Learning-Based, Safety and Stability-Certified Microgrid Control

Lizhi Wang, *Student Member, IEEE*, Songyuan Zhang, *Student Member, IEEE*, Yifan Zhou, *Member, IEEE*, Chuchu Fan, *Member, IEEE*, Peng Zhang, *Senior Member, IEEE*, and Yacov A. Shamash, *Life Fellow, IEEE*

2023 IEEE Power & Energy Society General Meeting (PESGM) | 978-1-6654-6441-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/PESGM52003.2023.10253396

***Abstract*—A neural-Lyapunov-barrier-enabled, physics-informed-learning-based control method is devised to provide certificated safe and stable hierarchical control of microgrids. The main contributions include: 1) a neural hierarchical control framework for microgrids with provable safety and stability guarantees; 2) a control Lyapunov barrier function (CLBF) considering the fast dynamics of distributed energy resources, loads, and networks in microgrids; 3) a physics-informed learning approach for CLBF-based neural hierarchical control synthesis, which learns safety and stability certificates and control policy simultaneously without a verification module. Case studies demonstrate the effectiveness of the approach in provably certifying the stability and safety of microgrids equipped with hierarchical inverter control.**

***Index Terms*—Microgrid control, learning-based control, control Lyapunov barrier function, certified control, microgrid stability.**

I. Introduction

The primary objective of microgrid control is to ensure the safety and stability of the system, meaning microgrid controllers must drive the system to a stable equilibrium operating point and avoid unsafe regions after severe disturbances. The increasing integration of distributed energy resources (DERs) is unprecedentedly challenging microgrid control. On the one hand, massive inverter interfaces can induce strongly nonlinear dynamics which can deteriorate microgrid stability because of reduction in inertia and damping [1]. On the other hand, the high variability of renewable energy sources and frequent changes in microgrid loads and structures can significantly perturb the system from its equilibrium point, leading to large voltage and frequency deviations [2]. Therefore, efficacious microgrid control that can assure large-disturbance stability and safety is needed.

The hierarchical control framework is widely adopted in microgrid control [3], [4]. However, controller synthesis based on linearized microgrid models [5] can only guarantee the small-signal stability of the system. The authors in [6] introduce distributed barrier functions for the safe operation of microgrids, and the sum-of-squares(SOS) optimization is used to find Lyapunov functions. However, the SOS optimization leads to a tradeoff between representation accuracy and computational complexity. Finding a qualified Lyapunov function for microgrids with massive inverter interfaces can be extremely challenging.

Recently, learning-based control approaches have emerged to gain increased attention in power system control. Ref. [7] introduces a deep learning-based control framework to discover Lyapunov functions and learn control strategies simultaneously. However, it employs a falsification module to produce controllers with performance guarantees, which retards the training process and hinders the method's applicability in large-scale systems. Ref. [8] introduce a reinforcement learning framework for frequency and voltage regulation, which only provides a local stability guarantee in a small region, and soft penalties are utilized to describe whether the system state leaves the prescribed ranges, which does not provide a certificated stability guarantee. In general, two major challenges remain in existing methods: I) Lack of certificates for microgrid safety and stability under different large disturbances and II) Lack of effective learning strategies to provide certificated safety and stability constraints without additional verification modules.

To bridge the gap, this paper establishes a neural-Lyapunov-barrier-enabled control framework for microgrids. We first construct a control Lyapunov barrier function (CLBF) for microgrids considering the dynamics of DERs, loads, and networks to explicitly and rigorously formulate the safety and stability certificates, and then we establish a CLBF-based, physics-informed learning approach to train the safety/stability certificates and control strategies simultaneously. Consequently, the dynamic performance of microgrids with large disturbance is certificated by CLBF during the training process without involving an additional verification module, which enables high efficiency for offline training and online application.

The remainder of this paper is organized as follows. Section II presents the neural hierarchical control framework of microgrids. Section III formulates the safety and stability certificates for microgrids. Section IV establishes the CLBF-enabled physics-informed learning for training the control policy and certificates simultaneously. Section V presents case studies. Section VI provides the conclusion of the paper.

II. Neural Hierarchical Control of Microgrids

This section establishes the formulation of the neural hierarchical control of microgrids. The kernel idea is to incorporate

This work was supported in part by the National Science Foundation under Grant No. OIA-2134840. This work relates to Department of Navy award N00014-22-1-2001 issued by the Office of Naval Research. The United States Government has a royalty-free license throughout the world in all copyrightable material contained herein.

L. Wang, Y. Zhou, P. Zhang and Y. A. Shamash are with the Department of Electrical and Computer Engineering, Stony Brook University, NY, USA (e-mail: yifan.zhou.1@stonybrook.edu).

S. Zhang and C. Fan are with the Department of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, USA

learning-based feedback control into DER controllers. By properly training the learning-based controllers, the global stability and safety of microgrids are certified.

Without loss of generality, a two-layer hierarchical control is considered. Mathematically, the neural hierarchical control for DER i is formulated as:

$$\begin{cases} \omega_i = \omega_i^* - m_p(P_i - P_i^*) + u_{p,i} \\ E_i = E_i^* - n_{q,i}(Q_i - Q_i^*) + u_{q,i} \end{cases} \tag{1}$$

Locally, (1) performs droop control for frequency and voltage regulation, where ω_i, E_i, P_i and Q_i respectively denote the angular speeds, output voltage magnitudes, active power and reactive power of DER i; superscript * denote the corresponding nominal values; $m_{p,i}$ and $n_{q,i}$ respectively denote the droop coefficients. Globally, (1) employs two learning-based feedback controllers, i.e., $u_{p,i}$ and $u_{q,i}$, to perform secondary control above the basic proportional controller.

The learning-based control signals of all the N DERs, i.e., $\boldsymbol{u} = [u_{p,1}, u_{p,2}, ..., u_{p,N}, u_{q,1}, u_{q,2}, ..., u_{q,N}]^T$, are functionally formulated as a neural network $\boldsymbol{u} = \boldsymbol{\pi}_\varphi(\boldsymbol{x})$, where $\boldsymbol{\pi}$ denotes the neural network describing the control policy; $\boldsymbol{u}$, $\boldsymbol{x}$ and φ respectively denote the output, input, and weights of the neural network. Specifically, the input features $\boldsymbol{x}$ denote the microgrid states, e.g., states of DERs, loads, and lines. Please refer to [2] for the detailed microgrid dynamic model.

With the consideration of load dynamics and line dynamics, the dynamics of a microgrid system can be formulated as a system of ordinary differential equations (ODE), which is rigorously equivalent to the original differential algebraic equation (DAE)-based formulation [2], [4]:

$$\dot{\boldsymbol{x}} = \boldsymbol{f}_\theta(\boldsymbol{x}) + \boldsymbol{g}_\theta(\boldsymbol{x})\boldsymbol{\pi}_\varphi(\boldsymbol{x}) \tag{2}$$

where $\boldsymbol{x} \in \boldsymbol{\chi} \subseteq \mathbb{R}^n$ denotes the microgrid states; $\boldsymbol{\pi} \subseteq \mathbb{R}^{2N}$; $\boldsymbol{f}_\theta : \mathbb{R}^n \to \mathbb{R}^n$ and $\boldsymbol{g}_\theta : \mathbb{R}^n \to \mathbb{R}^{n\times 2N}$ are functions describing the microgrid dynamics, which depend on microgrid parameters θ and are assumed to be locally Lipschitz.

Fig. 1 accordingly presents the structure of the neural hierarchical control for microgrids. The dynamics of each component (e.g., the load, line, and DER) form the dynamics of the entire microgrid system, and the neural control signal $\boldsymbol{u} = \boldsymbol{\pi}_\varphi(\boldsymbol{x})$ is trained using the microgrid dynamics to provide global control among DERs with safety and stability certificates of the whole system.

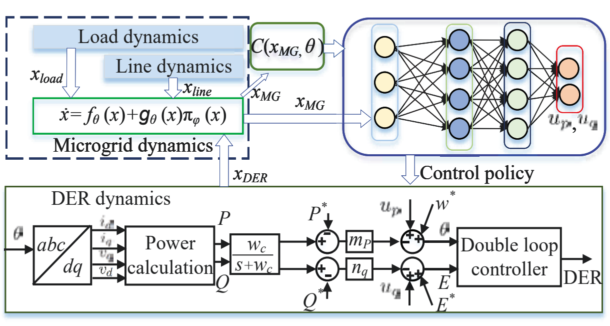


Fig. 1: Structure of the neural hierarchical control of microgrids

III. Safety and Stability-Certified Neural Hierarchical Control of Microgrids

This section presents the safety and stability certificates for microgrids under neural hierarchical control so that the dynamic performance of microgrids can be provably certified by the control Lyapunov barrier function (CLBF).

A. Formulation of Stability and Safety Requirements

As formulated in (2), a microgrid with neural hierarchical control can be modeled as a control-affine system, parameterized by θ (i.e., microgrid parameters). Denote the desired operating point of the microgrid as $\boldsymbol{x}_{\text{goal}}$. Denote the safe region and unsafe region as $\boldsymbol{\chi}_{\text{safe}} \subseteq \boldsymbol{\chi}$ and $\boldsymbol{\chi}_{\text{unsafe}} \subseteq \boldsymbol{\chi}$ (such that $\boldsymbol{\chi}_{\text{safe}} \cap \boldsymbol{\chi}_{\text{unsafe}} = \emptyset$ and $\boldsymbol{x}_{\text{goal}} \in \boldsymbol{\chi}_{\text{safe}}$). Define $\boldsymbol{x}(t) : \xi_\pi(\boldsymbol{x}_0, t)$ as the trajectory of the microgrid, i.e., the solution of (2), starting from an initial state x_0 under the control policy π.

According to the safe control theory, the stability and safety requirements of a control-affine system are described as [9]:

1) **Stability requirement**: For an appropriate norm, for every $\epsilon > 0$, there exists a $\delta > 0$ such that for all $t_2 \geq t_1 \geq 0$: $||x(t_1) - x_{\text{goal}}|| \leq \delta \Rightarrow ||x(t_2) - x_{\text{goal}}|| \leq \epsilon$;
2) **Safety requirement**: For all $t_2 \geq t_1 \geq 0$, $x(t_1) \in \boldsymbol{\chi}_{\text{safe}}$ implies $x(t_2) \notin \boldsymbol{\chi}_{\text{unsafe}}$.

In other words, to satisfy the stability requirement, the microgrid should be able to converge to the goal point state x_{goal} while avoiding the unsafe region $\boldsymbol{\chi}_{\text{unsafe}}$. To satisfy the safety requirement, the microgrid trajectories should not cross into the unsafe region once it is operating in a safe region.

Our target is to design a neural controller $\boldsymbol{u} = \boldsymbol{\pi}_\varphi(\boldsymbol{x})$ satisfying the aforementioned stability and safety requirements.

B. CLBF Certificates for Microgrids

This subsection presents how to design a control policy $\boldsymbol{u} = \boldsymbol{\pi}_\varphi(\boldsymbol{x})$ for a microgrid governed by (2) while satisfying the stability and safety requirements described in Subsection III-A. We introduce the control Lyapunov barrier function (CLBF) to provide microgrid stability and safety certificates. Basically, the CLBF is a special case of a control Lyapunov function where the safe and unsafe regions are respectively contained in sub- and super-level sets [10].

A function $V(\boldsymbol{x}) : \boldsymbol{\chi} \to \mathbb{R}$ is a CLBF, if, for some safe level c and $\lambda > 0$, it satisfies [10]:

$$V(\boldsymbol{x}_{\text{goal}}) = 0, \quad V(\boldsymbol{x}) > 0 \quad \forall \boldsymbol{x} \in \boldsymbol{\chi} \backslash x_{\text{goal}} \tag{3a}$$

$$\inf_u L_{f_\theta} V + L_{g_\theta} V u + \lambda V \leq 0 \quad \forall \boldsymbol{x} \in \boldsymbol{\chi} \backslash x_{\text{goal}} \tag{3b}$$

$$V(\boldsymbol{x}) \leq c \quad \forall \boldsymbol{x} \in \boldsymbol{\chi}_{\text{safe}} \tag{3c}$$

$$V(\boldsymbol{x}) > c \quad \forall \boldsymbol{x} \in \boldsymbol{\chi}_{\text{unsafe}} \tag{3d}$$

Equations (3a) and (3b) jointly define V as a Lyapunov function of the microgrid with the goal point $\boldsymbol{x}_{\text{goal}}$ being a stable equilibrium point, where $L_f V$ and $L_g V$ are respectively the Lie derivatives of V along $\boldsymbol{f}$ and $\boldsymbol{g}$ (i.e., specified in (2)); θ denotes the microgrid parameters. Equations (3c) and (3d) jointly establish the barrier function requirement.

Define the set of admissible controls as:

$$K(x) = \{u | L_{f_\theta} V + L_{g_\theta} V u + \lambda V \leq 0\} \tag{4}$$

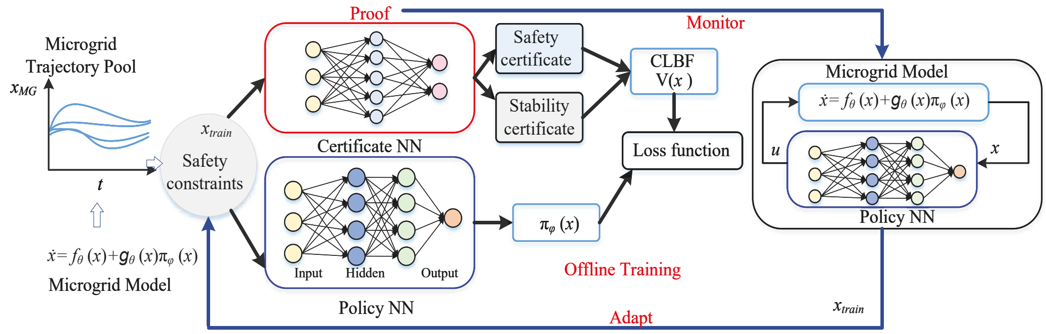


Fig. 2: Physics-informed training process of the safety-and-stability-certified neural hierarchical control

Ref. [10] has proved if $V(x)$ is a CLBF, then any control policy $\pi(x) \in K(x)$ will be both safe and stable when executed on a system specified by $\boldsymbol{f}_\theta$ and $\boldsymbol{g}_\theta$. Correspondingly, the CLBF-based neural hierarchical control of microgrids, if satisfying (3), can provably stabilize the microgrid without any safety violation.

IV. Physics-Informed Learning for Neural Hierarchical Control

This section designs a physics-informed supervised learning framework to synthesize the CLBF-based neural controller. As a combination of both physics-based and learning-based philosophy, this approach can resolve the challenges that model-based methods are hard to generalize and learning-based methods hardly provide certificated safety guarantees [11].

A. Physics-Informed Training Process

The physics-informed training process of the neural hierarchical control is shown in Fig. 2. The training process comprises three main parts: 1) training of the CLBF certificate neural network V, 2) training of the certificated control policy neural network $\boldsymbol{\pi}_\varphi$, 3) and using the trained controller to generate new training samples.

First, the microgrid physics model generates training samples x_{train} and hard safety constraints for the neural networks. Then the certificate neural network learns the safety and stability certificates that yield a CLBF for microgrids. Meanwhile, a control policy $\boldsymbol{u} \in K(x)$ is jointly learned. To improve the training performance and enable the sampling of training data from different portions of the state space, we further use the learned controller to generate new training samples after several epochs. The safety and stability of the control policy are certificated by designing loss functions for CLBF and control policy aligning with (3), which will be detailed in the next subsection. Therefore, no additional verification module will be required in the devised approach.

B. Design of Loss Functions

We first introduce the CLBF-related loss function [10], which is used to train a CLBF certificate neural network (see Fig. 2) such that the conditions in (3) are satisfied:

$$\mathcal{L}_{CLBF} = \mathcal{L}_1 + \mathcal{L}_2 + \mathcal{L}_3 + \mathcal{L}_4 \tag{5}$$

where

$$\mathcal{L}_1 = V(x_{\text{goal}})^2 \tag{6a}$$

$$\mathcal{L}_2 = \frac{a_1}{N_{\text{safe}}} \sum_{x \in \chi_{\text{safe}}} \sigma(\epsilon + V(x) - c) \tag{6b}$$

$$\mathcal{L}_3 = \frac{a_2}{N_{\text{unsafe}}} \sum_{x \in \chi_{\text{unsafe}}} \sigma(\epsilon + c - V(x)) \tag{6c}$$

$$\mathcal{L}_4 = \frac{a_3}{N_{\text{train}}} \sum_{x} \sigma(\epsilon + L_{f_\theta} V(x) + L_{g_\theta} V(x) \pi_\varphi(x) + \lambda V(x)) \tag{6d}$$

Here, the hyperparameters include positive tuning parameters a_1-a_3, a safe level c, λ, and ϵ.

Both the boundary loss (i.e., $\mathcal{L}_1$, $\mathcal{L}_2$ and $\mathcal{L}_3$) and the descent loss (i.e., $\mathcal{L}_4$) are considered in the CLBF loss function $\mathcal{L}_{CLBF}$. In the boundary loss, $\mathcal{L}_1$ defined in (6a) ensures that (3a) is satisfied. $\mathcal{L}_2$ and $\mathcal{L}_3$ utilize a ReLU function $\sigma(x) = \max(x, 0)$ to ensure (3c) and (3d) and the small parameter $\epsilon > 0$ encourages strict inequality satisfaction in the loss function. In the descent loss, $\mathcal{L}_4$ guarantees the stability requirement in (3b), which targets making sure the value of $L_{f_\theta} V + L_{g_\theta} V u + \lambda V$ is smaller than zero. Additionally, to ensure $V(\boldsymbol{x}) > 0 \quad (\forall \boldsymbol{x} \in \boldsymbol{\chi} \backslash x_{\text{goal}})$, along with the loss $\mathcal{L}_4$, the CLBF is designed as $V(\boldsymbol{x}) = h^T(\boldsymbol{x}) h(\boldsymbol{x}) \geq 0$, where $h(\boldsymbol{x})$ is the activation vector of the last hidden layer of the CLBF neural network.

We then define the loss function for the neural controller (i.e., the policy neural network in Fig. 2). Targeting learning a control policy from the admissible control set $K(x)$ (see (4)), intuitively, we define the loss function of the control policy as:

$$\mathcal{L}_u = ||u(x) - u_{\text{nominal}}||^2 \tag{7}$$

where u_{nominal} is a nominal controller that provides a training signal for neural network $\pi_\varphi(x)$.

Consequently, the final loss function for the neural hierarchical control training is constructed as:

$$\mathcal{L} = \mathcal{L}_{CLBF} + \beta \mathcal{L}_u \tag{8}$$

where β is a small weight to ensure the CLBF condition is preferentially satisfied during the training process [10].

C. Algorithm Flow

The pseudo-code for the proposed method is given in Algorithm 1. The hyperparameters to be pre-determined are

978-1-6654-6441-3/23/$31.00 ©2023 IEEE

c, λ, ϵ and the size of the CLBF neural network V and the control policy neural network $\boldsymbol{\pi}_{\varphi}$. A nominal controller is utilized to generate microgrid trajectories for initialization. Training data are sampled from the state space covered by the trajectories. To improve the training performance and broaden the space covered by training samples, we specify fixed percentages of training points sampled from the goal, safe, and unsafe regions and use the learned controller to regenerate new training samples to improve the training performance after several epochs.

Algorithm 1: Learning controller with certificates

$\triangleright$ ***Require***: Microgrid parameters Θ, learning rate α, batch size H, epochs I per episode and total epochs K
$\triangleright$ ***Input***: Microgrid initial states, safe region, unsafe region and system model (2) and initial weights φ for network
$\triangleright$ ***Training samples generation***:
$\dot{\boldsymbol{x}} = \boldsymbol{f}_\theta(\boldsymbol{x}) + \boldsymbol{g}_\theta \boldsymbol{u}_{\text{nominal}} \longrightarrow x_{\text{goal}}, x_{\text{safe}}, x_{\text{unsafe}}$
for *current_epoch* = 1 to K **do**
  Calculate total loss of all the batches
  $Loss = \mathcal{L}_{CLBF} + \beta \mathcal{L}_u$
  Update weights in the neural network by passing Loss to Adam optimizer
  Output $V(x)$ and $\pi_\varphi(x)$
  if *current_epoch* $\%\ I == 0$ **then**
    Update training samples :
    $\boldsymbol{x} : \dot{\boldsymbol{x}} = \boldsymbol{f}_\theta(\boldsymbol{x}) + \boldsymbol{g}_\theta \pi_\varphi(x)$
  end
end
$\triangleright$ ***Output***: Neural controller $u(x)$

V. Case Study

The CLBF-enabled neural hierarchical control method is tested in a typical microgrid detailed in [5]. The training was conducted on a workstation with a 16-core Intel i9 CPU and 1 NVIDIA Quadro T1000 GPU.

A. Algorithm Settings

Hyperparameters in (5) are set as $a_1 = a_2 = 100$ and $a_3 = 1$, $\beta = 10^{-5}$, $\lambda = 1.0$ and $\epsilon = 0.01$. We construct fully-connected neural networks with 2 hidden layers, 64 units at each layer, and tanh activation functions for all cases. Adam is used for neural network training. The LQR controller serves as the nominal controller to initialize the algorithm.

For the training data, we sample $0.2N_{\text{train}}$ uniformly from the goal region, $0.3N_{\text{train}}$ uniformly from the unsafe region, and $0.5N_{\text{train}}$ uniformly from the safe region. We generate $N_{\text{train}} = 40000$ training samples at the beginning. Then, during the training process, the samples are updated every 20 epochs using the learned controller.

Specifically, in this paper, we mainly consider the voltage safety constraints, i.e., fluctuations of transient voltages beyond the safe region can cause safety risks of damaging electrical equipment. Therefore, the safe region is defined as:

$$\underline{v_i} \leq v_i(t) \leq \overline{v_i} \tag{9}$$

where v_i is the voltage of DER i. Typical values for the limits during transients operation could be $\underline{v_i} = 0.88$ p.u. and $\overline{v_i} = 1.10$ p.u [12]. In this paper, stricter voltage limits $\underline{v_i} = 0.98$ p.u. and $\overline{v_i} = 1.02$ p.u. are adopted to verify that the proposed method can strictly promise the safety for a microgrid with higher safety requirements. Other forms of safety constraints will be considered in future work.

B. Validity of CLBF-based Neural Hierarchical Control

This subsection validates the efficacy of the proposed method under a typical large disturbance, i.e., a sudden load change. Fig. 3 shows the training and validation loss during the training process. The value of the loss function decreases to 10 after 20 epochs without changing anymore if no training samples are updated. After updating the training samples every 20 epochs, the loss function value converges to 0.

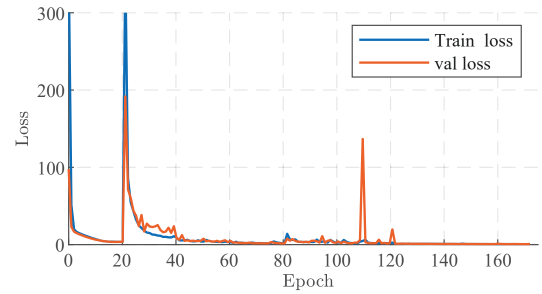


Fig. 3: Evolution of the training and validation loss

We then show the values of CLBF and the dynamic performance of the microgrid to verify the safety and stability certificates. Suppose the load at bus 3 experiences a step load occurring at t = 0.1s. Fig. 4 illustrates the contour plot of the CLBF $V(x)$ vs. voltage of DER1 and DER2. The safe and unsafe regions are also shown in the figure. The blue line describes the region under a safe level $c = 0.4$. The contour plot shows that the safe region is enclosed in the c-level set, which ensures (3c)-(3d) are satisfied with the safety requirement. Further, Fig. 5 (a) shows the trajectories of DER voltages. It can be seen that the system reaches a stable steady state within about 0.01 s after the load change. Meanwhile, the learned controller promises that DER voltages are enclosed in safe regions. Fig. 5 (b) further shows the value of CLBF $V(x)$. The result shows that the value of CLBF is always less than the safe level even if the system undergoes a step load change.

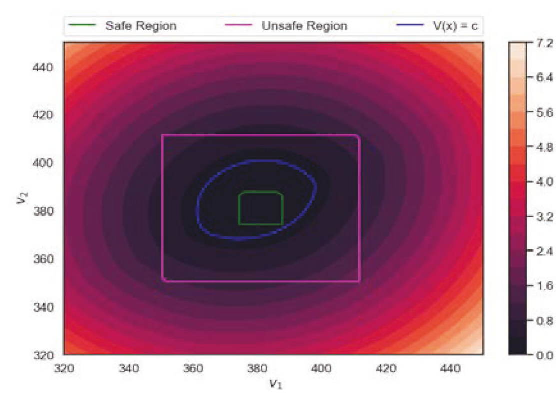
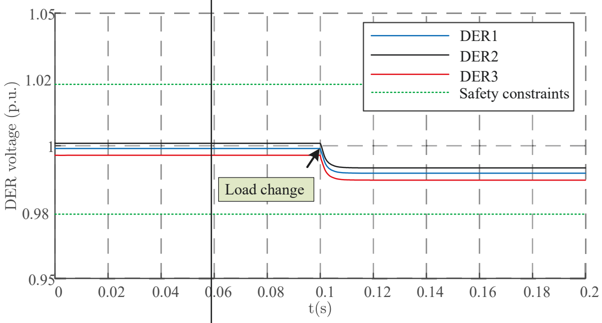


Fig. 4: Contour plots of CLBF $V(x)$ vs. v_1 and v_2 under step load change

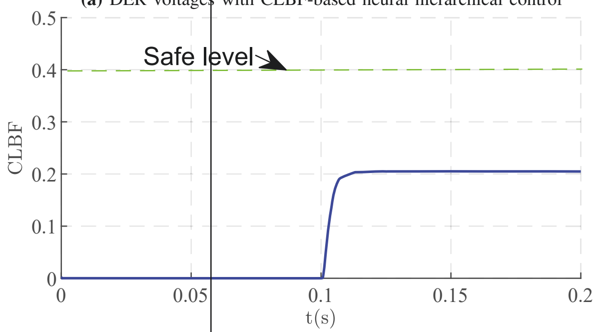
C. Necessity of CLBF-based Neural Hierarchical Control

In this subsection, we show that the proposed method can learn a nonlinear controller that outperforms the widely used distributed average proportional integral (DAPI) controller [3].

978-1-6654-6441-3/23/$31.00 ©2023 IEEE



(a) DER voltages with CLBF-based neural hierarchical control



(b) Value of CLBF $V(x)$

Fig. 5: Microgrid dynamics and the value of CLBF in the load change case

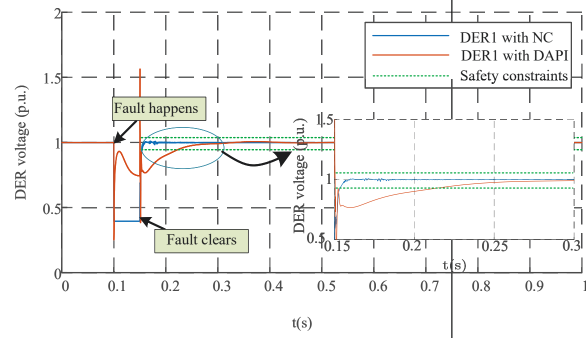


Fig. 7: DER1 voltage in short-circuit fault case under different control

Another typical large disturbance, i.e., the short-circuit fault, is studied. We generate dynamic trajectories when a short-circuit fault happens at different nodes in the microgrid with different fault duration. To obtain both safe and unsafe training data, we sample microgrid states from the trajectories during short periods after the fault clearance. To promise that neural hierarchical control can stick the system to safe regions after fault clearance, a relatively small safe level $c = 0.1$ is selected.

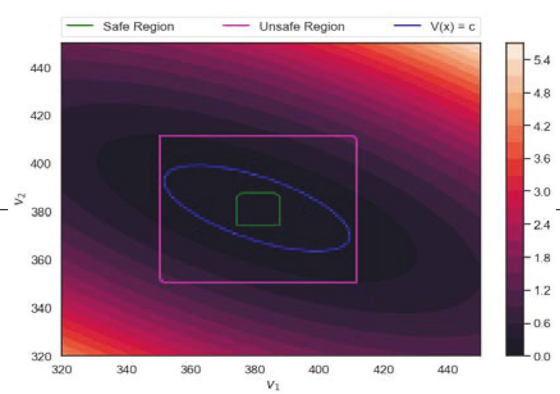


Fig. 6: Contour plots of CLBF vs. v_1 and v_2 in the short-circuit fault case

Fig. 6 shows the contour plots of CLBF vs. the voltage of DER1 and DER2 in the short-circuit fault case. The safe level set (shown by the blue line) encloses the safe region (shown by the green line), which demonstrates that the system's safety is guaranteed as long as the microgrid enters a safe region.

Fig. 7 shows the dynamics of the voltage of DER1 using different controllers. In this case, a short circuit fault occurs at 0.1s and is cleared at 0.15s. Simulation shows that after the fault is cleared, the DER voltage under DAPI control (shown by the red trajectories) undergoes a large fluctuation and enters an unsafe region. It takes about 0.15s for the DAPI controller to suppress the oscillation. In contrast, the devised neural controller (shown by the blue trajectories) stabilizes the system in a very short time after the fault is cleared and the voltages of DERs are always enclosed in the safe region.

VI. Conclusion

This paper presents a CLBF-based, physics-informed control method to synthesize the nonlinear neural hierarchical control of microgrids. Different from existing learning-based control methods, the nonlinear physical dynamics of DERs, power loads, and networks are fully considered in the simultaneous training of CLBF and the control policy, which therefore provides provable safety and stability certificates of microgrid dynamics under large disturbances and relieves the requirement on additional verification modules. For future work, we will exploit the devised method in networked microgrids under more complicated system operations.

References

[1] P. Zhang, *Networked microgrids*. Cambridge University Press, 2021.
[2] Y. Zhou, P. Zhang, and M. Yue, "Reachable dynamics of networked microgrids with large disturbances," *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 2416–2427, 2020.
[3] L. Wang, P. Zhang, Z. Tang, and Y. Qin, "Programmable crypto-control for iot networks: An application in networked microgrids," *IEEE Internet of Things Journal*, pp. 1–1, 2022.
[4] Y. Zhou and P. Zhang, "Neuro-reachability of networked microgrids," *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 142–152, 2022.
[5] N. Pogaku, M. Prodanovic, and T. C. Green, "Modeling, analysis and testing of autonomous operation of an inverter-based microgrid," *IEEE Transactions on Power Electronics*, vol. 22, no. 2, pp. 613–625, 2007.
[6] S. Kundu, S. Geng, S. P. Nandanoori, I. A. Hiskens, and K. Kalsi, "Distributed barrier certificates for safe operation of inverter-based microgrids," in *2019 American Control Conference (ACC)*, pp. 1042–1047, IEEE, 2019.
[7] T. Zhao, J. Wang, X. Lu, and Y. Du, "Neural lyapunov control for power system transient stability: A deep learning-based approach," *IEEE Transactions on Power Systems*, vol. 37, no. 2, pp. 955–966, 2021.
[8] W. Cui, Y. Jiang, and B. Zhang, "Reinforcement learning for optimal primary frequency control: A lyapunov approach," *IEEE Transactions on Power Systems*, 2022.
[9] C. Dawson, S. Gao, and C. Fan, "Safe control with learned certificates: A survey of neural lyapunov, barrier, and contraction methods," *arXiv preprint arXiv:2202.11762*, 2022.
[10] C. Dawson, Z. Qin, S. Gao, and C. Fan, "Safe nonlinear control using robust neural lyapunov-barrier functions," in *Conference on Robot Learning*, pp. 1724–1735, PMLR, 2022.
[11] L. Brunke, M. Greeff, A. W. Hall, Z. Yuan, S. Zhou, J. Panerati, and A. P. Schoellig, "Safe learning in robotics: From learning-based control to safe reinforcement learning," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 5, pp. 411–444, 2022.
[12] D. J. Narang and M. Ingram, "Highlights of ieee standard 1547-2018," tech. rep., National Renewable Energy Lab.(NREL), Golden, CO (United States), 2019.

978-1-6654-6441-3/23/$31.00 ©2023 IEEE