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Recurrent Neural Networks Based 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, and it is often necessary to measure system impedance through experiments. Traditional injection-based impedance measurement techniques require multiple online testing that lead to many disadvantages, including prolonged test time, operating point variations, and impedance values at limited frequency points. The impedance identification method proposed in this paper greatly reduces online testing time by modeling the system with recurrent neural networks with adequate accuracy. The recurrent networks are trained with measured signals from the system with only one stimulus injection per frequency decade. The measurement and identification processes are developed, and the effectiveness of this new technique is demonstrated by simulation and laboratory tests.**

***Index Terms*—Impedance measurement, recurrent neural network (RNN), stability analysis.**

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]–[7].

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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 obtain 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 circuits [8]–[10]. An impedance measurement technique utilizing a line-to-line current injection chopper circuit was recently proposed [11], which has a simple structure and is easier to implement compared with other methods.

A common drawback of existing 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 are processed to calculate the impedance value at each frequency. The main disadvantages of this procedure include: 1) it takes significant online time to complete the injections for all frequencies; 2) the operating point of the system may vary during the prolonged test procedure, which can lead to inconsistency in the measured system impedance characteristics; and 3) 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 power electronic 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 are 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 RNN is then used to obtain the impedance characteristics. Results from both simulation and laboratory tests show that the proposed method is capable of accurately identifying impedances of an example system.

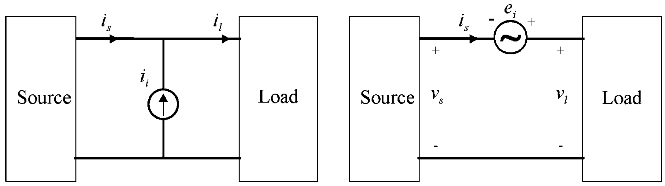


Fig. 1. Impedance measurement in dc systems. (a) Parallel injection/current injection. (b) Series injection/voltage injection.

II. Impedance Measurement for Stability Analysis

Many research works in the area of power electronic system stability analysis are based on the small-signal impedance characteristics of the source and load at a specific interface. In 1976, Middlebrook [2] proposed impedance-based design criteria for preventing input filter oscillation in switch-mode power converters. Since then, a variety of criteria have been introduced to address stability issues in both dc and three-phase ac systems [3]–[7]. Although stability analysis methods based on Bode plots are commonly used in switch-mode power supply design, the impedance-based criteria are more suitable for situations when two or more power electronic systems are integrated together. One of such situations is the system integration of modern all-electric shipboard power systems, where a large variety of switching converters and motor drive loads from different vendors are to be interconnected, and their dynamic mathematical models may not be readily available. A detailed example of using impedance information for power electronic system stability analysis can be found in [9].

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 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.

One commonly used technique for impedance measurement is based on the concept of small-signal perturbation injection. Both current and voltage signals can be injected to the system. For current perturbation signals, a parallel injection device can be used, while series injection device is used for voltage perturbation signals, as shown in Fig. 1.

Fig. 1(a) shows the shunt injection diagram for dc systems. The system is divided into two parts, designated as source and load, respectively, 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 to 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, respectively. 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 repeated, each time with a different injection frequency.

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. Network analyzers are commercially available, and have been widely used for impedance measurement in low-voltage low-power dc systems. For high-power systems, different configurations of chopper circuits are often used [8]–[11], in which switching devices are turned on and off to provide a varying impedance branch that creates the perturbations.

Regardless of the injection devices used, conventional impedance measurement techniques often require the injection of perturbation signals at a specific frequency each time, and repetitive injections are necessary to obtain the impedance characteristics over of frequency range of interest. Furthermore, the obtained impedance information only contain values at the injection frequencies.

In the following sections, a new impedance measurement method is proposed to solve the limitation of these problems, in order to extract the impedance information in the frequency domain as accurate as possible with minimal measurement time.

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 types 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 model can be created based on measurements of the input and output signals of the device.

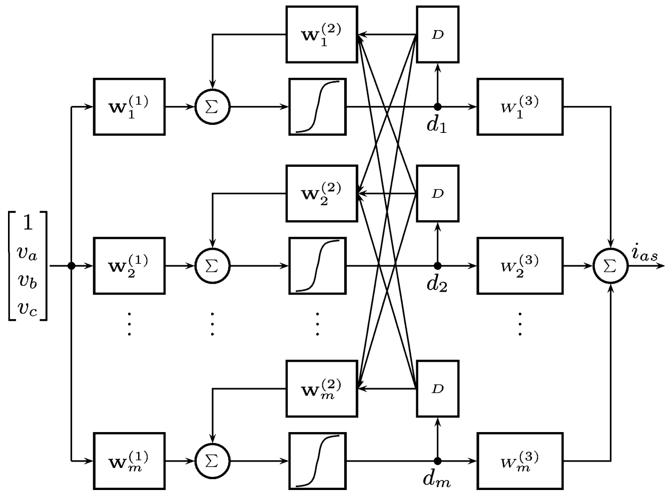


Fig. 2. Topology of the Elman recurrent network.

A. RNN as a Modeling Tool

For dynamic systems, an RNN 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 for the modeling.

Fig. 2 shows a simplified diagram of a two-layer Elman recurrent network structure, where the inputs are the voltages of a three-phase system, output is the *a*-phase current, and *m* hidden neurons are shown. Function block *D* designates unit delay. Generally, for a network with *l* inputs, *m* hidden neurons, and *n* outputs, the hidden layer equations are

$$\begin{aligned} s_k(t) &= \mathbf{w}^{(1)}\mathbf{x}(t) + \mathbf{w}^{(2)}\mathbf{d}(t-1) \\ &= \sum_{i=1}^{l} w_{ik}^{(1)} x_i(t) + \sum_{j=1}^{m} w_{jk}^{(2)} d_j(t-1) \end{aligned} \tag{2}$$

where

$$d_k(t) = \mathrm{sgm}(s_k(k)) \tag{3}$$

$\mathbf{x}(t)$ is the input vector, $\mathbf{w}^{(1)}$ is the weight matrix associated with the inputs and hidden neurons, and $\mathbf{w}^{(2)}$ is the weight matrix associated with the states and hidden neurons. The function sgm( ) used in this study is the hyperbolic tangent sigmoid transfer function.

The outputs of the network are determined by

$$y_k(t) = \mathbf{w}^{(3)}\mathbf{d}(t) = \sum_{i=1}^{m} w_{ik}^{(3)} d_i(t) \tag{4}$$

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

Past research has demonstrated the ability of the RNN to learn system dynamics and provide efficient prediction, and it has found application in many areas such as wind speed and power forecasting [12], design of a power system stabilizers [13], induction motor speed estimation [14], and prediction of elephant migration [15].

B. Modeling With RNN

To model a dynamic system with RNN, the network must be trained with measured data so that it learns the behavior 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 RNN 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, respectively.

The effectiveness of a RNN to accurately extract the impedance characteristics of a system depends on several factors. First, the structure network must be designed so that it is able to model the tested system as close as possible. For a two-layer Elman network, the important parameter here is the number of hidden neurons, which is similar to the number of states of the network. Generally, more hidden neurons enable the network to simulate more complex and higher order dynamic systems, at the cost of longer training time. If the structure of the system under study is known, the number of hidden neurons should be at least higher than the order of the system. In this study, eight hidden neurons were used in the Elman network to achieve accurate modeling with moderate amount of training time.

Second, the perturbation signals must have a wide spectrum that covers the frequency range of interest. They also should have a magnitude that is high enough to counter the effects of measurement noise.

Finally, given a well-designed RNN network and effective injection signals, the network needs to be trained so that it can closely mimic the dynamic behaviors of the tested system. 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 [16], [17]. A training method that combined back-propagation and particle swarm optimization algorithms [18] was used in this study, which is described in detail in [19]. The major purpose of the combined training method is to avoid being trapped in local minima, without being computationally demanding. The training process is terminated when a predefined mean square error (MSE) is achieved, or when the error gradient is lower than a threshold value.

C. Random Pulsewidth-Modulated (PWM) Signal Injection

Training of the RNN requires measurement data of a perturbed system, and thus, injection of perturbation signals is still

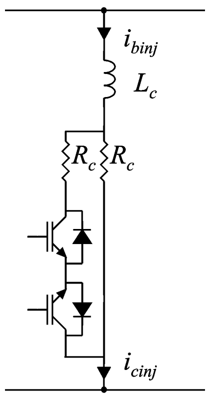


Fig. 3. Chopper circuit shown in dc system current injection.

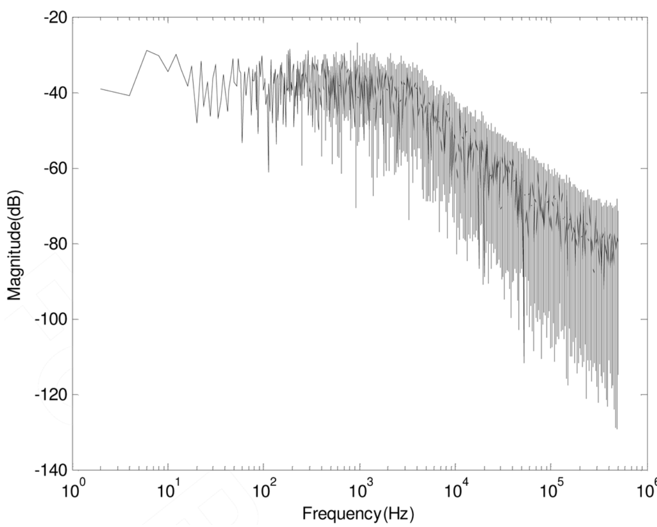


Fig. 4. Spectrum of a random PWM signal.

necessary in the proposed method. For the shunt injection, chopper circuits proposed in [8] are used to handle the high voltage and power of the tested system. Fig. 3 shows the circuit as being used for line-to-line current injection in a three-phase ac system. The circuit contains a bidirectional 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 [8] to generate a perturbation signal of a specific frequency.

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 a 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. 4 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 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 are 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 are 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).

Fig. 5 depicts the whole procedure with a flow chart. The process starts with one single injection of random PWM current (or voltage) signals into the system. The voltage and currents at the interface of interest are measured and recorded. An analog filter is needed before signal sampling to prevent aliasing from happening. The recorded data may be further filtered with digital filter algorithm before down-sampling, which produces less data points and can help reduce the time needed for RNN training. The sampled data are then normalized and fed into a randomly initialized RNN for training.

When the training process is complete, the RNN can be used to characterize the small-signal dynamic behavior of the system at a specific steady-state operating point. Pure sinusoidal signals at different frequencies are then used as inputs to the neural network to calculate the output. Because the input and output of the network represent the currents and voltages at the system source/load interface, these signals can be used to calculate the impedance/admittance at these frequencies.

E. Real-Time Impedance Measurement

By minimizing online test time, the method described before is best suited for measuring impedances of devices at some operating points of interest. A further step is to incorporate the

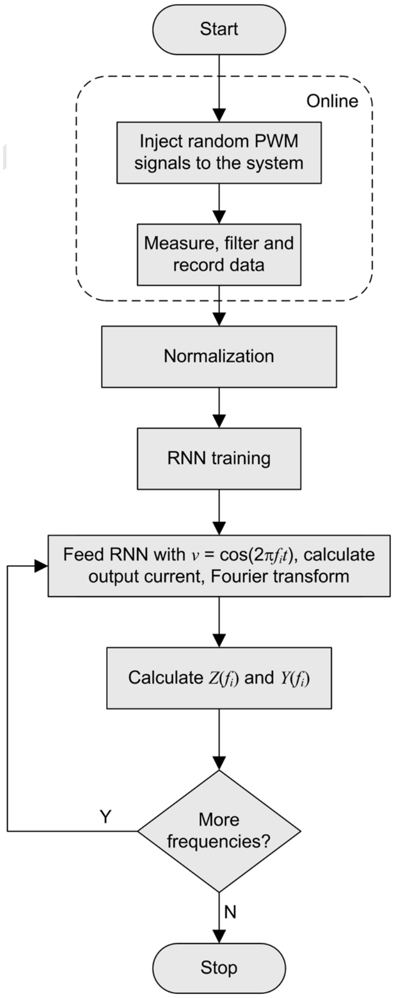


Fig. 5. Flow chart of the proposed impedance measurement procedure for dc systems.

injection-training-identification process into system operation. In this case, perturbation signals are periodically injected into the system, the measured signals are used for online training of RNN models, and the models are used to impedance identification while the system is running. A major benefit of such a scheme is that latest system signals are used to update the RNN model, which will then produce impedance information that reflects the current operating point. Combined with various impedance-based stability criteria, this method can be used for real-time stability analysis and prediction.

IV. Simulation Results

The proposed impedance measurement technique was verified with simulation at the interface, as shown in Fig. 8.

A. Test Results

A 3.7-kW variable-speed motor drive system is used for the dc test, and its diagram is shown in Fig. 6. From left to right, the example system consists of a three-phase ac voltage source, input harmonic filter, an active rectifier, a 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. 6, where the current source on the dc link represents the chopper circuit, as shown in Fig. 3. 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 are then normalized to be within the range from -1 to 1. An Elman RNN is trained with the voltage data as input and current data as output. The extracted impedance characteristics of the system on the right side of the injection device are shown in Fig. 7. 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. Evaluation of Impedance Accuracy

The accuracy of the proposed impedance identification method depends on several factors. First, 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. Second, the RNNs and their training process also contribute to impedance inaccuracies. For a limited number of training iterations, 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 RNNs 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.

V. Experimental Results

To further verify the effectiveness of the proposed impedance identification method, a laboratory prototype system similar to the one shown in Fig. 6 was built. The parameters of the passive components in the system are listed in Table I. Switching at 20 kHz, the active rectifier kept the dc bus voltage at a level of 300 V. The chopper injection circuit was connected at the dc bus, where the resistance was switched between 250 and 125 Ω. A resistive load is used in the place of the induction motor. In order to evaluate the accuracy of this method, the temperature effect was taken into account. The passive components were measured right after the inject test, before the system cooled down. Also, in the proposed method, the test period is rather short, and the system temperature rise is not significant. Therefore, there are only slight variations in the system components values. Also, the internal resistors of all the capacitors and inductors are measured and modeled for accurate reference.

Fig. 8 shows pictures of the system setup and the resistive chopper circuit.

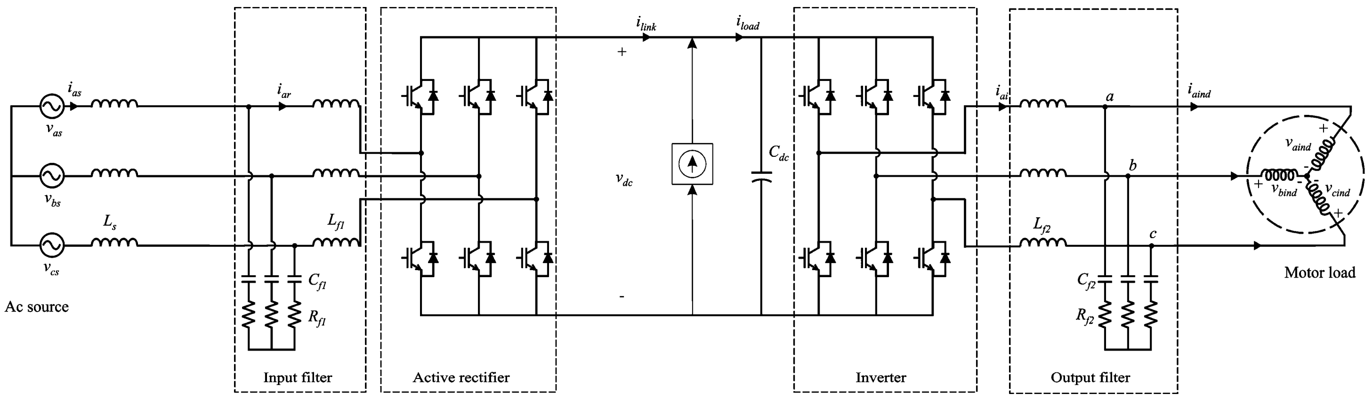


Fig. 6. Test system for dc impedance measurement.

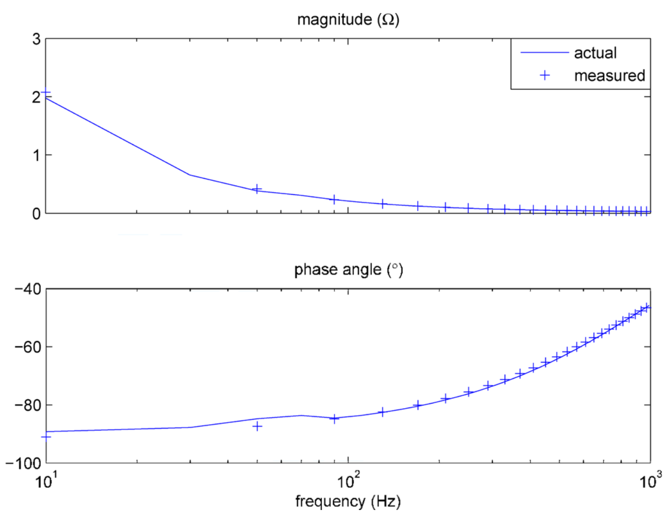


Fig. 7. Jacobian model and RNN extracted impedances of the dc subsystem.

TABLE I
COMPONENT PARAMETERS OF THE EXPERIMENTAL SYSTEM

L_s = 0.4 mH	r_s = 0.5 ohms
L_{f1} = 1.8 mH	L_{f2} = 1.2 mH
C_{f1} = 5 μF	C_{f2} = 5 μF
R_{f1} = 10.4 ohms	R_{f2} = 10.4 ohms
C_{dc} = 3900 μF	ESR(C_{dc}) = 0.2 ohms

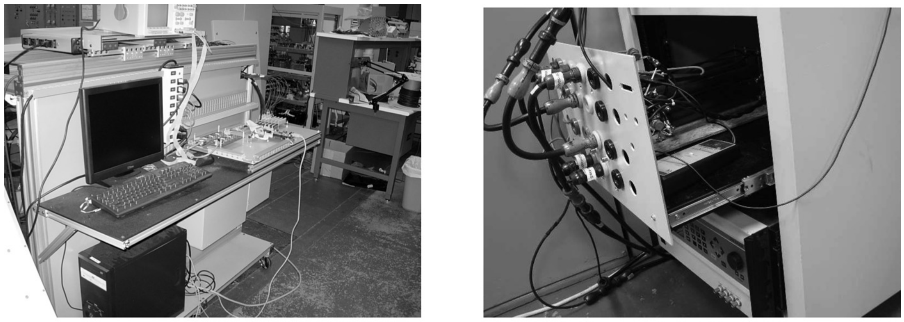
A practical concern arises when the proposed method is applied in a real-world system. Although the RNN model can be trained with recorded voltages and currents when random PWM signals are injected, it is difficult to choose one sampling rate of the recording device if the frequency range of interest is wide. In principle, the sampling rate should be at least twice as the maximum frequency of interest. On one hand, high sampling rate is desired to capture system responses to high-frequency signals. On the other hand, large number of training data points will significantly slow down the RNN training process if the sampling rate is high. It should be noted that different frequency bands have different requirements for sampling rate. For low-frequency bands, as long as aliasing can be avoided, low sampling rate is actually preferable because it is then possible to capture data over a longer period of time.

To address this issue, one solution is to divide the frequency range of interest into several bands. For example, if the desired frequency range is from 0.1 Hz to 1 kHz, four frequency bands can be considered: 0.1–1 Hz, 1–10 Hz, 10–100 Hz, and 100 Hz–1 kHz. In this case, one injection is needed for each decade, and the random PWM signal is designed to have the maximum energy at the center of the band. Four RNNs, each corresponding to a frequency band, are then used to process the four sets of recorded data. The identified impedance information can then be combined to be used for stability analysis. Although this approach is more complicated than the single-injection method, it can significantly reduce the training time of the RNNs. Compared with conventional methods, the number of injections it requires is still much lower.

Fig. 9 illustrates the training process of the RNN network for frequency band from 1 to 10 Hz. It can be seen that the MSE decreases rapidly during the initial several epochs. The reduction in MSE gradually slows down as the number of epochs increases. After about 20 iterations, the MSE settles down at a value slightly lower than 0.01. It is important to note that this value is much larger than those in simulation tests, which can be as low as 10^{-6}. The main reason for the discrepancy is that the experimental data contain much more noises, which have a negative impact on the RNN training process.

When the training is finished, the outputs of the RNN are compared with the measured data. The comparison is depicted in Fig. 10, where the solid trace shows the current signal data recorded from the system, and the dashed trace represents the RNN outputs. It can be clearly seen that there is a very good agreement between the two, which indicates that the trained RNN is an accurate model of the system under test. It is worth mentioning that the measured data are normalized before the training.

Fig. 11 shows the comparison between the actual dc load impedance and the values identified based on the trained RNNs, where the top traces represent the magnitudes and the bottom traces represent the phase angles. The effectiveness of the



(a) (b)

Fig. 8. Laboratory setup photos. (a) Rectifier/inverter. (b) Chopper device.

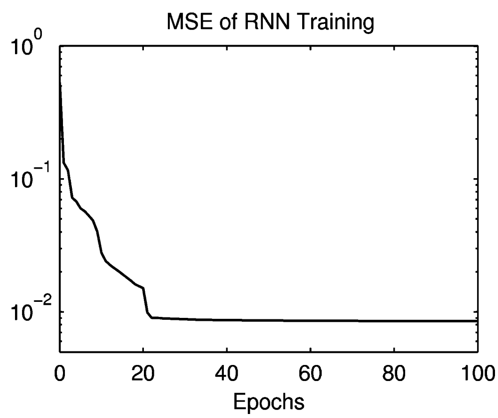


Fig. 9. MSE of RNN during the training process.

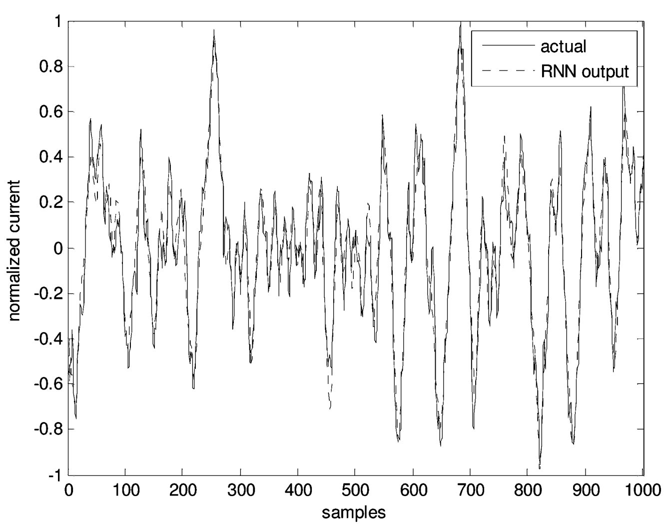


Fig. 10. Comparison between the measured (solid line) and output (dashed line) normalized current.

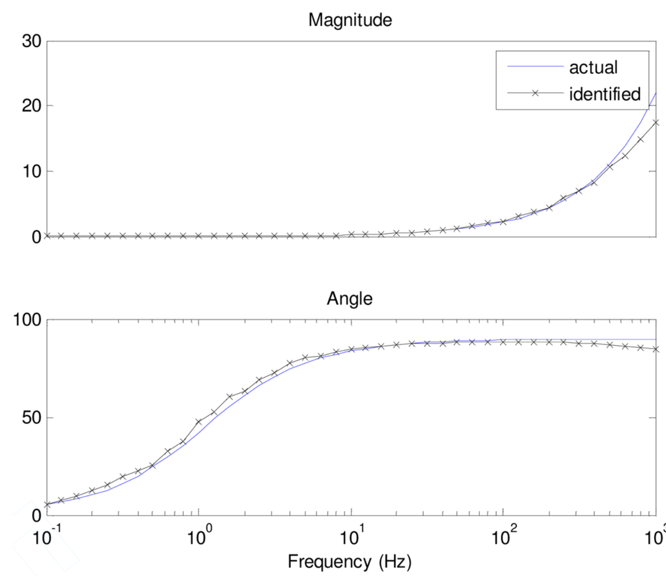


Fig. 11. Comparison between the actual and identified admittances.

proposed method is confirmed by the apparent agreement between the two traces.

It should be noted that at higher frequencies (near 1 kHz), the identified magnitude and phase values begin to diverge from the expected values. Several factors could contribute to this discrepancy. First, the high-frequency switching in the converter circuits generates a large amount of noise. Although the signals were processed with antialiasing filters, inaccuracies could still exist for higher frequency band. Second, the trained RNN gave very accurate output where the signals change slowly, but was not good at predicting output at sharp corners, as indicated in Fig. 10. This means that the accuracy of the model is not the same for all frequency ranges. Finally, at higher frequencies, the nominal values of the components used to calculate the expected impedances may vary due to frequency-dependent properties such as skin effects.

VI. Conclusion

By modeling the small-signal dynamics of a power electronic system with RNNs, the proposed impedance identification method significantly reduces 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. Compared with traditional single-frequency injection based techniques, the main advantages of the proposed method include the following.

1) A much smaller number of online injections are needed to produce the measurement data, which means less online time and disruption to the system.
2) During the injection and data acquisition, the system operating point is less likely to change, and therefore, the extracted impedance information is more consistent.
3) Once the RNN model is trained, it can be used to obtain impedance information at any frequency within the range of interest.

Both simulation and laboratory tests have been used to verify the effectiveness of the proposed method.

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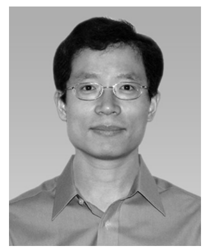

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