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Data-based stability and control for future grids

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Outline

- Introduction

- Remarks on learning

- Projects
  1. Stability assessment (TSA)
  2. Long-term voltage stability (LTVS)
  3. Data-based frequency regulation (DeePC)

- Conclusions

Remarks on learning

➢ Modelling

- Be wary of assumed probability distributions, e.g. Gaussian for Kalman Filter
- Uncertainty important RO vs SO vs DRO

➢ Methods

- Errors - model vs training, e.g. 97% looks good but why not 100%
- Balance offline vs online computation

➢ Aim for human-like control (Ref: Wang and Hill, CRC Press, 2010)

1. Data-Based Stability Assessment

Power System Transient Stability Assessment (TSA)

- **Model-Based TSA**

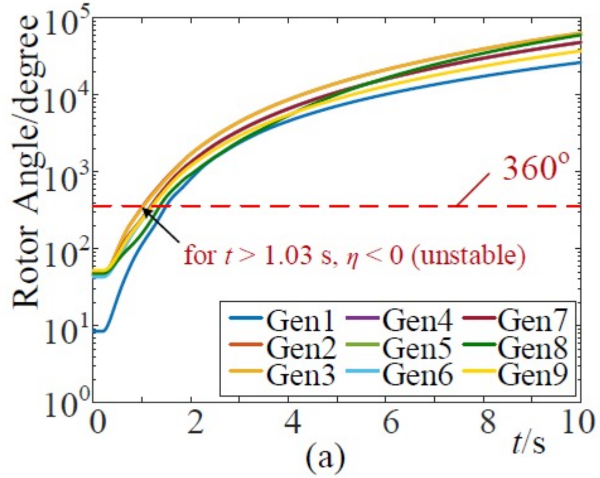
  - Time-domain simulation based analysis → modeling everything in detail, with heavy computational burdens.

  - Transient energy function (TEF) and related methods → difficult to build TEFs for large systems, implemented with highly simplified models (limited applicability).

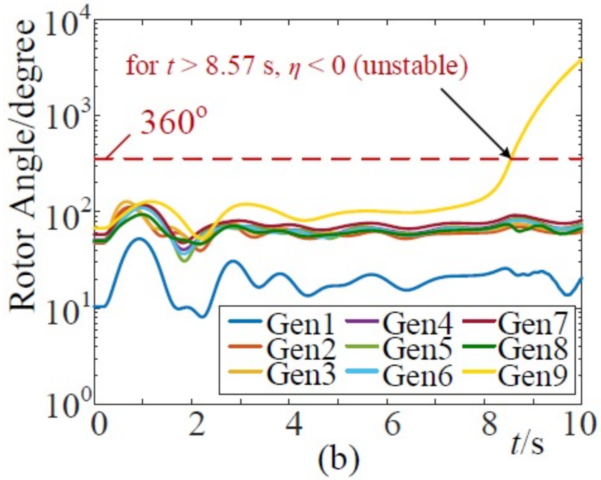
- **Data-Driven TSA**

  - Intelligently learning correlations between initial system states/responses and eventual system stability status from huge volumes of PMU data (machine learning).

  - High efficiency and reliability during online application, almost no limitation on system sizes or scales, great potential in new knowledge discovery.



Typical unstable case 1 (fast evolution)



Typical unstable case 2 (slow evolution)

Ref: L. Zhu, D. J. Hill, and C. Lu, TPWRS, 2020; L. Zhu and D. J. Hill, TPWRS, 2022.

1. Data-Based Stability Assessment

Overall Framework

- 1) Generating numerous transient cases and transforming them into pictorial images (for CNN)
- 2) Training a hierarchical deep learning machine (two-layer model based on divide-and-rule strategy)
- 3) online TSA (quantitative stability margin + qualitative stability status prediction)

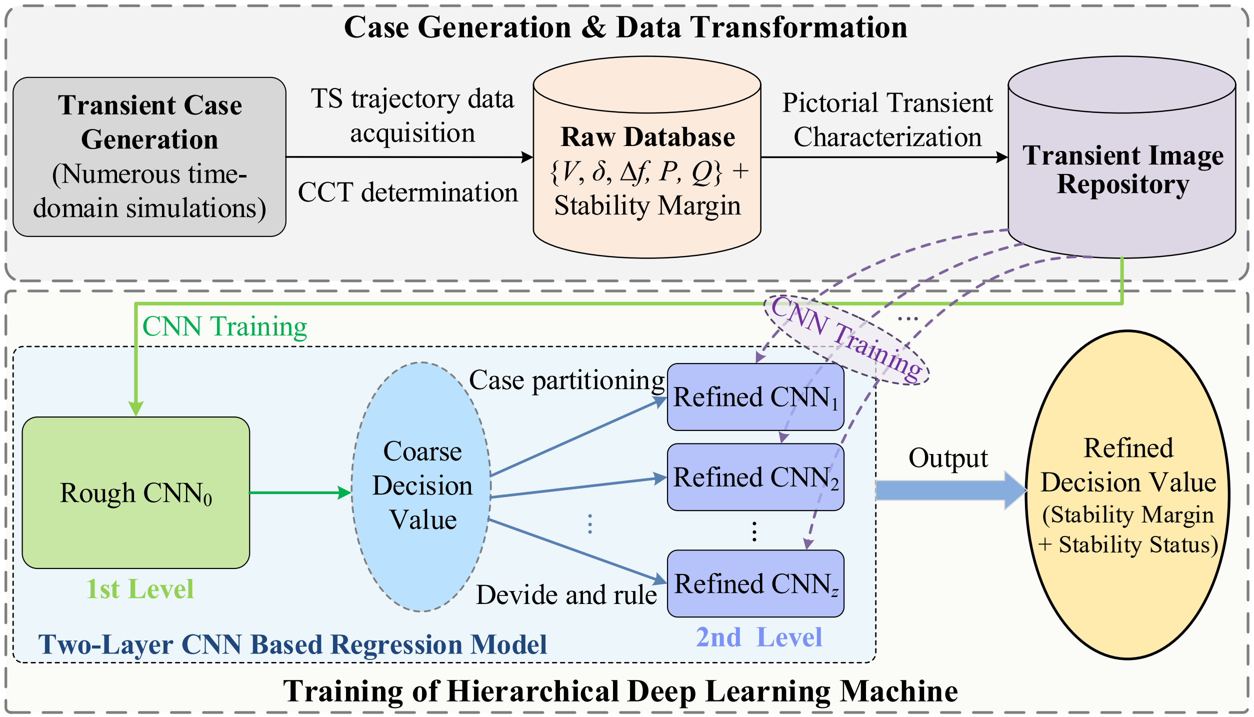


Fig. 4 Procedure of constructing the HDLM

Raw trajectory Inputs (generator buses):

$$\{V, \delta, \Delta f, P, Q\}$$

Transient stability criterion:

$$\eta = \frac{360^{\circ} - |\Delta\delta|_{\max}}{360^{\circ} + |\Delta\delta|_{\max}} < 0 \quad \Rightarrow \quad \text{unstable}$$

Transient stability margin:

$$SM_i = CCT_i - (t_{i,c} - t_{i,0})$$

Ref: L. Zhu, D. J. Hill, and C. Lu, TPWRS, 2020; L. Zhu, D. J. Hill, and C. Lu, Proc. PESGM, 2019.

1. Data-Based Stability Assessment

Pictorial Transient Characterization

- 1) Subsequence extraction with a L-point sliding time window:

$$\mathcal{T} = \{x_0, x_1, \ldots, x_{N-1}\} \quad \Rightarrow \quad \mathcal{T}_i = \{x_{i-1}, x_i, x_{i+1}, \ldots, x_{i+L-2}\}$$

- 2) Symbolic Aggregate approXimation (SAX):

$$\boldsymbol{C} = \left\{c_i \,\middle|\, c_i = \alpha_j, \text{if } \beta_{j-1} \le x_i < \beta_j\right\} \text{ (for } 1 \le i \le n)$$

$\boldsymbol{\alpha} = \{\alpha_1, \alpha_2, \ldots, \alpha_m\}$ (alphabet)

$\boldsymbol{\beta} = \{\beta_0, \beta_1, \ldots, \beta_m\}$ (breakpoint vector)

- 3) Symbolic word extraction: $\boldsymbol{A} = \left\{\boldsymbol{a}_i \,\middle|\, \boldsymbol{a}_i = \{c_i, c_{i+1}, \ldots, c_{i+L-1}\}, \text{for } 1 \le i \le n-L+1\right\}$

- 4) Counting frequencies of symbolic words:

$$f_{\alpha_i\alpha_j} = \frac{1}{n-2+1}\sum_{k=1}^{n-2+1} \chi\left(\boldsymbol{a}_k, \alpha_i\alpha_j\right), \quad \chi\left(\boldsymbol{a}_k, \alpha_i\alpha_j\right) = \begin{cases} 1 & \text{for } \boldsymbol{a}_k = \{\alpha_i, \alpha_j\} \\ 0 & \text{otherwise} \end{cases}$$

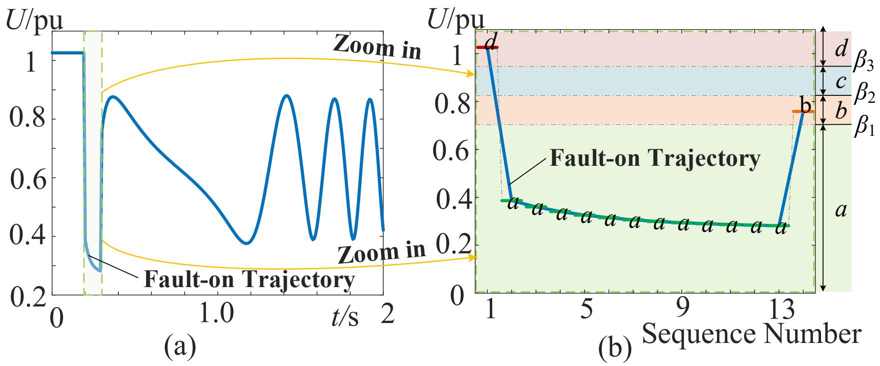


Illustration of SAX based trajectory quantization

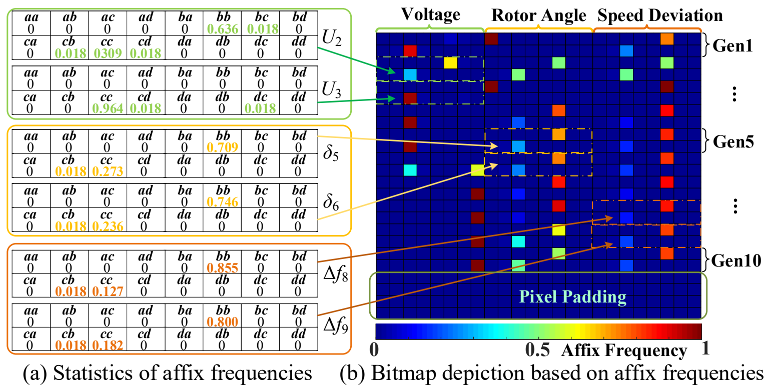
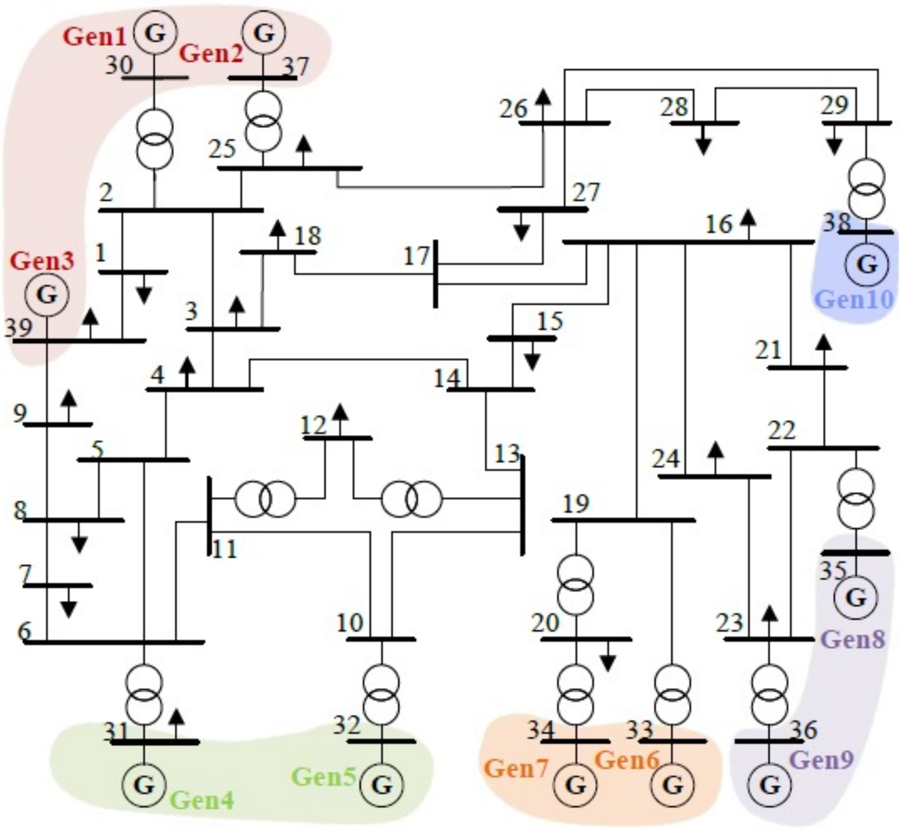


Illustration of 2-D pictorial representation

Ref: L. Zhu, D. J. Hill, and C. Lu, TPWRS, 2020; L. Zhu, D. J. Hill, and C. Lu, Proc. PESGM, 2019; J. Lin, E Keogh, et al, 2007.

1. Data-Based Stability Assessment

Numerical Case Study



One-line diagram of the IEEE 39-bus system

Note: 10 PMUs are assumed to install at the 10 generator buses, so as to acquire the (fault-on + 2) trajectories of $\{V, \delta, \Delta f\}$ from these buses (120-Hz reporting rate).

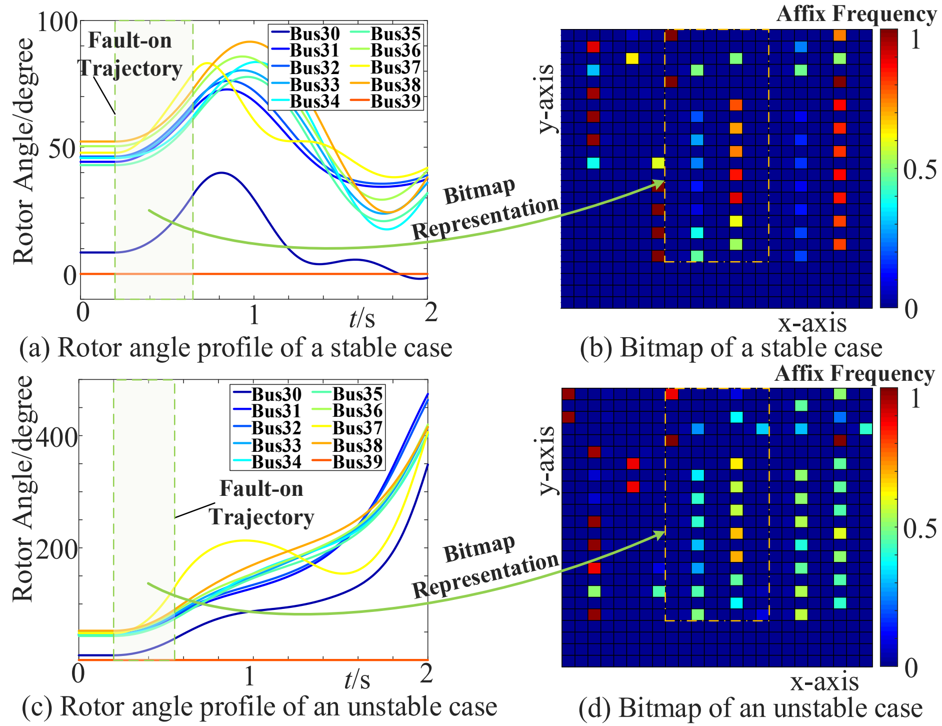


Illustration of bitmap based transient case representation. (a)~(b): stable case; (c)~(d): unstable case.

Stable profile: more red pixels (affix frequency close to 1) → moderate evolution.

Unstable profile: more diverse pixels (diverse frequency values) → drastic evolution.

Ref: L. Zhu, D. J. Hill, and C. Lu, TPWRS, 2020.

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A. Background

- Adaptive Coordinated Voltage Control (ACVC) for secondary voltage control (SVC) [6,7]
  - CVC: sequencing, timing and tuning control actions at various locations;
  - SVC: operating during 10secs - 1min after a disturbance to supply voltage by controlling transformer taps, switching capacitors banks and shedding loads;

Mechanism

- Offline: knowledge accumulation for anticipated faults;
- Online: searching for a feasible solution for unanticipated faults.

Limitation

- Limited applicability for unanticipated faults – search for a similar one or do the whole things online;
- Heavy computation burdens – the need to search all anticipated faults in the database;
- Low information utilization - only considering nearby bus data;

- Objective: to achieve an effective and efficient online voltage control by utilizing control knowledge from offline long-term optimization and learning.

[6] H. Ma and D. J. Hill, "Adaptive coordinated voltage control part i: Basic scheme," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp.1546-1553, 2013.
[7] H. Ma and D. J. Hill, "Adaptive coordinated voltage control part ii: Use of learning for rapid response," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1554-1561, 2014.

C. Data-based learning and control for LTVS

- Offline long-term optimization for anticipated faults

$$\min \sum_i \left| v_{i,ref} \middle| - v^m_{i,t_{k+1}^-} \right| \quad t = t_k \qquad (3.8)$$

- Offline learning system
  - PCA: reduce dimension (all bus data is considered)
  - Priority values: evaluate the control effects
  - FFBP: establish a direct mapping relationship

PC scores of system dynamics → priority values of control actions

- Online control system
  - Detection: voltage drop to the threshold value of 0.9.
  - Analysis: input system dynamics to PCA and FFBP.
  - Control: apply the obtain optimal control actions.

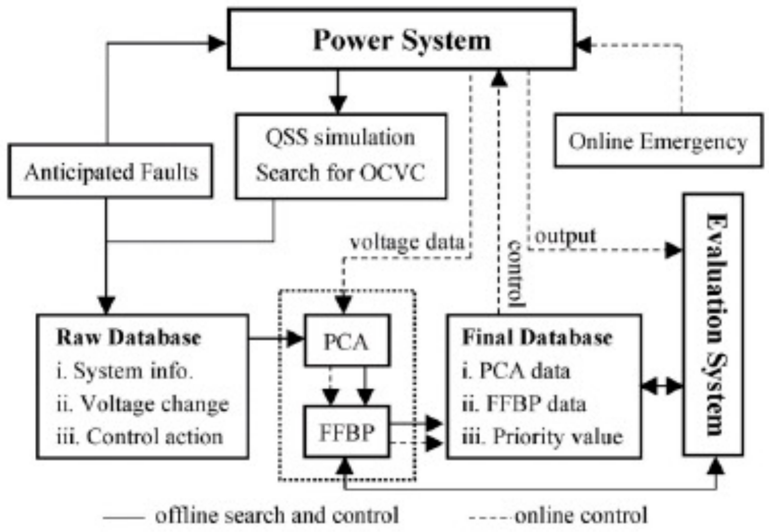


Fig. 6. Data-based learning and control system for LTVS

High applicability for unanticipated faults

High online efficiency

Ref: H.Cai, H.Ma and D.J.Hill, “A data-based learning and control method for long-term voltage stability,” IEEE Trans Power Systems, July 2020.

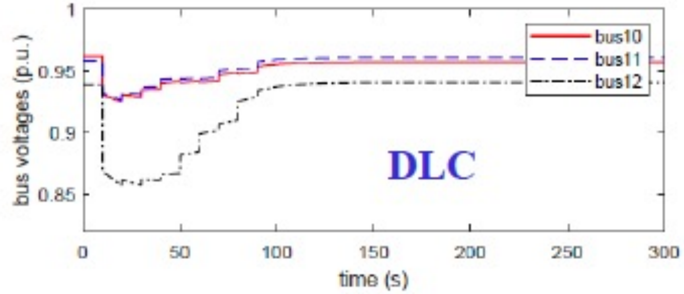
D. Case studies

- New England 39-bus System

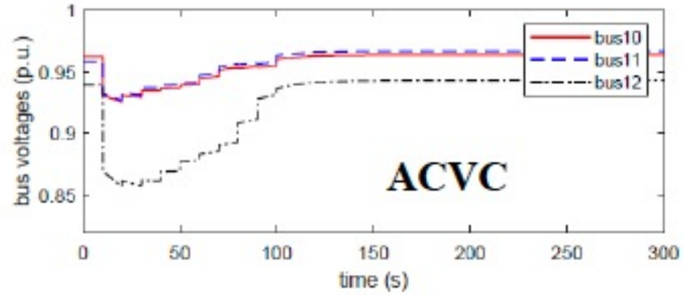
Table 3.4: Summary of Computation Time between Different Systems

System	Average computation time DLC (online)	Average computation time ACVC (online)	Case number of offline learning
6-bus	0.011 s	0.120 s	126
39-bus	0.012 s	0.291 s	414

More efficient for a larger power system.



(b) Simulation result of voltage at bus 5 and 6 with DLC online.



(c) Simulation result of voltage at bus 5 and 6 with ACVC online.

Fig. 9. Summary of the case study in 39-bus system.

- Iceland 189-bus system

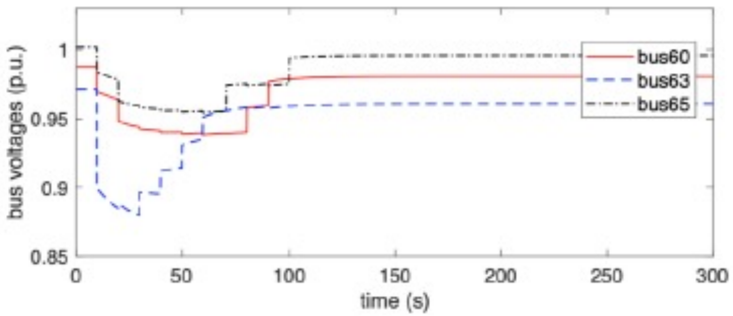


Fig. 10. Simulation result of voltage in bus 60, 63, 65.

Data-based Frequency Regulation of Power Systems

➢ *Data-enabled Predictive Control (DeePC) based Load Frequency Control (LFC):*

- Behavioral system theory based → model-free.
- Offline training is not required.
- Receding horizon online control.

▸ **Hankel Matrix** (constructed with pre-collected data)

$$\mathscr{H}_t(u_T^d) := \begin{bmatrix} U_\mathrm{p} \\ U_\mathrm{f} \end{bmatrix} \qquad \mathscr{H}_t(y_T^d) := \begin{bmatrix} Y_\mathrm{p} \\ Y_\mathrm{f} \end{bmatrix} \qquad \mathscr{H}_t(d_T^d) := \begin{bmatrix} D_\mathrm{p} \\ D_\mathrm{f} \end{bmatrix}$$

▸ **Optimization Problem** (solved at each sampling instant to find the optimal control signal u_r):

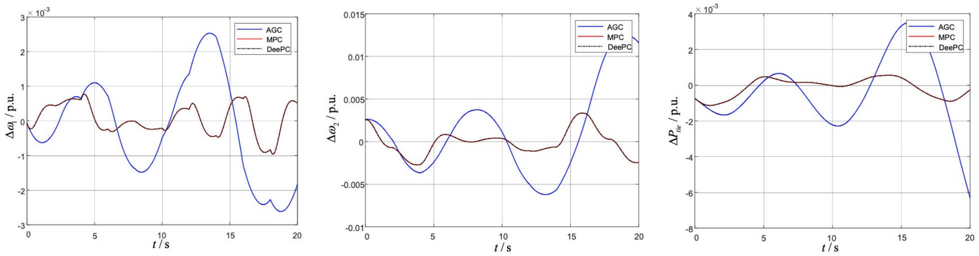
$$\min_{g,u_\mathrm{r},y_\mathrm{r},\sigma_d,\sigma_{d_\mathrm{r}}} \sum_{s=0}^{T_\mathrm{f}-1} \left(\|y_\mathrm{r}(s) - r(t_0+s)\|_Q^2 + \|u_\mathrm{r}(s)\|_R^2\right) + \lambda_g\|g\|_2^2 + \lambda_d\|\sigma_d\|_2^2 + \lambda_{d_\mathrm{r}}\|\sigma_{d_\mathrm{r}}\|_2^2$$

$$\text{s.t.} \begin{bmatrix} U_\mathrm{p} \\ D_\mathrm{p} \\ Y_\mathrm{p} \\ U_\mathrm{f} \\ D_\mathrm{f} \\ Y_\mathrm{f} \end{bmatrix} g = \begin{bmatrix} u_\mathrm{ini} \\ d_\mathrm{ini} \\ y_\mathrm{ini} \\ u_\mathrm{r} \\ d_\mathrm{r} \\ y_\mathrm{r} \end{bmatrix} + \begin{bmatrix} 0 \\ \sigma_d \\ 0 \\ 0 \\ \sigma_{d_\mathrm{r}} \\ 0 \end{bmatrix}$$

$$u_\mathrm{r}(s) \in \mathcal{U},\ \forall s \in \{0,1,\cdots,T_\mathrm{f}-1\},$$
$$y_\mathrm{r}(s) \in \mathcal{Y},\ \forall s \in \{0,1,\cdots,T_\mathrm{f}-1\},$$
$$d_\mathrm{r}(s) = d_\mathrm{pre}(t_0+s),\ \forall s \in \{0,1,\cdots,T_\mathrm{f}-1\}.$$

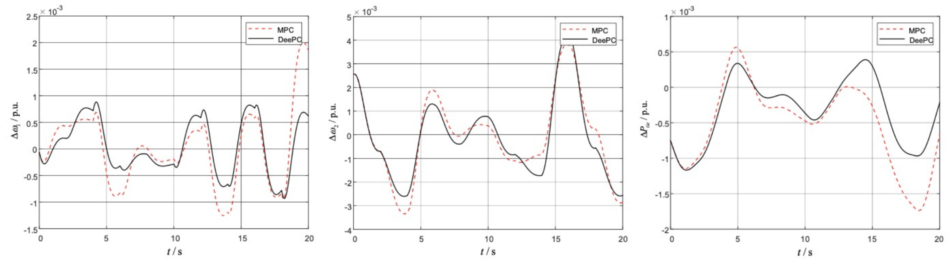
▪ **Results:**

▪ Control performance with accurate net load prediction:



Better than AGC & Close to MPC

▪ Control performance with inaccurate net load prediction:



Better robustness than MPC

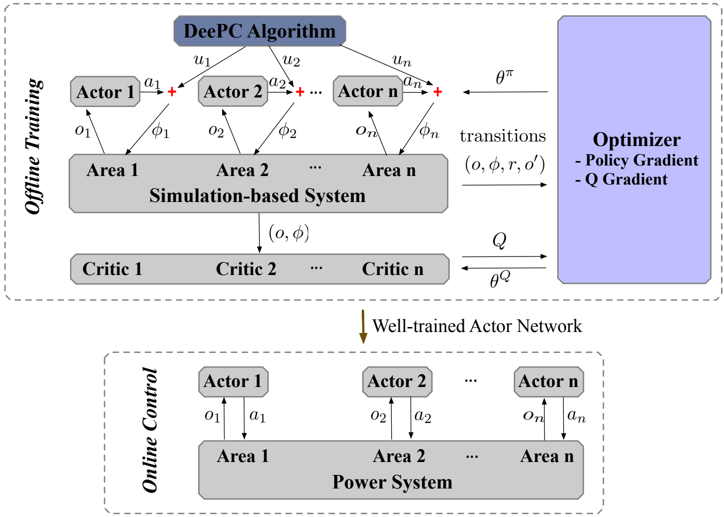
Ref: Zhao, Liu and Hill, A Data-Enabled Predictive Control Method for Frequency Regulation of Power Systems, ISGT Europe 2021.

Data-based Frequency Regulation of Power Systems

➢ ***Combination of DeePC & Reinforcement Learning (RL) for LFC:***

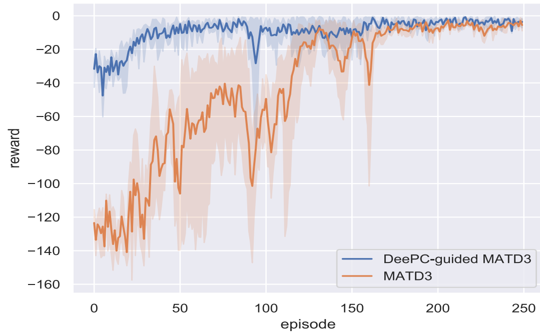
	DeePC	RL
Pros	• model-free • offline training is not required	• model-free • fast online control
Cons	• online computation burden	• complex offline training

● **Idea: Use the DeePC to guide the offline training of RL.**

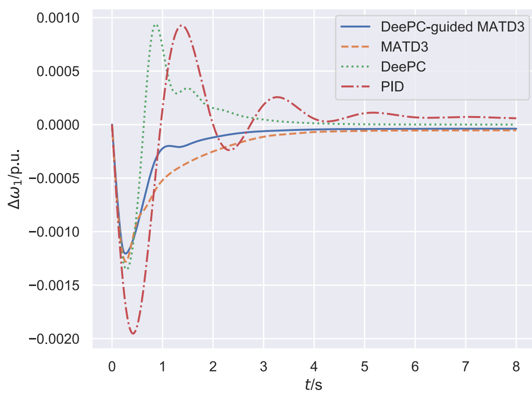


▪ **Results:**

▪ stable offline training:



▪ effective online control:



Ref: Zhao, Liu and Hill, A Multi-Agent Reinforcement Learning based Frequency Control Method with Data-Enabled Predictive Control Guided Policy Search, IEEE PES General Meeting 2022.

Unsolved Problems in Existing Data-Based Approaches

- Lack of unstable/risky scenarios to verify the real-world performances of a well-trained scheme.
- Insufficient consideration of practical implementation contexts, e.g., measurement errors/losses, communication delays and/or failures.
- Inadequate interpretability of many ML methods, especially emerging neural network-based DL approaches, being incomprehensible for power system operators in practice.
- How to systematically combine model-based and data-based approaches to derive more powerful solutions.
- ...

Annual Review of Control, Robotics, and Autonomous Systems

Stability and Control of Power Grids

Tao Liu,[1,*] Yue Song,[1,*] Lipeng Zhu,[1,2,*] and David J. Hill[1,3]

Ref: T. Liu, Y. Song, L. Zhu, and D. J. Hill, AR-CRAS, 2022.

Conclusions

- As complexity increases data-based/learning methods becoming more popular in research
- Not just about applying standard ML tools and accepting answers
- Questions on how to get the physical knowledge included
- New stability phenomena emerging, e.g. oscillations in wind/HVDC
- Models are are now spatio-temp-hierarchical (kW to GW) with less time-scale separation, i.e. GFL, GFM inverters taking over from synch generators
- After 100 years or so of slow changes, a new era of fundamentals is suddenly here in a larger PE community, but dynamics and control is no less important
- And at levels of rigor established in the past

New stability

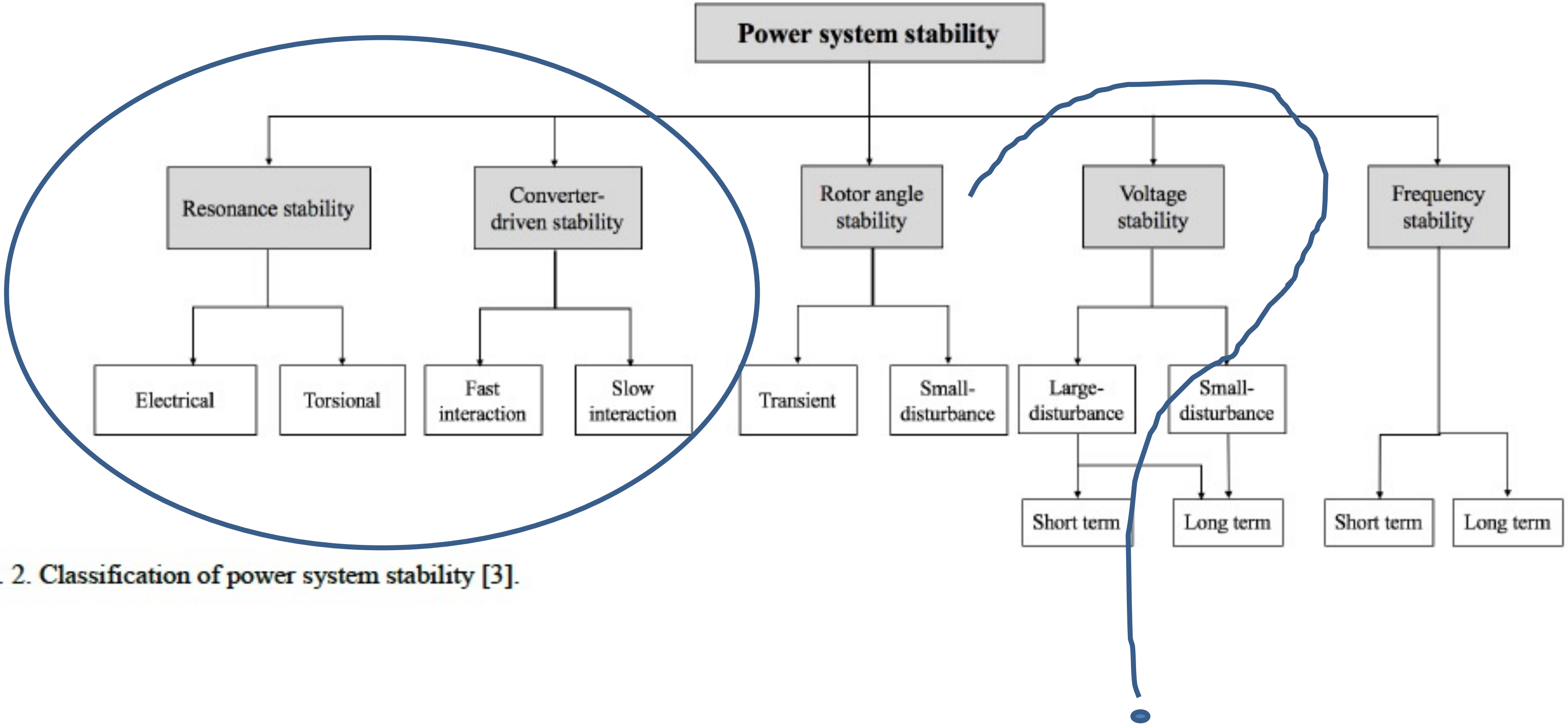


Fig. 2. Classification of power system stability [3].

Ref: N.Hatziargyriou, …D.J.Hill, … "Definition and Classification of Power System Stability – Revisited & Extended," *IEEE Trans Power Systems*, July 2021.