MLMVNN FOR PARAMETERS FAULTS DETECTION IN A DC-DC BOOST CONVERTER

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Abstract − This paper aims to propose an effective approach in the fault diagnosis based on neural networks. In particular, a MultiLayer based on MultiValued Neuron artificial Neural Network (MLMVNN) with a complex QR-decomposition is used to identify parameters values changing (i.e. faults detection) on a Boost converter starting from voltages and currents in steady state measurements.

Keywords: Neural Networks, Boost converter, Faults Detection, Diagnostics.

1. INTRODUCTION

Advancements in semiconductor technology have opened new roads for application of power electronic converters in safety critical application such as: hybrid automotive power systems, artificial heart power supply systems, underwater vehicles power systems. Faults occurring in such applications can lead to fatal consequences thus it is vital to identify faults in such systems to act quickly following a device failure, to prevent propagation of faults that may lead to catastrophic failure of the converter affecting the load, source, and connected systems [1-9]. A DC-DC converter [10] is made up by inductors, capacitors and integrated circuits containing the switching elements. Inductor and capacitor have the greatest impact on the converter's operation because faults and aging manifest as changes in the value of this parameters out of tolerances.

Detecting a fault may involve different search strategies; using intelligent systems such as Artificial Neural Networks (ANN) involves the use of a knowledge base consisting of a database that involves facts and information about system parameter characteristics, normal working conditions, past experiences on fault diagnosis obtained from steady-state measurements or simulations [11-13].

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 will be given and, finally, an application example will discuss.

2. SAPWINPE SIMULATION SOFTWARE

The authors have worked to set up a software which is able to perform time-domain simulations of DC-DC switching converters [14].

It is a simulator of DC-DC converters that uses a symbolic approach, that is able to evaluate the time domain response of the converter by calculating in the intermediate time the symbolic transfer function of the circuit. This represents something totally innovative and it is essential for this work. A PWM DC-DC power converter, in fact, switches high voltages and currents in very short times. This causes several numerical simulators to have convergence problems that stop the time domain simulation after it is running for a certain time. This makes simulations time-wasting and useless in the case of repeated multi-parametric simulation as requested in a fault diagnosis problem. Convergence problems are, often, overcome by reducing the simulation accuracy. 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 Boost DC-DC converter with parasitic parameters.
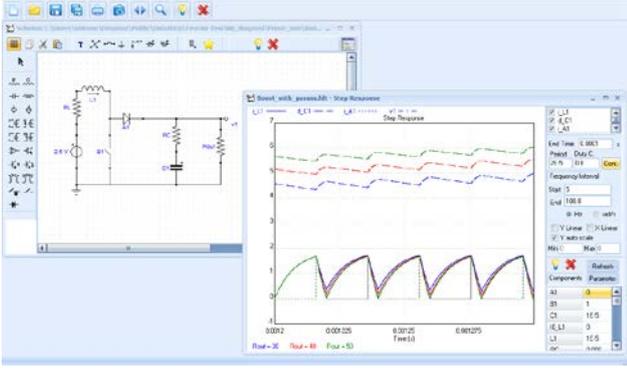
Fig. 1. SapWinPE screenshot with steady state response of a Boost converter with parasitic components.

3. COMPLEX-VALUED NEURAL NETWORK

The particular kind of neural network used in this work is based on the Multi-Valued Neuron (MVN), which was presented in [15-16] as a neural element based on the principles of multiple-valued threshold logic in the field of complex numbers. The continuous version of MVN used in this work maps n inputs to a single output. This mapping is described by a multi-valued (k-valued) function of n variables $f(x_1,\ldots,x_n)$, that, in the case of continuous type of activation function, has its inputs and output located on the unit circle. Therefore, the MVN activation function is:

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

where $z = w_0 + w_1 x_1 + \ldots w_n x_n$ is the weighted sum, and $\mathrm{Arg}(z)$ is the main value of the argument (phase) of the complex number z. Thus, for the continuous MVN, the output is the projection of the weighted sum on the unit circle, as it is determined by the activation function (1) (see Fig. 2).
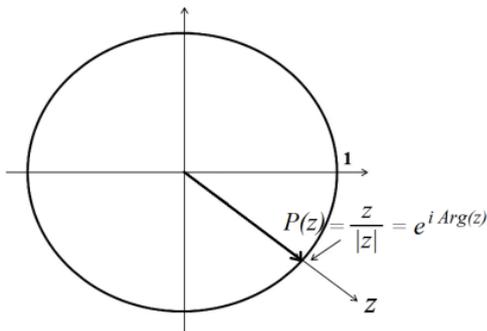

Fig. 2: Geometrical interpretation of the continuous MVN activation function.

The MVN learning algorithm performs an error-correction not based on derivative rules. Assuming D and Y, respectively, as 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 neuron input vector with the complex-conjugate components, r is the index of the learning iteration, n is the number of neuron inputs (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.

The multilayer neural network with multivalued neurons (MLMVN), which is a member of complex-valued neural networks family, has already demonstrated a number of important advantages over other techniques [17]. A new approach for calculation of the errors of the output layer neurons and a modified learning procedure for this layer based on a batch process, minimizing the learning error of every training epoch by means of the linear least squares (LLS) algorithm using the complex QR decomposition, is given in [17] and drastically reduce the number of epochs necessary to reach the optimum result.

4. FAULT IDENTIFICATION APPROACH

The inductor element of a DC-DC converter consists of a magnetic core on which is wound a wire conductor and its equivalent model is the series of an inductance with a resistance.

Faults are physically due to the following factors:

1. the value of the current which manifests the saturation of the magnetic core due to the magnetization level the material can withstand. When it happens, it is manifested as a decrease of the inductance value out of tolerances;
2. the maximum DC current that inductor can support, which leads to the losses in the conductor wires that cause overheating. It is manifested as an increase of the resistance value out of tolerances.

The capacitor element consists of two parallel conductive plates separated by an isolation and its equivalent model is a series of a capacitance with a resistance. In DC-DC converters, the most common type is the electrolytic capacitor.

Faults in such type of capacitor are physically due to the following factors:

1. High voltage conditions: that leads to a decrease of the capacitance value out of tolerances;
2. Strong vibrations: that lead to open/short circuits and the capacitance's value decreasing out of tolerances;
3. High ripple current value: that causes an internal heating leading to an increase of the equivalent series resistance.

In this work, to the aim of locating anomalies and errors, a MLMVNN with a complex QR decomposition algorithm is trained starting from 1600 Monte Carlo simulations of the Boost converter operating in CCM performed on SapwinPE simulator. Simulations are performed on circuits parameters values varying in their respective tolerance intervals which grant the maintaining of CCM operation and output voltage ripple less than 1%. Then the trained network is used to verify the faults conditions of the circuit.

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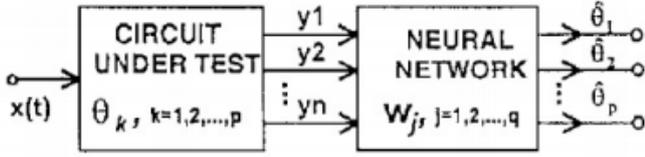

Fig. 3. ANN Identification System.

After training the weights are fixed so the MLMVNN can be used as a Fault Locator Instrument: time domain measures y_i, $i = 1..n$ are applied to the input of the MLMVNN and this produces p parameter estimates at its output and the values can be interpreted as nominal values or faults values.

5. BOOST CONVERTER PARAMETER FAULT DETECTION

The device takes into account in this research is a boost converter with ideal switching elements and parasitic resistance is considered, as shown in Fig. 4.
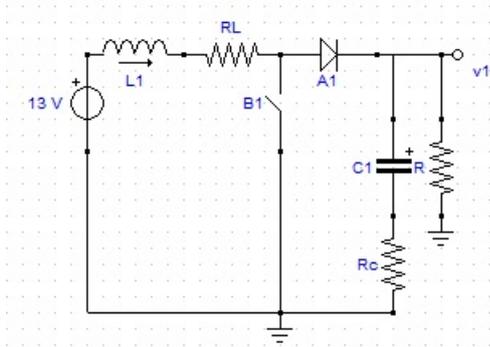

Fig. 4. Boost Converter circuit scheme.

The circuits is designed to be operated, under CCM (Continuous Conduction Mode) with a switching frequency $f = 200$ kHz, and to satisfy the following specifications $V_{in} = 12\text{-}15$ V, $V_{out} = 24$ V, $V_{pk\text{-}pk} \leq 1\%$.

Inductor and capacitor values are given by

$$L_{CR} = \frac{(1-D)^2 D R_{min}}{2f} \qquad (3)$$

$$C_{CR} = \frac{V_O R}{V_{pk-pk} f} \qquad (4)$$

In Figure 5 the areas where the Boost converter can be operated under CCM or DCM (Discontinuous Conduction Mode) in function of the values of L, load resistance R, duty-cycle D, and frequency f.
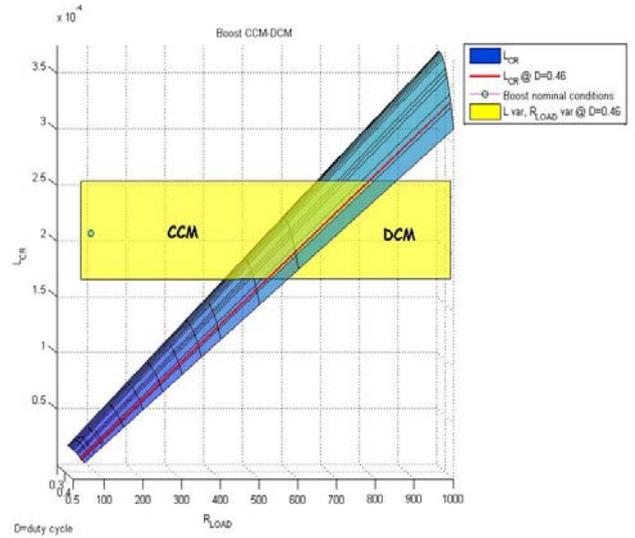

Fig. 5. Boost Converter CCM and DCM operation as determined by L, R, and D values.

The values of inductor and capacitor have been chosen among market available devices and they can be summarized as follow: $C = 10$ μF ± 10% ,$R_C = 0.006$ Ω ± 10%, $L = 220$ μH ± 10% AND $R_L = 0,7$ Ω ± 40%, to allows the converter to be operated under CCM and with an output voltage ripple lower than 1%.

The software program SapwinPE was utilized to derive a "training" file for a circuit operated at D = 0.5. The training file is a N x $(n+p)$ where
  – N = 1600 is the number of simulations,
  – $n = 8$ is the number of the time domain samples (i.e. inductive current and its ripple, voltage across capacitor and its ripple, capacitive current and its ripple, output voltage and its ripple),
  – p = 5 is the number of varying parameters, that is (C, L, R_c, R_L, R).

The boost converter testability is maximum and this allows for the identification of each specific component of the circuit through the neural network.

Actually, one of the most used definitions of testability is associated with the solvability degree of the nonlinear fault equations used in parametric fault diagnosis techniques and it indicates the ambiguity resulting from an attempt to solve such equations in presence of almost any failure. Therefore, this testability measure allows us to know a priori if a unique solution of the fault diagnosis problem exists. On the other hand, if this solution does not exist, this criteria gives a quantitative measure of how far we are from it, i.e. how many components cannot be diagnosed with the given test point set [11]. Given that the testability is maximum, all the circuits components are identifiable.

The various faults scenarios were simulated on SapwinPE software.

As a first step a Boost converter operating in DCM mode was simulated. Note that DCM operation is reached starting from a CCM operation when L values decrease and R ranges out of tolerance even keeping the CCM mode.

Figure 6 shows the inductor current when the circuit operates under DCM. The DCM operating mode can be

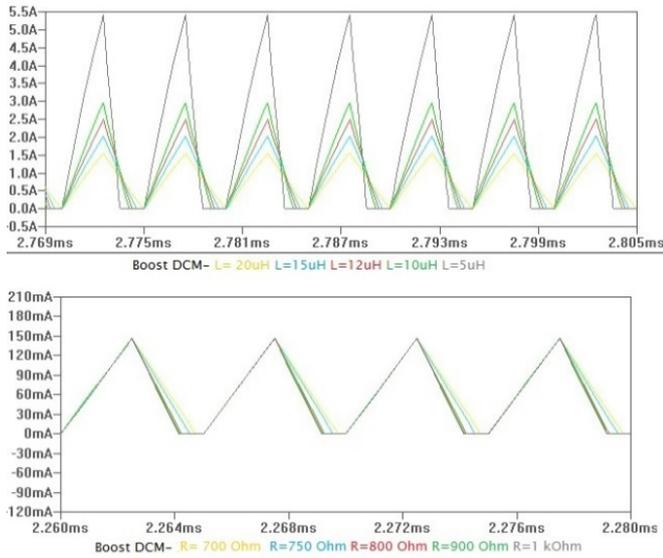caused either by a change of *L* and also from a load variation.

Fig. 6. DCM Inductor Currents.

Figure 7 shows the plot of *L* as a function of *R* and *D*. Inside this plot the set of values determining the converter operation under CCM and DCM are shown. This figure also shows the "testing working points" and the "identified working points".
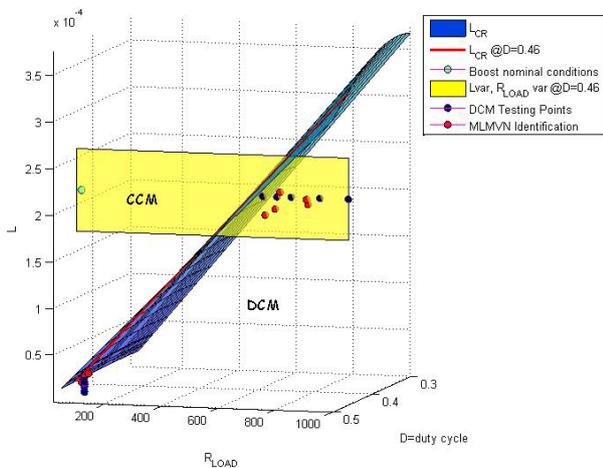

Fig. 7. MLMVN DCM Identification.

It can clearly be seen that the neural network is able to identify whether the abnormal behavior is given by inductor *L* or by load resistance *R* values.

With regard to the diagnosis in the case where the output voltage ripple exceeds the specification value of 240mV the network is able to identify the "working zone" of the circuit, being able to discriminate whether the side effect is caused by C. The results are specifically shown in the Fig. 8 where are reported the results of the network for all parameters.
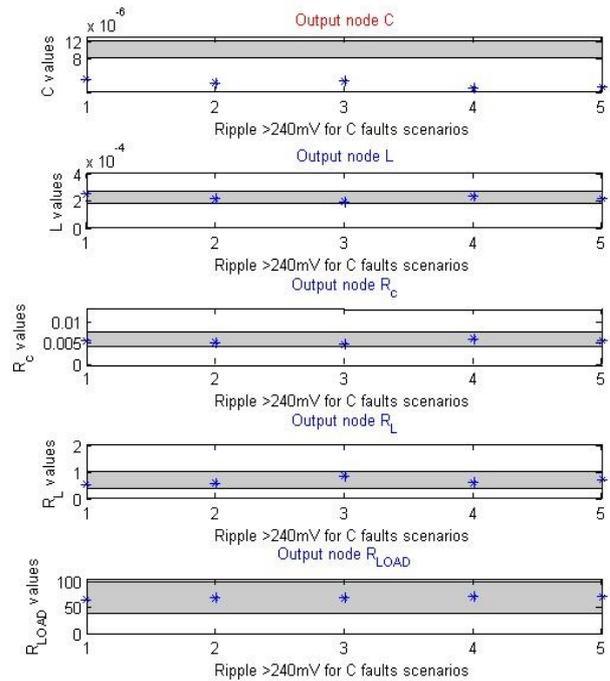

Fig. 8. MLMVN ripple> 1% for *C* value decreasing Identification.

Another fault condition of the boost converter is when the capacitor and inductor are subjected to overheating. In this case their parasitic resistance value increase. Even in this case the proposed network identifies this change in all 10 faults scenarios.

6. CONCLUSIONS

Fault diagnosis represents a key issue in any modern application in order to guarantee the availability and safety requirements. When a fault occurs it can leads to critical consequences thus it is extremely important to identify the presence of a fault condition.

Power electronic converters are widely used in safety critical application therefore monitoring activity during their functioning focalized on fault diagnosis is mandatory in order to prevent faults propagation that may lead to catastrophic failure of the converter and connected systems.

Many approach can be used in the diagnostic of a system. One of the most attractive is represented by the neural networks. In particular, in this work an application of a MultiValued Neuron artificial Neural Network for identifying parameters faults in a Boost converter is presented. The results obtained suggest that this tool is a very effective method for faults detection.

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