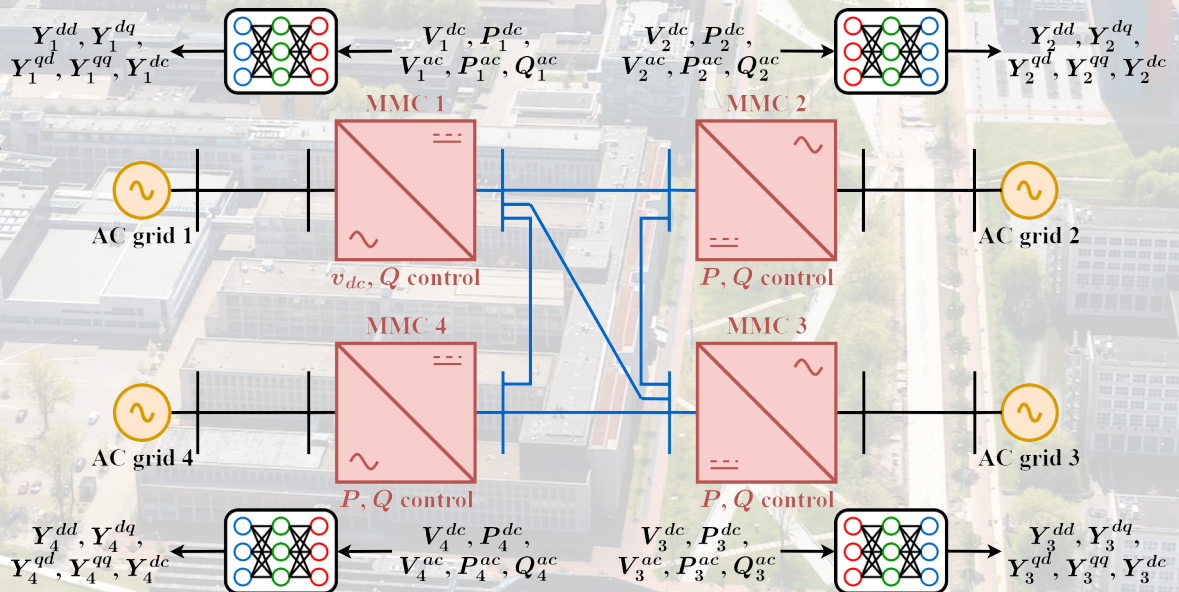


Transfer Learning Framework for Impedance Characterization of Modular Multilevel Converters

Master of Science (MSc.) Thesis

Rahul Rane



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Abstract

Voltage source converters (VSCs), particularly modular multilevel converters (MMCs), play a pivotal role in modern power grids due to their application in inter-connected systems and renewable energy integration. However, their complex internal dynamics and control systems can cause stability issues under a variety of operating conditions. Impedance-based stability analysis is critical for understanding these interactions and ensuring grid reliability. Traditional small-signal models based on physics and circuit analysis often neglect nonlinearities and practical implementation details, limiting their accuracy. In contrast, black-box impedance measurement techniques necessitate significant computational resources and human effort, particularly when analysing both AC and DC side impedances.

This thesis presents a transfer learning framework for accurate impedance characterization of MMCs. The framework uses a combination of linear time-invariant (LTI) modeling and black-box impedance measurements to estimate impedances based on system-level parameters such as AC and DC side voltages, active power, and reactive power. The methodology involves pre-training artificial neural network (ANN) models on a diverse dataset derived from LTI models, followed by fine-tuning with real-time electromagnetic transient (EMT) simulations. Unlike traditional approaches, which use a single ANN model across the entire frequency range, this study discusses the use of multiple smaller ANN models tailored to specific frequency ranges and operating points, which improves prediction accuracy.

The effectiveness of the proposed transfer learning framework is demonstrated with a practical MMC converter from the CIGRE B4 DC grid test system. The results show that impedance estimation outperforms traditional ANN methods even in scenarios involving confidential converter parameters. This approach allows for precise impedance characterization while reducing computational complexity and data requirements.

Keywords

Artificial neural network (ANN), HVDC, impedance model, machine learning, MMC, power grid stability, real-time simulation, voltage source converter (VSC)

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List of Abbreviations

AC	Alternating Current
ANN	Artificial Neural Network
CCC	Circulating Current Control
CIGRE	International Council on Large Electric Systems
DC	Direct Current
dq	Direct-Quadrature
EMT	Electromagnetic Transient
GNC	Generalized Nyquist stability Criterion
HVDC	High-Voltage Direct Current
LTI	Linear Time-Invariant
MMC	Modular Multilevel Converter
OCC	Output Current Control
PCC	Point of Common Coupling
PLL	Phase-Locked Loop
RTDS	Real-Time Digital Simulator
RSCAD	Real-time Simulation Computer Aided Design
VSC	Voltage Source Converter
ZCC	Zero-sequence circulating Current Control

1

Introduction

1.1. Background

Power electronic-based voltage source converters (VSCs), notably modular multilevel converters (MMCs), have become increasingly significant in the power grid. This trend is driven by the growing interest in developing interconnected systems and the rise of renewable energy resources [1]. As the proportion of VSCs in the power grid increases, ensuring the stability and desired performance of the power system across a wide range of operating points is critical. However, the interaction between the converter's internal dynamics, control loops, and the rest of the grid can lead to stability issues on both the AC and DC sides [2], [3].

Impedance-based stability analysis is a prominent method for effectively identifying the interactions between the converter and the rest of the grid. The changing operating conditions of the converter result in varying impedance responses, requiring accurate modeling to conduct stability analysis [4], [5]. Moreover, the impedance characteristics of converters vary significantly depending on the controllers in use, such as phase-locked loop (PLL), active and reactive power control, and DC voltage control. Accurately estimating impedance characteristics under uncertain scenarios by considering multiple operating points and control types is crucial for analyzing system stability at the point of common coupling (PCC) using the generalized Nyquist stability criterion (GNC) [6].

1.2. Physics- and Circuit-based Small Signal Models

Small-signal models derived from physics, mathematical formulations, and circuit analysis can determine the impedance characteristics of VSCs across various operating points, assuming all physical parameters are known. However, most existing studies have primarily focused on either the AC or the DC system, often neglecting the influence of the entire system [3], [5], [7]–[16]. Studies in [17]–[19] show that both the AC and DC sides have similar properties in the presence of high-frequency interactions, making it important to include both sides in the analysis simultaneously. Nonetheless, developing such small-signal models requires a deep understanding of various system aspects, including control structure parameters and measurement filters. These models often overlook several nonlinearities such as control dead-time, sampling error, digital delay, variable frequency switching, and a nonlinear control framework [20]. Additionally, the practical implementation of hardware and software introduces deviations and non-idealities in physical parameters, significantly impacting converter impedances [20], [21]. Consequently, the reliability and accuracy of small-signal models are limited, especially for converters with complex control structures.

1.3. Black-box Impedance Measurement

The black-box impedance measurement technique accurately determines converter impedances without requiring knowledge of system parameters or control structure [2], [22], [23]. However, conducting impedance measurements or simulations across various operating points demands substantial human labor and computational resources, often relying on signal processing methods and electromagnetic transient (EMT) simulations [20]. Furthermore, obtaining both AC and DC side impedances can significantly increase the time and resources required. Therefore, a computationally efficient and precise method is needed to acquire converter impedances for both AC and DC sides.

1.4. Data-Driven Methods for Impedance Characterization

In recent years, there has been a growing interest in applying machine learning techniques to power grid analysis. Zhang, Wang, *et al.* [24] proposed a method utilizing artificial neural networks (ANNs) to predict impedance characteristics accurately across various operating conditions. However, this approach relies heavily on extensive impedance measurements, making it data-intensive. To mitigate this dependency, Zhang, Xu, *et al.* [25] proposed a physics-informed neural network model that leverages the inherent physical properties of two-level VSCs, significantly reducing the training effort needed. These methods, however, focus solely on impedance variations along a single operating point variable. In contrast, Li, Liao, Wang, *et al.* [26] and Li, Liao, Zhao, *et al.* [20] extend the analysis to include a broader range of operating point variables, such as AC side voltage, active power, and reactive power at the AC side terminal. In ad-

dition, these works present a transfer learning-based methodology using a small-signal model to estimate the impedances of a two-level converter. Notably, none of these prior studies addressed the DC side impedances.

As the deployment of MMC-based HVDC systems escalates, thorough analysis and precise estimation of their impedance characteristics become essential. MMCs have distinct internal dynamics compared to conventional two-level converters, introducing harmonic distortions into the system. These distortions significantly influence impedance characteristics due to their nonlinear relationship with the operating point. To the best of the authors' knowledge, there are limited studies on applying data-driven approaches for estimating impedances in MMC-based converters. Zhang, Zhang, *et al.* [27] presents a transfer learning-based approach with ANNs to characterize the AC side impedances of an MMC, comprising exclusively of the inner control loops. Similar to Zhang, Wang, *et al.* [24] and Zhang, Xu, *et al.* [25], the operating point is defined by a single variable. An ANN-based approach for simulating impedances for wind farm integration stability assessment using MMCs is used by Lyu *et al.* [28]. However, their methodology is data-intensive and does not include all control loops. Practical high-power MMC systems typically feature complex control structures comprising outer and inner control loops and measurement filters. Consequently, the impedances vary considerably, rendering previous methods unsuitable. Moreover, estimating impedances across a broad spectrum of operating points, such as AC side voltage, active power, reactive power at the AC terminal, and DC side voltage, is crucial for MMC-based systems.

1.5. Objective of this Work

This work overcomes the limitations of the previous methodologies by providing a more comprehensive approach, building on top of the transfer learning approach introduced in [20] and [27]. The proposed approach assesses both the AC and DC side impedances of MMCs controlled using power and DC voltage control based on the operating points, which include the AC side voltage V_{ac} , active power P_{ac} , reactive power Q_{ac} , and DC side voltage V_{dc} at the respective terminal. The primary concept of this study involves pre-training the ANN model with a diverse dataset of operating samples derived from a linear time-invariant (LTI) small-signal model. Subsequently, a smaller dataset obtained from real-time EMT simulations conducted using RTDS simulators is utilized to fine-tune the ANN model and enhance its accuracy significantly. Leveraging the LTI model assists in fulfilling the substantial data requirements of ANNs. Moreover, rather than training a single ANN model throughout the entire frequency range of 1 to 1000 Hz, three smaller ANN models are used, each tuned to the impedance characteristics determined by the operating points and frequency in a specific range. A practical MMC converter sourced from the CIGRE B4 DC grid test system [29] serves as the testbed for developing the impedance-based model. This approach enables accurate impedance identification with smaller ANN architectures and a reduced amount of simulated data.

The main contributions of this work are listed below:

- A transfer learning framework is introduced, which combines LTI state space modeling and black-box impedance measurements for accurate impedance estimation of MMCs. The proposed approach determines the AC and DC side impedances of MMCs controlled by power and DC voltage control based on the system-level parameters.
- The effectiveness of using several smaller ANN models rather than a single ANN model over the entire frequency range in predicting impedance responses is demonstrated. The proposed transfer learning framework is validated, demonstrating its superiority over traditional ANN methods, particularly in scenarios where manufacturers keep certain converter parameters confidential.

1.6. Thesis Structure

This thesis is structured as follows:

- [Chapter 2](#) explains the black-box impedance measurement procedure for both the AC and DC sides. This approach is applicable to individual MMCs or MMCs coupled to a grid impedance, and can also be adapted for bipolar MMC configurations. The procedure has been implemented using real-time simulations of a practical converter from the CIGRE B4 DC grid test system. Additionally, the effects of various controller types and filter dynamics have been thoroughly examined.
- [Chapter 3](#) outlines an LTI framework for modeling the AC and DC side impedances of MMCs. The LTI model from [18] is extended to incorporate measurement filters used in practical converters. The model's validity is demonstrated by comparing simulation results for a practical converter from the CIGRE B4 DC grid test system. Additionally, the chapter thoroughly examines the impact of various controller types and parameters, including time delay, DC side capacitance, and filter dynamics. Furthermore, the LTI model can also be used with an energy controller, as demonstrated in this chapter through various case studies.
- [Chapter 4](#) presents a transfer learning framework employing neural networks to model AC and DC side impedances of MMCs. By integrating the black-box impedance measurement procedure with the LTI model, this approach achieves precise MMC impedance estimation with reduced simulated data. Effectiveness is validated with a practical converter from the CIGRE B4 DC grid test system for power and voltage control modes. Furthermore, utilizing multiple smaller neural networks customized to specific frequency ranges enhances impedance characterization.
- [Chapter 5](#) concludes this work and outlines the future scope.

2

AC and DC Side Impedance Measurement of VSCs

2.1. Introduction

This chapter details the steps for measuring the impedances on both the AC and DC sides using the black-box impedance measurement procedure. The described approach can be used to measure the impedances of individual MMCs or MMCs coupled to a grid impedance. Similar procedure can also be used to determine the impedances of a bipolar configuration for MMCs. Additionally, the black-box impedance measurement procedure has been implemented using real-time simulations for a practical converter from the CIGRE B4 DC grid test system. Furthermore, the effects of various controller types and filter dynamics have been thoroughly examined.

Notation

The system diagram of a grid-connected MMC in a monopolar configuration is shown in Figure 2.1. In this configuration, R_g and L_g denote grid resistance and inductance, respectively; R_r and L_r denote reactor resistance and inductance; and R_{filter} and L_{filter} denote filter resistance and inductance, respectively. The converter is connected to an AC grid with voltage $v_g \angle 0^\circ$ and a DC bus with voltage v_{dc} . The AC grid is connected to the converter through a converter transformer, which has a star-delta configuration for the primary and secondary windings, respectively. The voltage and phase at the PCC, which is the primary side of the converter transformer, are denoted as $v_{pcc} \angle \theta$, while the voltage on the secondary side is represented as $v_{conv} \angle \phi$.

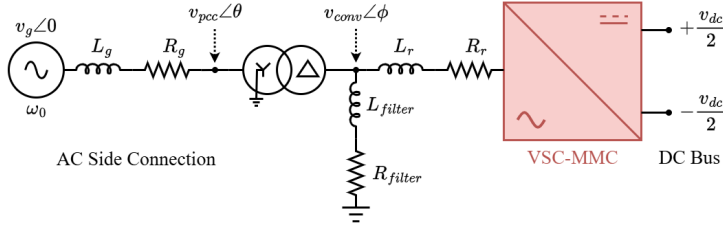


Figure 2.1: Equivalent circuit diagram of a three-phase grid-connected VSC-MMC.

2.2. Measurement Procedure

The system diagram for the measuring setup, which is used to measure the AC and DC side impedances and is also implemented in the RSCAD simulation, is depicted in Figure 2.2. For simplicity, the DC and AC side impedances are depicted together in Figure 2.2. However, in actual simulations, they need to be measured independently.

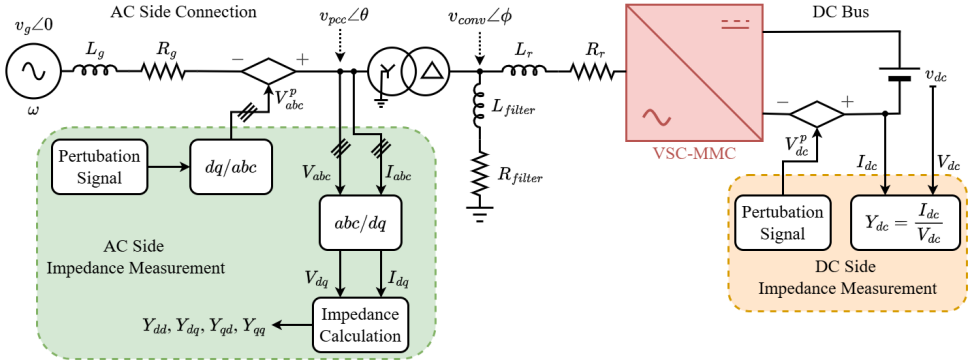


Figure 2.2: AC and DC side impedance measurement configuration.

The basic principle for measuring both AC and DC side impedances is similar. The initial step is to bring the system to a steady state at a specific operating point. Then, a perturbation voltage V^p is injected into the system, and the resulting voltages and currents at the respective terminals are measured. Using these measured quantities, the respective impedances at the corresponding operating point and frequency are computed, as detailed in further subsections.

2.2.1. AC Side Impedance Measurement

The dq impedance model is commonly used for modeling the impedances of a balanced and symmetrical three-phase AC system. To determine system impedances, a small signal model of the converter is established by linearizing the voltages and currents around

the system's steady state operating point, as given in (2.1).

$$\begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix} = Z_{dq} \begin{bmatrix} \Delta I_d \\ \Delta I_q \end{bmatrix} = \begin{bmatrix} Z_{dd} & Z_{dq} \\ Z_{qd} & Z_{qq} \end{bmatrix} \begin{bmatrix} \Delta I_d \\ \Delta I_q \end{bmatrix} \quad (2.1)$$

where Δ represents a small signal variation of the corresponding variables from the equilibrium point. However, during the small signal analysis, the converter functions as a current source; hence, the impedance model is rewritten in terms of admittances, as shown in (2.2).

$$\begin{bmatrix} \Delta I_d \\ \Delta I_q \end{bmatrix} = Y_{dq} \begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix} = \begin{bmatrix} Y_{dd} & Y_{dq} \\ Y_{qd} & Y_{qq} \end{bmatrix} \begin{bmatrix} \Delta V_d \\ \Delta V_q \end{bmatrix} \quad (2.2)$$

Using the small signal model stated in (2.2), the detailed procedure for measuring and computing the AC side dq impedance is given in Figure 2.3. Initially, the perturbation signal is designed, which includes deciding on its amplitude, frequency, and type. The magnitude of the perturbation signal must be carefully calibrated to adequately engage the converter's dynamics. It should be small enough to ensure that the system does not deviate from its steady-state operating point but large enough to overcome the noise present in the system operation. Typically, this magnitude is around 1-2% of the rated values and should not exceed 10% of the rated values [30], [31]. In this study, the magnitude of the perturbation signal is set to 1% of the rated PCC voltage.

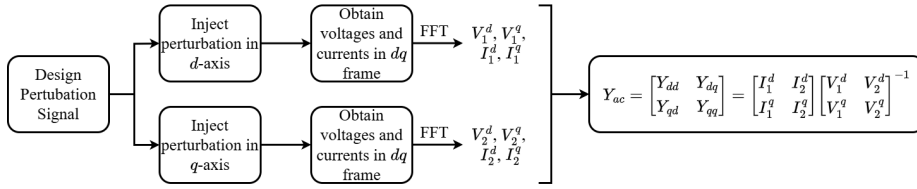


Figure 2.3: Steps performed for measuring AC side impedance in dq frame.

Once the perturbation signals are carefully designed, they need to be injected into the system at the PCC to capture the voltage and current responses of the converter, as depicted in Figure 2.2. Generally, two methods are employed: series voltage injection and shunt current injection. Shunt current injection is ideal for measuring systems with low impedances, whereas series voltage injection is more suitable for systems with high impedances. In this work, a series voltage injection is adopted for the impedance measurement, as depicted in Figure 2.2.

A single perturbation is insufficient to compute all the elements of the Y_{dq} matrix given in (2.2). To compute all the Y_{dq} matrix elements, two linearly independent perturbations must be introduced into the system. Hence, these perturbations need to be introduced in the dq frame. To achieve this, the synchronization phase angle must be determined to define the perturbation signal in the dq frame. Using this phase angle as a reference, a perturbation signal is generated along the d -axis with the q -axis component set to zero. Likewise, a second perturbation signal is generated along the q -axis while maintaining the d -axis component at zero.

Following the injection of the perturbation signals, the voltages and currents at the terminal are measured and then transformed into the rotating dq frame using the synchronization phase angle as a reference. If a high-bandwidth PLL is employed for this transformation, it is crucial to account for the impact of the synchronization phase angle on the impedance calculation [22], [23]. Subsequently, by applying FFT to the transformed variables in the dq frame, the magnitude and phase of the measured signals at the respective frequencies are extracted. After following the aforementioned steps, the voltages and currents V_1^d , V_1^q , I_1^d , and I_1^q are acquired following the injection of the first perturbation, while V_2^d , V_2^q , I_2^d , and I_2^q are obtained after injecting the second perturbation. Finally, the converter impedance is calculated in the dq frame using the obtained magnitude and phase values, as described in (2.3) [32].

$$\begin{bmatrix} Y_{dd} & Y_{dq} \\ Y_{qd} & Y_{qq} \end{bmatrix} = \begin{bmatrix} I_1^d & I_2^d \\ I_1^q & I_2^q \end{bmatrix} \begin{bmatrix} V_1^d & V_2^d \\ V_1^q & V_2^q \end{bmatrix}^{-1} \quad (2.3)$$

2.2.2. DC Side Impedance Measurement

The procedure for determining the DC-side impedance is similar to that for determining the AC-side impedance. However, a single perturbation is enough to calculate the DC impedance at the specified operating point and frequency. As a result, a single perturbation with the desired frequency is injected into the system through one of the DC bus terminals as depicted in Figure 2.2. The magnitude of the perturbation signal is calculated using the same criteria as for AC impedance measurement. The voltage and current responses of the converter at the DC bus are then recorded, and the DC side admittance is computed using (2.4).

$$Y_{dc} = \frac{I_{dc}}{V_{dc}} \quad (2.4)$$

where V_{dc} and I_{dc} are the measured voltage and current values.

2.3. Impedance Measurement of Converter A1 from CIGRE B4 DC Grid Test System

The impedance measurement system depicted in Figure 2.2 is employed on a well-established converter model derived from the CIGRE B4 DC grid test system [29]. The converter A1 is part of the DC grid test systems developed by CIGRE working group B4-57. Figure 2.4 depicts the control architecture implemented in the converter. The outer control includes DC voltage control, power control, and reactive power control, while the inner control includes the output current control (OCC) and circulating current control (CCC). The rated values, control parameters, and measurement filter parameters for the converter are stated in Tables 2.1 to 2.3, respectively.

The converter A1 is obtained from the CIGRE B4 DC grid test system implemented

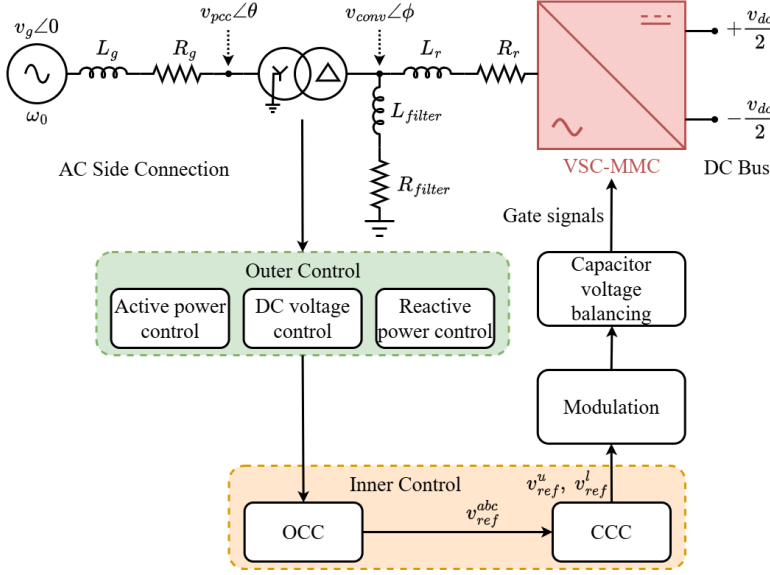


Figure 2.4: Control system architecture of converter A1 from CIGRE B4 DC grid test system [29].

in RSCAD example models [33]. The AC and DC side impedances of the converter are acquired by executing the procedure outlined in Section 2.2. Because this study only focuses on the impedances of MMCs, R_g and L_g are set to zero. The "Harmonic Scan" component in RSCAD is used to inject perturbation signals and perform the appropriate post-processing steps to acquire impedance values [33]–[35]. The frequency chosen for measurement spans from 1 Hz to 1000 Hz.

Table 2.1: Rated Values of converter A1 from CIGRE B4 DC grid test system [29].

Type	Symbol	Value	Symbol	Value
System	S_{rated}	800 MVA	ω	$2\pi 50$ rad/s
Submodule	N	200	C	10 mF
Arm losses	R_{arm}	0Ω	L_{arm}	29 mH
Phase reactor	R_r	0.363Ω	L_r	35 mH
Converter	$V_{conv,L-L rated}$	220 kV	$V_{dc,P-P rated}$	400 kV
PCC	$V_{pcc,L-L rated}$	380 kV	θ	0°

2.3.1. Variation of Impedances with Change in Controllers

Controllers have a considerable impact on the converter's dynamics, which in turn affects its impedance characteristics. As a result, impedances for both power control and DC voltage control modes must be analyzed separately. When the converter is simulated in power control mode, the DC side is treated as a rigid DC source with voltage v_{dc} [36], as shown in Figure 2.5a. However, in DC voltage control mode, the DC side bus is mod-

Table 2.2: Control parameters of converter A1 from CIGRE B4 DC grid test system [29].

Type	Symbol	Value	Symbol	Value
PLL	K_p^{PLL}	300 p.u.	K_I^{PLL}	200 p.u.
OCC control	$K_p^{\Delta dq}$	0.48 p.u.	$K_I^{\Delta dq}$	149 p.u.
CCC control	$K_p^{\Sigma dq}$	0.8 p.u.	$K_I^{\Sigma dq}$	100 p.u.
DC voltage control	K_p^{dc}	8 p.u.	K_I^{dc}	272 p.u.
Active power control	K_p^P	0 p.u.	K_I^P	33 p.u.
Reactive power control	K_p^Q	0 p.u.	K_I^Q	33 p.u.

Table 2.3: Measurement filter parameters of the test converter [29].

Type	Symbol	Value	Symbol	Value
v_{pcc}^{dq} filter	$T_{v_{pcc}^{dq}}$	0.0909		
P_{ac} filter	$\zeta_{P_{ac}}$	0.7	$\omega_{P_{ac}}$	$2\pi 16$ rad/s
Q_{ac} filter	$\zeta_{Q_{ac}}$	0.7	$\omega_{Q_{ac}}$	$2\pi 16$ rad/s
v_{ac} filter	$\zeta_{v_{ac}}$	0.7	$\omega_{v_{ac}}$	$2\pi 16$ rad/s
v_{dc} filter	$\zeta_{v_{dc}}$	0.7	$\omega_{v_{dc}}$	$2\pi 1000$ rad/s

ified as a variable DC voltage system with an ideal power source, where the DC voltage v_{dc} represents the dynamic state of the DC side capacitor C_{dc} [36], as represented in Figure 2.5b.

The value of the DC side capacitor C_{dc} has a considerable impact on system dynamics and must be carefully selected to ensure effective impedance acquisition. The corresponding DC side capacitance of MMCs can be given by $C_{dc} = \frac{6C}{N} = 300 \mu\text{F}$ [29]. However, as seen in Figure 2.6a, setting C_{dc} to $200 \mu\text{F}$ or $300 \mu\text{F}$ causes high-magnitude oscillations in the DC voltage throughout all operating points. Increasing C_{dc} beyond $300 \mu\text{F}$, as shown in Figure 2.6b, stabilizes the system and prevents any high magnitude oscillations. Therefore, this study uses a value of C_{dc} larger than $300 \mu\text{F}$.

The admittance characteristics for power control and DC voltage control are illustrated in the Figure 2.7. Table 2.4 provides the operating point of the system at which admittance characteristics are acquired in this and all subsequent scenarios in Chap-

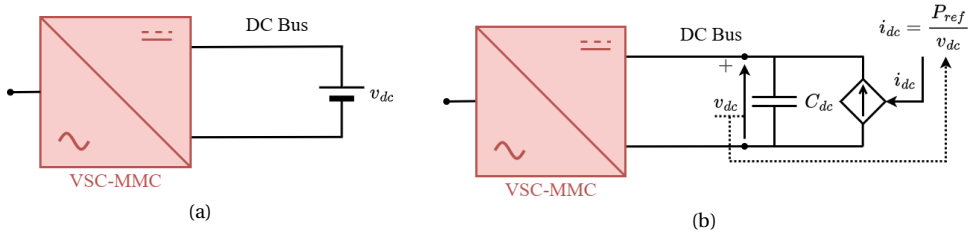


Figure 2.5: Connection of the DC bus source for (a) power control, and (b) DC voltage control.

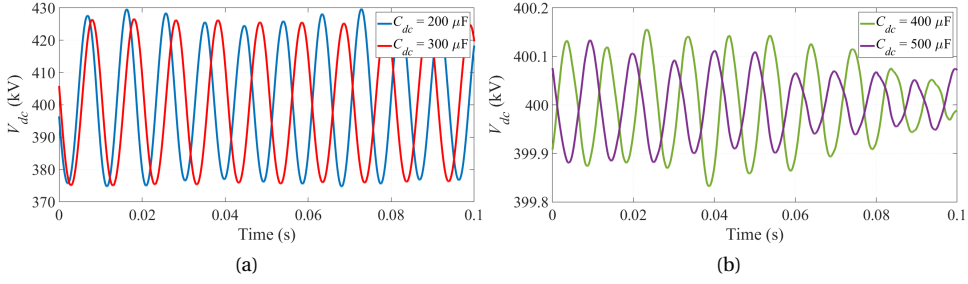


Figure 2.6: Time variation of V_{dc} when C_{dc} is set to (a) 200 μF and 300 μF (a) 400 μF and 500 μF .

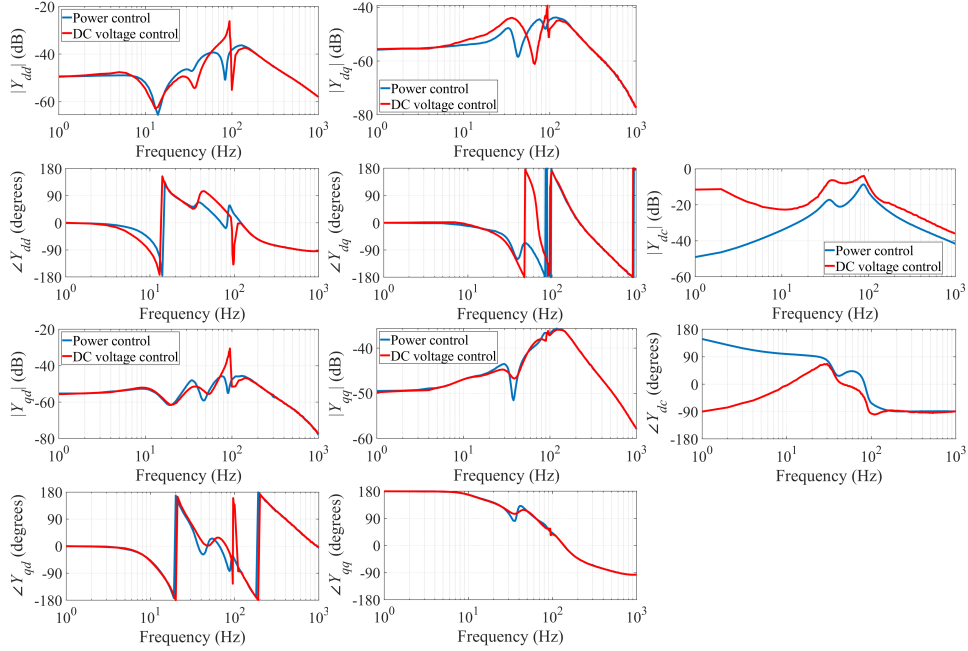


Figure 2.7: Effect of change in controller on the AC and DC admittance characteristics.

Table 2.4: Steady state values for AC and DC side voltages and powers.

V_{dc}	P_{dc}	V_{ac}	P_{ac}	Q_{ac}
1 p.u.	-0.6 p.u.	1 p.u.	-0.6 p.u.	0.3 p.u.

ters 2 and 3. The value of C_{dc} is set to 500 μF when the MMC operates in DC voltage control mode. The change in controller type has a considerable impact on both the AC side (dq) and the DC side impedances.

2.3.2. Effect of Filter Dynamics on Impedance Characteristics

Filtering measured signals is often required for stable operation of the controllers in order to eliminate noise and correctly track changes in control variables. Filters also improve system stability by reducing undesirable high-frequency oscillations, resulting in more reliable and precise control. However, each filter in the system has a considerable effect on the converter's impedance characteristics. The admittance variation for MMC operating in power control mode with a change in the filter cut-off frequency of measurement filters for P_{ac} , Q_{ac} , and V_{ac} is illustrated in Figure 2.8. These parameters serve as inputs in the active power control and the reactive power control. The four cases in Figure 2.8 correspond to the following cases:

1. $f_{P_{ac}} = 16$ Hz, $f_{Q_{ac}} = 16$ Hz, and $f_{V_{ac}} = 16$ Hz
2. $f_{P_{ac}} = 16$ Hz, $f_{Q_{ac}} = 16$ Hz, and $f_{V_{ac}} = 140$ Hz
3. $f_{P_{ac}} = 140$ Hz, $f_{Q_{ac}} = 140$ Hz, and $f_{V_{ac}} = 16$ Hz
4. $f_{P_{ac}} = 140$ Hz, $f_{Q_{ac}} = 140$ Hz, and $f_{V_{ac}} = 140$ Hz

where f_x denotes the cut-off frequency for each filter and x denotes P_{ac} , Q_{ac} , and V_{ac} .

Figure 2.8 shows that when the V_{ac} filter has a cut-off frequency of 16 Hz (cases 1 and 3), there is a significant variation in both the magnitude and phase of admittance

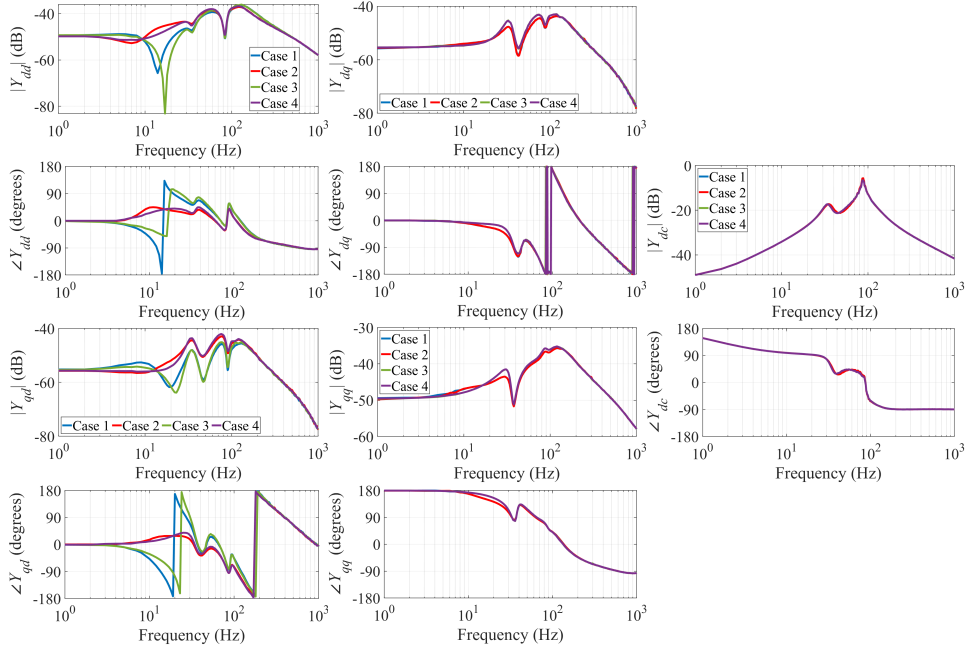


Figure 2.8: Admittance variation for MMC operating in power control with change in filter cut-off frequency.

values for Y_{dd} and Y_{qd} values. This causes a decrease in admittance magnitude and a sharp phase shift, specifically at 16 Hz. When the V_{ac} filter has a higher cut-off frequency (cases 2 and 4), there is no substantial difference, especially at 16 Hz. The admittance values of Y_{dq} , Y_{qq} , and Y_{dc} are comparable in all cases, with small differences in cases 2 and 4.

2.4. Chapter Conclusion

In conclusion, this chapter has presented a detailed methodology for measuring impedances on both the AC and DC sides using the black-box impedance measurement procedure. This approach is applicable to individual MMCs, MMCs coupled to grid impedance, and bipolar MMC configurations. The effectiveness of the procedure has been validated through real-time simulations for a practical converter from the CIGRE B4 DC grid test system. Additionally, a thorough examination of the effects of various controller types and filter dynamics has been conducted, ensuring a comprehensive understanding of their impact on impedance measurements.

3

LTI Framework for Impedance Modeling of MMCs

3.1. Introduction

This chapter describes an LTI framework for modeling the MMC's AC and DC side impedances. The LTI model presented in [18] has been extended to include measurement filters that are present in the practical converters. Additionally, validation of the LTI model is provided by comparing it with simulation results for a practical converter from the CIGRE B4 DC grid test system. The effects of different controller types and parameters, such as time delay, DC side capacitance, and filter dynamics, are addressed in detail. The LTI model can also be used in the presence of an energy controller, as demonstrated in this chapter through various case studies.

Notation

Vectors are denoted by using lowercase bold identifiers, such as $\mathbf{x}$, and matrices by using uppercase bold identifiers, such as $\mathbf{X}$. The operator $\circ$ refers to the Hadamard product. $\mathbf{I}_n$ is the representation of an $n \times n$ identity matrix, whereas

$$\mathbf{J}_2 = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{and} \quad \mathbf{J}_3 = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (3.1)$$

The Fourier transform variable s is defined as $s = j\omega$, where j is the imaginary unit $j = \sqrt{-1}$ and ω represents the angular frequency.

The Park's transformation, described in (3.2), converts three-phase voltages and currents from the abc frame to the rotating dqz frame.

$$\mathbf{P}_\omega(t) = \frac{2}{3} \begin{bmatrix} \cos(\omega t) & \cos(\omega t - \frac{2\pi}{3}) & \cos(\omega t - \frac{4\pi}{3}) \\ \sin(\omega t) & \sin(\omega t - \frac{2\pi}{3}) & \sin(\omega t - \frac{4\pi}{3}) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \quad (3.2)$$

The inverse Park's transformation is defined as stated in (3.3).

$$\mathbf{P}_\omega^{-1}(t) = \frac{3}{2} \mathbf{P}_\omega^T(t) + \frac{1}{2} \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad (3.3)$$

3.2. MMC Dynamics

The detailed dynamics of the converter model are presented using the procedure developed in [18], [36]–[39]. Figure 3.1 shows a single-phase architecture for a three-phase MMC, with all variables defined for all the phases, $k \in \{a, b, c\}$. The submodules are represented by an averaged equivalent model, allowing the voltages and currents in the upper and lower arms to be described by (3.4).

$$v_{su,l}^k = m_{u,l}^k v_{cu,l}^k \quad i_{su,l}^k = m_{u,l}^k i_{u,l}^k \quad (3.4)$$

where $m_{u,l}^k$ are the corresponding upper and lower arm insertion indices.

The Σ – Δ nomenclature can be used to represent the variables in the upper and lower arms [37] as stated in (3.5).

$$i^{\Delta k} = i_u^k - i_l^k \quad i^{\Sigma k} = \frac{i_u^k + i_l^k}{2} \quad (3.5a)$$

$$v_c^{\Delta k} = \frac{v_{cu}^k - v_{cl}^k}{2} \quad v_c^{\Sigma k} = \frac{v_{cu}^k + v_{cl}^k}{2} \quad (3.5b)$$

$$m^{\Delta k} = m_u^k - m_l^k \quad m^{\Sigma k} = m_u^k + m_l^k \quad (3.5c)$$

$$v_s^{\Delta k} = \frac{-v_{su}^k + v_{sl}^k}{2} = -\frac{m^{\Delta k} v_c^{\Sigma k} + m^{\Sigma k} v_c^{\Delta k}}{2} \quad (3.5d)$$

$$v_s^{\Sigma k} = \frac{v_{su}^k + v_{sl}^k}{2} = \frac{m^{\Sigma k} v_c^{\Sigma k} + m^{\Delta k} v_c^{\Delta k}}{2} \quad (3.5e)$$

The differential equations describing the dynamic behavior of the MMC can be derived by using the variables stated in (3.5).

$$\dot{\mathbf{i}}^{\Delta dq} = \frac{\mathbf{v}_s^{\Delta dq} - (\omega L_t \mathbf{J}_2 + R_t \mathbf{I}_2) \mathbf{i}^{\Delta dq} - \mathbf{v}_{pcc}^{dq}}{L_t} \quad (3.6a)$$

$$\dot{\mathbf{i}}^{\Sigma dq} = -\frac{\mathbf{v}_s^{\Sigma dq} + (R_a \mathbf{I}_2 - 2\omega L_a \mathbf{J}_2) \mathbf{i}^{\Sigma dq}}{L_a} \quad (3.6b)$$

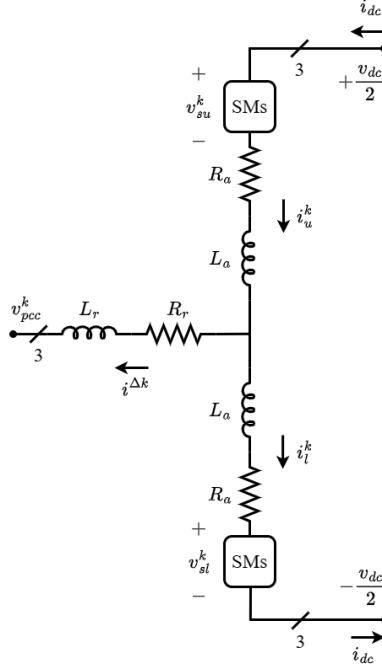


Figure 3.1: Basic per-phase ($k \in \{a, b, c\}$) MMC topology consisting of submodules (SMs), equivalent arm resistance (R_a) and inductance (L_a).

$$i^{\Sigma z} = \frac{v_{dc}}{2L_a} - \frac{v_s^{\Sigma z} + R_a i^{\Sigma z}}{L_a} \quad (3.6c)$$

$$\dot{\mathbf{v}}_c^{\Delta dq} = \frac{N}{2C} \mathbf{i}_s^{\Delta dq} - \omega \mathbf{J}_2 \mathbf{v}_c^{\Delta dq} \quad (3.6d)$$

$$\dot{\mathbf{v}}_c^{\Delta Zdq} = -\frac{N}{8C} \Psi - 3\omega \mathbf{J}_2 \mathbf{v}_c^{\Delta Zdq} \quad (3.6e)$$

$$\dot{\mathbf{v}}_c^{\Sigma dqz} = \frac{N}{2C} \mathbf{i}_s^{\Sigma dqz} + 2\omega \mathbf{J}_3 \mathbf{v}_c^{\Sigma dqz} \quad (3.6f)$$

$$\dot{v}_{dc} = \frac{1}{C_{dc}} (i_{dc} - 3i^{\Sigma z}) \quad (3.6g)$$

where,

$$\mathbf{i}_s^{\Delta dq} = \mathbf{P}_\omega(t) \left(\mathbf{P}_{-2\omega}^{-1}(t) \mathbf{m}_{\tau_d}^{\Sigma dqz} \circ \frac{\mathbf{P}_\omega^{-1}(t) \mathbf{i}^{\Delta dqz}}{2} + \mathbf{P}_\omega^{-1}(t) \mathbf{m}_{\tau_d}^{\Delta dqZ} \circ \mathbf{P}_{-2\omega}^{-1}(t) \mathbf{i}^{\Sigma dqz} \right) \quad (3.7a)$$

$$\mathbf{i}_s^{\Sigma dq} = \mathbf{P}_{-2\omega}(t) \left(\mathbf{P}_{-2\omega}^{-1}(t) \mathbf{m}_{\tau_d}^{\Sigma dqz} \circ \mathbf{P}_{-2\omega}^{-1}(t) \mathbf{i}^{\Sigma dqz} + \mathbf{P}_\omega^{-1}(t) \mathbf{m}_{\tau_d}^{\Delta dqZ} \circ \mathbf{P}_\omega^{-1}(t) \frac{\mathbf{i}^{\Delta dqz}}{2} \right) \quad (3.7b)$$

$$\mathbf{v}_s^{\Delta dqz} = -\frac{\mathbf{P}_\omega}{2}(t) \left(\mathbf{P}_\omega^{-1}(t) \mathbf{m}_{\tau_d}^{\Delta dqZ} \circ \mathbf{P}_{-2\omega}^{-1}(t) \mathbf{v}_c^{\Sigma dqz} + \mathbf{P}_{-2\omega}^{-1}(t) \mathbf{m}_{\tau_d}^{\Sigma dqz} \circ \mathbf{P}_\omega^{-1}(t) \mathbf{v}_c^{\Delta dqz} \right) \quad (3.7c)$$

$$\mathbf{v}_s^\Sigma = \frac{\mathbf{P}_{-2\omega}}{2}(t) \left(\mathbf{P}_\omega^{-1}(t) \mathbf{m}_{\tau_d}^{\Delta dqZ} \circ \mathbf{P}_\omega^{-1}(t) \mathbf{v}_c^{\Delta dqz} + \mathbf{P}_{-2\omega}^{-1}(t) \mathbf{m}_{\tau_d}^{\Sigma dqz} \circ \mathbf{P}_{-2\omega}^{-1}(t) \mathbf{v}_c^{\Sigma dqz} \right) \quad (3.7d)$$

$$\Psi = \begin{bmatrix} i^{\Delta d} m_{\tau_d}^{\Sigma d} + 2i^{\Sigma d} m_{\tau_d}^{\Delta d} + i^{\Delta q} m_{\tau_d}^{\Sigma q} + 2i^{\Sigma q} m_{\tau_d}^{\Delta q} + 4i^{\Sigma z} m_{\tau_d}^{\Delta Z d} \\ i^{\Delta q} m_{\tau_d}^{\Sigma d} + 2i^{\Sigma d} m_{\tau_d}^{\Delta q} - i^{\Delta d} m_{\tau_d}^{\Sigma q} - 2i^{\Sigma q} m_{\tau_d}^{\Delta d} + 4i^{\Sigma z} m_{\tau_d}^{\Delta Z q} \end{bmatrix} \quad (3.7e)$$

N = number of submodules

C = submodule capacitance

R_a = arm resistance

L_a = arm inductance

$R_t = R_r + \frac{R_a}{2}$ = equivalent AC resistance

$L_t = L_r + \frac{L_a}{2}$ = equivalent AC inductance

C_{dc} = equivalent DC side capacitance

Equation (3.6) represents variables using multiple dqz -frames by applying Park's transformation at different frequencies. The Δ state variables are derived using the angular frequency components ω and 3ω , whereas the Σ variables use -2ω components [37].

The insertion indices $\mathbf{m} = [\mathbf{m}^{\Delta dq} \quad \mathbf{m}^{\Delta Z dq} \quad \mathbf{m}^{\Sigma dqz}]^T$ are obtained as stated in (3.8).

$$\mathbf{m} = \frac{2}{v_{dc}} \begin{bmatrix} -\mathbf{v}_{s,ref}^{\Delta dqZ} \\ \mathbf{v}_{s,ref}^{\Sigma dqz} \end{bmatrix} \quad (3.8)$$

3.3. Time Delays

The MMC's impedance characteristics are highly susceptible to time delays (computational time delay, sampling delay, modulation delay, etc.) in the system, particularly in the low (10–100 Hz) and high (several kHz) frequency ranges [9]. Therefore, these time delays must be considered during the modeling of the impedances. For simplicity, all time delays within the control architecture are consolidated into a single delay, based on the assumption that this aggregated delay can effectively represent the impact of the computational time delay on the impedance characteristics [18].

The time delay (τ_d) can be expressed as a rational transfer function using the Padé approximation stated in (3.9), where m and n are the numerator and denominator approximation orders, respectively [18], [40].

$$\mathbf{T}_{delay} = e^{-s\tau_d} \approx \frac{b_0 + b_1(\tau_d s)^1 + \dots + b_m(\tau_d s)^m}{a_0 + a_1(\tau_d s)^1 + \dots + a_n(\tau_d s)^n} \quad (3.9)$$

The rational transfer function approximation is then converted into the state space

form [40], which is given in (3.10).

$$\begin{aligned}\dot{\mathbf{x}}_{\tau_d}(t) &= \mathbf{A}_{\tau_d} \mathbf{x}_{\tau_d}(t) + \mathbf{B}_{\tau_d} \mathbf{u}_{\tau_d}(t) \\ \mathbf{y}_{\tau_d}(t) &= \mathbf{C}_{\tau_d} \mathbf{x}_{\tau_d}(t) + \mathbf{D}_{\tau_d} \mathbf{u}_{\tau_d}(t)\end{aligned}\quad (3.10)$$

where, $\mathbf{u}_{\tau_d}(t) = [\mathbf{m}^{\Delta dq} \quad \mathbf{m}^{\Sigma dqz}]^T$ are the insertion indices obtained from the controller outputs as given in (3.8) and $\mathbf{y}_{\tau_d}(t) = [\mathbf{m}_{\tau_d}^{\Delta dqz} \quad \mathbf{m}_{\tau_d}^{\Sigma dqz}]^T$ are the insertion indices which are used in the differential equations given in (3.6). A third-order ($m = n = 3$) approximation is used in this study because it accurately represents the impact of computational delay up to 1 kHz frequency range.

3.4. Controller Dynamics

The voltage references in (3.8) are obtained as an output of the controllers and the 13 differential equations stated in (3.6). The controllers can specify the voltage references, but by default, all voltage reference values are set to zero, except for $v_{c,ref}^z$, which is set to $\frac{v_{dc}}{2}$. When the controller specifies the voltage references, additional differential equations are required to represent the PI controllers in the dqz frames [18], [37], [41].

The primary (inner) and secondary (outer) controllers that constitute the framework

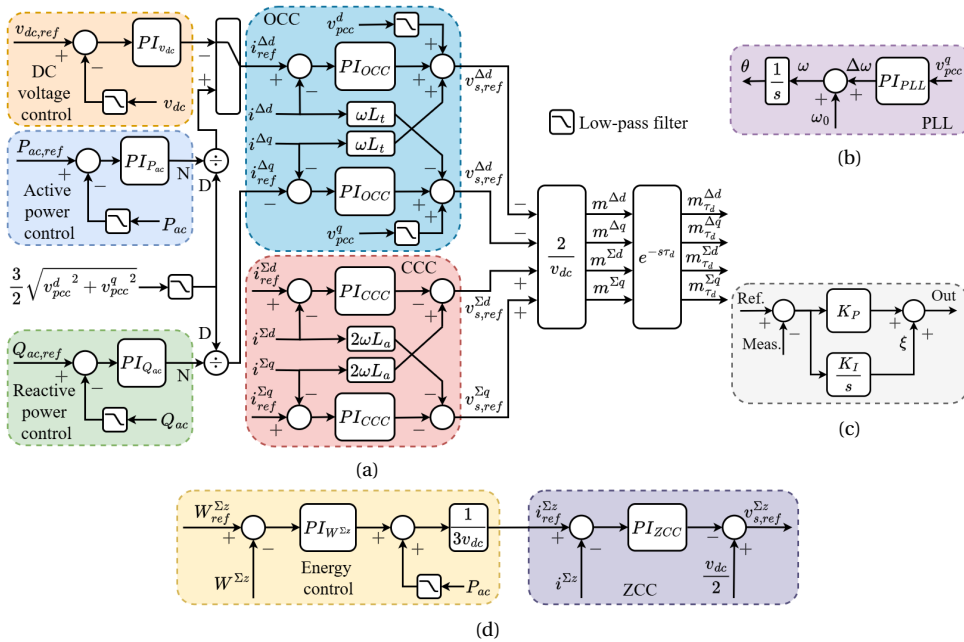


Figure 3.2: MMC control architecture consisting of (a) inner controllers, outer controllers and time delay, (b) PLL, (c) generic PI structure, and (d) energy and zero-sequence circulating current controllers.

of the MMC control architecture are shown in Figures 3.2a and 3.2d. DC voltage control, active power control, and reactive power control, and energy control act as the outer controllers, whereas output current control (OCC), circulating current control (CCC) and zero-sequence circulating current control (ZCC) act as the inner controllers. For the PI structure illustrated in Figure 3.2c, each controller and the phase-locked loop (PLL), shown in Figure 3.2b, can be defined using a set of differential equations provided in (3.11).

$$\begin{aligned}\dot{\xi} &= \text{Ref.} - \text{Meas.} \\ \text{Out} &= K_P(\text{Ref.} - \text{Meas.}) + K_I\xi\end{aligned}\quad (3.11)$$

Using the following formulas from (3.12), the measured values for multiple controllers are calculated.

$$P_{ac} = \frac{3}{2}(v_{pcc}^d i^{\Delta d} + v_{pcc}^q i^{\Delta q}) \quad (3.12a)$$

$$Q_{ac} = \frac{3}{2}(-v_{pcc}^d i^{\Delta q} + v_{pcc}^q i^{\Delta d}) \quad (3.12b)$$

$$W^{\Sigma z} = \frac{3C}{2N} \left(\sum_{x \in \{d, q, z\}} (v_c^{\Delta x})^2 + \sum_{dq} (v_c^{\Sigma dq})^2 + 2(v_c^{\Sigma z})^2 \right) \quad (3.12c)$$

The next subsections provide specific information about each controller separately.

3.4.1. PLL

When a PLL is present, the system is considered to have two separate dq frames: the grid dq frame and the converter dq frame. The grid dq frame rotates at ω_0 , while the converter dq frame rotates at $\omega_0 + \Delta\omega$, where $\Delta\omega$ denotes the divergence from the nominal system frequency ω_0 . The PLL tracks the deviation $\Delta\omega$, which represents the angle of separation between two rotating frames θ . The PLL dynamics are represented in the LTI model by (3.13) [42], [43].

$$\begin{aligned}\dot{\xi}_{PLL} &= -v_{pcc}^q \\ \dot{\theta} &= \Delta\omega \\ \Delta\omega &= -K_P^{PLL} v_{pcc}^q + K_{I,PLL} \xi_{PLL} \\ \omega &= \omega_0 + \Delta\omega\end{aligned}\quad (3.13)$$

Variables from the grid dq frame ($\mathbf{x}_{pcc}^{dq}$) are transformed into the converter dq frame ($\mathbf{x}_{conv}^{dq}$) using the transformation given in (3.14a), and the inverse is performed using (3.14b).

$$\mathbf{x}_{pcc}^{dq} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \mathbf{x}_{conv}^{dq} \quad (3.14a)$$

$$\mathbf{x}_{conv}^{dq} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \mathbf{x}_{pcc}^{dq} \quad (3.14b)$$

3.4.2. OCC ($i^{\Delta dq}$)

The OCC uses (3.15) to set the output currents to their reference values, $i_{ref}^{\Delta dq}$.

$$\begin{aligned}\dot{\xi}^{\Delta dq} &= i_{ref}^{\Delta dq} - i^{\Delta dq} \\ v_{s,ref}^{\Delta dq} &= K_P^{\Delta dq} (i_{ref}^{\Delta dq} - i^{\Delta dq}) + K_I^{\Delta dq} \xi^{\Delta dq} + \omega L_t J_2 i^{\Delta dq} + v_{pcc}^{dq}\end{aligned}\quad (3.15)$$

3.4.3. CCC ($i^{\Sigma dq}$)

The CCC employs (3.16) to set the circulating currents $i^{\Sigma dq}$ to zero.

$$\begin{aligned}\dot{\xi}^{\Sigma dq} &= i_{ref}^{\Sigma dq} - i^{\Sigma dq} \\ v_{s,ref}^{\Sigma dq} &= -K_P^{\Sigma dq} (i_{ref}^{\Sigma dq} - i^{\Sigma dq}) - K_I^{\Sigma dq} \xi^{\Sigma dq} + 2\omega L_a J_2 i^{\Sigma dq}\end{aligned}\quad (3.16)$$

3.4.4. ZCC ($i^{\Sigma z}$) control

ZCC applies (3.17) to regulate the zero-sequence circulating current $i^{\Sigma z}$ to the desired value $i_{ref}^{\Sigma z}$.

$$\begin{aligned}\dot{\xi}^{\Sigma z} &= i_{ref}^{\Sigma z} - i^{\Sigma z} \\ v_{s,ref}^{\Sigma z} &= \frac{v_{dc}}{2} - K_P^{\Sigma z} (i_{ref}^{\Sigma z} - i^{\Sigma z}) - K_I^{\Sigma z} \xi^{\Sigma z}\end{aligned}\quad (3.17)$$

3.4.5. Energy ($W^{\Sigma z}$) control

The energy control uses (3.18) to compute a reference value for the zero-sequence circulating current $i_{ref}^{\Sigma z}$ based on the total energy stored in the converter $W^{\Sigma z}$.

$$\begin{aligned}\dot{\xi}_{W^{\Sigma z}} &= W_{ref}^{\Sigma z} - W^{\Sigma z} \\ i_{ref}^{\Sigma z} &= \frac{K_P^{\Sigma W} (W_{ref}^{\Sigma z} - W^{\Sigma z}) + K_I^{\Sigma W} \xi_{W^{\Sigma z}} + P_{ac}}{3v_{dc}}\end{aligned}\quad (3.18)$$

3.4.6. DC voltage (v_{dc}) control

Using (3.19), the DC voltage control calculates the reference value for the d -axis component of the output current $i_{ref}^{\Delta d}$ based on the v_{dc} variation.

$$\begin{aligned}\dot{\xi}_{v_{dc}} &= v_{dc,ref} - v_{dc} \\ i_{ref}^{\Delta d} &= -K_P^{dc} (v_{dc,ref} - v_{dc}) - K_I^{dc} \xi_{v_{dc}}\end{aligned}\quad (3.19)$$

3.4.7. Active and reactive power (P , Q) control

The power control provides the reference values for AC currents $i_{ref}^{\Delta dq}$ using (3.20).

$$\dot{\xi}_P = P_{ac,ref} - P_{ac} \quad (3.20a)$$

$$\dot{\xi}_Q = Q_{ac,ref} - Q_{ac} \quad (3.20b)$$

$$P_{ref}^{\Delta d} = K_P^P (P_{ac,ref} - P_{ac}) + K_I^P \xi_P \quad (3.20c)$$

$$Q_{ref}^{\Delta q} = -K_P^Q (Q_{ac,ref} - Q_{ac}) - K_I^Q \xi_Q \quad (3.20d)$$

Power-to-current function

A dedicated power-to-current function is implemented in the converters to convert the output references $P_{ref}^{\Delta d}$ and $Q_{ref}^{\Delta q}$ from the active and reactive power (P , Q) controllers to their corresponding reference currents $i_{ref}^{\Delta d}$ and $i_{ref}^{\Delta q}$. The function divides the output references $P_{ref}^{\Delta d}$ and $Q_{ref}^{\Delta q}$ by the measured voltage at the PCC. This function can be modeled using (3.21).

$$i_{ref}^{\Delta d} = \frac{2}{3} \cdot \frac{P_{ref}^{\Delta d}}{\sqrt{v_{pcc}^{d^2} + v_{pcc}^{q^2}}} \quad (3.21a)$$

$$i_{ref}^{\Delta q} = \frac{2}{3} \cdot \frac{Q_{ref}^{\Delta q}}{\sqrt{v_{pcc}^{d^2} + v_{pcc}^{q^2}}} \quad (3.21b)$$

3.5. Measurement Filters

As detailed in Chapter 2, filters have a considerable effect on the converter's impedance characteristics. As a result, these filters must be considered during modeling. They can be modeled as first- or second-order low-pass filters, depending on the variable they govern.

Commonly filtered variables in the MMC control structure are marked in Figure 3.2a. The variables v_{pcc}^{dq} in the OCC are filtered out using a first-order low-pass filter utilizing (3.22) to obtain filtered voltages $v_{pcc,filt}^{dq}$.

$$\dot{\xi}^{filt} = -\frac{1}{T_{filt}} \xi + v_{pcc}^{dq} \quad (3.22a)$$

$$v_{pcc,filt}^{dq} = \frac{1}{T_{filt}} \xi^{filt} \quad (3.22b)$$

where T_{filt} represents the time constant of the first-order low-pass filter. The cut-off frequency for the filter is $f_{filt} = \frac{1}{T_{filt}}$.

Similarly, the measured input variables of outer controllers such as P_{ac} , Q_{ac} , and v_{dc} are subjected to second-order low-pass filters, which can be represented using (3.23).

$$\dot{\xi}_1^{filt} = -\omega_{filt}^2 \xi_2^{filt} - 2\zeta \omega_{filt} \dot{\xi}_1^{filt} + x \quad (3.23a)$$

$$\dot{\xi}_2^{filt} = \xi_1^{filt} \quad (3.23b)$$

$$x_{filt} = \omega_{filt}^2 \xi_2^{filt} \quad (3.23c)$$

where x represents the input variables P_{ac} , Q_{ac} , and v_{dc} , x_{filt} represents the filtered variables $P_{ac,filt}$, $Q_{ac,filt}$, and $v_{dc,filt}$, respectively, ω_{filt} is the filter natural frequency, and ζ is the damping factor.

3.6. Operating Point

A power flow or steady-state simulation can be used to determine the operating point of the converter [18]. Using this approach, the following parameters are determined: DC voltage magnitude V_{dc} , active power at the DC terminal P_{dc} (flowing from the AC side to the DC side), AC voltage magnitude and phase V_{ac} and θ , respectively, active power at the AC terminal P_{ac} (flowing from the AC side to the DC side), and reactive power at the AC terminal Q_{ac} (flowing from the AC side to the DC side). The converter's reference values are then obtained using the values for the AC and DC voltages and powers, as specified in (3.24).

$$v_{dc,ref} = V_{dc} \quad (3.24a)$$

$$v_{pcc}^d = V_{ac} \cos(\theta) \quad v_{pcc}^q = -V_{ac} \sin(\theta) \quad (3.24b)$$

$$P_{ac,ref} = -P \quad Q_{ac,ref} = Q \quad (3.24c)$$

$$i_{ref}^{\Delta d} = \frac{2(v_{pcc}^d P + v_{pcc}^q Q)}{3(v_{pcc}^d{}^2 + v_{pcc}^q{}^2)} \quad i_{ref}^{\Delta q} = \frac{2(v_{pcc}^q P - v_{pcc}^d Q)}{3(v_{pcc}^d{}^2 + v_{pcc}^q{}^2)} \quad (3.24d)$$

$$i_{ref}^{\Sigma z} = \frac{P_{dc}}{3V_{dc}} \quad (3.24e)$$

$$W_{ref}^{\Sigma z} = \frac{3CV_{dc}^2}{N} \quad (3.24f)$$

3.7. Steady State Solution and Admittance Model

After modeling all the necessary differential equations for the MMC and controllers, an equilibrium point is obtained using the Julia package NLSolve [44], which represents the solution to these differential equations. Further, the system of differential equations is represented as a multi-input multi-output (MIMO) system in a linearized form, as given in (3.25).

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A}_{MMC} \mathbf{x}(t) + \mathbf{B}_{MMC} \mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C}_{MMC} \mathbf{x}(t) + \mathbf{D}_{MMC} \mathbf{u}(t) \end{aligned} \quad (3.25)$$

where $\mathbf{x}$ represents all the state variables given in (3.6) and additional state variables introduced by the applied controllers, $\mathbf{u} = \begin{bmatrix} v_{dc} & v_{pcc}^d & v_{pcc}^q \end{bmatrix}^T$ is the input vector, and $\mathbf{y} = \begin{bmatrix} i_{dc} & i^{\Delta d} & i^{\Delta q} \end{bmatrix}^T$ is the output. When the MMC controls the DC voltage, the input and output vectors are redefined as $\mathbf{u} = \begin{bmatrix} i_{dc} & v_{pcc}^d & v_{pcc}^q \end{bmatrix}^T$ and $\mathbf{y} = \begin{bmatrix} v_{dc} & i^{\Delta d} & i^{\Delta q} \end{bmatrix}^T$.

The associated matrices $\mathbf{A}_{MMC}$, $\mathbf{B}_{MMC}$, $\mathbf{C}_{MMC}$, and $\mathbf{D}_{MMC}$, expressed in (3.25), are determined as Jacobians around the aforementioned equilibrium point using the Julia package ForwardDiff [45]. Using the Laplace transform, the equations in (3.25) can be transformed into a MIMO transfer function.

$$\mathbf{Y}_{MMC}(s) = \mathbf{C}_{MMC}(s\mathbf{I} - \mathbf{A}_{MMC})^{-1}\mathbf{B}_{MMC} + \mathbf{D}_{MMC} \quad (3.26)$$

where $\mathbf{Y}_{MMC}(s)$ represents the admittance matrix of the system and is given by:

$$\mathbf{Y}_{MMC}(s) = \begin{bmatrix} Y_{1,1}(s) & Y_{1,2}(s) & Y_{1,3}(s) \\ Y_{2,1}(s) & Y_{2,2}(s) & Y_{2,3}(s) \\ Y_{3,1}(s) & Y_{3,2}(s) & Y_{3,3}(s) \end{bmatrix} \quad (3.27)$$

By separating the AC and DC side impedances from $\mathbf{Y}_{MMC}$, (3.28) is obtained.

$$\mathbf{Y}_{ac}(s) = \begin{bmatrix} Y_{dd}(s) & Y_{dq}(s) \\ Y_{qd}(s) & Y_{qq}(s) \end{bmatrix} = \begin{bmatrix} -Y_{2,2}(s) & Y_{2,3}(s) \\ Y_{3,2}(s) & -Y_{3,3}(s) \end{bmatrix} \quad (3.28a)$$

$$Y_{dc}(s) = Y_{1,1}(s) \quad (3.28b)$$

where $Y_{ac}(s)$ represents the AC side impedance in dq frame and $Y_{dc}(s)$ represents the DC side impedance.

However, when the MMC controls the DC voltage, a subsequent step is needed after computing $\mathbf{Y}_{MMC}(s)$ using (3.26). This step involves transforming the positions of $v_{dc}(s)$ and $i_{dc}(s)$ and removing the effect of the capacitance C_{dc} . The DC side impedance can then be calculated using (3.29).

$$Y_{dc}(s) = 2 \left(\frac{1}{Y_{1,1}(s)} - sC_{dc} \right) \quad (3.29)$$

3.8. Per Unit to Rated Conversion

System parameters are typically provided in the per-unit domain in literature, converter datasheets, and simulation tools. However, the LTI model presented in this chapter requires that actual values be used in the equations. As a result, it is critical to understand and implement the conversion formulae for conversion between the per unit domain and the rated domain.

For a system with base frequency ω_0 and base power S_{base} , the AC and DC side electrical quantities (voltages and currents), as well as related electrical characteristics (impedance, inductance, capacitance) can be determined as stated in (3.30).

$$\text{AC side base voltage} = V_{ac,base} = V_{ac,L-N,peak} = \sqrt{\frac{2}{3}} V_{ac,L-L,rms} \quad (3.30a)$$

$$\text{AC side base current} = I_{ac,base} = \sqrt{\frac{2}{3}} \frac{S_{base}}{V_{ac,L-L,rms}} = \frac{2}{3} \frac{S_{base}}{V_{ac,base}} \quad (3.30b)$$

$$\text{AC side base impedance} = Z_{ac,base} = \frac{V_{ac,L-L,rms}^2}{S_{base}} = \frac{3}{2} \frac{V_{ac,base}^2}{S_{base}} \quad (3.30c)$$

$$\text{AC side base inductance} = L_{ac,base} = \frac{Z_{ac,base}}{\omega_0} \quad (3.30d)$$

$$\text{AC side base capacitance} = C_{ac,base} = \frac{1}{\omega_0 Z_{ac,base}} \quad (3.30e)$$

$$\text{DC side base voltage} = V_{dc,base} = V_{dc,P-P} \quad (3.30f)$$

$$\text{DC side base current} = I_{dc,base} = \frac{S_{base}}{V_{dc,base}} \quad (3.30g)$$

$$\text{DC side base impedance} = Z_{dc,base} = \frac{V_{dc,base}}{I_{dc,base}} = \frac{V_{dc,base}^2}{S_{dc,base}} \quad (3.30h)$$

$$\text{DC side base inductance} = L_{dc,base} = \frac{Z_{dc,base}}{\omega_0} \quad (3.30i)$$

$$\text{DC side base capacitance} = C_{dc,base} = \frac{1}{\omega_0 Z_{dc,base}} \quad (3.30j)$$

Similarly, using the values in (3.30), the base value of the energy stored in the system may be computed as given in (3.31).

$$W_{base}^{\Sigma z} = \frac{3CV_{dc,base}^2}{N} \quad (3.31)$$

To convert the K_P and K_I values for each controller, separate factors can be computed using the system base parameters. Table 3.1 lists the conversion factors for converting K_P and K_I values from per unit to natural values.

3.9. Admittance Characteristics of Converter A1 from CIGRE B4 DC Grid Test System

This section presents an analysis of the admittance characteristics using the LTI model, based on converter A1 from the CIGRE B4 DC Grid Test System, as described in Chapter 2.

Table 3.1: Conversion of K_P and K_I parameters for each controller

Type	Parameter	Factor
PLL	K_P^{PLL} / K_I^{PLL}	$\frac{1}{V_{ac,base}}$
OCC ($i^{\Delta dq}$) control	$K_P^{\Delta dq} / K_I^{\Delta dq}$	$\frac{V_{ac,base}}{I_{ac,base}}$
CCC ($i^{\Sigma dq}$) control	$K_P^{\Sigma dq} / K_I^{\Sigma dq}$	$\frac{Z_{dc,base}}{I_{ac,base}}$
DC voltage (v_{dc}) control	K_P^{dc} / K_I^{dc}	$\frac{V_{dc,base}}{V_{dc,base}}$
Active and reactive power (P, Q) control	K_P^{PQ} / K_I^{PQ}	1
ZCC ($i^{\Sigma z}$) control	$K_P^{\Sigma z} / K_I^{\Sigma z}$	$\frac{Z_{dc,base}}{S_{ac,base}}$
Energy ($W^{\Sigma z}$) control	$K_P^{\Sigma W} / K_I^{\Sigma W}$	$\frac{W_{z,base}^{\Sigma}}{W_{z,base}^{\Sigma}}$

3.9.1. Validation of LTI Model

The LTI model given in this chapter is validated using the parameters of converter A1 from the CIGRE B4 DC grid test system described in Chapter 2. Using the converter parameters and operating point details from Chapter 2 and a time delay of 600 μs , the admittance characteristics for both the AC and DC sides are derived with the LTI model. Figures 3.3 and 3.4 show the admittance plots for power and DC voltage control modes, respectively. The results show that the LTI model accurately describes the admittance characteristics, with just slight differences in the values of all variables. However, the phase values of the cross-coupling elements Y_{dq} and Y_{qd} show slightly higher deviations.

3.9.2. Effect of DC Side Capacitance C_{dc} on Admittance Characteristics

The LTI model is used to explore the variations in admittance characteristics for different DC side capacitance values C_{dc} when the MMC operates in DC voltage control mode. As seen in Figure 3.5, lower values of C_{dc} result in significant peaks in the magnitude of the AC side admittances at 100 Hz, and as C_{dc} increases, these peaks diminish. Near 10 Hz, the drop in admittance magnitude of Y_{dd} diminishes as C_{dc} increases, and the frequency at which the drop occurs shifts towards lower frequency values. The DC side admittance remains unaffected by changes in the C_{dc} value.

3.9.3. Effect of Time Delay on Admittance Characteristics

The LTI model is utilized to investigate the differences in admittance characteristics for various values of time delay τ_d , as shown in Figure 3.6. In this scenario, the MMC is in power control mode. However, the effects of time delay are independent of the type of control applied. As the time delay rises, admittance values on the AC side substantially increase, and the phase of Y_{dq} and Y_{qd} shifts downward. Although barely noticeable, the

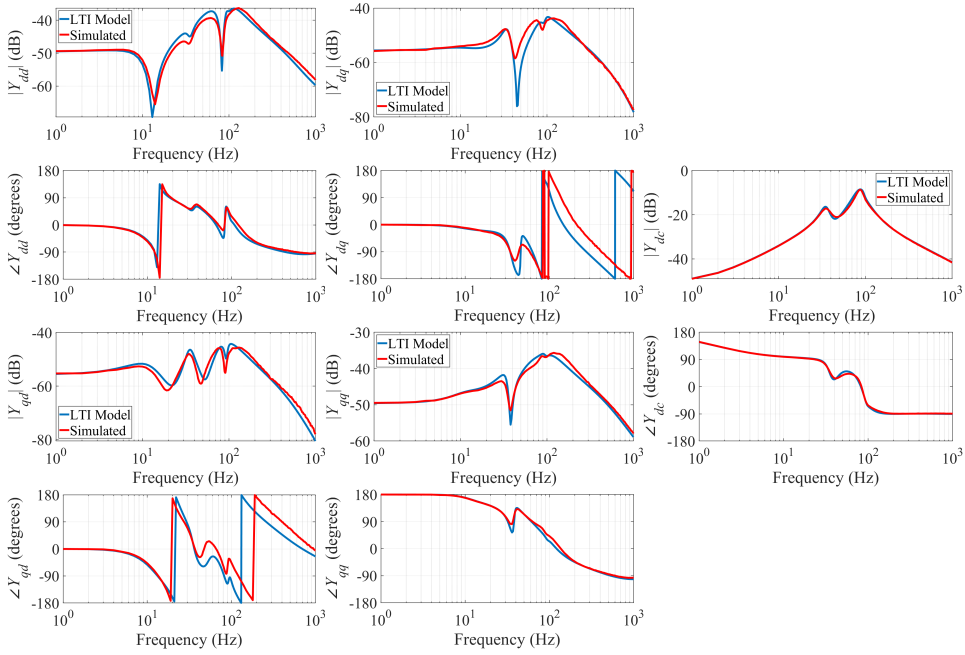


Figure 3.3: Comparison of LTI model with simulated results for power controlled MMC.

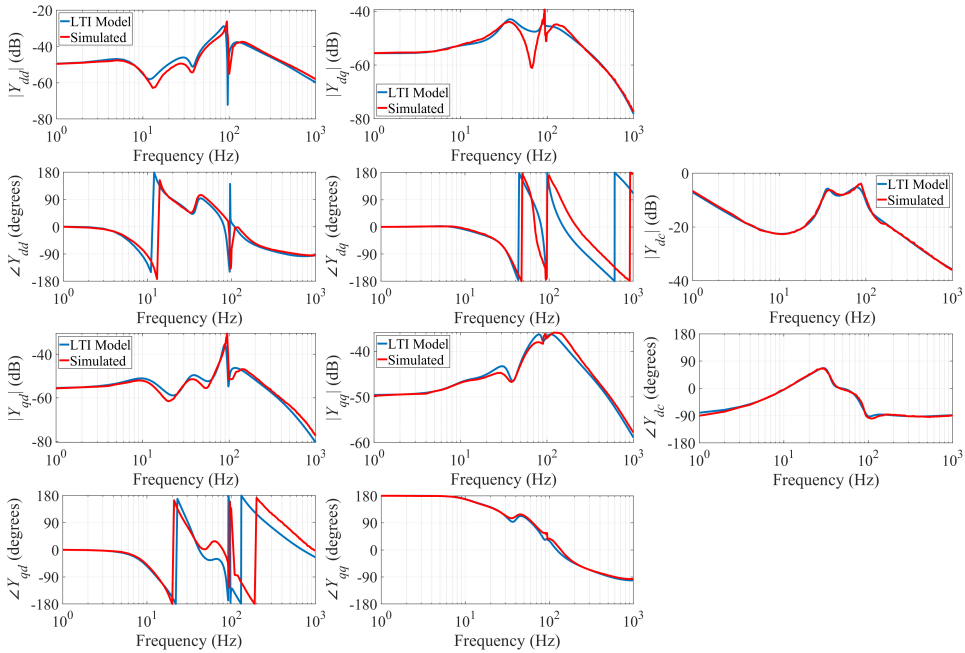


Figure 3.4: Comparison of LTI model with simulated results for DC voltage controlled MMC.

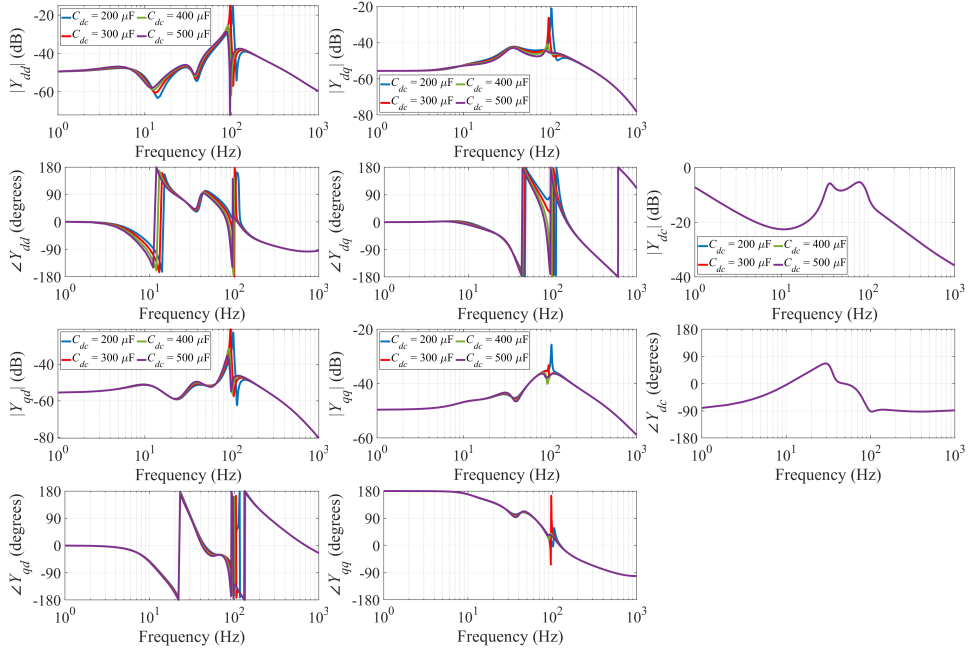


Figure 3.5: Variation of AC and DC side admittances with change in C_{dc} for DC voltage controlled MMC.

DC side admittance decreases slightly near the peaks as the time delay increases.

3.9.4. Effect of Filter Dynamics on Admittance Characteristics

Similar to the analysis in Chapter 2, the LTI model is used to assess its ability to accurately represent the filter's dynamics in the admittance characteristics. Figure 3.7 illustrates the admittance variation for an MMC operating in power control mode with changes in the filter cut-off frequency for measurement filters of P_{ac} , Q_{ac} , and V_{ac} . The four cases specified correspond to those mentioned in Chapter 2. Comparing with the simulated results from Chapter 2, it can be observed that the LTI model accurately captures the admittance characteristics even with different filter parameters.

3.10. Admittance Characteristics with ZCC and Energy Control

The LTI model can also be employed to model the admittance characteristics of the converter in the presence of ZCC and energy control. This section details specific case studies that utilize energy control and ZCC in the converters. The admittance characteristics for these cases are obtained and analyzed.

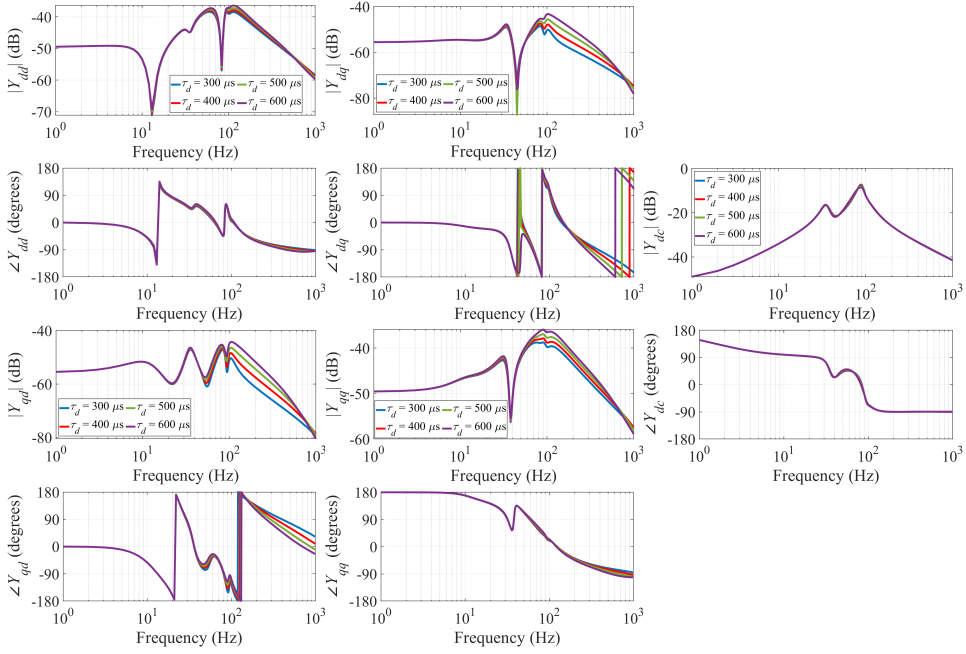


Figure 3.6: Variation of AC and DC side admittances with change in τ_d for power controlled MMC.

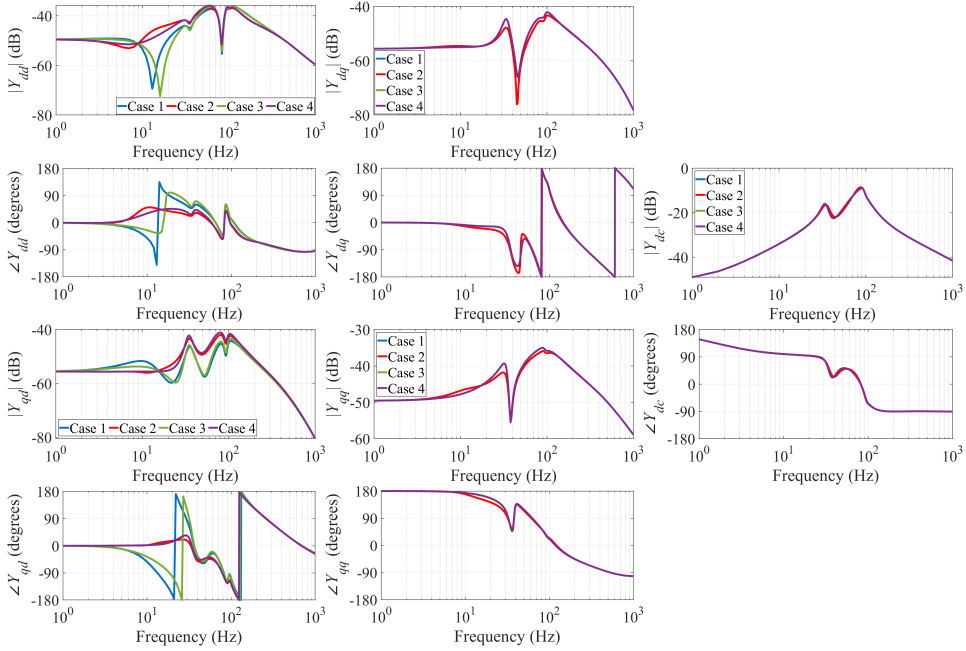


Figure 3.7: Admittance variation for MMC operating in power control with change in filter cut-off frequency.

3.10.1. Case Study 1: Two Terminal Point-to-Point HVDC System

In the first case study, a two-terminal point-to-point HVDC system, depicted in Figure 3.8, as implemented in [18] is examined. The system and control parameters of the MMCs are detailed in Table 3.2, while the operating point parameters are listed in Table 3.3. Using these parameters and operating points, the admittance characteristics for the MMCs operating in the two-terminal point-to-point HVDC system are obtained, as shown in Figure 3.9.

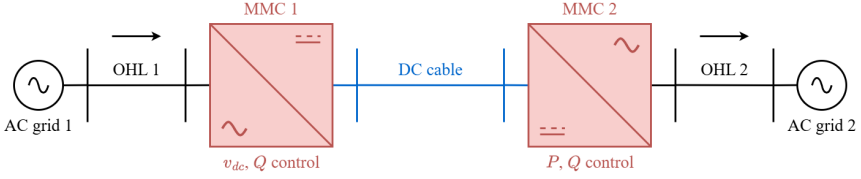


Figure 3.8: Two-terminal point-to-point HVDC system as implemented in [18].

Type	Symbol	Value	Symbol	Value
System	S_{rated}	1000 MVA	ω	$2\pi 50$ rad/s
Submodule	N	400	C	10 mF
Arm losses	R_a	1.07 Ω	L_a	50 mH
Phase reactor	R_r	0.512 Ω	L_r	60 mH
Delay	τ_d	150 μ s	C_{dc}	$\frac{6C}{N}$
PLL	K_p^{PLL}	300 p.u.	K_I^{PLL}	200 p.u.
$i^{\Delta dq}$ control	$K_p^{\Delta dq}$	1.06 p.u.	$K_I^{\Delta dq}$	766.49 p.u.
$i^{\Sigma dq}$ control	$K_p^{\Sigma dq}$	0.05 p.u.	$K_I^{\Sigma dq}$	10.99 p.u.
v_{dc} control	K_p^{dc}	2.61 p.u.	K_I^{dc}	522 p.u.
P, Q control	K_p^{PQ}	0.08 p.u.	K_I^{PQ}	40 p.u.
$i^{\Sigma z}$ control	$K_p^{\Sigma z}$	0.05 p.u.	$K_I^{\Sigma z}$	10.99 p.u.
$W^{\Sigma z}$ control	$K_p^{\Sigma W}$	3.68 p.u.	$K_I^{\Sigma W}$	12.26 p.u.

Table 3.2: System and control parameters for the MMCs in the two terminal point-to-point HVDC system [18].

	V_{dc}	P_{dc}	V_{ac}	θ	P_{ac}	Q_{ac}
MMC 1	640 kV	522 MW	262.9 kV	-8.5°	502.5 MW	0 MVAR
MMC 2	639.9 kV	-483.2 MW	282.8 kV	7.46°	-500 MW	0 MVAR

Table 3.3: Steady state values for AC and DC side voltages and powers for the MMCs in the two terminal point-to-point HVDC system [18].

3.10.2. Case Study 2: Four Terminal Meshed HVDC System

In the second case study, a four-terminal meshed HVDC system, depicted in Figure 3.10, as implemented in [39] is examined. The system and control parameters of the MMCs

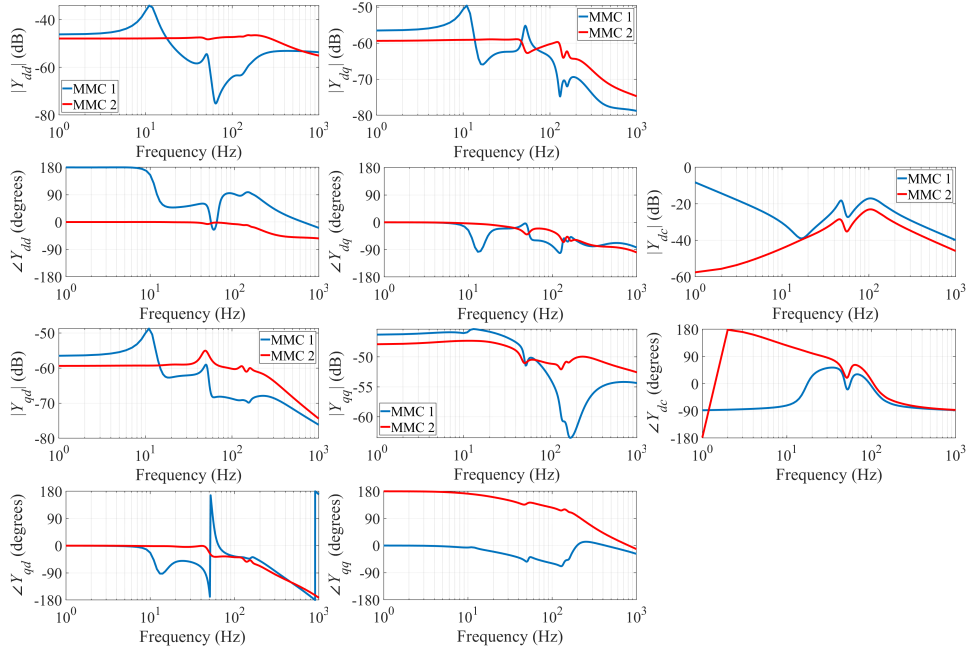


Figure 3.9: Variation of AC and DC side admittances for the MMCs present in the two terminal point-to-point HVDC system.

are detailed in Table 3.4, while the operating point parameters are listed in Table 3.5. The inner controllers' control parameters can be determined as per (3.32), in accordance with the pole-zero placement method outlined in [41].

$$K_P^{\Delta dq} = 2\zeta^{\Delta dq} \omega_n^{\Delta dq} L_t - R_t \quad (3.32a)$$

$$K_I^{\Delta dq} = L_t (\omega_n^{\Delta dq})^2 \quad (3.32b)$$

$$K_P^{\Sigma dq} = 2\zeta^{\Sigma dq} \omega_n^{\Sigma dq} L_a - R_a \quad (3.32c)$$

$$K_I^{\Sigma dq} = L_a (\omega_n^{\Sigma dq})^2 \quad (3.32d)$$

$$K_P^{\Sigma z} = 2\zeta^{\Sigma z} \omega_n^{\Sigma z} L_a - R_a \quad (3.32e)$$

$$K_I^{\Sigma z} = L_a (\omega_n^{\Sigma z})^2 \quad (3.32f)$$

Using these parameters and operating points, the admittance characteristics for the MMCs operating in the four-terminal meshed HVDC system are obtained, as shown in Figure 3.11.

Type	Symbol	Value	Symbol	Value
System	S_{rated}	1000 MVA	ω	$2\pi 50$ rad/s
Submodule	N	200	C	4.23 mF
Arm losses	R_a	0.6017Ω	L_a	30.6 mH
Phase reactor	R_r	0.3429Ω	L_r	62.9 mH
Delay	τ_d	$100 \mu s$	C_{dc}	$\frac{6C}{N}$
PLL	K_P^{PLL}	300 p.u.	K_I^{PLL}	200 p.u.
$i^{\Delta dq}$ control	$\zeta^{\Delta dq}$	0.7	$\omega_n^{\Delta dq}$	1000 rad/s
$i^{\Sigma dq}$ control	$\zeta^{\Sigma dq}$	0.7	$\omega_n^{\Sigma dq}$	300 rad/s
v_{dc} control	K_P^{dc}	0.01 AV^{-1}	K_I^{dc}	$2 \text{ AV}^{-1} \text{ s}^{-1}$
P, Q control	K_P^{PQ}	0.12	K_I^{PQ}	60 s^{-1}
$i^{\Sigma z}$ control	$\zeta^{\Sigma z}$	0.7	$\omega_n^{\Sigma z}$	300 rad/s
$W^{\Sigma z}$ control	$K_P^{\Sigma W}$	120 JA^{-1}	$K_I^{\Sigma W}$	$400 \text{ JA}^{-1} \text{ s}^{-1}$

Table 3.4: System and control parameters for the MMCs in the four-terminal meshed HVDC system [39].

	V_{dc}	P_{dc}	V_{ac}	θ	P_{ac}	Q_{ac}
MMC 1	640 kV	120.01 MW	399.80 kV	-0.05 rad	120.03 MW	0 MVAR
MMC 2	639.98 kV	-60 MW	405.07 kV	0.00 rad	-60 MW	0 MVAR
MMC 3	639.98 kV	-20 MW	404 kV	-0.01 rad	-20 MW	0 MVAR
MMC 4	639.99 kV	-40 MW	404.54 kV	-0.01 rad	-40 MW	0 MVAR

Table 3.5: Steady state values for AC and DC side voltages and powers for the MMCs in the four-terminal meshed HVDC system [39].

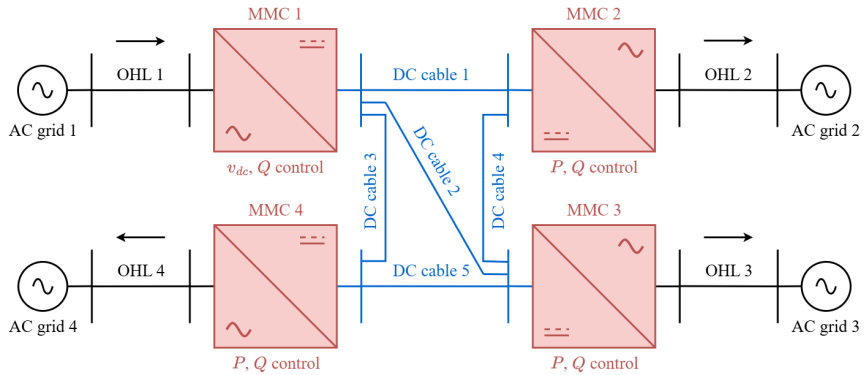


Figure 3.10: Four terminal system given in [39].

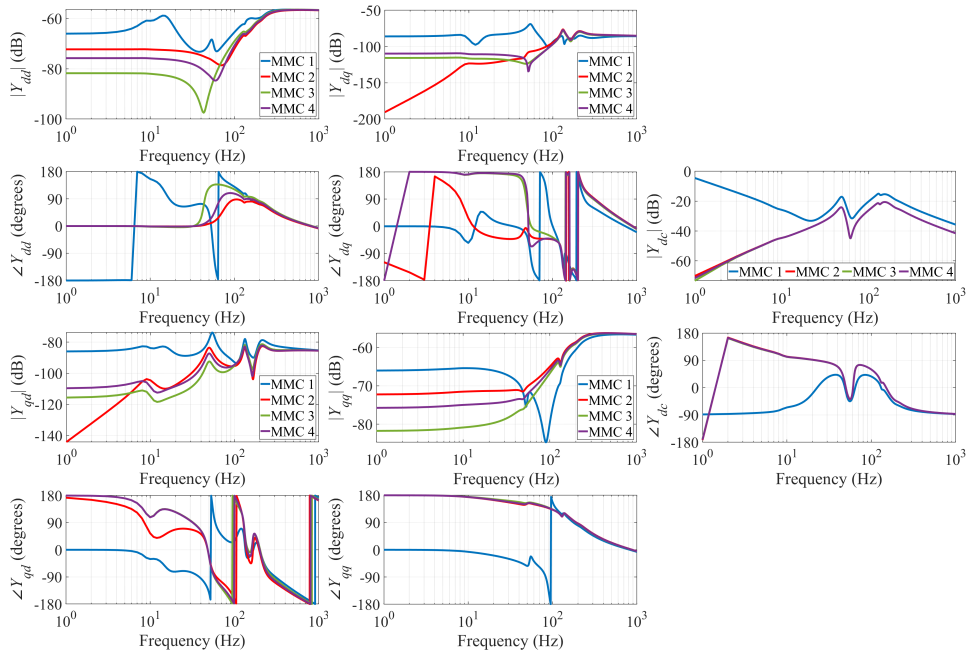


Figure 3.11: Variation of AC and DC side admittances for the MMCs present in the four-terminal meshed HVDC system.

3.11. Chapter Conclusion

In conclusion, this chapter has effectively introduced an LTI framework for modeling the AC and DC side impedances of MMCs. The extended LTI model, now incorporating measurement filters as present in practical converters, has been validated through thorough comparisons with simulation results from the CIGRE B4 DC grid test system. A detailed analysis of various controller types and parameters, such as time delay, DC side capacitance, and filter dynamics, has provided significant insights into their impact on impedance characteristics. Finally, various case studies demonstrate that the LTI model can be effectively applied in the presence of an energy controller.

4

Transfer Learning and Neural Networks

4.1. Introduction

This chapter describes a transfer learning framework that uses neural networks to model the AC and DC side impedances of the MMCs. This approach achieves accurate MMC impedance estimation while requiring less simulated data by combining the black-box impedance measurement procedure and the LTI model. The framework's effectiveness is demonstrated using a practical converter from the CIGRE B4 DC grid test system for both power and voltage control modes. Furthermore, employing multiple smaller neural networks tailored to specific frequency ranges improves impedance characterization.

Notation

The real and imaginary components of a complex number $x \in \mathbb{C}$ are denoted by the symbols $\Re\{x\}$ and $\Im\{x\}$.

4.2. Neural Network Training

A typical ANN structure used for this study is shown in Figure 4.1. It consists of one input layer with five neurons, representing the MMC's operating point (V_{dc} , V_{ac} , P_{ac} , Q_{ac} , and f); m hidden layers with $u_1, u_2, \dots, u_n$ neurons; and one output layer with ten neurons, representing the AC and DC side admittances of the converter ($\Re\{Y_{dd}\}$, $\Im\{Y_{dd}\}$,

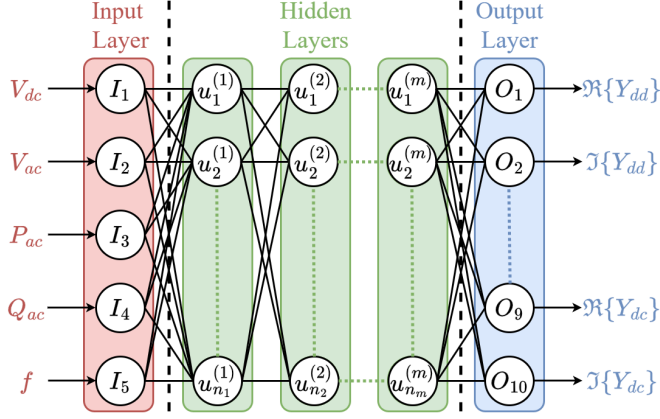


Figure 4.1: Structure of a typical ANN with the inputs being the converter operating point and the outputs being the admittances.

$\Re\{Y_{dq}\}$, $\Im\{Y_{dq}\}$, $\Re\{Y_{qd}\}$, $\Im\{Y_{qd}\}$, $\Re\{Y_{qq}\}$, $\Im\{Y_{qq}\}$, $\Re\{Y_{dc}\}$, and $\Im\{Y_{dc}\}$. Each neuron in the ANN, specifically in the i th hidden layer, is modeled using (4.1).

$$\mathbf{u}^{(i)} = a^{(i)}\{\mathbf{w}^{(i)}\mathbf{u}^{(i-1)} + \mathbf{b}^{(i)}\} \quad (4.1)$$

where $a^{(i)}$ denotes the i th hidden layer's activation function, and $\mathbf{u}^{(i)}$, $\mathbf{w}^{(i)}$, and $\mathbf{b}^{(i)}$ denote the neuron values, weights, and biases in the i th hidden layer. These parameters are provided by (4.2).

$$\mathbf{u}^{(i)} = \begin{bmatrix} u_1^{(i)} & u_2^{(i)} & \cdots & u_{n_i}^{(i)} \end{bmatrix}^T \quad (4.2a)$$

$$\mathbf{w}^{(i)} = \begin{bmatrix} w_{1,1}^{(i)} & w_{1,2}^{(i)} & \cdots & w_{1,n_{i-1}}^{(i)} \\ w_{2,1}^{(i)} & w_{2,2}^{(i)} & \cdots & w_{2,n_{i-1}}^{(i)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n_i,1}^{(i)} & w_{n_i,2}^{(i)} & \cdots & w_{n_i,n_{i-1}}^{(i)} \end{bmatrix} \quad (4.2b)$$

$$\mathbf{b}^{(i)} = \begin{bmatrix} b_1^{(i)} & b_2^{(i)} & \cdots & b_{n_i}^{(i)} \end{bmatrix}^T \quad (4.2c)$$

The neuron values for the output layer and the first hidden layer may be obtained from (4.1) using (4.3).

$$\mathbf{u}^{(1)} = a^{(1)}\{\mathbf{w}^{(1)}\mathbf{I} + \mathbf{b}^{(1)}\} \quad (4.3a)$$

$$\mathbf{O} = \mathbf{w}^{(m+1)}\mathbf{u}^{(m)} + \mathbf{b}^{(m+1)} \quad (4.3b)$$

where $\mathbf{I} = [I_1 \ I_2 \ \cdots \ I_5]^T$ represent the 5 input values, and $\mathbf{O} = [O_1 \ O_2 \ \cdots \ O_{10}]^T$

represent the 10 output values, and

$$\mathbf{w}^{(m+1)} = \begin{bmatrix} w_{1,1}^{(m+1)} & w_{1,2}^{(m+1)} & \cdots & w_{1,n_m}^{(m+1)} \\ w_{2,1}^{(m+1)} & w_{2,2}^{(m+1)} & \cdots & w_{2,n_m}^{(m+1)} \\ \vdots & \vdots & \ddots & \vdots \\ w_{10,1}^{(m+1)} & w_{10,2}^{(m+1)} & \cdots & w_{10,n_m}^{(m+1)} \end{bmatrix} \quad (4.4a)$$

$$\mathbf{b}^{(m+1)} = [b_1^{(m+1)} \quad b_2^{(m+1)} \quad \cdots \quad b_{10}^{(m+1)}]^T \quad (4.4b)$$

The performance of the ANN with different configurations of neurons in each hidden layer is systematically evaluated using techniques such as grid search or random search, aiming to identify the optimal architecture that maximizes predictive accuracy while avoiding overfitting. For simplicity, the number of neurons in each hidden layer is kept equal. Subsequently, the Optuna framework [46] is employed to optimize the hyperparameters. The kernel regularization parameter for the neurons, the activation function in each hidden layer, and the learning rate of the Adam optimizer are tuned through 50 trials. This optimization process helps avoid overfitting and achieves optimal performance on the training, validation, and test sets.

The ANN model described above undergoes a comprehensive training process. The overall dataset is initially divided into three parts: 70% for training, 15% for validation, and 15% for testing. During each epoch of the training process, the training and validation sets are randomly shuffled to ensure that every item has an equal chance of being used for training. This shuffling process enhances the robustness and generalization capability of the model.

Next, the ANN is trained using the back-propagation algorithm, which employs the mean squared error (MSE) loss function and the mean absolute error (MAE) metric to evaluate the difference between the ANN's predictions and the provided admittance data. The primary objective of the training process is to minimize the MSE by updating the weights and biases of each neuron using the Adam optimizer. The Adam optimizer is chosen for its efficiency in handling large datasets and its adaptive learning rate capabilities, which make it suitable for this complex modeling task.

Finally, the trained ANN model is evaluated using the test set. Its performance is assessed using several metrics: MSE, MAE, and the coefficient of determination (R^2). These metrics provide a comprehensive evaluation of the model's accuracy and its ability to generalize to unseen data. An R^2 value close to 1 indicates that the model accurately captures the variance in the admittance data. If a n prediction vector is constructed from a sample of n data points, then the MSE, MAE, and R^2 values can be given by (4.5).

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (4.5a)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i) \quad (4.5b)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n \left(y_i - \frac{1}{n} \sum_{i=1}^n y_i \right)^2} \quad (4.5c)$$

where, y_i is the i th data point value in the observed vector, and $\hat{y}_i$ is the i th data point value in the prediction vector.

4.3. Transfer Learning Framework

Conventional ANN models typically demand extensive datasets to accurately estimate MMC impedances. However, obtaining AC and DC side impedance responses through separate simulations consumes a considerable amount of time, particularly when generating impedance data across a wide spectrum of operating points. In response to this challenge, this paper proposes a transfer learning framework, illustrated in Figure 4.2, for accurate estimation of MMC impedances. The central concept of this framework is to leverage a diverse dataset encompassing a broad array of operating points generated using the LTI model and subsequently train a neural network. Following this, detailed simulations in RSCAD are employed to conduct impedance measurements for a smaller subset of operating points. Finally, the pre-trained ANN model undergoes fine-tuning using the simulated data to achieve optimal accuracy.

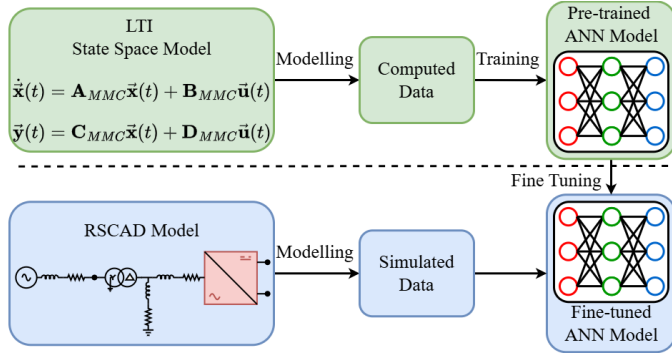


Figure 4.2: Proposed transfer learning framework-based framework for impedance characterization of MMCs.

The process of collecting converter admittances involves iterative steps using both the impedance measurement procedure detailed in Chapter 2 and the LTI model defined in Chapter 3. This iterative approach entails sweeping through a series of operating points specified according to reasonable power system operation criteria [47]. For each control mode, two datasets are generated: computed data and simulated data. The computed data corresponds to values computed based on the LTI model, whereas simulated data is obtained from real-time simulations. Both datasets are constructed similarly, with the operating ranges of the converters normalized on a per-unit basis: $V_{dc} \in [0.9, 1.1]$, $V_{ac} \in [0.9, 1.1]$, $P_{ac} \in [-1, 1]$, and $Q_{ac} \in [-1, 1]$.

4.4. Experimental Dataset Construction

To validate the proposed transfer learning framework, the application of converter A1, modeled similarly to the system diagram shown in Figure 2.2, is employed from the CIGRE B4 DC grid test system [29]. The rated values, control parameters, and filter parameters for the converter are detailed in Chapter 2. Following the procedure outlined in Chapter 2 multiple times, the AC and DC side impedances of the converter are iteratively obtained for normalized operating points and frequency steps as given in (4.6).

$$\text{Simulated data} = \begin{cases} V_{dc} \in [0.9, 1.1] \text{ p.u. in steps of } 0.1 \text{ p.u.} \\ V_{ac} \in [0.9, 1.1] \text{ p.u. in steps of } 0.1 \text{ p.u.} \\ P_{ac} \in [-1, 1] \text{ p.u. in steps of } 0.4 \text{ p.u.} \\ Q_{ac} \in [-1, 1] \text{ p.u. in steps of } 0.3 \text{ p.u.} \\ f = \begin{cases} [1, 10] \text{ p.u. in steps of } 1 \text{ Hz} \\ [10, 100] \text{ p.u. in steps of } 3 \text{ Hz} \\ [100, 1000] \text{ p.u. in steps of } 30 \text{ Hz} \end{cases} \end{cases} \quad (4.6)$$

Similarly, using the LTI model, a diverse dataset is acquired for the normalized operating points and frequency steps as given in (4.7), considering a computational time delay in the converter of $600 \mu\text{s}$.

$$\text{Computed data} = \begin{cases} V_{dc} \in [0.9, 1.1] \text{ p.u. in steps of } 0.1 \text{ p.u.} \\ V_{ac} \in [0.9, 1.1] \text{ p.u. in steps of } 0.1 \text{ p.u.} \\ P_{ac} \in [-1, 1] \text{ p.u. in steps of } 0.2 \text{ p.u.} \\ Q_{ac} \in [-1, 1] \text{ p.u. in steps of } 0.2 \text{ p.u.} \\ f = \begin{cases} [1, 10] \text{ p.u. in steps of } 1 \text{ Hz} \\ [10, 100] \text{ p.u. in steps of } 1 \text{ Hz} \\ [100, 1000] \text{ p.u. in steps of } 10 \text{ Hz} \end{cases} \end{cases} \quad (4.7)$$

Both datasets exclude operating points leading to over-modulation and over-current conditions, and separate datasets are obtained for each control mode.

4.5. Variation of Admittances with respect to Input Variables

Because the admittance values generated by the LTI model and the simulated model are comparable, they can accurately depict changes in admittance values with respect to the operating point variables. Moreover, since computed data encompasses data for additional operating points, it allows for a more comprehensive analysis to be conducted. As a result, computed data is selected for analysis in this section.

Figures 4.3 and 4.4 present a subset of the dataset for power control mode. To simplify the presentation, only 3 out of the 10 output admittance variables are plotted. How-

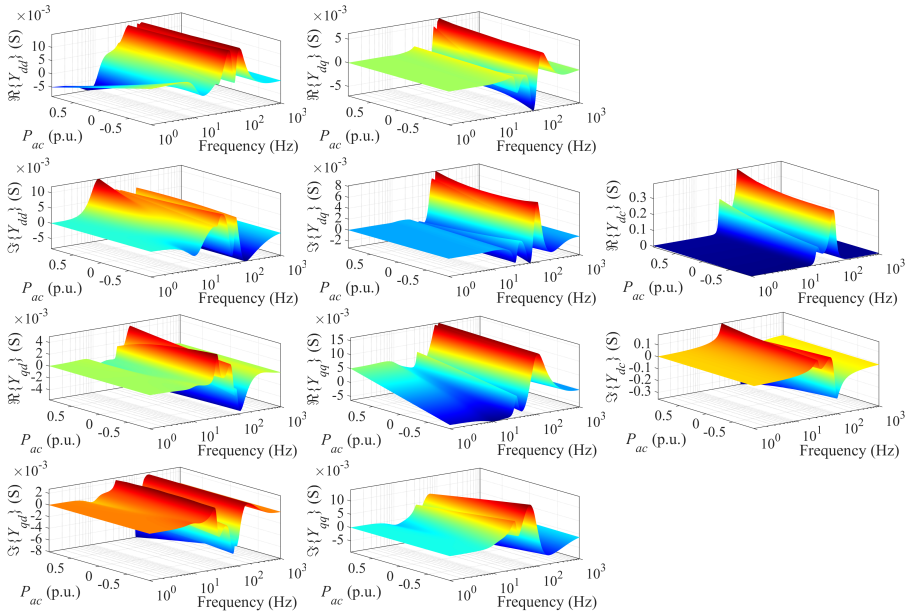


Figure 4.3: Variation of admittances with respect to P_{ac} and f when $V_{ac} = 1$ p.u., $V_{dc} = 1$ p.u., and $Q_{ac} = 0$ p.u. and the MMC operates in power control mode.

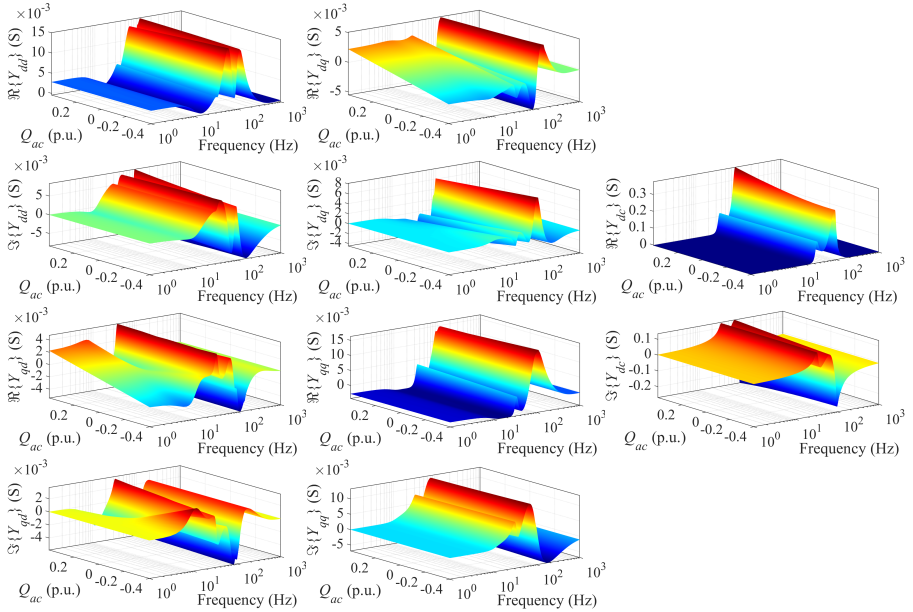


Figure 4.4: Variation of admittances with respect to Q_{ac} and f when $V_{ac} = 1$ p.u., $V_{dc} = 1$ p.u., and $P_{ac} = -0.5$ p.u. and the MMC operates in power control mode.

ever, the remaining variables exhibit similar behavior. For instance, changes in parameters similarly affect both the dd and qq admittances, as well as the dq and qd admittances. Additionally, the impact of parameter changes on the real parts is similar to their effect on the imaginary parts.

It is observed that the admittances Y_{dd} and Y_{qq} are primarily influenced by P_{ac} , while Y_{dq} and Y_{qd} are mainly dependent on Q_{ac} . In contrast, the admittance Y_{dc} varies with both P_{ac} and Q_{ac} . The relationship of the voltages V_{ac} and V_{dc} to the admittances is minor compared to that of P_{ac} and Q_{ac} . Similar variations are noted in DC voltage control datasets except that the voltages V_{ac} and V_{dc} exhibit significant variation in relation to the admittance Y_{dc} .

4.6. When Converter is Controlled using Power Control

4

After acquiring the necessary datasets, the proposed method is initially tested for an MMC operating in power control mode. Traditional methods from previous studies employ a single ANN model for the entire frequency range. However, the dependency of the admittances on the input variables varies with frequency. This subsection provides details on this approach and its testing, both when using a single ANN model for the entire frequency range and when using separate models for different frequency ranges.

4.6.1. Single ANN over the Whole Frequency Range

Initially, the entire frequency range is considered and trained using a single ANN model for power control mode. The neural network architecture for this purpose includes three hidden layers, each with 100 neurons, due to the complex nature of the admittances concerning frequency. First, the large neural network structure is pre-trained on the dataset obtained from the LTI model and then fine-tuned using the dataset obtained from EMT simulations. The batch size is set to 128 to ensure smooth loss gradients during training. The pre-trained model is used to predict the admittances for a set of test operating points. These points include all data points in the plane $V_{ac} = 1$ p.u., $V_{dc} = 1$ p.u., and $Q_{ac} = 0$ p.u., which are not considered in the training or validation set. The corresponding errors between the pre-trained model and the actual admittances obtained from EMT simulations in the same plane are plotted as depicted in Figure 4.5. It can be observed that the pre-trained model significantly deviates from the actual admittance data generated using EMT simulations. This deviation is due to several types of nonlinearities and non-modelable quantities, such as sampling error and the exact value of computational time delay, which are not considered in the LTI model. Therefore, the use of transfer learning and fine-tuning is required.

Finally, the errors between the models obtained using the conventional ANN method (trained solely with simulated data), the transfer learning method, and the actual admittances obtained from EMT simulations are depicted in Figures 4.6 and 4.7, respectively.

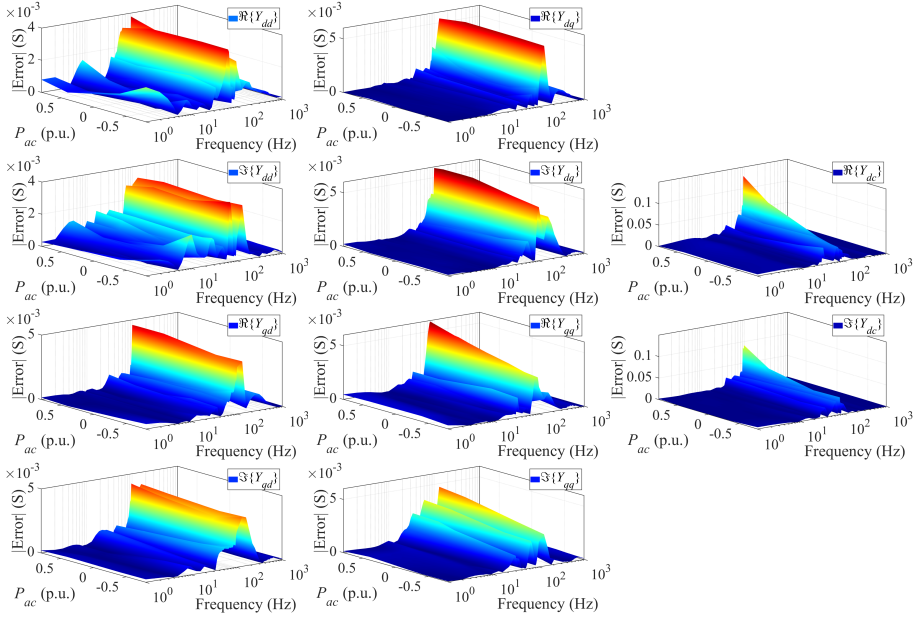


Figure 4.5: Error between ANN trained using the LTI model and simulated data when the MMC operates in power control mode.

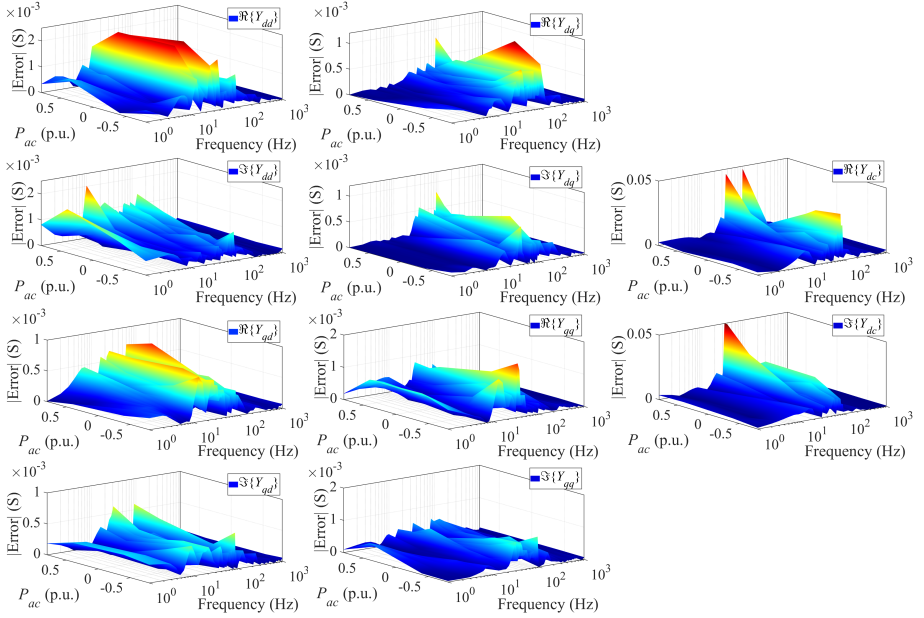


Figure 4.6: Error between ANN trained on simulated data over the entire frequency range and a set of test operating points when the MMC operates in power control mode.

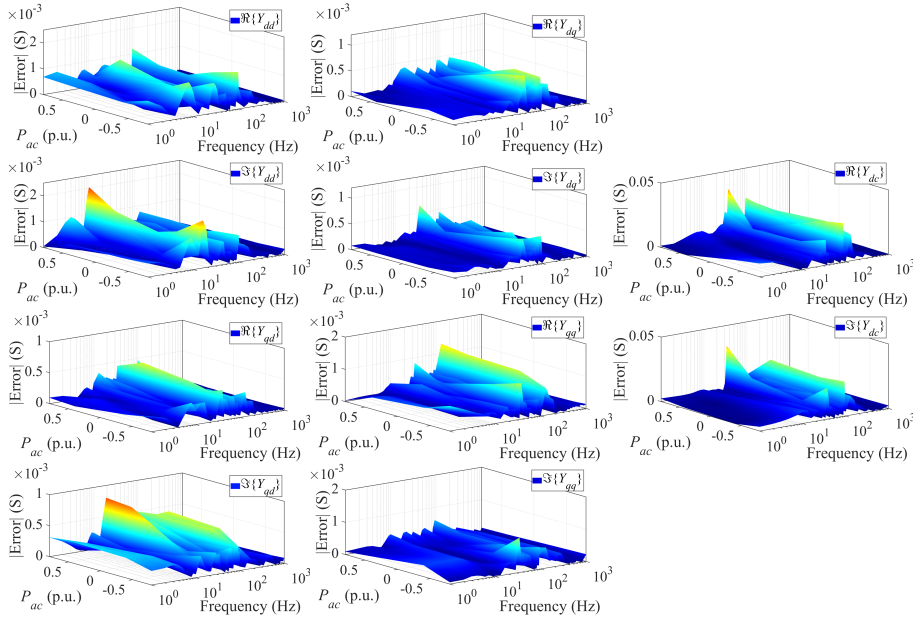


Figure 4.7: Error between ANN trained using transfer learning over the entire frequency range and a set of test operating points when the MMC operates in power control mode.

The errors in the conventional ANN method are higher (around 2 to 3 times) than those in the proposed method, as the model cannot generalize for unseen operating points and frequency steps due to limited data availability. This comparison shows that transfer learning-based models can achieve better performance and be generalized appropriately across all operating points and frequency steps, even with limited simulation data availability.

4.6.2. Splitting Models based on Frequency Range

Further analysis of the dataset reveals that admittances vary at different scales across certain frequency ranges. Additionally, the dependency of the admittances on the input variables changes with frequency. Admittances in the 1-10 Hz frequency range depend highly on active and reactive power. In the 10-100 Hz frequency range, admittances primarily depend not only on active and reactive power but also on frequency. Lastly, in the 100-1000 Hz frequency range, admittances are predominantly dependent on frequency. Therefore, each frequency region has a distinct dependency on the input variables.

Leveraging the data dependency within each frequency range, separate ANN models are implemented to optimize the impedance identification process. Instead of using a single ANN model for the entire frequency range, smaller ANN architectures are utilized to estimate admittances within specific frequency ranges. Based on the non-linearity of

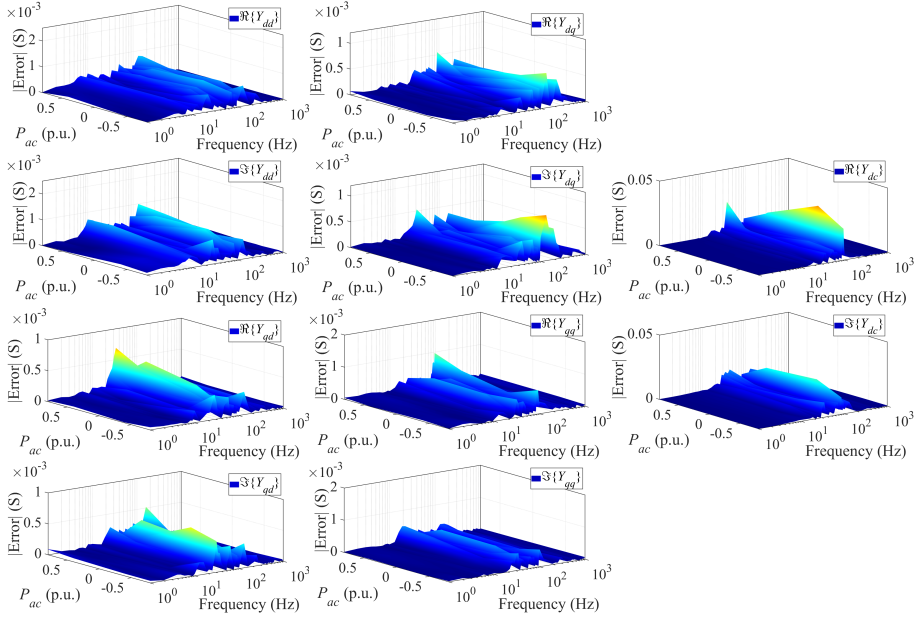


Figure 4.8: Error between the ANN trained using transfer learning, with models split based on frequency range, and a set of test operating points when the MMC operates in power control mode.

the admittance values, 1, 3, and 2 hidden layers are implemented for the 1–10 Hz, 10–100 Hz, and 100–1000 Hz frequency ranges, respectively. Each hidden layer contains 50 neurons, while the batch size during training is set to 64.

For MMC controlled in power control mode, the error between the ANN trained using the proposed method by splitting models based on frequency range and the simulated data is depicted in Figure 4.8. Comparing Figures 4.7 and 4.8, it is evident that splitting models based on frequency range can reduce the error between the trained ANN model and the simulated data, resulting in a better fit. This method significantly improves accuracy, particularly in the low-frequency range of 1–10 Hz.

4.7. When Converter is Controlled using DC Voltage Control

Similar to the power-controlled MMC, the proposed method accurately estimates the admittances for the MMC controlled using a DC voltage controller. An important observation is demonstrated by setting the parameter C_{dc} to 600 μF in the LTI model, contrasting with its value of 500 μF in the simulation model. Despite the slight variation in this parameter, which causes significant deviations in the admittances, the proposed method exhibits substantial accuracy compared to the conventional ANN approach. This is highlighted in the corresponding errors depicted in Figures 4.9 and 4.10.

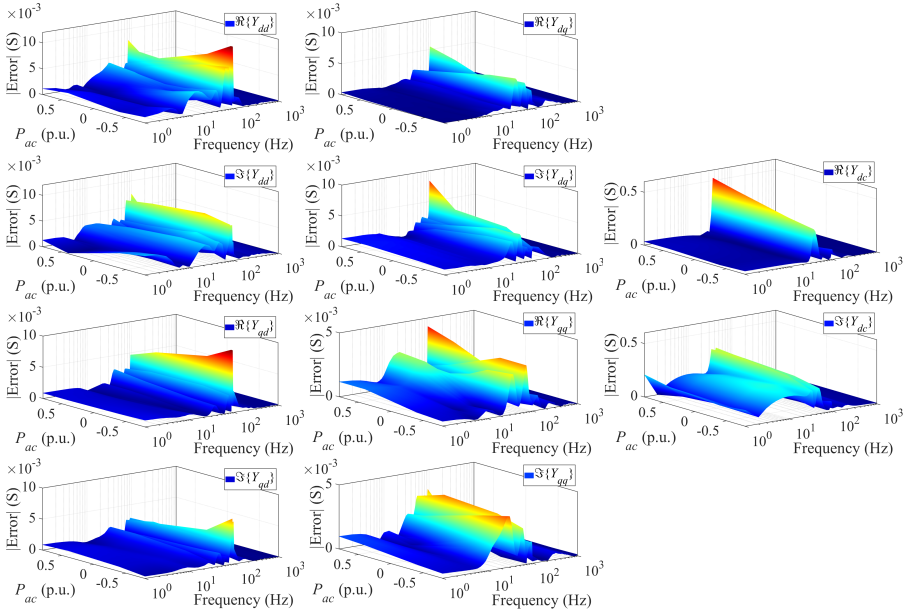


Figure 4.9: Error between ANN trained on simulated data over the entire frequency range and a set of test operating points for when the MMC operates in DC voltage control mode.

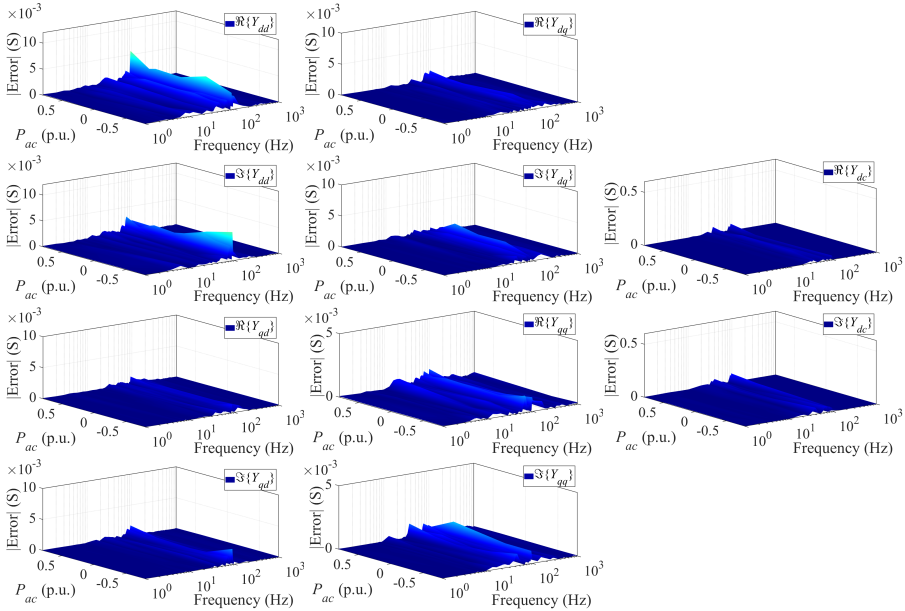


Figure 4.10: Error between the ANN trained using transfer learning, with models split based on frequency range, and a set of test operating points when the MMC operates in DC voltage control mode.

4.8. When Several Control Parameters are Unknown

In certain scenarios, manufacturers keep converter data confidential, making it impossible to accurately estimate impedance characteristics using the LTI model. However, the proposed transfer learning method allows for training the ANN model on a large dataset generated using the LTI model with slightly different parameters. This pre-trained model can then be fine-tuned using simulated data to achieve an accurate representation.

To further demonstrate the proposed method for such scenarios, the dataset generated using the LTI model for power control mode is obtained with a different set of control parameters compared to the simulated dataset. Specifically, the values of $K_P^{\Delta dq}$, $K_I^{\Delta dq}$, K_I^P , and K_I^Q are set to 0.72 p.u., 223.5 p.u., 16.5 p.u., and 16.5 p.u., respectively, while the parameters for the simulated dataset remain unchanged. By comparing the error obtained when the ANN is trained using the transfer learning method shown in Figure 4.11 to the error obtained when the ANN is trained solely on simulated data as presented in Figure 4.6, it can be observed that the ANN trained using the proposed method accurately estimates the converter admittances even when the control parameters in the two datasets differ.

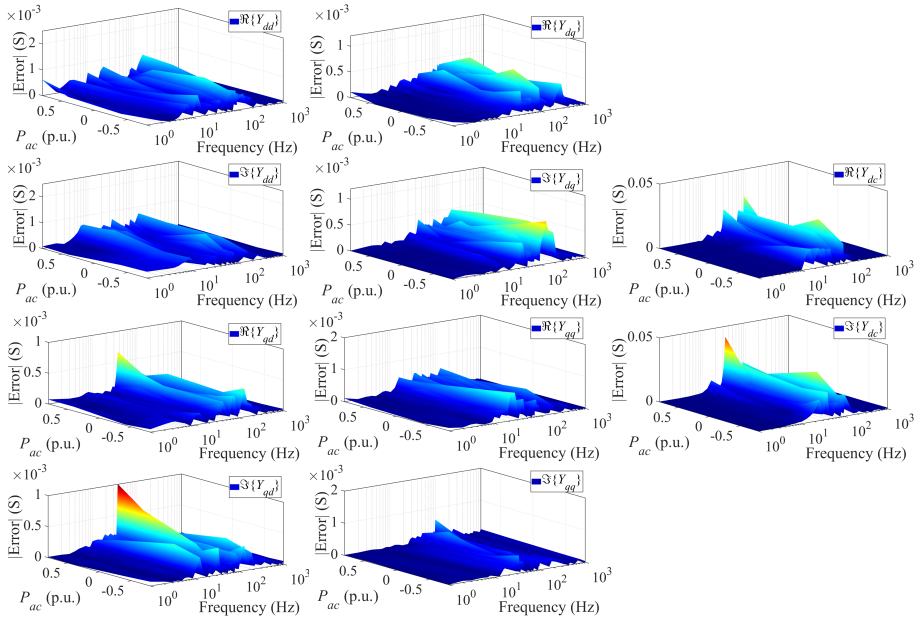


Figure 4.11: Error between the ANN trained using transfer learning, with models split based on frequency range, and a set of test operating points when the MMC operates in power control mode. The ANN model is pre-trained using the LTI model with control parameters different from those in the simulation model.

4.9. Chapter Conclusion

In conclusion, this chapter has detailed a transfer learning framework utilizing neural networks for modeling the AC and DC side impedances of MMCs. By combining the black-box impedance measurement procedure with the LTI model, the approach achieves accurate MMC impedance estimation while minimizing the required simulated data. The effectiveness of the framework has been demonstrated using a practical converter from the CIGRE B4 DC grid test system under both power and voltage control modes. Additionally, employing multiple smaller neural networks tailored to specific frequency ranges has been shown to enhance impedance characterization.

5

Conclusion and Future Scope

This thesis presents a transfer learning framework for impedance characterization of modular multilevel converters (MMCs), which addresses limitations in traditional small-signal models and black-box impedance measurement techniques. The method uses LTI modeling and black-box impedance measurements to estimate AC and DC side impedances under power and DC voltage control. By pre-training ANN models with LTI-derived datasets and fine-tuning them with real-time electromagnetic transient simulations, the framework significantly reduces computational burden and data requirements. Given the limited data availability of impedance characteristics obtained through simulations, the proposed method accurately predicts impedance characteristics at different operating points and frequency steps. Furthermore, the effectiveness of using multiple smaller ANN models tailored to specific frequency ranges and operating points is demonstrated, resulting in improved impedance prediction accuracy. The proposed framework is validated using a practical MMC converter from the CIGRE B4 DC grid test system, demonstrating superior advantages over traditional ANN methods, especially in scenarios where manufacturers keep certain converter parameters confidential.

Future research could investigate combining the proposed method with advanced controllers to improve MMC impedance modeling in complex grids. Furthermore, investigating alternative machine learning approaches such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) could provide insights into potentially improving MMC impedance models' predictive capabilities. Furthermore, extending the framework to model wind farm impedances offers a promising solution to the evolving challenges of renewable energy integration and grid stability.

References

- [1] A. Sajadi, R. W. Kenyon, and B.-M. Hodge, "Synchronization in electric power networks with inherent heterogeneity up to 100% inverter-based renewable generation," *Nature communications*, vol. 13, no. 1, p. 2490, 2022.
- [2] X. Wang and F. Blaabjerg, "Harmonic stability in power electronic-based power systems: Concept, modeling, and analysis," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2858–2870, 2018.
- [3] X. Wang, L. Harnefors, and F. Blaabjerg, "Unified impedance model of grid-connected voltage-source converters," *IEEE Transactions on Power Electronics*, vol. 33, no. 2, pp. 1775–1787, 2017.
- [4] B. Wen, D. Boroyevich, R. Burgos, P. Mattavelli, and Z. Shen, "Analysis of dq small-signal impedance of grid-tied inverters," *IEEE Transactions on Power Electronics*, vol. 31, no. 1, pp. 675–687, 2015.
- [5] Y. Liao and X. Wang, "Stationary-frame complex-valued frequency-domain modeling of three-phase power converters," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 8, no. 2, pp. 1922–1933, 2019.
- [6] J. Sun, "Impedance-based stability criterion for grid-connected inverters," *IEEE Transactions on Power Electronics*, vol. 26, no. 11, pp. 3075–3078, 2011.
- [7] B. Wen, D. Dong, D. Boroyevich, R. Burgos, P. Mattavelli, and Z. Shen, "Impedance-based analysis of grid-synchronization stability for three-phase paralleled converters," *IEEE Transactions on Power Electronics*, vol. 31, no. 1, pp. 26–38, 2015.
- [8] J. Khazaei, M. Beza, and M. Bongiorno, "Impedance analysis of modular multi-level converters connected to weak ac grids," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4015–4025, 2017.
- [9] A. Bayo Salas, "Control interactions in power systems with multiple vsc hvdc converters," 2018.
- [10] Y. Liu and Z. Chen, "Stability analysis of multi-infeed hvdc system applying vsc-hvdc," in *IEEE PES General Meeting*, IEEE, 2010, pp. 1–7.
- [11] H. Saad, J. Mahseredjian, S. Dennerière, and S. Nguefeu, "Interactions studies of hvdc–mmc link embedded in an ac grid," *Electric Power Systems Research*, vol. 138, pp. 202–209, 2016.
- [12] T. Yin *et al.*, "Impedance-based stability analysis and stabilization control strategy of mmc-hvdc considering complete control loops," *IEEE Access*, vol. 8, pp. 142 900–142 915, 2020.

- [13] Z. Li, Z. Wang, *et al.*, “Accurate impedance modeling and control strategy for improving the stability of dc system in multiterminal mmc-based dc grid,” *IEEE Transactions on Power Electronics*, vol. 35, no. 10, pp. 10 026–10 049, 2020.
- [14] J. Pedra, L. Sainz, and L. Monjo, “Three-port small signal admittance-based model of vscs for studies of multi-terminal hvdc hybrid ac/dc transmission grids,” *IEEE Transactions on Power Systems*, vol. 36, no. 1, pp. 732–743, 2020.
- [15] C. M. Freitas, E. H. Watanabe, and L. F. Monteiro, “Dq small-signal model for grid-forming mmc and its application in electromagnetic-transient simulations,” *Energies*, vol. 16, no. 5, p. 2195, 2023.
- [16] D. del Giudice, A. Brambilla, D. Linaro, and F. Bizzarri, “Modular multilevel converter impedance computation based on periodic small-signal analysis and vector fitting,” *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 69, no. 4, pp. 1832–1842, 2022.
- [17] S. Shah and L. Parsa, “Impedance modeling of three-phase voltage source converters in dq, sequence, and phasor domains,” *IEEE Transactions on Energy Conversion*, vol. 32, no. 3, pp. 1139–1150, 2017.
- [18] Ö. C. Sakinci, A. Lekić, and J. Beerten, “Generalized impedance-based ac/dc power system modeling for harmonic stability analysis,” *International Journal of Electrical Power & Energy Systems*, vol. 143, p. 108 456, 2022.
- [19] A. Lekić and J. Beerten, “Generalized multiport representation of power systems using abcd parameters for harmonic stability analysis,” *Electric Power Systems Research*, vol. 189, p. 106 658, 2020.
- [20] Y. Li, Y. Liao, L. Zhao, *et al.*, “Machine learning at the grid edge: Data-driven impedance models for model-free inverters,” *IEEE Transactions on Power Electronics*, 2024.
- [21] B. Wen, D. Boroyevich, R. Burgos, P. Mattavelli, and Z. Shen, “Influence of phase-locked loop on dq frame impedance of three-phase voltage source converters and the impact on system stability,” in *2013 CPES Power Electronics Conference*, 2013, pp. 1–11.
- [22] H. Gong, D. Yang, and X. Wang, “Impact analysis and mitigation of synchronization dynamics for dq impedance measurement,” *IEEE Transactions on Power Electronics*, vol. 34, no. 9, pp. 8797–8807, 2018.
- [23] H. Gong, D. Yang, and X. Wang, “Impact of synchronization phase dynamics on dq impedance measurement,” in *2018 IEEE 19th Workshop on Control and Modeling for Power Electronics (COMPEL)*, IEEE, 2018, pp. 1–7.
- [24] M. Zhang, X. Wang, D. Yang, and M. G. Christensen, “Artificial neural network based identification of multi-operating-point impedance model,” *IEEE Transactions on Power Electronics*, vol. 36, no. 2, pp. 1231–1235, 2020.
- [25] M. Zhang, Q. Xu, and X. Wang, “Physics-informed neural network based online impedance identification of voltage source converters,” *IEEE Transactions on Industrial Electronics*, vol. 70, no. 4, pp. 3717–3728, 2022.

- [26] Y. Li, Y. Liao, X. Wang, *et al.*, “Neural network models and transfer learning for impedance modeling of grid-tied inverters,” in *2022 IEEE 13th International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*, IEEE, 2022, pp. 1–6.
- [27] M. Zhang, Y. Zhang, and Q. Xu, “Transfer learning based online impedance identification for module multilevel converters,” *IEEE Transactions on Power Electronics*, 2023.
- [28] J. Lyu, Y. Rao, Z. Wang, J. Dai, and X. Cai, “Data-driven impedance identification and stability online assessment of wind farm connected with mmc-hvdc,” *IEEE Transactions on Industry Applications*, 2023.
- [29] T. K. Vrana, Y. Yang, D. Jovcic, S. Denetière, J. Jardini, and H. Saad, “The CIGRE B4 DC grid test system,” *Electra*, vol. 270, no. 1, pp. 10–19, 2013.
- [30] A. Riccobono, M. Mirz, and A. Monti, “Noninvasive online parametric identification of three-phase ac power impedances to assess the stability of grid-tied power electronic inverters in lv networks,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 6, no. 2, pp. 629–647, 2017.
- [31] H. Gong, D. Yang, and X. Wang, “Impact of nonlinear dynamics on converter dq impedance measurement,” in *2019 20th Workshop on Control and Modeling for Power Electronics (COMPEL)*, IEEE, 2019, pp. 1–6.
- [32] G. Francis, R. Burgos, D. Boroyevich, F. Wang, and K. Karimi, “An algorithm and implementation system for measuring impedance in the dq domain,” in *2011 IEEE Energy Conversion Congress and Exposition*, IEEE, 2011, pp. 3221–3228.
- [33] Y. Qi, H. Ding, Y. Zhang, X. Shi, and A. M. Gole, “Identification of sub-synchronous interaction in mmc systems using frequency scanning,” in *2020 IEEE Power & Energy Society General Meeting (PESGM)*, IEEE, 2020, pp. 1–5.
- [34] X. Jiang and A. Gole, “A frequency scanning method for the identification of harmonic instabilities in hvdc systems,” *IEEE Transactions on Power Delivery*, vol. 10, no. 4, pp. 1875–1881, 1995.
- [35] Y. Qi, A. Gole, H. Ding, and Y. Zhang, “Evaluation of the accuracy of real-time digital simulator voltage source converter models determined from frequency scanning,” in *IPST conference in Seoul*, 2017.
- [36] J. Freytes, “Small-signal stability analysis of modular multilevel converters and application to mmc-based multi-terminal dc grids,” Ph.D. dissertation, Ecole Centrale de Lille, 2017.
- [37] G. Bergna-Diaz, J. Freytes, X. Guillaud, S. D’Arco, and J. A. Suul, “Generalized voltage-based state-space modeling of modular multilevel converters with constant equilibrium in steady state,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 6, no. 2, pp. 707–725, 2018.
- [38] G. Bergna-Diaz, D. Zonetti, S. Sanchez, R. Ortega, and E. Tedeschi, “Pi passivity-based control and performance analysis of mmc multiterminal hvdc systems,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 7, no. 4, pp. 2453–2466, 2018.

- [39] A. Lekić, H. Ergun, and J. Beerten, “Initialisation of a hybrid ac/dc power system for harmonic stability analysis using a power flow formulation,” *High Voltage*, vol. 5, no. 5, pp. 534–542, 2020.
- [40] Y. Wang, X. Wang, F. Blaabjerg, and Z. Chen, “Harmonic instability assessment using state-space modeling and participation analysis in inverter-fed power systems,” *IEEE Transactions on Industrial Electronics*, vol. 64, no. 1, pp. 806–816, 2016.
- [41] Ö. C. Sakinci and J. Beerten, “Generalized dynamic phasor modeling of the mmc for small-signal stability analysis,” *IEEE Transactions on Power Delivery*, vol. 34, no. 3, pp. 991–1000, 2019.
- [42] Ö. C. Sakinci and J. Beerten, “Impact of pll dynamics on the small-signal stability of the mmc using dynamic phasor modeling in the abc frame,” *Electric Power Systems Research*, vol. 189, p. 106 729, 2020.
- [43] D. Yang and X. Wang, “Unified modular state-space modeling of grid-connected voltage-source converters,” *IEEE Transactions on Power Electronics*, vol. 35, no. 9, pp. 9700–9715, 2020.
- [44] P. Mogensen *et al.*, *Nlsolve.jl*, 2020.
- [45] J. Revels, M. Lubin, and T. Papamarkou, “Forward-mode automatic differentiation in julia,” *arXiv Preprint*, 2016.
- [46] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, “Optuna: A next-generation hyperparameter optimization framework,” in *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, 2019, pp. 2623–2631.
- [47] Y. Liao and X. Wang, “Impedance-based stability analysis for interconnected converter systems with open-loop rhp poles,” *IEEE Transactions on Power Electronics*, vol. 35, no. 4, pp. 4388–4397, 2019.