Transfer Learning based Impedance Identification of Voltage Source Converters

Mengfan Zhang, *Student Member, IEEE*, Xiongfei Wang, *Senior Member, IEEE*, Qianwen Xu, *Member, IEEE*

Abstract- The black-box impedance of the voltage source converters (VSCs) can be directly identified at the converter terminal without access to its internal control details, which greatly facilitates the converter-grid interactions. However, since the limited impedance data amount in practical industrial applications, the existing impedance identification methods cannot accurately capture characteristics of the impedance model at various operating scenarios, which is the indicators of the VSCs system stability at the changing profiles of renewables and loads. In this paper, a transfer learning based impedance identification is proposed to fill this research gap. This method can significantly reduce the required data amount used in impedance identification so that the black-box impedance-based stability method could be applied for the practical industrial application. The comparison results confirm the accuracy of the impedance model obtained by this transfer learning based impedance identification method.

I. INTRODUCTION

Voltage source converters (VSCs) are increasingly used as the interface of the grid and renewables, which makes modern power grid more flexible, sustainable and efficient [1]. However, the interaction of the VSCs and grid impose new challenges to system stability [2], [3].

The impedance-based method is widely applied for stability analysis of VSC systems since it does not need to formulate models of the whole system. Instead, it predicts the system stability based on the impedance ratio of the equivalent converter impedance and the equivalent grid impedance [4], [5]. Considering the asymmetry caused by the phase locked loop (PLL) of the VSC, the multi-input multi-output (MIMO) impedance model is used to evaluate the grid-connected power system stability in the frequency domain using the generalized Nyquist criterion (GNC). A typical application is reported in [6], a dq -frame impedance model of the grid-connected VSC is derived, and the grid-converter interaction is then characterized with the equivalent grid impedance and the derived VSC impedance.

However, in practical industry applications, since no or limited information of the internal control system is available from the vendors, the impedance model of inverter systems cannot be obtained with the theoretical derivation. The impedance measurement is thus increasingly applied in practical stability analysis without intellectual property (IP) contamination. An impedance-based stability analysis is reported in [7], the measured grid-connected VSC impedance and the known grid impedance are used for the stability estimation of the grid-converter system. Yet, the existing

impedance-based stability analysis methods are conducted only at the stiff operating scenario. Since the VSC is inherently a nonlinear system when the phase-locked loop (PLL) and the outer control loop are considered, the measured impedance of converters will change along with the operating point [8]. In order to predict the stability of the interaction system in different operating points, and considering the fluctuations of renewables and loads in the system, there is always a demand for the impedance of VSC in varying operating points.

To address this challenge, few methods are reported in previous literature. A polytopic model for dc-dc converters is reported in [9], where the identified small-signal models at multiple operating points are combined with weighting functions, and thus a multi-operating-point (MOP) impedance model can be obtained. Yet this model can just predict the impedance at limited operating points and hard to guarantee the accuracy. An improved method is to adapt the artificial neural network (ANN) technique to generate the MOP-impedance model with the measured impedance [10]. The ANN based impedance model trained with the measured impedance can describe the characteristics of the VSC at varying operating points. Nevertheless, the impedance data used in the model training need to be measured by repeated experiments with different operating points, as the operating point is the four-dimension vector, it is unrealistic to measure enough data for model training in field applications. The limited data amount will consequently introduce the over-fitting phenomena that are harmful to the accuracy of the trained impedance model [11] and then affect the accuracy of stability estimation.

To overcome the bottleneck imposed by limited data amount in practical impedance identification, this paper proposes a transfer learning based impedance identification method. Transfer learning is an effective technique to deal with the data limitation issue in computer science by transferring the knowledge learned while solving one problem to solving another related problem [12]. Inspired by this concept, we propose a new physics based transfer learning method that if a neural network structure can be constructed in a way to resemble the inherent structure of the physical model of VSC, the accuracy of the trained models can be improved with limited data amount. The proposed method consists of following steps: First, the analytical model of the VSC is derived and an ANN structure is constructed based on the achieved analytical model. Next, numerical offline tests are conducted to generate the large amount impedance data, which are fed into the constructed ANN structure to generate the

The transfer functions with the additional superscript “m” represent the symmetric transfer matrices, which are shown below:

$$Y_{p,dq}^m(s) = Y_{o,dq}^m(s) = \frac{1}{L(s^2 + \omega_1^2)} \begin{bmatrix} s & \omega_1 \\ \omega_1 & s \end{bmatrix} \quad (9)$$

$$G_{i,dq}^m(s) = \begin{bmatrix} G_i(s) & 0 \\ 0 & G_i(s) \end{bmatrix} \quad (10)$$

$$G_{del}^m(s) = \begin{bmatrix} G_{del}(s) & 0 \\ 0 & G_{del}(s) \end{bmatrix} \quad (11)$$

where ω_1 is the grid fundamental frequency. The PLL effects are modeled by two transfer matrices

$$\begin{bmatrix} \Delta I_{PLL,d} \\ \Delta I_{PLL,q} \end{bmatrix} = \begin{bmatrix} 0 & -G_{PLL}(s)I_{s,q} \\ 0 & G_{PLL}(s)I_{s,d} \end{bmatrix} \begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix} = G_{I,PLL}^m \begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix} \quad (12)$$

$$\begin{bmatrix} \Delta V_{PLL,d} \\ \Delta V_{PLL,q} \end{bmatrix} = \begin{bmatrix} 0 & -G_{PLL}(s)V_{s,q} \\ 0 & G_{PLL}(s)V_{s,d} \end{bmatrix} \begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix} = G_{V,PLL}^m \begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix}$$

where $I_{s,d}$, $I_{s,q}$ and $V_{s,d}$, $V_{s,q}$ denote the steady-state complex space vectors of current and voltage in d -axis and q -axis, respectively. Thus the block diagram of small-signal transfer matrices of the grid-connected VSC system is derived as shown in Fig. 3.

The closed-loop current response is derived as:

$$\begin{bmatrix} I_d \\ I_q \end{bmatrix} = G_{cl,dq}^m(s) \begin{bmatrix} I_{ref,d} \\ I_{ref,q} \end{bmatrix} - \left\{ [I^m + T_{dq}^m(s)]^{-1} Y_{to,dq}^m(s) - G_{cl,dq}^m(s) Y_{PLL}^m(s) \right\} \begin{bmatrix} V_d \\ V_q \end{bmatrix} \quad (13)$$

where I_m is the unitary diagonal matrix, the other transfer functions are shown below:

$$Y_{to,dq}^m(s) = Y_{p,dq}^m(s) - Y_{p,dq}^m(s) G_{del}^m(s) G_{V,PLL}^m(s)$$

$$T_{dq}^m(s) = Y_{p,dq}^m(s) G_{del}^m(s) G_{c,dq}^m(s) \quad (14)$$

$$G_{cl,dq}^m(s) = [I^m + T_{dq}^m(s)]^{-1} T_{dq}^m(s)$$

Thus, the closed-loop admittance matrix of VSC can be derived as:

$$Y_{icl,dq}^m(s) = [I^m + T_{dq}^m(s)]^{-1} Y_{to,dq}^m(s) - G_{cl,dq}^m(s) Y_{PLL}^m(s) \quad (15)$$

As shown in (15), if the control structure of the VSC is fixed, the converter admittance model is dependent by the steady state operating point, frequency and the control parameters. In piratical industry applications, the detailed control parameters are not available in real application, so that the admittance shown in (15) is a structural model with the unknown control parameters.

III. TRANSFER LEARNING BASED IMPEDANCE IDENTIFICATION

Based on the admittance model derived in Section II, a transfer learning based impedance identification method is proposed, consisting of knowledge based offline phase and real-time measurement based online phase.

A. Statement

Fig. 4. Framework of the proposed transfer learning based impedance identification method.

1) Dataset structure statement

In industrial applications, the steady state operating points i.e., $I_{s,dq}$ and $V_{s,dq}$ are variable in different operating scenarios, the closed-loop admittance thus are variable. Due to the admittance model derived in (15), the admittance model is affected by the operating point. Thus the structure of multi-operating-point admittance model is established, where the operating point of the VSC in dq -frame, i.e., (V_d, V_q, I_d, I_q) and frequency f_p are selected as the input of the model to reveal the operating-point-dependent and frequency-dependent feature. The magnitude and the phase of admittance in the dq -frame are selected as the outputs of the model.

2) Problem statement

As mentioned in section II, for the VSCs provided by different vendors, the control structure is known while the control parameters are uncertain. The purpose of proposed method is to utilize the impedance model trained by measured data and the analytical model for the VSCs with the different control parameters that are not learned by the model before.

The domain data consists of a feature space of input X and a marginal probability distribution $P(X)$. Denoted by $D_s = \{(\mathbf{x}_{s1}, \mathbf{y}_{s1}), \dots, (\mathbf{x}_{sn}, \mathbf{y}_{sn})\}$ the simulated source-domain labeled data, where the input X_s are operating points and frequency of the system, i.e., (f, V_d, V_q, I_d, I_q) and $\mathbf{y}_s$ are the corresponding admittance, i.e., $(Y_{dd}, Y_{dq}, Y_{qd}, Y_{qq})$. Similarly, the field-measured impedance data in the target domain is denoted as $D_t = \{(\mathbf{x}_{t1}, \mathbf{y}_{t1}), \dots, (\mathbf{x}_{tm}, \mathbf{y}_{tm})\}$, where $m < n$. In the transfer learning setting, if the data in the source and target domain follow the same distribution, i.e., $X_s \neq X_t, P(X_s) = P(X_t)$, the transferred admittance model can achieve a satisfactory application accuracy [15]. The distribution of the measured data and the simulated data are guaranteed the same in this paper.

B. Framework description

The framework of the proposed transfer learning based impedance identification method is shown in Fig. 4. The implementation of the method are divided as the offline phase and online phase.

In the offline phase, first, the simulation model is established in Matlab/Simulink, the simulated impedance data are obtained with the impedance measurement technique in the simulation. Second, the structure model that is derived in

Section II is used to restructure the ANN structure, which can reduce the demand for simulated data. After that, the offline ANN-based multi-operating-point impedance model is trained with the initialized ANN structure and the fed simulated impedance data.

In the online phase, the field impedance data of the new converter VSC I with the impedance measurement technique are fed into the offline-trained impedance model, where the parameters and the structure remain from the offline phase. As mentioned in Section III. B, the distribution of the fielded data should be the same. After the training, the multi-operating-point impedance model of the VSC I are achieved.

IV. IMPLEMENTATION OF TRANSFER LEARNING BASED IMPEDANCE IDENTIFICATION

To implement the transfer learning based impedance identification method, the dq -impedance measurement is proposed to generate the dataset used for ANN training. And the ANN structure is generated with the analytical structure model derived in Section II.

A. Dq -impedance measurement

The dq -impedance measurement is proposed in variable operating points and frequency to obtain the dataset considering the variation of the operating points in different frequency.

Fig. 5 shows the diagram of dq -impedance measurement of the VSC. The current source-type perturbation is injected into the VSC at the point of common coupling (PCC). By extracting the response at PCC, the output impedance data of VSI can be calculated.

The detailed flowchart of the impedance measurement procedure in the dq -frame is shown in Fig. 6 that consists of perturbation injection, data processing, and impedance calculation.

The first step is to inject the perturbation at the specific frequency f_p into the VSC system at PCC. Before the measurement, the magnitude of this perturbation signal has to be appropriately designed to extract the converter dynamics [16]. On the one hand, the magnitude of the perturbation has to be small to ensure the steady state of the operating point of the VSC system is stable. On the other hand, it has to be large to reject the influence of measurement noise. Generally, the magnitude of the perturbation is should be between 5% and 10% of steady-state values [17], [18].

Fig. 5: Dq -impedance measurement diagram.

Fig. 6: Dq -impedance measurement workflow.

The next step is to obtain the voltage and current response of the VSC at PCC and process the data. The measured output current and voltage of the VSC are the abc -frame signals, the Park's transformation are used to transform the signal to dq -frame, i.e. $U_{d1}, U_{q1}, I_{d1}, I_{q1}$. The $U_{d1}, U_{q1}, I_{d1}, I_{q1}$ are the time series signal with the fixed sampling frequency. By applying the fast Fourier transform (FFT) algorithm, the voltage and current at the injected frequency can be extracted, i.e., $U_{d1}(f_p), U_{q1}(f_p), I_{d1}(f_p), I_{q1}(f_p)$. To acquire the four entries of the impedance matrix $Y_{dq}^m(f_p)$, two linearly independent perturbations are injected [19]. Based on another extracted voltage and current at the injected frequency, i.e., $U_{d2}(f_p), U_{q2}(f_p), I_{d2}(f_p), I_{q2}(f_p)$, the admittance of the VSC at specific frequency f_p is calculated as follow

$$Y_{dq}^m(f_p) = \begin{bmatrix} Y_{dd}(f_p) & Y_{dq}(f_p) \\ Y_{qd}(f_p) & Y_{qq}(f_p) \end{bmatrix} \quad (16)$$

$$= \begin{bmatrix} U_{d1}(f_p) & U_{d2}(f_p) \\ U_{q1}(f_p) & U_{q2}(f_p) \end{bmatrix}^{-1} \begin{bmatrix} I_{d1}(f_p) & I_{d2}(f_p) \\ I_{q1}(f_p) & I_{q2}(f_p) \end{bmatrix}$$

After the procedure, the magnitude and phase of the VSC impedance with a specific frequency f_p and operating point are obtained. Repeating this procedure with by changing the frequency of the perturbation and operating point of VSC, the admittance dataset with variation are established, in which operating points and frequency are inputs while the corresponding magnitude and phase of the admittance are the outputs.

B. ANN restructuring

The conventional deep learning method needs a large amount of data to configure the ANN structure and the weights of the connection. If some parts of the ANN can be pre-decided, the demand of data can be greatly reduced. Based on the theoretical structure admittance model of VSC derived in Section II, this section shows the how to apply this structure model in the neural network restructuring.

The structure model in (15) can be represented as following:

$$Y_{dq}^m(s) = [A_{dq}^m(s) - B_{dq}^m(s) \cdot V_{dq}^m - C_{dq}^m(s) \cdot I_{dq}^m] \cdot [D_{dq}^m(s)]^{-1} \quad (17)$$

where:

$$A_{dq}^m(s) = \begin{bmatrix} \frac{s}{L \cdot (s^2 + \omega_1^2)} & \frac{\omega_1}{L \cdot (s^2 + \omega_1^2)} \\ \frac{\omega_1}{L \cdot (s^2 + \omega_1^2)} & \frac{s}{L \cdot (s^2 + \omega_1^2)} \end{bmatrix}$$

$$B_{dq}^m(s) = \frac{s \cdot k_{pll-p} + k_{pll-i}}{s^2 + (s \cdot k_{pll-p} + k_{pll-i})v_{id}} \cdot \begin{bmatrix} s & \omega_1 \\ -\omega_1 & s \end{bmatrix}$$

$$C_{dq}^m(s) = \frac{1}{L(s^2 + \omega_1^2)} \cdot \frac{s \cdot k_{pll-p} + k_{pll-i}}{s^2 + (s \cdot k_{pll-p} + k_{pll-i})v_{id}} \cdot e^{-1.5T_s \cdot s} \cdot \begin{bmatrix} s & \omega_1 \\ -\omega_1 & s \end{bmatrix}$$

$$D_{dq}^m(s) = \begin{bmatrix} 1 + \frac{1}{L(s^2 + \omega_1^2)} \cdot e^{-1.5T_s \cdot s} \cdot \left(k_p + \frac{k_i}{s}\right) \cdot s & \frac{1}{L(s^2 + \omega_1^2)} \cdot e^{-1.5T_s \cdot s} \cdot \left(k_p + \frac{k_i}{s}\right) \cdot \omega_1 \\ -\frac{1}{L(s^2 + \omega_1^2)} \cdot e^{-1.5T_s \cdot s} \cdot \left(k_p + \frac{k_i}{s}\right) \cdot \omega_1 & 1 + \frac{1}{L(s^2 + \omega_1^2)} \cdot e^{-1.5T_s \cdot s} \cdot \left(k_p + \frac{k_i}{s}\right) \cdot s \end{bmatrix}$$

$$V_{s,dq}^m = \begin{bmatrix} 0 & V_{s,d} \\ 0 & V_{s,q} \end{bmatrix}, I_{s,dq}^m = \begin{bmatrix} 0 & I_{s,d} \\ 0 & I_{s,q} \end{bmatrix}$$

(18)

Fig. 7. ANN structure diagram.

As (17) shows, this structure model is naturally separated into the operating-point-dependent function and the frequency-dependent function. For simplification, (18) can be rewritten as:

$$\begin{aligned} A_{dq}^m(s) &= \begin{bmatrix} A_{dd}(s) & A_{dq}(s) \\ A_{qd}(s) & A_{qq}(s) \end{bmatrix}, B_{dq}^m(s) = \begin{bmatrix} B_{dd}(s) & B_{dq}(s) \\ B_{qd}(s) & B_{qq}(s) \end{bmatrix}, \\ C_{dq}^m(s) &= \begin{bmatrix} C_{dd}(s) & C_{dq}(s) \\ C_{qd}(s) & C_{qq}(s) \end{bmatrix}, [D_{dq}^m(s)]^{-1} = \begin{bmatrix} D_{dd}^{-1}(s) & D_{dq}^{-1}(s) \\ D_{qd}^{-1}(s) & D_{qq}^{-1}(s) \end{bmatrix} \end{aligned} \quad (19)$$

Thus, (17) can be written as follows:

$$\begin{aligned} Y_{dd}(s) &= A_{dd}(s) D_{dd}^{-1}(s) + D_{qd}^{-1}(s) \cdot \\ &\quad (A_{qd}(s) - (V_q \cdot B_{dq}(s) + V_d \cdot B_{dd}(s)) - (I_q \cdot C_{dq}(s) + I_d \cdot C_{dd}(s))) \\ Y_{qd}(s) &= A_{qd}(s) D_{dd}^{-1}(s) + D_{qd}^{-1}(s) \cdot \\ &\quad (A_{qq}(s) - (V_d \cdot B_{dq}(s) + V_q \cdot B_{qq}(s)) - (I_d \cdot C_{qd}(s) + I_q \cdot C_{qq}(s))) \\ Y_{dq}(s) &= A_{dd}(s) D_{dq}^{-1}(s) + D_{dq}^{-1}(s) \cdot \\ &\quad (A_{qd}(s) - (V_q \cdot B_{dq}(s) + V_d \cdot B_{dd}(s)) - (I_q \cdot C_{dq}(s) + I_d \cdot C_{dd}(s))) \\ Y_{qq}(s) &= A_{qd}(s) D_{dq}^{-1}(s) + D_{qq}^{-1}(s) \cdot \\ &\quad (A_{qq}(s) - (V_d \cdot B_{dq}(s) + V_q \cdot B_{qq}(s)) - (I_d \cdot C_{qd}(s) + I_q \cdot C_{qq}(s))) \end{aligned} \quad (20)$$

Take Y_{dd} as example:

$$\begin{aligned} Y_{dd}(s) &= F_1(s) - V_q \cdot F_2(s) - V_d \cdot F_3(s) - I_q \cdot F_4(s) - I_d \cdot F_5(s) \\ &= G[F_1(s), F_2(s), F_3(s), F_4(s), F_5(s), V_q, V_d, I_q, I_d] \end{aligned} \quad (21)$$

where $F_1(s)$, $F_2(s)$, $F_3(s)$, $F_4(s)$, $F_5(s)$ are the nonlinear functions of frequency while the linear calculation function G , that consists of these nonlinear functions and the operating points.

As the output of measured datasets consist of the magnitude and phase of the VSC admittance, the outputs of the neural network are written as follows:

$$\begin{aligned} Y_{dd-mag} &= \text{Mag}[G[F_1(s), F_2(s), F_3(s), F_4(s), F_5(s), V_q, V_d, I_q, I_d]] \\ Y_{dd-pha} &= \text{Ang}[G[F_1(s), F_2(s), F_3(s), F_4(s), F_5(s), V_q, V_d, I_q, I_d]] \end{aligned} \quad (22)$$

where the nonlinear functions Mag and Ang can calculate the magnitude and phase of the impedance.

As a conclusion, the structure model of the impedance is separated into two nonlinear functions and one linear calculation function. Thus, the restructured ANN structure is shown in Fig. 6. This neural network is split into 3 layers. Layer I is the nonlinear calculation layer, which generates the nonlinear output the nonlinear functions $F_1(s)$, $F_2(s)$, $F_3(s)$, $F_4(s)$, $F_5(s)$. Layer II is the linear calculation layer, which represents the linear function G . Layer III is the magnitude and phase calculation layer, which generates the output of the whole ANN.

V. CASE STUDY AND VALIDATION

To verify the proposed transfer learning based impedance identification method, a case study of modeling the VSC systems using the physicals and measured data is designed.

A. Case study description

A three-phase VSC system marked as VSC II with the PI current controller and the PLL shown in Fig. 1 is the target VSC. A source VSC is designed with the same control structure and different parameters and is marked as VSC I. The detailed parameters of the VSCs are shown in Table I.

TABLE I. VSC PAERMETERS

Symbol	Description	VSC I Value	VSC II Value
V_{dc}	Inverter input dc voltage	700 V	700 V
f_{sw}	Switching frequency	20 kHz	10 kHz
f_0	Line frequency	50 Hz	50 Hz
L_f	Inductance of inverter output inductor	1 mH	3 mH
R_{Lf}	Parasitic resistance of inverter inductor	0.3 m Ω	0.9 m Ω
K_{p_i}	Proportional gain of current controller	10.5	31.4
K_{i_i}	Integral gain of current controller	5900	16449
K_{p_pll}	Proportional gain of inverter PLL	1.2	1.4
K_{i_pll}	Integral gain of inverter PLL	257	324

As mentioned in the framework described in Section III, the task is solving the impedance model of target VSC using the existing physical knowledge derived in Section IV and the model generated impedance model of the source VSC. The

impedance data of the source VSC need is measured, then the impedance data are fed into the ANN structure and the impedance model of the source VSC is generated. To show the effectiveness of the proposed method, the comparison between

Fig. 8. Output admittance dataset of source VSC used for training.

Fig. 10. Generated MOP-admittance model of source VSC.

the conventional ANN based identification method and the proposed transfer learning based identification method using the same measured impedance dataset is conducted.

B. Transfer learning based impedance identification

Before training the impedance model of the target VSC, the impedance model of source VSC need to be generated. The impedance measurement are conducted to obtain the training dataset. In this paper, the data are extracted by the simulation model, which is validated by the field measurements [20]. To make the result easily visible, only the operating point I_d is variable. In the dataset, the frequency f_p was swept from 1 Hz to 100 Hz with an interval of 1 Hz, whereas the operating current I_d was swept from 20 A to 70 A with an interval of 1 A. The results are separated into Y_{dd} , Y_{dq} , Y_{qd} , Y_{qq} . The obtained output admittance dataset for training is shown in Fig. 9. Then the obtained dataset is fed into the restructured ANN. After the training process, the admittance model of the source VSC Y_{VSC-I} is generated as shown in Fig. 10.

The model of source VSC is used to train the admittance model of the target VSC. In the impedance dataset of target VSC, the frequency f_p was swept from 1 Hz to 101 Hz with an interval of 5 Hz, whereas the operating current I_d was swept

from 20 A to 70 A with an interval of 5 A. In such case, only 200 data points are needed, which is shown in Fig. 11. Then feed the dataset into the admittance model Y_{VSC-I} , the admittance model of the target VSC Y_{VSC-II} is generated as shown in Fig. 12.

To verify the accuracy of the target VSC admittance model Y_{VSC-II} , the generated ANN-based model needs to be compared with the verification dataset that is not used in training with the corresponding frequency f_{p_v} and operating current I_{d_v} . In the verification dataset, the frequency f_{p_v} was swept from 1 Hz to 100 Hz with an interval of 0.1 Hz, whereas the operating current I_{d_v} was swept from 20 A to 70 A with an interval of 0.1 A. The corresponding errors between the verification data and the generated model are shown in Fig. 13, where the errors become large when the data used in training is sparse, yet the largest error is only 1 % of the verification data. Hence, the proposed transfer learning based impedance identification method can accurately model the VSC considering the operating point variation.

C. Comparison with the conventional ANN method

The comparison between the conventional ANN method and the proposed transfer learning based identification method

Fig. 11. Output admittance dataset of target VSC used for training.

Fig. 12. Generated MOP-admittance model of target VSC.

Fig. 13. Corresponding errors between multi-operating-point admittance model and verification data of proposed transfer learning method.

Fig. 14. Corresponding errors between multi-operating-point admittance model and verification data of conventional ANN method.

using the same measured impedance dataset is conducted to show the effectiveness of the transfer learning based method. The same dataset as shown in Fig. 11 are fed into a two-hidden-layer random initialized ANN. After the training, the model $Y_{VSC-II-O}$ is generated. To directly show the comparison result of two models. The corresponding errors between the verification data with the same distribution and the generated model are shown in Fig. 14.

Compared to the errors shown in Fig. 13, the conventional ANN method cannot have the good performance with the sparse dataset, where the proposed transfer learning based method can reduce the data amount requirement. Thus the proposed approach can address the disadvantages of the existing impedance identification methods in capturing the operating point-dependent feature of the impedance model.

VI. CONCLUSIONS

This paper proposes a transfer learning based impedance identification method to address the data limitation issue in

impedance identification under changing operating conditions. An artificial neural network model is used to characterize the operating-point dependent impedance model. Considering the data amount limitation in this application, the transfer learning technique is employed in this paper. By combining the deep learning theory and impedance modeling knowledge, a transfer learning based impedance identification method is proposed. The proposed impedance identification method could be effectively applied for practical impedance identification and stability analysis with limited data. The comparison results can verify the superior of the proposed impedance identification method to existing methods.

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