

# Holistic Small-Signal Modeling and AI-Assisted Region-Based Stability Analysis of Autonomous AC and DC Microgrids

Yuxi Men  
College of Engineering  
Temple University  
Philadelphia, PA, USA  
yuxi.men@temple.edu

Lizhi Ding  
College of Engineering  
Temple University  
Philadelphia, PA, USA  
lizhi.ding@temple.edu

Yuhua Du  
College of Engineering  
Temple University  
Philadelphia, PA, USA  
yuhua.du@temple.edu

Xiaonan Lu  
College of Engineering  
Temple University  
Philadelphia, PA, USA  
xiaonan.lu@temple.edu

Dongbo Zhao  
Energy Systems Division  
Argonne National Laboratory  
Lemont, IL, USA  
dongbo.zhao@anl.gov

Yue Cao  
School of Electrical Engineering  
and Computer Science  
Oregon State University  
Corvallis, OR, USA  
yue.cao@oregonstate.edu

**Abstract**—In this paper, a holistic small-signal model of hybrid AC and DC microgrids is developed, including AC subsection, DC subsection, and interface inverters between AC and DC buses. Based on the derived complete small-signal model, a region-based stability analysis approach is proposed and developed. Meanwhile, to obtain the steady-state operating points used in the region-based stability analysis, practical and effective power flow calculation is conducted for droop-controlled hybrid AC and DC microgrids. Rather than following a conventional point-by-point stability evaluation procedure, the stability region implemented in this work is derived based on the selected cross-domain parameters from either control systems or main power circuits. Furthermore, an artificial intelligence (AI) assisted Kernel Ridge Regression (KRR) algorithm is implemented to derive the stability boundary with enhanced computational efficiency. Simulation tests are presented to demonstrate the effectiveness of the proposed method.

**Keywords**—Hybrid AC and DC Microgrids, Kernel Ridge Regression, Small-signal Stability, Stability Region

## I. INTRODUCTION

Increasing penetration of inverter-based resources challenges modern distribution systems with insufficient inertia and increasing generation intermittency. To mitigate the impacts of operational uncertainties, the concept of microgrids (MGs) was proposed for effectively integrating distributed energy resources (DERs) and enhancing grid operational performance. In the past years, AC MGs have been extensively studied, given that conventional grids are implemented based upon AC electricity [1]. Meanwhile, with increasing penetration of DC-coupled resources (e.g., photovoltaics [PVs], battery energy storage, etc.), the technology frontier of DC MGs has been significantly advanced that enables a hybrid architecture with both AC and DC resources, i.e., hybrid AC and DC MGs [2].

Given that the DER interface inverters are commonly parallel-connected in MGs, effective controls play a vital role in MG operation, especially for proportional output power sharing among multiple inverters. Various control strategies have been developed to achieve accurate power sharing in MGs, including centralized control approaches (e.g., master-slave control [3], central current control [4], etc.), decentralized control (e.g., droop control [5], [6], virtual synchronous generators [7], etc.), and distributed control (e.g., hierarchical control [8], [9], consensus-based control [10]–[14], etc.), among which given the simplicity in implementation and the effectiveness, droop control is commonly used to achieve proper power sharing among DGs in MGs.

Note that hybrid AC and DC MGs have relatively complex operational dynamics due to the hybrid and inverter dominated configuration. Therefore, it is critical and also challenging for small-signal stability analysis compared to conventional power grids [15]. Meanwhile, it is worth mentioning that conventional small-signal stability analysis follows a point-by-point procedure, i.e., the derived small-signal models are only applicable at specific operating points. Therefore, for hybrid AC and DC MGs, considering the large-scale integration of inverter-based resources and the requirements of a scalable architecture, there are additional obstacles of deriving a holistic small-signal model of the entire system and conducting stability analysis accordingly. In [15], the small-signal modeling of a hybrid AC and DC MG is presented, focusing on AC MG, DC MG and interlink converters between common AC and DC buses. Meanwhile, synthetic droop characteristics for regulating interlink converters are implemented to control the power exchange between AC and DC MGs. In [16], the modeling and control of the inverter dominated AC MG is studied in detail to conduct small-signal analysis. In [17], a reduced-order model is

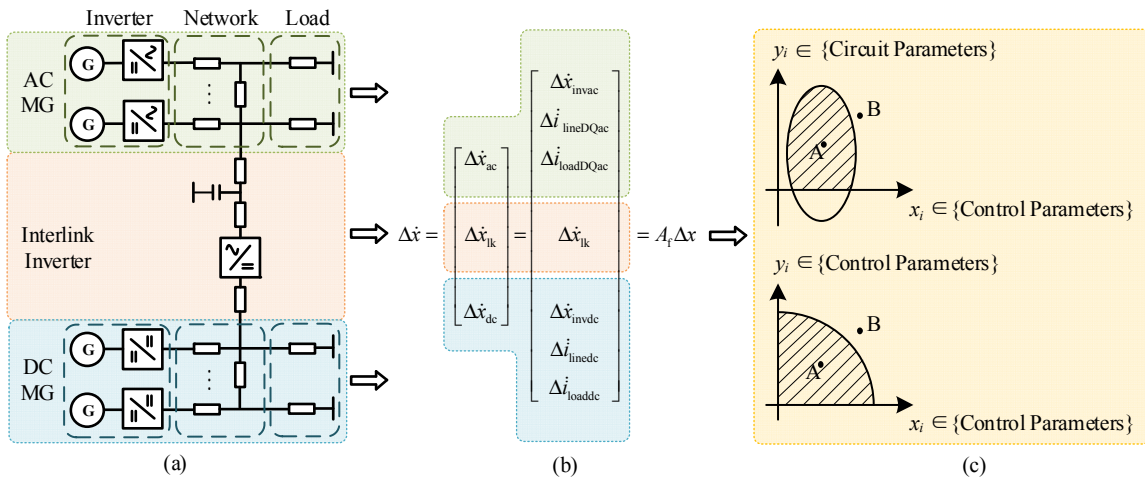


Fig. 1. Configuration of a typical autonomous AC and DC hybrid MG. (a) System architecture; (b) Small-signal modeling of each subsection; (c) Stability region.

developed to analyze the stability of low-voltage DC MG. However, although the existing work has studied the small-signal models of different sections in hybrid AC and DC MGs, a complete solution covering various control functions (e.g., droop control, virtual impedance, etc.) and all the corresponding sections (i.e., AC section, DC section, and interface inverters between AC and DC buses) should be developed to derive a holistic model for stability analysis.

Given the complexity of small-signal models and the corresponding stability analysis of hybrid AC and DC MGs, it is necessary to develop an intuitive and computationally efficient approach that can identify system stability margin with real-time operating conditions. It is noteworthy that region-based stability was proposed and studied in transmission systems focusing on dynamic networks with multiple rotational generators [18]. The idea was originated from small-signal stability analysis while provided a stable region and depicted a stability margin based on the distance between the operating point and the region boundary. Rather than a point-by-point approach designed for each specific operating point, a stability region shows a feasible and stable operating range in a straightforward way, focusing on the selected cross-domain parameters from the control diagram and main power circuit. However, considering that a hybrid AC and DC MG with multiple interface inverters is a high-order system, which is more complicated compared to conventional transmission grids, the applicability of the existing stability region should be further studied. Additionally, it should also be noted that deriving the stability region boundary is critical to implement a practical region-based stability analysis. Conventionally, the stability boundary is derived from exhausting the operating points with selected minimum steps [19], which could involve a tradeoff between the accuracy of the stability boundary and the required resolution. Therefore, a more efficient approach should be designed to simplify the procedure of identifying stability boundaries.

In this paper, to better understand the operation dynamics and the interactions among multiple sections, a holistic small-signal model of a hybrid AC and DC MG is derived, considering AC subsection, DC subsection, and interlink inverters in

between. Furthermore, a region-based stability analysis is thereby conducted based on the derived holistic small-signal model and the selected cross-domain parameters from control diagram and main power circuit throughout the entire hybrid AC and DC MGs. Further, to efficiently and effectively derive the stability boundary, an Artificial Intelligence (AI) assisted approach is designed. Particularly, the Kernel Ridge Regression (KRR) approach is used to identify the stability region, which only relies on limited data points along the stability region and avoids the potential tradeoff between computational efficiency and required resolution.

The remainder of this paper is organized as follows: Section II introduces the small-signal modeling of droop-controlled autonomous AC and DC hybrid MGs. Section III studies the region-based stability analysis based on the KRR approach. Section IV presents two case studies on a hybrid AC and DC MG to verify the proposed solution. Section V summarizes the paper and draws the conclusion.

## II. SMALL SIGNAL MODELING OF HYBRID AC/DC MGs

As depicted in Fig. 1 (a), a typical hybrid AC and DC MG includes AC MG, DC MG and interlink inverters between common AC and DC buses. Meanwhile, for both AC and DC subsections, they are separated into three segments, i.e., DER interface inverters, networks, and loads. The individual small-signal model of each section is detailed in this section, and the complete model of a hybrid AC and DC MG is derived by combining these individual models in Fig. 1 (b).

### A. Modeling of DC Subsection

The entire DC MG is derived into three parts, i.e., interface converters, coupling lines connecting to the local point of interconnection (POI), and loads. The small-signal model of each part is derived, considering both control dynamics and main power circuits. Further, it is assumed that the DC MG is comprised of  $s$  converters,  $n$  lines,  $m$  buses, and  $p$  loads.

1) *Interface DC-DC Converters*: For the models of interface converters, the instantaneous active power in DC MGs is calculated by the measured output voltage and current.





where the state matrix  $A_{ac}$  of the AC subsection is given at the bottom of this page.

### C. Modeling of Interlink Inverters between AC and DC Buses

To satisfy the operating conditions in both AC and DC MGs, a  $V$ - $P$  droop control is used at the DC side for each interlink inverter, which is aligned with other sources at the DC MG, as shown below:

$$v_{lk\_dc}^* = V_{ndc} - m_{lk} P_{lk\_dc} \quad (22)$$

where  $m_{lk}$  is the droop coefficient;

To smooth power exchange between AC and DC subsections, at the DC side of the interlink inverter, DC-link voltage is controlled to balance the active power while reactive power is controlled at the AC side locally. Thus, the average active power at the DC side and the average reactive power at the AC side are calculated as:

$$P_{lk\_dc} = \frac{\omega_c}{s + \omega_c} v_{lk\_dc} i_{lk\_dc} \quad (23)$$

$$Q_{lk\_ac} = \frac{\omega_c}{s + \omega_c} (v_{oqlk\_ac} i_{odlk\_ac} - v_{odlk\_ac} i_{oqlk\_ac})$$

A multi-loop control diagram is utilized in interlink inverters. Particularly, the outer control diagram includes DC-link voltage and reactive power control loops, and the inner control diagram includes the proportional-integral (PI) based current control loops, which is used to calculate the interlink inverter output voltage  $v_{odqk\_ac}$  at the AC side.

Furthermore, the power balance between the AC and DC sides of the interlink inverter is derived below based on the power balance across the interlink inverter.

$$p_{lk\_ac} = -p_{lk\_dc} \cdot \eta \quad (24)$$

$$v_{odlk\_ac} i_{odlk\_ac} + v_{oqlk\_ac} i_{oqlk\_ac} = -v_{lk\_dc} (i_{lk\_dc} + C_{lk\_dc} \dot{v}_{lk\_dc}) \cdot \eta$$

where  $v_{odqk}$  and  $i_{odqk}$  are the interlink inverter output voltage and current in  $dq$  reference frame, respectively;  $C_{lk\_dc}$  is the filter capacitor at the DC side of the interlink converter;  $\eta$  is the efficiency of interlink inverter.

Meanwhile, the DC side of interlink inverter connects to the DC bus using the coupling inductance  $L_{clk\_dc}$ :

$$\dot{i}_{lk\_dc} = \frac{1}{L_{clk\_dc}} (v_{lk\_dc} - v_{blk\_dc}) - \frac{R_{clk\_dc}}{L_{clk\_dc}} i_{lk\_dc} + \omega i_{lk\_dc} \quad (25)$$

On the other hand, considering the LC filter and the coupling impedance ( $R_{clk\_ac}$ ,  $L_{clk\_ac}$ ) between the interlink inverter and local AC bus, the following state equations with the state variables  $i_{odqk}$ ,  $v_{dqk}$  and  $i_{dqk}$  are derived:

$$\dot{v}_{dqk\_ac} = \frac{1}{C_f} (i_{dqk\_ac} - i_{odqk\_ac}) \pm \omega v_{dqk\_ac} \quad (26)$$

where the  $v_{dqk\_ac}$  is the voltage of capacitor  $C_f$  at the AC side of interlink inverter; Developing the state equations of  $i_{odqk\_ac}$  and  $i_{dqk\_ac}$  are similar to those of DC coupling inductance in (25).

Finally, considering the angle difference  $\delta_{lk}$  between the interlink inverter and the common DQ frame, the local AC bus voltage  $v_{bdqk\_ac}$  connecting the AC side of the interlink inverter and the corresponding injected current  $i_{dqk\_ac}$  can be transferred to the common DQ frame, respectively.

Combining (22)–(26), there are 13 state variables in total, including  $\Delta\delta_{lk}$ ,  $\Delta P_{lk\_dc}$ ,  $\Delta Q_{lk\_ac}$ ,  $\Delta v_{odqk\_ac}$ ,  $\Delta i_{odqk\_ac}$ ,  $\Delta v_{dqk\_ac}$ ,  $\Delta i_{dqk\_ac}$ ,  $\Delta v_{lk\_dc}$ , and  $\Delta i_{lk\_dc}$  for an interlink inverter. The corresponding small-signal representation is thereby obtained:

$$[\Delta \dot{x}_{lk}] = A_{lk} [\Delta x_{lk}] \quad (27)$$

where  $A_{lk}$  is the state matrix of the interlink inverter.

### D. Complete Model of Hybrid AC and DC MGs

Based on the small-signal models derived in Section II-A to II-C, combining (11), (21) and (27), a complete small-signal model of an autonomous AC and DC hybrid MG is obtained:

$$[\Delta \dot{x}] = [\Delta \dot{x}_{ac} \quad \Delta \dot{x}_{lk} \quad \Delta \dot{x}_{dc}]^T = A_f [\Delta x] \quad (28)$$

where  $A_f$  is the coefficient matrix of the entire hybrid AC and DC MG;  $B_{ac\_lk}$ ,  $B_{dc\_lk}$ ,  $B_{lk\_ac1}$ ,  $B_{lk\_ac2}$ ,  $B_{lk\_dc1}$ , and  $B_{lk\_dc2}$  are coupling elements among the AC MG, DC MG, and interlink inverters.

$$A_f = \begin{bmatrix} A_{ac} & B_{ac\_lk} & 0 \\ B_{lk\_ac1} & A_{lk} + B_{lk\_ac2} + B_{lk\_dc2} & B_{lk\_dc1} \\ 0 & B_{dc\_lk} & A_{dc} \end{bmatrix}.$$

## III. REGION-BASED STABILITY ANALYSIS

Based on the small-signal model in (28), a stability region can be derived to evaluate system stability and identify small-signal stability margin. It is noteworthy that the stability region is defined and established based upon a parameter space with cross-domain parameters from control diagrams and main power circuits. As depicted in Fig. 1 (c), a selected point inside the stability region indicates that the system is stable with the given parameters while the system is unstable if a selected point is outside the stability region. The boundary of the stability region represents a marginally stable condition. Note that a stability region can be flexibly established with different combinations of control or main power circuit parameters. For example, it can be used to identify the interactions between two key control parameters (e.g., virtual impedance and droop coefficient), or quantify the impacts of parameter mismatch of passive components in main power circuits (e.g., filter inductance and capacitance). Therefore, region-based stability analysis can be regarded as a versatile solution to study various stability-related problems.

It is worth mentioning that the stability region boundary is derived using an AI-assisted regression algorithm, i.e., Kernel Ridge Regression (KRR). The stability boundary can be thereby derived based on only some sample points located along the region boundary rather than point-by-point with every parameter

$$A_{ac} = \begin{bmatrix} A_{invac} + B_{invac} R_{Nac} M_{invac} C_{invac} & B_{invac} R_{Nac} M_{netac} & B_{invac} R_{Nac} M_{loadac} \\ B_{1netac} R_{Nac} M_{invac} C_{invac} + B_{2netac} C_{inv\theta ac} & A_{netac} + B_{1netac} R_{Nac} M_{netac} & B_{1netac} R_{Nac} M_{loadac} \\ B_{1loadac} R_{Nac} M_{invac} C_{invac} + B_{2loadac} C_{inv\theta ac} & B_{1loadac} R_{Nac} M_{netac} & A_{loadac} + B_{1loadac} R_{Nac} M_{loadac} \end{bmatrix}$$

combination considered. The detailed design procedure is summarized in the flow chart in Fig. 2. Particularly, there are three main steps in the KRR method: data set generation, stability region boundary approximation, and KRR-based performance evaluation.

#### A. Dataset Generation

As depicted in Fig. 2, taking a parameter space  $X = \{x_1, x_2\}$  as an example, an initial stable operating point  $X_0 = \{x_{1_0}, x_{2_0}\}$  in the parameter space is selected, and starting from this point, a sampling direction  $d$  is determined to identify stability region boundary, where  $n_d$  is the total number of sampling directions and  $\Delta x_d$  is sampling intervals. Note that the maximum real part of the system eigenvalue  $\sigma_{\max}$  is the critical variable to determine if the stability boundary is reached. When  $\sigma_{\max}$  is less than 0, the corresponding parameter combination in the sampling direction leads to a stable operation condition; when it is larger than 0, the corresponding parameter combination indicates an unstable condition. Therefore, the stability boundary is identified when  $\sigma_{\max}$  first changes to a positive value, and when the boundary is reached in the sampling direction  $d$ , the corresponding parameter combination  $\{x_{1b}, x_{2b}\}$  is collected into the generated dataset for the following KRR stage. Further, given that it is challenging or even infeasible to derive  $\{x_{1b}, x_{2b}\}$  with  $\sigma_{\max}$  equals 0, an interval of  $\sigma_{\max}$  is involved in tolerating the potential mismatch in the searching process. Here, the samples within the range of  $[\delta_1, \delta_2] = [-0.2, 0]$  are preserved to enhance the resolution along the stability region boundary, while samples in the remaining area are selected with a sparse density. Therefore, the dataset of parameter space  $X$  can be obtained, and it is further divided into a training set and a validation set for the following KRR stage. Since there is no practical experience to follow and determine the capacities of the training set and the validation set, the generated dataset can be split into two randomly selected sets whose capacities are 50% of the original dataset.

It is worth mentioning that to calculate  $\sigma_{\max}$ , system steady-state operating points are needed. Therefore, as shown as one step in the flow chart in Fig. 2, power flow calculation in hybrid AC and DC MGs should be conducted. Particularly, compared to the conventional Newton Raphson method in power flow analysis, a practical and effective modified Newton Raphson (MNR) approach [20] is used for power flow calculation in this study. For the MNR approach, due to the absence of the slack bus in an autonomous MG, Bus #1 with droop control is selected as the voltage reference in the power flow calculation. Meanwhile, the system angular frequency  $\omega$  is also taken as another unknown variable since it is not a constant in droop-control MGs. Further, the droop-controlled buses at the AC and DC sides are formulated as:

$$P_{kac}^{i+1} = \frac{(\omega_0 - \omega^i)}{m_{pac}} \quad Q_{kac}^{i+1} = \frac{(|V_0| - |V_{ack}^i|)}{n_{qack}} \quad P_{kdc}^{i+1} = \frac{(|V_0| - |V_{dck}^i|)}{m_{pdck}} \quad (29)$$

where  $P_{kac}$  and  $Q_{kac}$  are the active and reactive powers of the droop-controlled  $k^{\text{th}}$  bus at the AC side;  $P_{kdc}$  is the output power of the droop-controlled  $k^{\text{th}}$  bus at the DC side.

In this study, to combine the power flow in the entire hybrid system, the interlink inverter is used as the bridge to satisfy the power flow calculation in both AC and DC subsections.

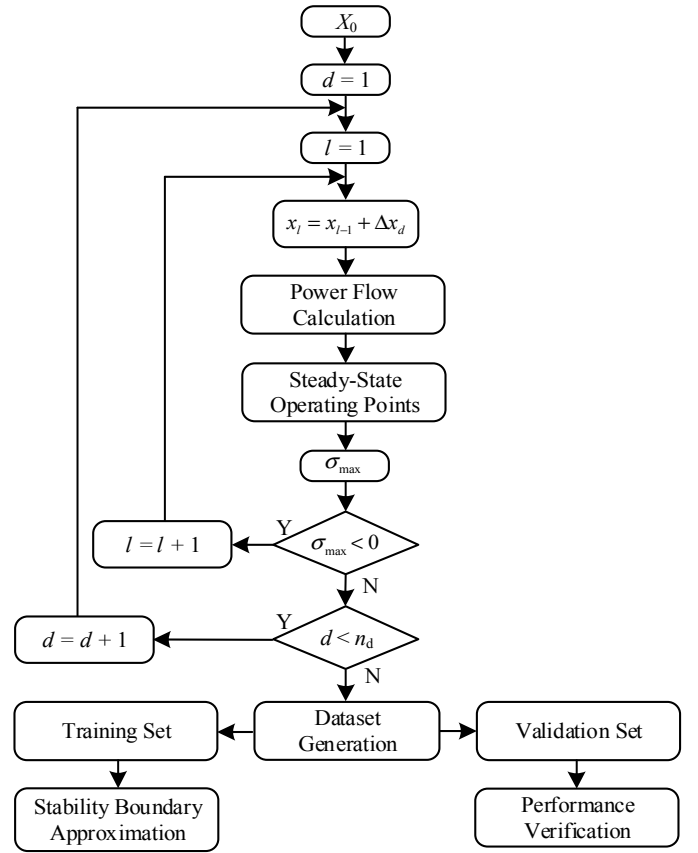


Fig. 2. Flow chart of KRR method for deriving the stability region boundary.

Particularly, as shown in (24), at the DC side, the interlink inverter is modeled as a droop-controlled bus; since power is balanced in both AC and DC sides, the active power at the AC side is determined by the calculated DC power, and the reactive power at the AC side is controlled locally (e.g., set to zero). Therefore, after modeling the interlink inverters, the power flow calculation in hybrid AC and DC MGs can be implemented following a two-step procedure. In Step 1, the power flow can be calculated in the DC subsection; in Step 2, given the above interlink inverter model, active power flowing through the interlink inverter is used as the shared variable, and power flow in the AC subsection can be thereby derived.

#### B. Stability Boundary Approximation

There exists a mapping function  $f(\cdot)$  that links a parameter combination  $x$  to the corresponding stability index  $\sigma_{\max}$ . This function  $f(\cdot)$  represents the target stability region boundary, which can be derived using the KRR approach based on the sample points in the training dataset.

However,  $f(x) = 0$  cannot be derived analytically due to the severe nonlinearity of the equation. Therefore, a sufficient-order polynomial function is used to estimate the anonymous function:

$$\hat{f}(x) = 0 \quad (30)$$

Then based on the nonlinear transformation [21], a 2-order polynomial is taken as an example to approximate the function:

$$\begin{aligned}
\hat{f}(x) &= \sum_{i=1}^{n_{tr}} \alpha_i (x_{1i}^2 x_1^2 + x_{2i}^2 x_2^2 + 2x_{1i} x_{2i} x_1 x_2 + 2x_{1i} x_1 + 2x_{2i} x_2 + 1) \\
&= \alpha_1 (x_{11}^2 x_1^2 + x_{21}^2 x_2^2 + \dots + 1) + \dots + \alpha_{n_{tr}} (x_{1n_{tr}}^2 x_1^2 + x_{2n_{tr}}^2 x_2^2 + \dots + 1) \\
&= c_1 x_1^2 + c_2 x_2^2 + c_3 x_1 x_2 + c_4 x_1 + c_5 x_2 + c_6
\end{aligned} \tag{31}$$

where  $n_{tr}$  is the size of the training set;  $x_1$  and  $x_2$  are the variables in the parameter space;  $c_1 \sim c_6$  are the corresponding coefficients for each term of the 2-order polynomial function. This result can be generalized into  $h$ -order polynomial function. For example, there are nine coefficients for 3-order polynomial function and 15 coefficients for 4-order polynomial function.

In (31), the coefficient  $\alpha$  is calculated as:

$$\alpha = (K + \lambda I)^{-1} \sigma_{\max} \tag{32}$$

where  $\sigma_{\max} = [\sigma_{\max_1}, \sigma_{\max_2}, \dots, \sigma_{\max_{n_{tr}}}]^T$ , and  $K$  is a matrix with its element calculated by  $K_{i,j} = (x_i^T x_j + 1)^h$ ;  $I$  is an identity matrix with dimension  $n_{tr}$ ;  $\lambda$  is estimated from the initial parameter settings  $\lambda_{\min}$  and  $\lambda_{\max}$ , which separately correspond to the minimum eigenvalue and the maximum eigenvalue of matrix  $K$ .

Therefore, the training set separated from the generated dataset is used to determine coefficients in (31), which is used to approximate the original stability region boundary in (30).

### C. Performance Verification

Based on the validation set, the derived approximate stability boundary can be validated by calculating the root-mean-square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n_{va}} \sum_{i=1}^{n_{va}} \gamma_i^2} \tag{33}$$

where  $n_{va}$  is the size of the validation set;  $\gamma_i$  is the error between the estimated function in (6) and the value of the  $\sigma_{\max}$ .

Further, to estimate the polynomial order  $h$ , a simple method is that increasing the value of order  $h$  while searching for the optimal  $\lambda$  in the interval  $\{\lambda_{\min}, \lambda_{\max}\}$  until (33) is smaller than a given threshold. In general, the error band is less than 5%. Additionally, if the validation error is less than a required threshold, the derived stability region boundary is satisfactory.

## IV. CASE STUDIES

As shown in Fig. 3., a 10-bus test system of an autonomous and hybrid AC and DC MG is comprised of two DGs, two loads and one line in the AC subsection, two DGs, two loads and one line in the DC subsection, as well as one interface inverter between AC and DC buses.

### Case I: Stability Boundary with Parameter Space $\{L_{cdc}, R_{vac}\}$

By selecting the physical inductance  $L_{cdc}$  in the DC subsection and the virtual resistance  $R_{vac}$  in the AC subsection to establish a parameter space  $\{L_{cdc}, R_{vac}\}$ , a stability region is derived following the steps below. First, the dataset with 82 samples is generated based on the parameter space  $\{L_{cdc}, R_{vac}\}$ . Second, the sizes of the training set and the validation set are set to 50% of the retained samples, and the sample points are randomly selected. Third, the approximate stability boundary, as well as the corresponding four-order approximate boundary given by the KRR method, is shown in Fig. 4. Finally, in this case, the RMSE is calculated as 0.59% using the validation set, which satisfies our required threshold. In the meanwhile, Points A and B are selected as two examples, which indicate stable and

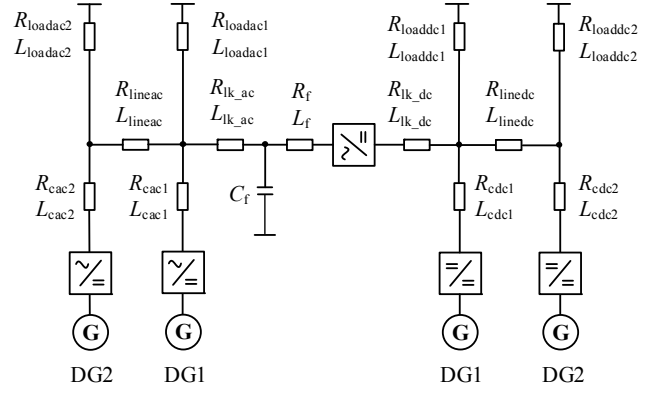


Fig. 3. Test system under case studies.

unstable operation conditions, respectively. Their corresponding time-domain simulation waveforms are shown in Fig. 5, which are in accordance with operating conditions shown in the stability region in Fig. 4.

### Case II: Stability Boundary with Parameter Space $\{R_{vac}, k_{pv}\}$

Similarly, the parameter space in Case II is comprised of virtual resistance  $R_{vac}$  in the AC subsection and the proportional gain  $k_{pv}$  of the outer DC-link voltage loop of interlink inverter. Then the dataset formed with 90 samples is used for deriving the stability boundary and its fourth-order approximation, as shown in Fig. 6. The RMSE is eventually computed as 1.39% in this case. Additionally, Point A and B are selected as two instances to indicate stable and unstable operation conditions, respectively. Their corresponding simulation test results in terms of operating conditions are following the theoretical region-based stability analysis, as shown in Fig. 7.

## V. CONCLUSION

In this study, a holistic small-signal model of a hybrid AC/DC MG is established combining AC subsection, DC subsection, and interlink inverters. Additionally, the stability margin of the obtained model is identified by using the proposed region-based stability approach considering the selected cross-domain parameter space with elements from either the control diagram or the main power circuit. As an AI-assisted and computationally efficient approach, the KRR algorithm is employed to estimate the stability boundary. The proposed framework and method are verified using time-domain simulation tests.

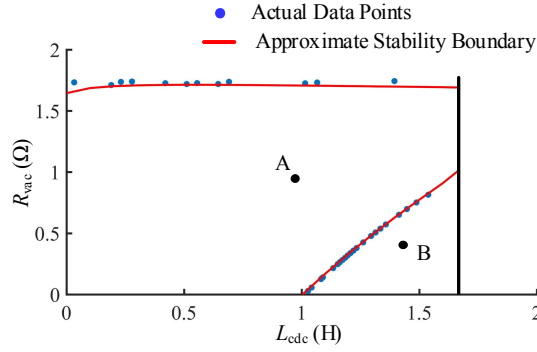
## ACKNOWLEDGMENT

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Solar Energy Technologies Office award (Award Number: 34225).

## REFERENCES

- [1] F. Nejabatkhah and Y. W. Li, "Overview of Power Management Strategies of Hybrid AC/DC Microgrid," *IEEE Trans. Power Electron.*, vol. 30, no. 12, pp. 7072-7089, 2015.
- [2] X. Liu, P. Wang and P. C. Loh, "A Hybrid AC/DC Microgrid and Its Coordination Control," *IEEE Trans. Smart Grid*, vol. 2, no. 2, pp. 278-286, June 2011.





$$0.126L_{dc}^4 + 0.826R_{vac}^4 + 2.787L_{dc}^3R_{vac} - 3.093L_{dc}^2R_{vac}^2 - 0.853L_{dc}R_{vac}^3 - 5.411L_{dc}^3 - 1.375R_{vac}^3 - 0.928L_{dc}^2R_{vac} + 8.278L_{dc}R_{vac}^2 + 11.744L_{dc}^2 - 2.3R_{vac}^2 - 10.22L_{dc}R_{vac} - 3.187L_{dc} + 5.82R_{vac} - 3.282 = 0$$

Fig. 4. Approximate stability boundary (red) and sample points along the boundary (blue) in the parameter space  $\{L_{dc}, R_{vac}\}$ .

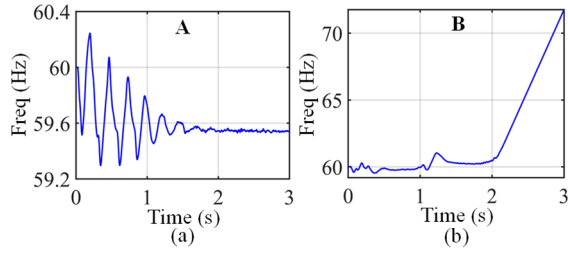
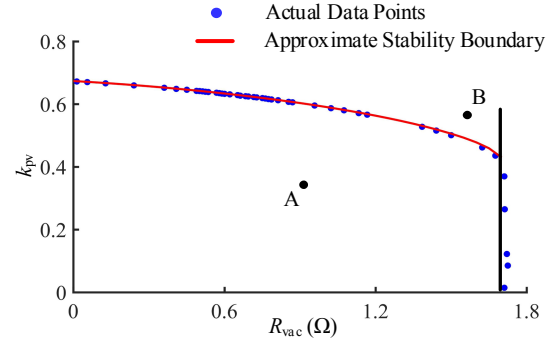


Fig. 5. Time-domain waveforms of Point A and Point B. (a) Stable operation condition; (b) Unstable operation condition.



$$-0.144R_{vac}^4 + 5.926k_{pv}^4 - 0.105R_{vac}^3k_{pv} - 9.153R_{vac}^2k_{pv}^2 - 4.521R_{vac}k_{pv}^3 - 0.281R_{vac}^3 + 4.971k_{pv}^3 + 6.126R_{vac}^2k_{pv} + 10.383R_{vac}k_{pv}^2 + 0.672R_{vac}^2 + 9.196k_{pv}^2 - 6.313R_{vac}k_{pv} + 1.837R_{vac} - 6.58k_{pv} - 2.485 = 0$$

Fig. 6. Approximate stability boundary (red) and sample points along the boundary (blue) in the parameter space  $\{R_{vac}, k_{pv}\}$ .

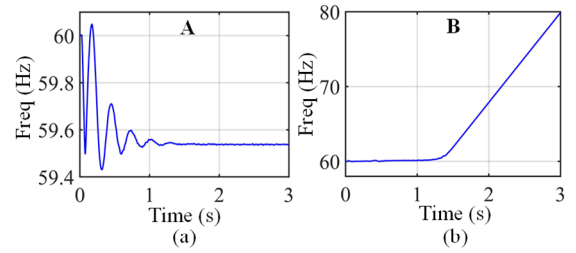


Fig. 7. Time-domain waveforms of Point A and Point B. (a) Stable operation condition; (b) Unstable operation condition.

- [3] J. Rajagopalan, K. Xing, Y. Guo, and F. C. Lee, "Modeling and dynamic analysis of paralleled dc/dc converters with master-slave current sharing control," in *Proc. IEEE Appl. Power Electron. Conf.*, pp. 678–684, 1996.
- [4] A. P. Martins, A. S. Carvalho, and A. S. Araújo, "Design and implementation of a current controller for the parallel operation of standard USPs," in *Proc. IEEE IECON*, pp. 584–589, 1995.
- [5] J. M. Guerrero, L. G. de Vicuna, J. Matas, M. Castilla and J. Miret, "A wireless controller to enhance dynamic performance of parallel inverters in distributed generation systems," *IEEE Trans. Power Electron.*, vol. 19, no. 5, pp. 1205–1213, Sept. 2004.
- [6] Y. W. Li and C. Kao, "An Accurate Power Control Strategy for Power-Electronics-Interfaced Distributed Generation Units Operating in a Low-Voltage Multibus Microgrid," *IEEE Trans. Power Electron.*, vol. 24, no. 12, pp. 2977–2988, Dec. 2009.
- [7] Q. Zhong and G. Weiss, "Synchronverters: Inverters That Mimic Synchronous Generators," *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1259–1267, April 2011.
- [8] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuna and M. Castilla, "Hierarchical Control of Droop-Controlled AC and DC Microgrids—A General Approach Toward Standardization," *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 158–172, Jan. 2011.
- [9] X. Lu, J. M. Guerrero, *et al*, "Hierarchical Control of Parallel AC-DC Converter Interfaces for Hybrid Microgrids," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 683–692, March 2014.
- [10] V. Nasirian, S. Moayedi, A. Davoudi and F. L. Lewis, "Distributed Cooperative Control of DC Microgrids," *IEEE Trans. Power Electron.*, vol. 30, no. 4, pp. 2288–2303, April 2015.
- [11] Y. Du, X. Lu, J. Wang and S. Lukic, "Distributed Secondary Control Strategy for Microgrid Operation with Dynamic Boundaries," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5269–5282, Sept. 2019.
- [12] Y. Du, X. Lu, H. Tu, J. Wang and S. Lukic, "Dynamic Microgrids with Self-Organized Grid-Forming Inverters in Unbalanced Distribution Feeders," *IEEE J. of Emerging and Selected Topics in Power Electron.*, vol. 8, no. 2, pp. 1097–1107, June 2020.
- [13] Y. Du, X. Lu, *et al*, "Dynamic Microgrids in Resilient Distribution Systems with Reconfigurable Cyber-Physical Networks," *IEEE J. of Emerging and Selected Topics in Power Electron.*, 2020.
- [14] H. Tu, Y. Du, *et al*, "Resilient Information Architecture Platform for the Smart Grid (RIAPS): A Novel Open-Source Platform for Microgrid Control," *IEEE Trans. Ind. Electron.*, 2019.
- [15] Z. Li and M. Shahidehpour, "Small-Signal Modeling and Stability Analysis of Hybrid AC/DC Microgrids," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 2080–2095, 2019.
- [16] N. Pogaku, M. Prodanovic and T. C. Green, "Modeling, analysis and testing of autonomous operation of an inverter-based microgrid," *IEEE Trans. Power Electron.*, vol. 22, no. 2, pp. 613–625, March 2007.
- [17] S. Anand and B. G. Fernandes, "Reduced-Order Model and Stability Analysis of Low-Voltage DC Microgrid," *IEEE Trans. Ind. Electron.*, vol. 60, no. 11, pp. 5040–5049, 2013.
- [18] Y. Pan, S. Mei, *et al*, "Admissible Region of Large-Scale Uncertain Wind Generation Considering Small-Signal Stability of Power Systems," *IEEE Trans. Sust. Energy*, vol. 7, no. 4, pp. 1611–1623, Oct. 2016.
- [19] Y. Guo, L. Chen, *et al*, "Region-Based Stability Analysis for Active Dampers in AC Microgrids," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 7671–7682, Nov.-Dec. 2019.
- [20] F. Mumtaz, M. H. Syed, M. A. Hosani and H. H. Zeineldin, "A Novel Approach to Solve Power Flow for Islanded Microgrids Using Modified Newton Raphson With Droop Control of DG," *IEEE Trans. Sust. Energy*, vol. 7, no. 2, pp. 493–503, April 2016.
- [21] B. Jayasekara and U. D. Annakkage, "Derivation of an Accurate Polynomial Representation of the Transient Stability Boundary," *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1856–1863, Nov. 2006.