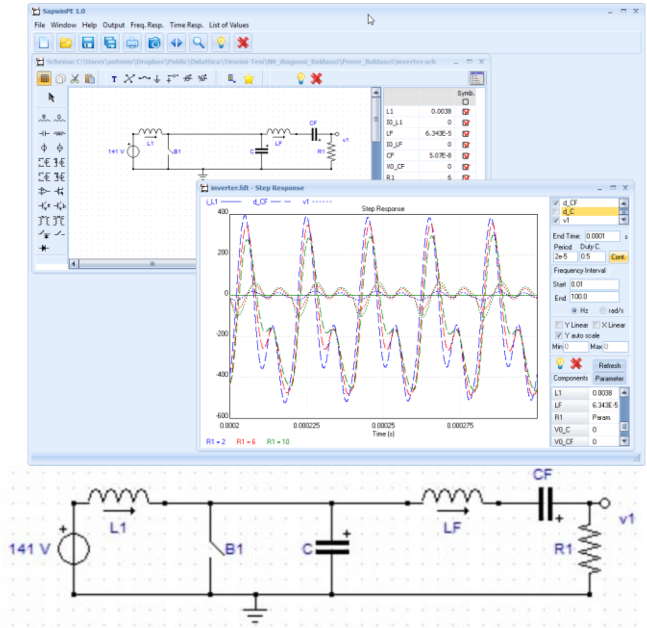


Fig. 1. SapWinPE screenshot with steady state response of a Class E inverter.

The MVN learning algorithm is based over an error-correction rule not based on derivative operations. Naming D and Y, respectively, the desired and actual outputs of the continuous MVN, then the weight adjustment formula is:

$$W_{r+1} = W_r + \frac{C_r}{(n+1)|z_r|}(D-Y)\bar{X} \qquad (2)$$

where $\bar{X}$ is the complex-conjugate of the neuron input vector, r is the learning iteration index, n is the number of input elements (dimension of the input vector), W_r and W_{r+1} are the complex weight vectors, respectively before and after correction, C_r is the learning rate.

A plenty of advantages have been demonstrated along last few years in the utilization of a multilayer neural network with multivalued neurons (MLMVN) with respect to other techniques [17]. Moreover, a new approach that drastically reduces the number of epochs necessary to reach the optimum result has been introduced in [18] for this kind of networks. It is based on a batch process, that minimizes the learning error of every training epoch by means of the linear least squares (LLS) algorithm using the complex QR decomposition.

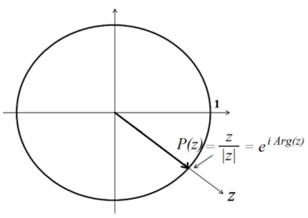


Fig. 2: Geometrical interpretation of the continuous MVN activation function.

3 Fault Identification approach

Inductor and capacitor are the critical components inside a power converter circuit. An inductor consists of a magnetic core on which a wire conductor is wound and its equivalent model is the series of an inductance with a resistance. A capacitor consists of two parallel conductive plates separated by an insulator and its equivalent model is a series of a capacitance with a resistance.

Inductor faults depend on:

1. Magnetic core saturation: high peak current values result in high flux density operation of the inductor core. When flux density exceeds its limit, the core is saturated and this results in a reduction of the actual inductance value, which can go out of tolerance;
2. Inductor overheating: if the rms current value of the inductor increases, inductor winding losses increase. When the wiring temperature increases, also its resistance increases and, therefore, the inductor equivalent series resistance can run out of tolerance.

Capacitor faults depend on:

1. High voltage operation resulting in a decreased capacitance value, which can run out of tolerance;
2. Strong vibrations leading to open/short circuits and the capacitance's value decreasing out of tolerances;
3. High ripple current values causing an internal heating and increasing the capacitor equivalent series resistance.

To the aim of locating anomalies and errors, a MLMVN described earlier is trained starting from 1500 Monte Carlo simulations of the Class E inverter, performed on SapwinPE simulator. Simulations are performed on circuit parameter values varying in their respective tolerance intervals. 1000 samples are then used for training the network and 500 for the validation. Finally the trained network is used to verify the fault conditions of the circuit.

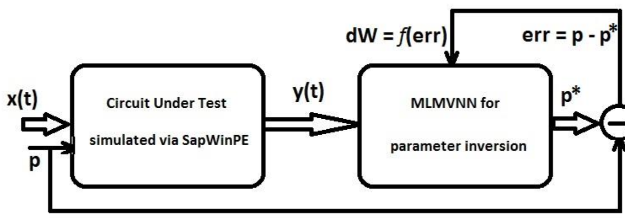


Fig. 3. ANN Identification System.

Once trained properly, the MLMVN estimates the parameters (**p***) basing on the observed Circuit Under Test (CUT) responses **y(t)**. This estimator approximates the presumed one-to-one unique mapping from the circuit observation space to the parameter space as illustrated in Fig. 3.

After training the weights are fixed so the MLMVN can be used as a Fault Locator Instrument: time domain measures **y(t)**, are applied to the input of the MLMVN and this result in the estimation of vector of parameters **p** at its output and the values can be interpreted as presumed values or faults elements.

4 Class-E DC-AC inverter parameter fault detection

A class-E DC-AC inverter operating under the following specifications has been investigated: output power P_o = 1kW, resonant circuit quality factor Q = 7, switching frequency f = 100 kHz, efficiency η = 0.93, controlled switch duty cycle D = 0.5. According to Fig. 1 the component values are: input inductance L_1 = 3.8 mH, controlled switch parallel capacitance C = 39nF, resonant inductance L_F = 64.3µH, resonant capacitance C_F = 50.7 nF, ac load resistance for a class-E inverter optimum operation [10] R_l = 6.7 **Ω**.

The ANN has been trained assuming that a proper operation of the inverter is achieved if the controlled switch turns-on at zero voltage, therefore, the inverter is operated at Zero Voltage Switching (ZVS) and the output voltage THD is lower than 10%, as shown in Fig. 4.

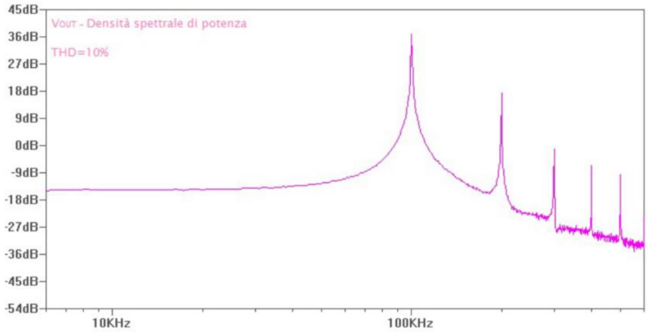
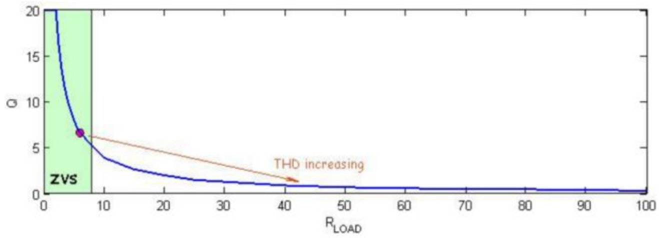


Fig. 4. Output voltage spectral distribution.

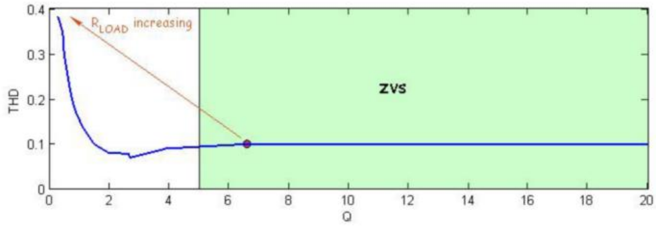
Figs. 5 (a) and (b) show the class-E inverter parameters ranges. The areas noted as ZVS represent the range of parameter values resulting in proper operation of the converter, which have been utilized to train the neural network.

Figs. 6 (a) to (d) show how the inverter component values affect the voltage waveforms across the switch when the ZVS operation is maintained. Figs. 7 (a) to (d) show the voltage waveforms across the switch when the ZVS is lost and also shows that these waveforms are very sensitive to parameter value changes.

Actually, 24 samples in one single switching period with the inverter operated under ZVS were utilized to train the neural network. Once the network is trained, random samples acquired from simulation derived from both ZVS and no-ZVS operation of the converter are utilized for the neural network operation. Results of this operation are shown in Figs. 8 to 11.

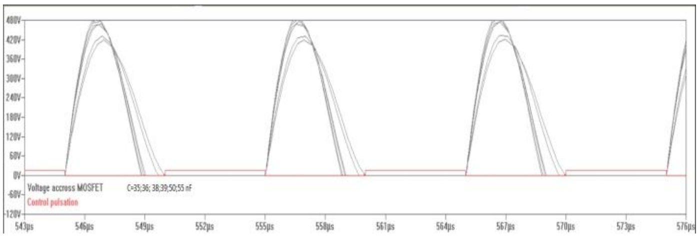


(a)

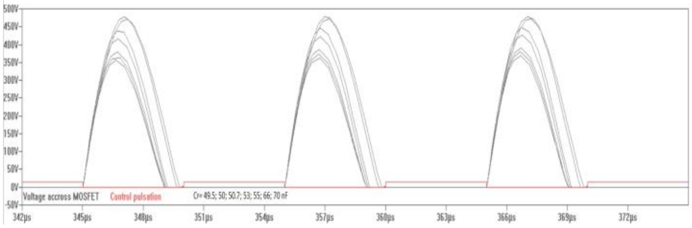


(b)

Fig. 5. Class-E inverter “right” operation parameters: (a) quality factor versus load resistance; (b) THD versus quality factor.



(a)



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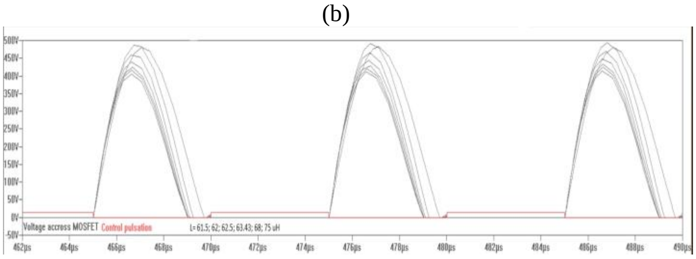
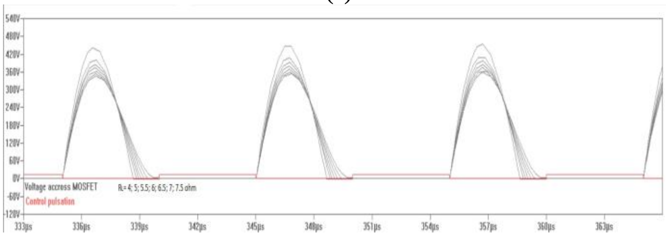
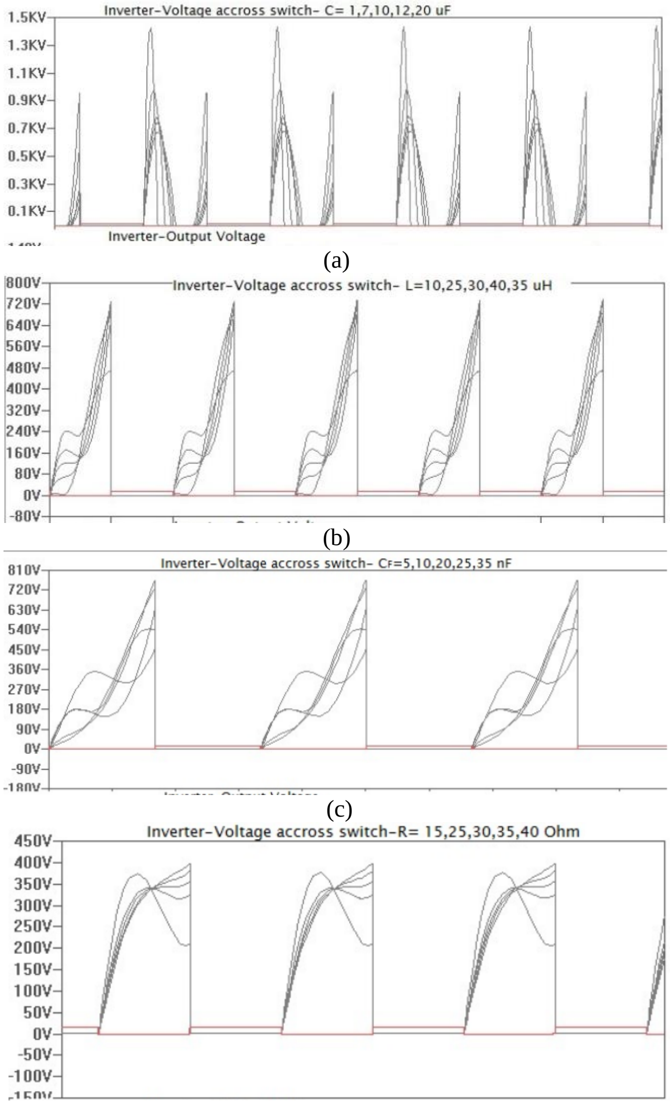


(c)



(d)

Fig. 6. Switch voltage waveforms under ZVS operation as simulated by SapwinPE and with circuit components as parameters: (a) parallel capacitor C as a parameter; (b) resonant inductance L_F as a parameter; (c) resonant capacitance C_F as a parameter; (d) load resistance R_l as a parameter.



(a)

(b)

(c)

(d)

Fig. 7. Switch voltage waveforms at no ZVS operation as simulated by SapwinPE and with circuit components as parameters: (a) parallel capacitor C as a parameter; (b) resonant inductance L_F as a parameter; (c) resonant capacitance C_F as a parameter; (d) load resistance R_l as a parameter.

Fig. 8 shows the results of measured waveforms with the MOSFET parallel capacitance values out of the range allowing for a converter ZVS operation. The neural network recognizes that only the parallel capacitance causes the fault (no-ZVS) condition, which does not depend on the other converter components. Actually, in all the five simulations, the neural network recognizes the other component values to be inside their tolerance ranges. This means that the fault detection is obtained with no ambiguity.

As shown by Figs. 9 to 11, the neural network operates with not ambiguous results also when the resonant inductor, the resonant capacitor, and load resistance values are out of their tolerance ranges.

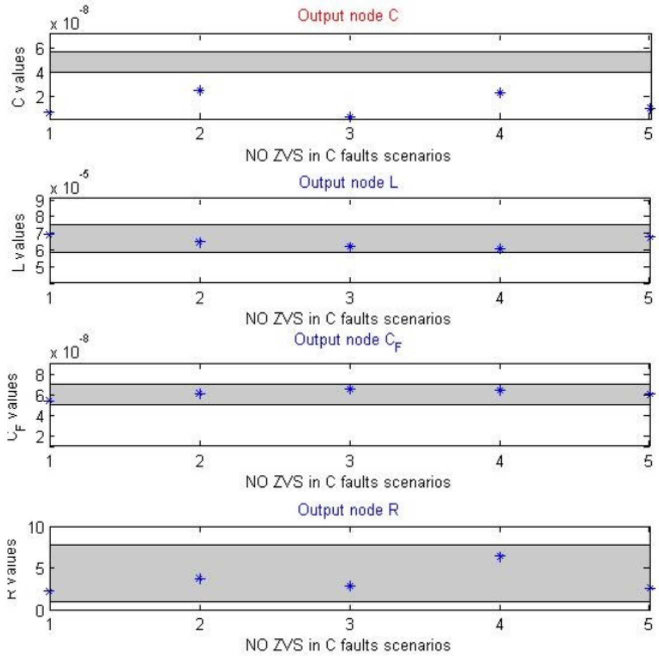


Fig. 8. MOSFET parallel capacitor fault scenarios.

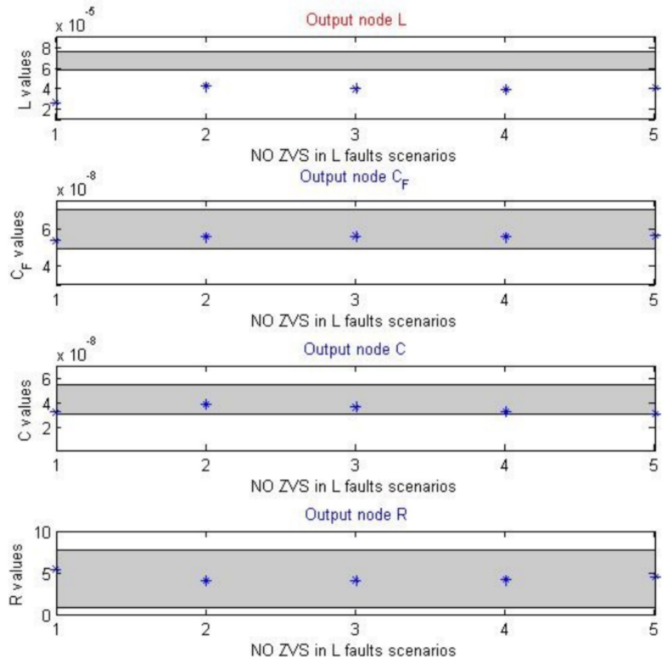


Fig. 9. Resonant inductor fault scenarios.

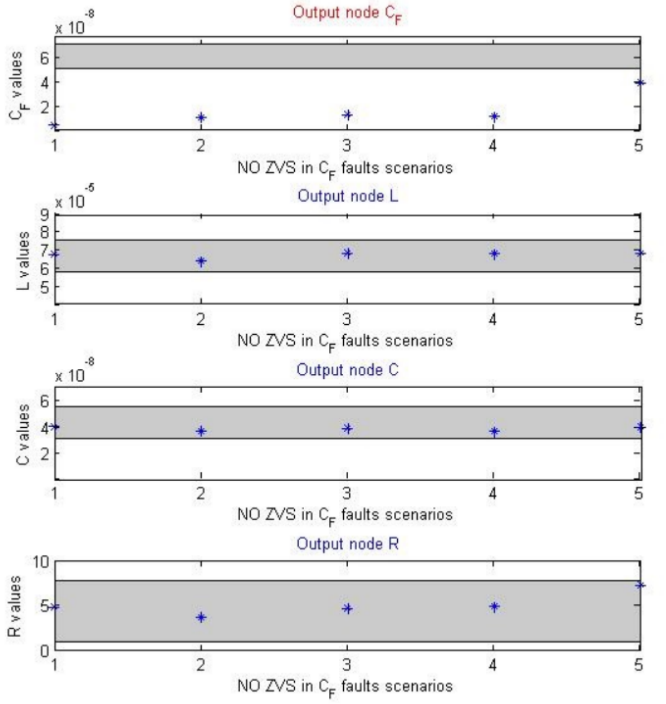


Fig. 10. Resonant capacitor fault scenarios.

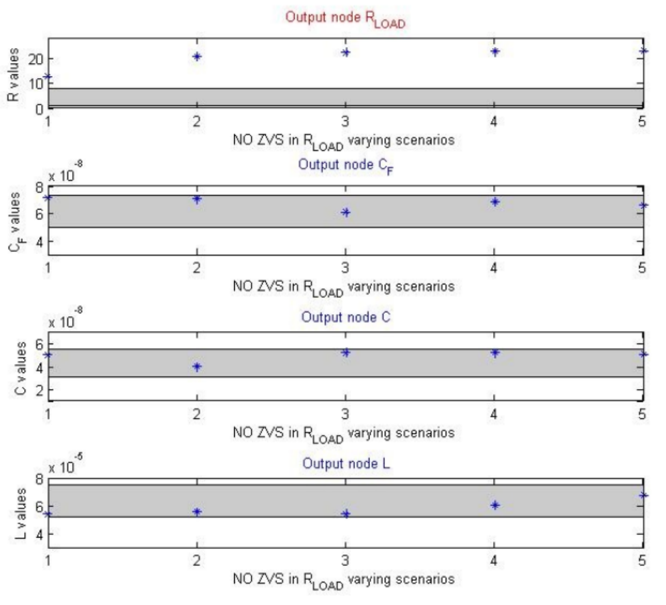


Fig. 11. Load resistance fault scenarios.

5 Conclusions

Fault diagnosis represents a key issue in any modern application where availability and safety are required; actually, it is extremely important to identify a fault condition to avoid critical consequences. Since power converters are widely used in safety critical application, their operation must be monitored to prevent fault propagation that may lead to catastrophic failure of the connected systems. When resonant converters are involved, the switching conditions are crucial for their efficiencies, their working temperatures and, therefore, their reliability, because of their high switching-frequency operations.

In this work an application of a MultiValued Neuron artificial Neural Network (MLMVN) for identifying parameter faults in a Class E inverter is presented. The results obtained suggest that this tool is a very effective method for fault detection.

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