Conducted Electromagnetic Interference Prediction of the Buck Converter via Neural Networks

Sumin Han, Fuzhong Wang
School of Electrical Engineering and Automation, Henan Polytechnic University, 2001 Century Avenue Jiaozuo, 454000, P.R.China
hansumin@hpu.edu.cn; wangfzh@hpu.edu.cn
www.henan polytechnic university.edu

Abstract

This paper proposes an approach using neutral networks to predict conducted electromagnetic interference (EMI) on the power supply line in the buck converter. The experimental scheme is designed to collect the input and output target samples. It establishes a three-layer network including one hidden layer, whose activation function is of the hyperbolic tangent type .By the conducted EMI predicting model trained, interference prediction waveforms is obtained and analyzed . The results demonstrate that the approach is decent.

Keywords: EMI prediction; DM; CM; neural networks; buck converter

1 Introduction

EMI prediction is the key point to realize electromagnetic compatibility (EMC) of the power electronic system. It can also provide a referential opinion for EMC evaluation and design. Because of the existence of nonlinear switching devices in a power electronic system, which frequently switch their working states, producing high di/dt and du/dt signal. Consequently, the dramatic signal can conduct to the sensitive elements by conducted coupled channel, causing interference. Due to the nonlinearity of power electronic elements, and the uncertainty of the interference sources and coupling channels in which parasitic elements may be physically inaccessible inside the module package, EMI prediction problem has been a very complicated and challenging task[1-3]. Prediction accuracy is difficult to improve for many factors of influencing interference.

Deep study of EMI prediction theory has been done throughout the world. Some specialists construct various analysis and prediction models such as: source model, sensitive equipment model, the coupling model and system analysis model and so on. These methods finish prediction through the physical, or equivalent circuit, or the spice model. In general, the model study method is effective to the certain kinds of circuits, whose effectiveness for other circuits is difficult to verify. Furthermore, the modeling process itself is relative complex [4-6].

Some scholars and engineers have proposed many measurement methods to obtain the EMI emission[7-9].These methods of systems generally require relatively large amount of calculation and specialized equipment .Moreover, the different circuit topological structure needs the specific testing scheme. Thus the proposed methods are short of universality to enlarge their usages. Therefore, seeking a more reasonable forecast and analysis method without much measurement has always been a research focus for the scientific research workers in EMC field

The objective of this paper is to employ neural networks to predict the conducted DM EMI on the power line of a buck converter. Section II designs the neural networks of the DM EMI of the buck converter, including the collection of input and output samples and experiment. Section III trains the samples and demonstrates the results and their comparison. Finally, section IV concludes the paper.

2. BP Neural Networks Design

The input signal is passed from the input to output layer through the hidden layer in the typical BP network. Namely, each layer's neurons can only affect the state of the next layer. If the values of the output layer is not expected, the error is propagated backward. According to the prediction error, BP network adjusts the weights and thresholds, so that the predicted values can approximate gradually the expected output[10-11].

The neural network design consists of the following parts: input and output sample collection and preprocessing, BP network training and predicting and the analysis of the results.

2.1. *Input and output samples' acquisition and preprocessing*

The DM and CM interference on the power supply line in the buck converter are identified as the output samples, which produces mainly from the nonlinear switching devices. There are two switching devices in the common buck converter shown in Fig.1, which are MOSFET and diode respectively. Hence, we can preliminarily determine the voltage at the drain and source electrode of the MOSFET, drain current, the diode voltage are most relevant to DM and CM signals. The experimental electric circuit is designed and shown in Fig.2. The values of the electrical components of the buck converter in Fig.1 are

$$R = 100\Omega, \quad L = 1\,\mathrm{mH} \quad, C = 100\mu\mathrm{F}$$

The power supply voltage is set at 5V.

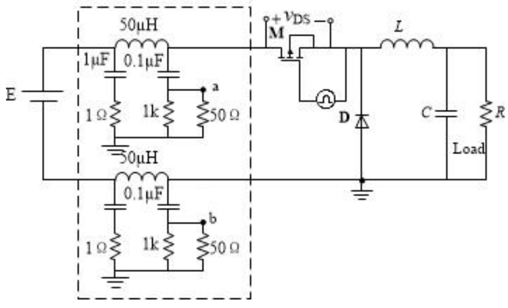

Fig.1 Buck converter and samples collecting scheme

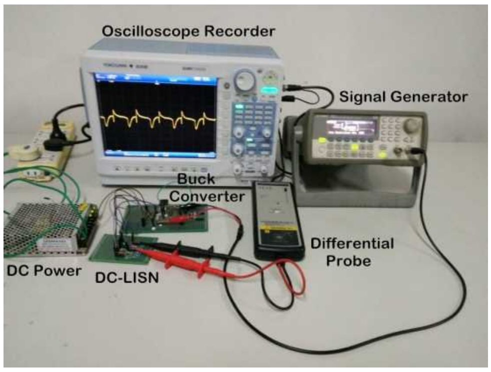

Fig.2 Experiment of the input and output samples collection of the buck converter

As shown in Fig.1, a DC-LISN(Line Impedance Stabilization Network) is connected between the power supply and the converter for acquiring the DM and CM interference signals. The MOSFET of the circuit shown in Fig.2 is driven by a pulse signal working at the basic frequency of 100kHz, which is produced by a function generator.

All the signals are obtained by a scope recorder with a voltage probe ,or a differential voltage probe or a current probe ,as is shown in Fig.2 .Particularly, the DM and CM interference signals still need processing after getting the potential of node a and b,as is expressed

$$v_{\mathrm{dm}} = \frac{v_{\mathrm{a}} - v_{\mathrm{b}}}{2}, \qquad v_{\mathrm{dm}} = \frac{v_{\mathrm{a}} + v_{\mathrm{b}}}{2}$$

where, v_{dm} is the DM signal ,while v_{cm} the CM one. Consequently we get the waveforms of the input and output signals illustrated in Fig.3.There are five kinds of signals, which are the voltage at the drain and source electrode of the MOSFET, expressed *v*ds, drain current ids and the diode voltage *v*d respectively. Each signal is collected a total of 5001 samples over the five cycles, as is illustrated in Fig.3.

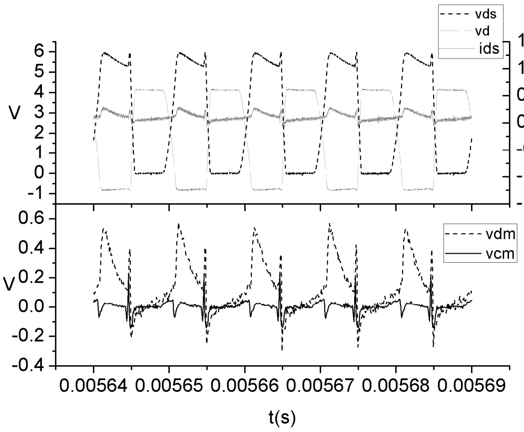

Fig.3 Input and output samples' waveforms

2.2. *Correlation analysis*

The degree of linear correlation between variables can be analyzed by correlation coefficient. The correlation coefficient formula is:

$$\rho_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}} \tag{1}$$

where $\overline{x}$ and $\overline{y}$ are the means of each variable. Results are listed in Tab.1,which shows the DM interference v_{dm} is strongly relevant to the drain-source voltage $v$ds and the diode voltage vd with the correlation

Tab.1 Correlation coefficient of output and input signals

		input		
		Vds	ids	vd
Output	v_{dm}	0.78356	0.0422	-0.73634
	v_{cm}	-0.00795	0.0007886	0.04268

coefficients of 0.78356 and -0.73634,respectively. While it has hardly relation to the drain current ids with 0.0422.However, the CM interference has a unclear characteristic with the three input signals. Each correlation coefficient is very small, almost approaching to zero. The reason is that there may be other motivators to produce CM interference.

3. BP Neural Networks Training and Forecasting

The BP neural network adopts a three-layer structure, namely input layer, hidden layer and output layer, with three input variables and two output variables, which are represented as x and y respectively. According to the experience and continuous trial and error, we determine that the hidden layer includes seven neurons. The activation function of the output layer is linear identical function, while the hidden layer activation function the hyperbolic tangent. Then, we train the selected samples according to the following algorithm. The hidden layer nodes are represented by h_k ;output layer nodes y_i; thresholds of hidden layer nodes θ_i; thresholds of input layer node θ_k; the connection weights between the input layer and hidden layer nodes v_{ki}; the connection weights between the hidden layer and output layer nodes ω_{jk} ; the desired output t_j, ; the error between the output and expectations Δ_j. Steps are as follows.

(i) Select the initial weights of v and ω, generally between (1, 1).

(ii) Calculate the information of output layer nodes for all training input sample.

(a) Calculate the output values of the hidden layer nodes.

$$h_k = f_1(\sum_{i=1}^{n} v_{ki}x_i - \theta_i) \tag{2}$$

(b) Calculate the output values of the output layer nodes

$$y_i = f_2(\sum_{k=1}^{q} \omega_{jk}z_k - \theta_k)$$

(c) Sum the errors between the actual output and the expected output of all the samples.

$$e = \frac{1}{2}\sum_{k=1}^{m}\sum_{i=1}^{q}(t_i - y_i)^2 \tag{4}$$

After training the input and output samples, the BP network predicting model is obtained. The model can be applied to predict the DM and CM interference by inputting the tested data. The predicted waveforms and the actual waveforms are as shown in Fig. 4.

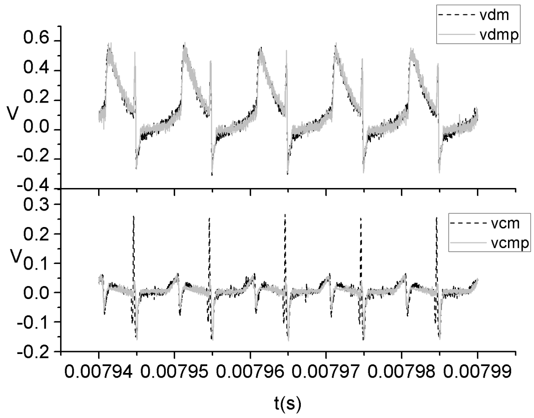

Fig.4. Predicted and actual waveforms of the DM and CM

As can be seen from Fig.4, the predicted DM and CM interference illustrated by vdmp and vcmp are in well accordance with the actual signals illustrated by vdm and vcm. Analysis data show that the relative error of the dependent variable of the scale of DM is 0.045, and CM is 0.582.Namely, the deviation is bigger.

4. Conclusion

This paper proposes the EMI prediction scheme via BP neural network. On the basis of the principle the conducted EMI emission of the buck converter, the structure of the neural network is determined which includes three-layer, three input signals and two signals. The authors adopt BP algorithm to train the network and establish the interference predicting model, by which they obtain the predicted DM and CM waveforms in time domain. Then analysis as well as comparison between the measured and predicted waveforms also demonstrate the predicted results is satisfactory and the validity of the proposed approach. However, the proposed approach still performs effective illustrated in the paper but for a slightly low precision. The predicting approach of this paper can be extended to other topological types of power electronics circuits.

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