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A Novel Impedance Measurement Technique for Power Electronic Systems

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Abstract - **When designing and building power systems that contain power electronic switching sources and loads, system integrators must consider the frequency-dependent impedance characteristics at an interface to ensure system stability. Stability criteria have been developed in terms of source and load impedance for both dc and ac systems and it is often necessary to measure system impedance through experiments. Traditional injection-based impedance measurement techniques require multiple online tests which lead to many disadvantages. The impedance identification method proposed in this paper greatly reduces online test time by modeling the system with recurrent neural networks. The recurrent networks are trained with measured signals from the system with only one injection. The measurement and identification processes for dc and three-phase ac interfaces are developed. Simulation tests demonstrate the effectiveness of this new technique.**

I. INTRODUCTION

Stability analysis in power electronics based distributed power systems is a more crucial task than in conventional power systems due to the nearly ideal control capability of many modern power converters. The excellent load regulation capability of a converter is a desirable feature in many applications, but it also makes the converter a constant-power load device, which is a potential cause of negative impedance instability [1].

For small-signal stability analysis, most research focuses on the impedance/admittance method that involves examining the Nyquist contour of the product of the source impedance and load admittance in a dc system [2]. In recent years, based on the impedance/admittance method, a variety of stability criteria and design approaches for both dc and ac systems have been proposed [3-4].

In the design, integration and analysis of distributed power systems, it is often necessary to obtain the small-signal impedance/admittance characteristics of an existing power electronic component or subsystem at a given operating point. To get the frequency-dependent characteristics by experiment, periodic voltage or current perturbations are usually injected to the system while it is under operational power. Measurements of the perturbed system are then taken and processed to determine the impedance at a specific frequency. Several methods have been proposed for impedance measurement in high-power ac systems, including utilization of three-phase bridge converters, wound-rotor induction machines and three-phase chopper circuit [5-6]. An impedance measurement technique utilizing a line-to-line current injection chopper circuit was recently proposed [7], which has a simple structure and is much easier to implement compared with other methods.

A common problem of these impedance measurement techniques is that they require injection of perturbation signals to the system one frequency at a time. To obtain the impedance characteristics over a wide frequency range for stability analysis, multiple tests must be repeatedly performed. During each test, a perturbation signal of a specific frequency is injected into the system, and the voltages and currents are measured and recorded. When tests for all frequencies are finished, the recorded data is processed to calculate the impedance value at each frequency. The main disadvantages of this procedure include: (i) It takes a long online time to complete the injections for all frequencies; (ii) The operating point of the system may vary during the prolonged test procedure, which can lead to inconsistency in the measured system impedance characteristics; (iii) If the impedances at additional frequencies are needed, new tests must be performed on the system, which may cause interruption to the normal operation of the system.

In this paper, a different approach is taken to identify the impedance characteristics of a dc or three-phase ac system. Instead of measuring system impedance at one specific frequency each time, the proposed method requires only one injection and measurement process. The recorded data is used not to directly calculate impedances, but to build a model of the system at the specified operating point by training a recurrent neural network (RNN). The trained neural network is then used to obtain the impedance characteristics. Simulation results show that the proposed method is capable of accurately identifying impedances of both dc and three-phase ac systems.

II. IMPEDANCE MEASUREMENT FOR STABILITY ANALYSIS

The analysis of small-signal stability around steady states of a power electronic system is important for both control design and component integration. In the design stage, if the mathematical model of the system is known, it can be used to extract the impedance characteristics of the system. In

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addition, models of different system components can be connected together to simulate their behaviors under different operating conditions, and linearization tools are usually available to determine the state-space matrices of the system. The situation is different in the component integration stage, when the hardware components are connected together to form a system. In this case, the detailed models of the components are often not available, especially when the components are designed and manufactured by different vendors. To evaluate the stability of the integrated system, measurements and tests are necessary to obtain the impedance information of each component.

The injection-based impedance measurement techniques utilize small voltage or current signals to perturb the system under study, while it is operating in steady state. Various injection devices have been proposed. For low-power systems, power amplifiers can be used. For high-power systems, different configurations of chopper circuits are often used, in which switching devices are turned on and off to provide a varying impedance branch that creates the perturbations.

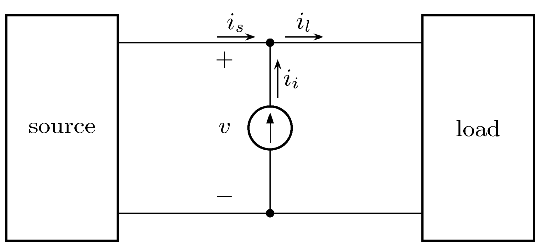

Fig. 1. Impedance Measurement in dc systems.

Fig. 1 shows the shunt injection diagram for dc systems. The system is divided into two parts, designated as source and load, although the actual power flow can be either from the load to the source or from the source to the load. The injection device is connected at their common interface. In the shunt injection system, a current signal of a specific frequency is injected into the system at a steady-state operating point. The dc voltage at the interface, together with the load and source currents, are measured. The waveforms of these signals are recorded. Fourier transform is then used to process these signals and determine the magnitudes and phase angles of the components at the injection frequency. The small signal impedances of the load and source can then be calculated with

$$Z_s(f_i) = -\frac{V(f_i)}{I_s(f_i)} \qquad Z_l(f_i) = \frac{V(f_i)}{I_l(f_i)} \tag{1}$$

where f_i is the injection frequency, V, I_s and I_l are complex numbers obtained from Fourier transform of the dc voltage, source current, and load current signals. This single injection test gives the impedance information of the system at a single frequency f_i. To obtain impedances at other frequencies, the same test procedure is be repeated, each time with a different injection frequency.

The impedance measurement test for three-phase ac systems is more complicated. As shown in Fig. 2, the shunt injection requires a three-phase current source and measurement of nine signals. Also, the impedance information for the source and load is represented by a 3 by 3 matrix. For three-phase balanced systems without neutral wire, reference frame transformation theory provides a convenient way to study the impedance characteristics. In the synchronous reference frame, the impedance and admittance take matrix forms

$$\begin{bmatrix} V_q \\ V_d \end{bmatrix} = \mathbf{Z} \begin{bmatrix} I_q \\ I_d \end{bmatrix} \qquad \begin{bmatrix} I_q \\ I_d \end{bmatrix} = \mathbf{Y} \begin{bmatrix} V_q \\ V_d \end{bmatrix} \tag{2}$$

where

$$\mathbf{Z} = \begin{bmatrix} Z_{qq} & Z_{qd} \\ Z_{dq} & Z_{dd} \end{bmatrix} \qquad \mathbf{Y} = \mathbf{Z}^{-1} = \begin{bmatrix} Y_{qq} & Y_{qd} \\ Y_{dq} & Y_{dd} \end{bmatrix} \tag{3}$$

To determine the four impedance entries in the matrix, two sets of injection signals are needed at each frequency. This actually doubles the number of tests needed to identify the system impedance characteristics over a wide frequency range.

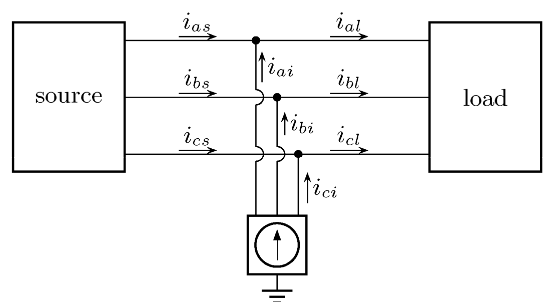

Fig. 2. Impedance Measurement in three-phase ac systems.

III. RNN-BASED IMPEDANCE IDENTIFICATION METHOD

The key point of the proposed method is the modeling of a dynamic system under study. If a model can be built to accurately produce the small-signal time-domain responses of the system to all kinds of inputs, then it also has the ability to produce the frequency-domain characteristics of the system. For an existing hardware system, the internal device parameters are often unavailable, thus it is impractical to build the model based on knowledge of the device's internal structure and control algorithms. Instead, the modeling process has to rely on measurement of its input and output signals.

A. Recurrent Neural Network as a Modeling Tool

For dynamic systems, recurrent neural network has been demonstrated to be an effective modeling tool in many applications. Unlike the widely-used multilayer feedforward neural networks that can only establish static mapping relationship between inputs and outputs, RNNs contain internal feedback loops and states. The outputs of RNNs are functions of internal states as well as the inputs, just as they are in dynamic systems. The feedback mechanism provides a memory to the recurrent networks so that they are capable of modeling systems with internal dynamics. In this study, the Elman RNN topology is chosen as the modeling tool.

Fig. 3 shows a simplified diagram of a two-layer Elman recurrent network structure. For a network with l inputs, m hidden neurons, and n outputs, the hidden layer equations are

$$s_k(t) = \sum_{i=1}^{l} w_{ik}^{(1)} x_i(t) + \sum_{j=1}^{m} w_{jk}^{(2)} d_j(t-1) \tag{4}$$

where
$$d_k(t) = \mathrm{sgm}(s_k(k)) \tag{5}$$

$\boldsymbol{x}(t)$ is the input vector, $\boldsymbol{w}^{(1)}$ is the weight matrix associated with the inputs and hidden neurons, and $\boldsymbol{w}^{(2)}$ is the weight matrix associated with the states and hidden neurons.

The outputs of the network are determined by

$$y_k(t) = \sum_{i=1}^{m} w_{ik}^{(3)} d_i(t) \tag{6}$$

where $\boldsymbol{w}^{(3)}$ is the weight matrix associated with the hidden neurons and the outputs.

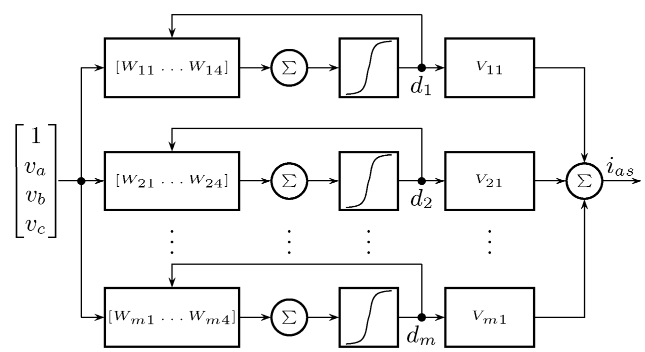

Fig. 3. Topology of the Elman recurrent network.

Past research has demonstrated the ability of the RNN to learn process dynamics and provide efficient forecasts, and it has found application in many areas such as wind speed and power forecasting [8], design of a power system stabilizer [9], induction motor speed estimation[10], and prediction of elephant migration [11].

B. Modeling with RNN

To model a dynamic system with RNN, the network must be trained with measured data so that it learns the behaviors of the system. It should be noted that the purpose of the training is not to obtain a complete model of the complex nonlinear power electronic system. Instead, throughout the test, the system is running at a specific steady-state operating point. Small variations of voltage or current are added to the system to create perturbations. The neural network is then used to model the behavior of the system responding to small signal inputs.

The measured signals are voltage and current waveforms at the interface of the source and load. These waveforms are used as training data for the input and target output of the RNN. During the training process, input data are fed to the network to calculate the output, and the internal weight parameters of the RNN are adjusted based on the output error. Several RNN training algorithms are available. Both back-propagation and particle swarm optimization algorithms [12] are used in this study.

C. Random PWM Signal Injection

Training of the RNN requires measurement data of a perturbed system, thus injection of perturbation signals is still necessary in the proposed method. For the shunt injection, chopper circuits proposed in [7] are used to handle the high voltage and power of the tested system. Fig. 4 shows the circuit as being used for line-to-line current injection in a three-phase ac system. The circuit contains a bi-directional switch that controls the branch's impedance, which in turn causes variations in the branch current. A properly designed switching pattern can thus introduce a perturbation current signal into the system. A fixed-frequency fixed-duty-cycle PWM switching scheme was used in [7] to generate a perturbation signal of a specific frequency.

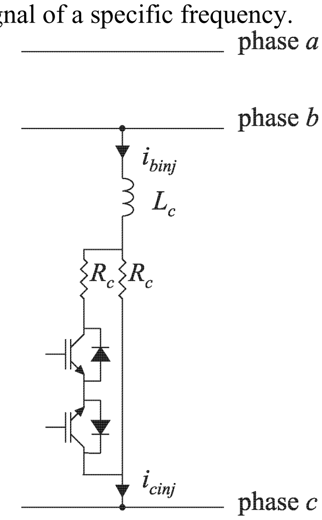

Fig. 4. Chopper circuit shown in three-phase system injection.

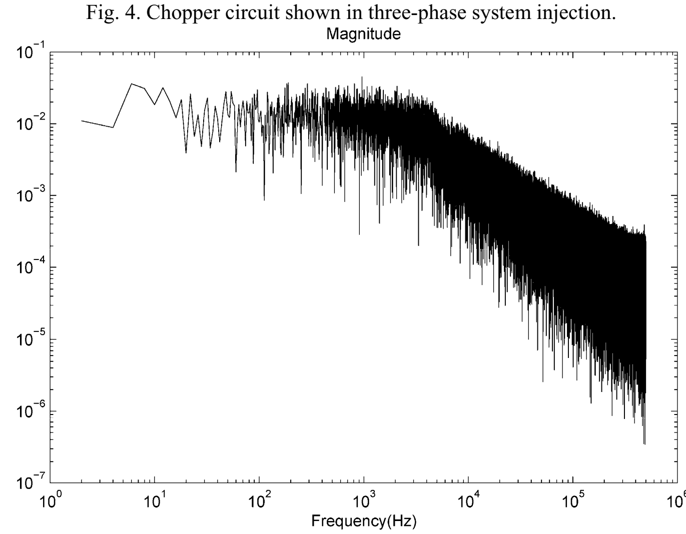

Fig. 5. Spectrum of a random PWM signal.

For the RNN to learn the dynamic behavior of the system, the spectrum of the perturbation signal must cover a wide frequency range. A random PWM signal with limited bandwidth is used in this study, which can be generated by a PWM switching scheme with random duty cycle and random switching frequency. In each PWM cycle, the switching frequency is randomly chosen between two bounds, $f_{\min}$ and $f_{\max}$, which are determined according to the frequency range of interest. Fig. 5 shows the spectrum of such a switching signal, with $f_{\min}$ = 1 kHz and $f_{\max}$ = 5 kHz. It can be seen that the signal has a relatively even magnitude at frequencies below 3 kHz. At frequencies above 3 kHz, the magnitude decreases with a slope between 20 dB/decade and 40 dB/decade.

During the period when the system is being perturbed by a random PWM switching circuit, the voltage and current signals of the source and load are measured, filtered and recorded. For a dc system, the recorded data is normalized and used directly to train the RNN. Either the voltage or the current signal can be used as the input, and the other signal is used as the target output. For a three-phase ac system, the measured signals are first transformed into the synchronous reference frame so that the fundamental components become dc signals. After normalization, the data is then used for RNN training.

The training process of the RNN involves repeatedly feeding the network with the input data, calculating the outputs, and comparing the calculated outputs with the target outputs. The network weights are modified in each epoch to minimize the error. The training stops when the error is below a certain threshold value.

A well-trained RNN can produce correct outputs even when the inputs are different from its training data. It is this generalization capability of RNNs that makes them suitable for impedance characteristics extraction. The trained RNN can be seen as an accurate small-signal model of the system, and tests can be performed on the RNN instead of on the real system to obtain the impedance information.

D. *Identification Process for dc Systems*

For a dc system, to determine the impedance value at a frequency f_i, a sinusoidal signal of frequency f_i is fed to the trained RNN to produce the output. The input and output signals are then processed with Fourier transform to determine their magnitudes and phase angles. The impedance/admittance of the system at f_i can be calculated with (1).

E. *Identification Process for Three-Phase ac Systems*

For a three-phase ac system, if the RNN is trained with currents as inputs and voltages as outputs, then it is relatively easier to calculate the impedance matrix. For each frequency f_i, there are four impedance values to be determined and two steps are needed.

In the first step, a sinusoidal signal of frequency f_i is fed to the trained RNN as i_q, while the input signal i_d is set to a zero vector. The RNN output voltages v_q and v_d are then calculated with (4)-(6). According to (2), two impedance entries can be determined by

$$Z_{qq}(f_i) = \frac{V_q(f_i)}{I_q(f_i)} \qquad Z_{dq}(f_i) = \frac{V_d(f_i)}{I_q(f_i)} \tag{7}$$

where V_q, V_d and I_q are the complex results from Fourier transform of v_q, v_d and i_q, respectively. The second step is similar to the first one except that the sinusoidal signal is fed to the RNN as i_d, while i_q is set to zero. The other two impedance entries can be determined by

$$Z_{dd}(f_i) = \frac{V_d(f_i)}{I_d(f_i)} \qquad Z_{qd}(f_i) = \frac{V_q(f_i)}{I_d(f_i)} \tag{8}$$

Fig. 6 shows a flowchart of the proposed impedance measurement procedure for three-phase ac systems. It can be seen that the online part of the procedure only includes the injection of the random PWM signal and data measurement, and the rest of the process only requires offline training and calculations.

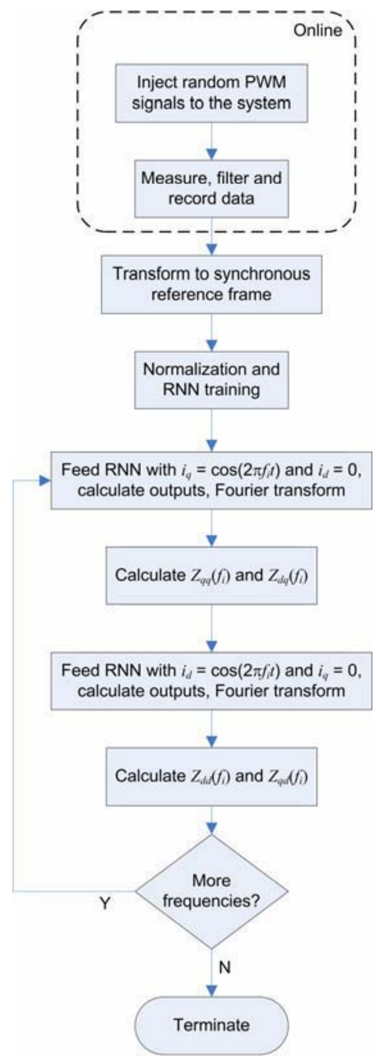

Fig. 6. Flow chart of the proposed impedance measurement procedure for three-phase ac systems..

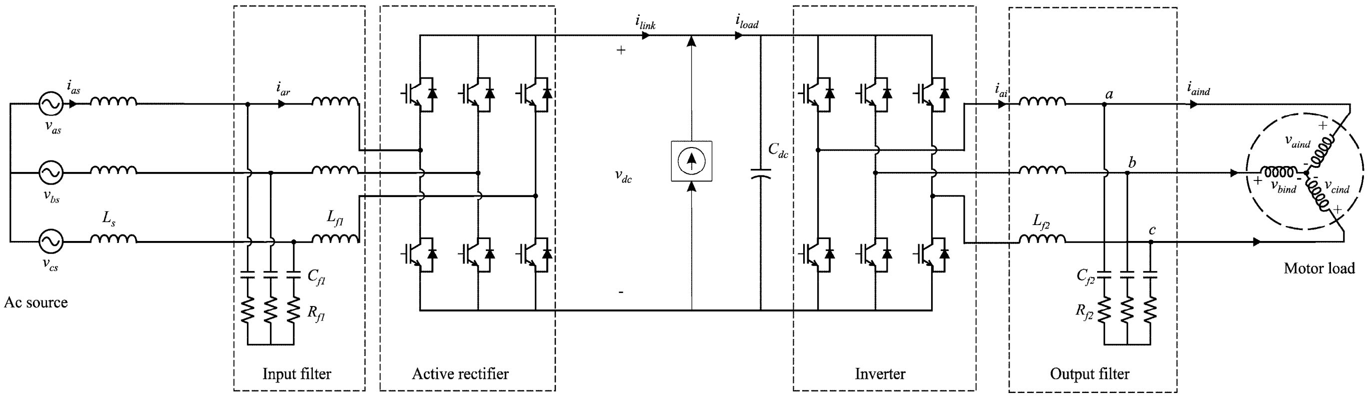

Fig. 7. Test system for dc impedance measurement.

IV. Simulation Results

The proposed impedance measurement technique was verified with simulation results of both dc and three-phase ac systems.

A. Test Results in dc Systems

A 3.7 kW variable-speed motor drive system is used for the dc test, and its diagram is shown in Fig. 7. The example system consists of a three-phase active rectifier, 300 V dc link, a three-phase inverter, and a 5 hp induction motor. Input and output filters are used to reduce the PWM switching noises.

The dc link interface of a rectifier-inverter-induction motor system is used for the dc signal injection. The location of the injection device is shown in Fig. 7, where the current source on the dc link represents the chopper circuit as shown in Fig. 4. To measure the impedance of the subsystem to the right of the injection device, both v_{dc} and i_{load} are measured and saved. The frequency range of interest is from 10 Hz to 1 kHz, and the frequency bounds of the random PWM signal is set to be 400 Hz and 1 kHz. The measured signals are filtered to avoid aliasing, and sampled at a frequency of 10 kHz. The data is then normalized to be within the range from -1 to 1. An Elman recurrent neural network is trained with the voltage data as input and current data as output. The extracted impedance characteristics are shown in Fig. 8. The actual impedance curves are obtained based on the linearized state-space matrix in a simulation model of the system. As can be seen, a very close match between the measured and actual values is achieved.

B. Test Results in ac Systems

The ac test system includes a salient-pole synchronous generator feeding an *R-L* load ($R = 27.29\ \Omega$, $L = 19.9$ mH). The chopper circuit is connected to the *b* and *c* phases of the generator terminals. The injection and data processing conditions are similar to those in the dc test, except that the *abc* signals are transformed into the synchronous reference frame before normalization. An Elman RNN is used for the training, where the inputs are the currents and the outputs are the voltages.

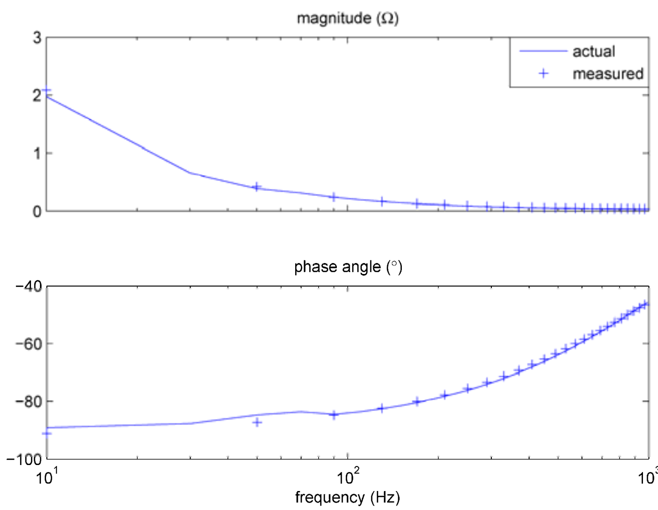

Fig. 8. Actual and measured impedances of the dc subsystem..

For a symmetric three-phase *R-L* load, its impedance matrix in the synchronous reference frame can be expressed as

$$\mathbf{Z}_{RL}(\omega) = \begin{bmatrix} R + j\omega L & \omega_e L \\ -\omega_e L & R + j\omega L \end{bmatrix} \tag{9}$$

where ω_e is the speed of the synchronous reference frame. Figs. 9 and 10 clearly show the agreement between (9) and the measured impedance characteristics.

Fig. 11 shows the measured magnitude curves of Z_{qq} and Z_{dd} of the synchronous generator. The impedances identified with the proposed method are very close to the actual values. The *q*- and *d*-axis impedances are different because of rotor saliency of the generator.

C. Evaluation of Impedance Accuracy

The accuracy of the proposed impedance identification method depends on several factors. Firstly, signal measurement errors have a large impact on the RNN training data because the small perturbation signals are usually added to very large steady-state currents and voltages. Secondly, the RNNs also contribute to impedance inaccuracies. The number of hidden neurons is directly related to the modeling capabilities of a network. Generally more neurons are needed for the RNN to accurately model systems with complex dynamics. Finally, since recurrent networks contain internal states, their initial values also affect the accuracy of the model. Their effects can be reduced by discarding the first portion of the input and output data in the identification process.

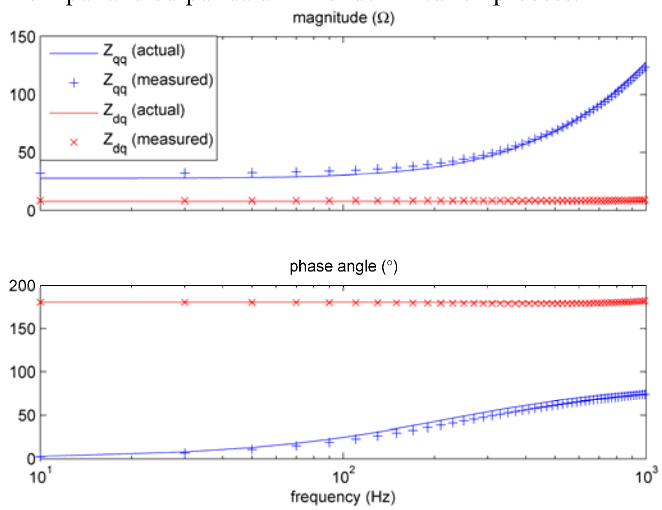

Fig. 9. Zqq and Zdq of a three-phase RL load

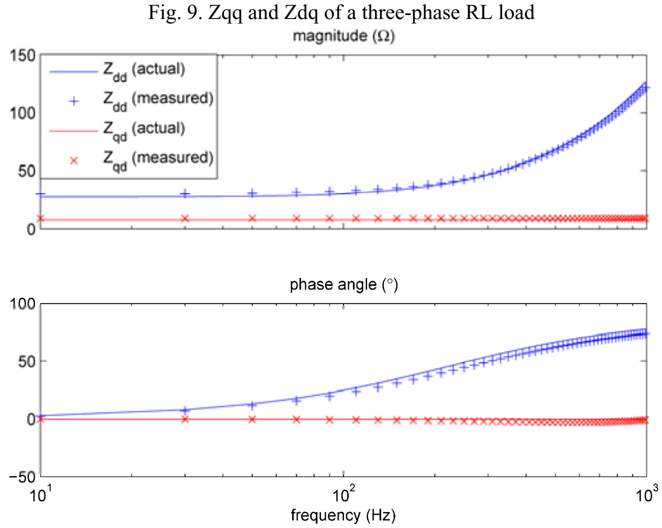

Fig. 10. Zdd and Zqd of a three-phase RL load.

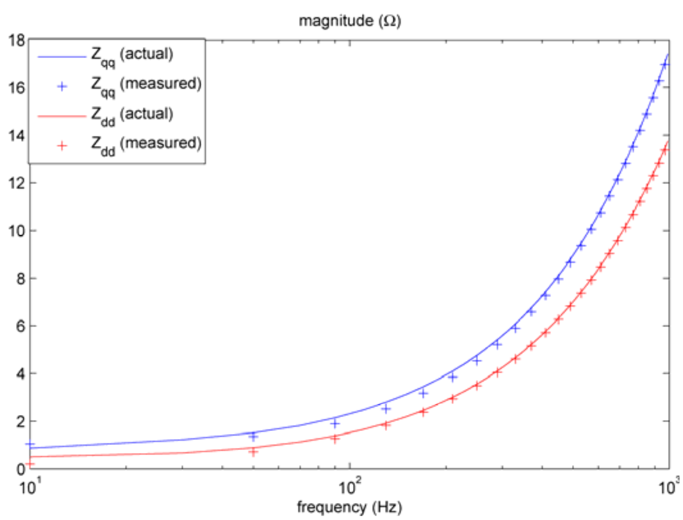

Fig. 11. Zqq and Zdd of a three-phase synchronous generator.

V. CONCLUSIONS

By modeling the small-signal dynamics of a power electronic system with recurrent neural networks, the proposed impedance identification method significantly reduces the online test time to extract the frequency-dependent impedance characteristics, which provide vital information for stability analysis. Random PWM signals and resistive chopper circuits are used to inject perturbation signals into the system under test, which produces voltage and current signals for RNN training. A laboratory test platform has been built to further verify the effectiveness of the proposed method.

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