Predicting System Dynamics with Machine Learning

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TUDelft DAI ENER ERGY

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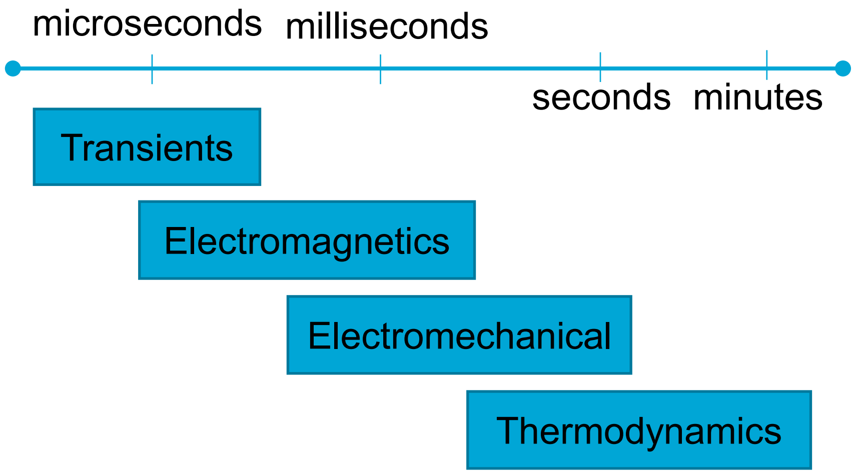
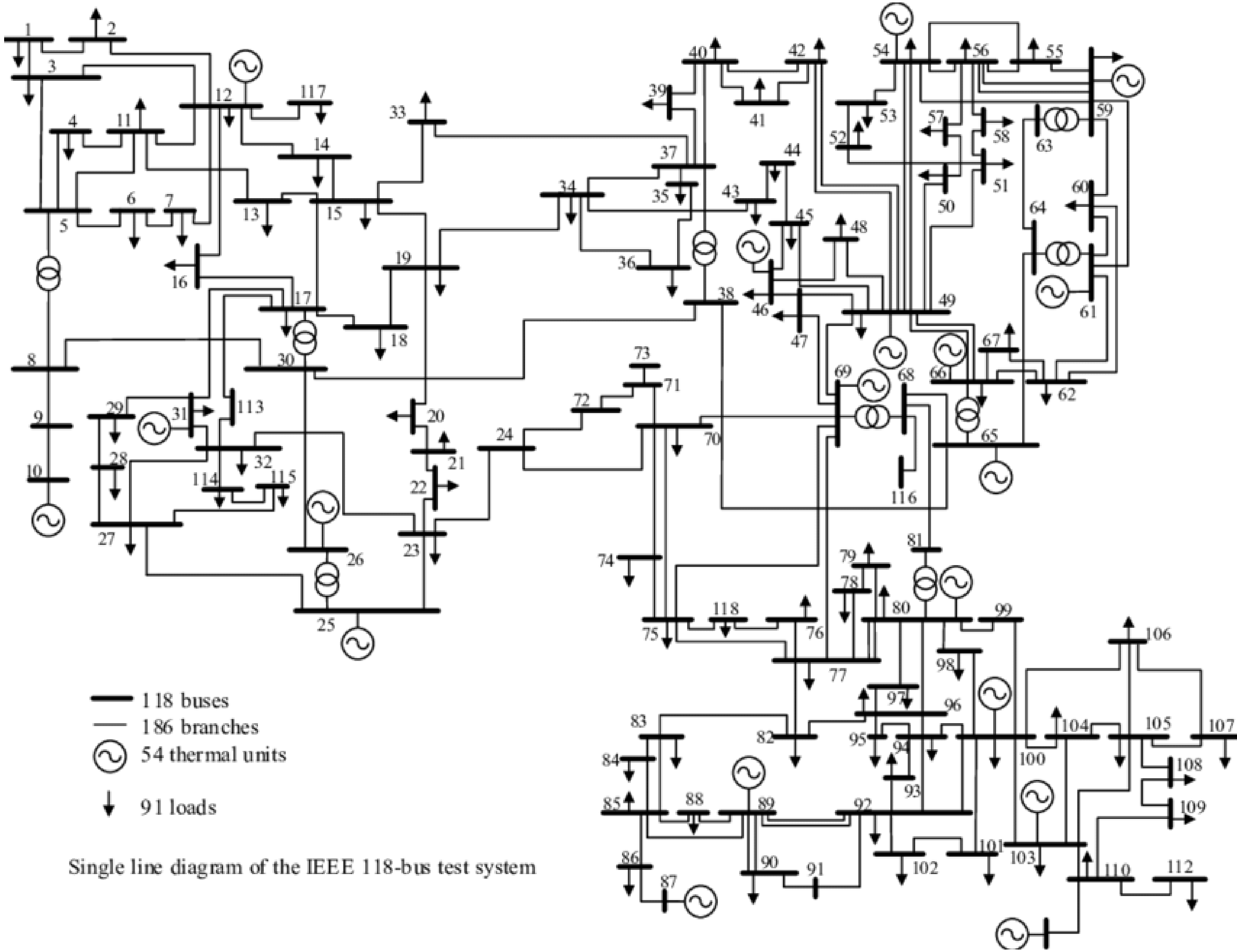
Power System Dynamic Stability & Security

Current Power Systems

- Synchronous machines
- Power electronic interfaced equipment
- Active distribution grids





Single line diagram of the IEEE 118-bus test system

Power System Dynamic Stability & Security

Current Power Systems

- Synchronous machines
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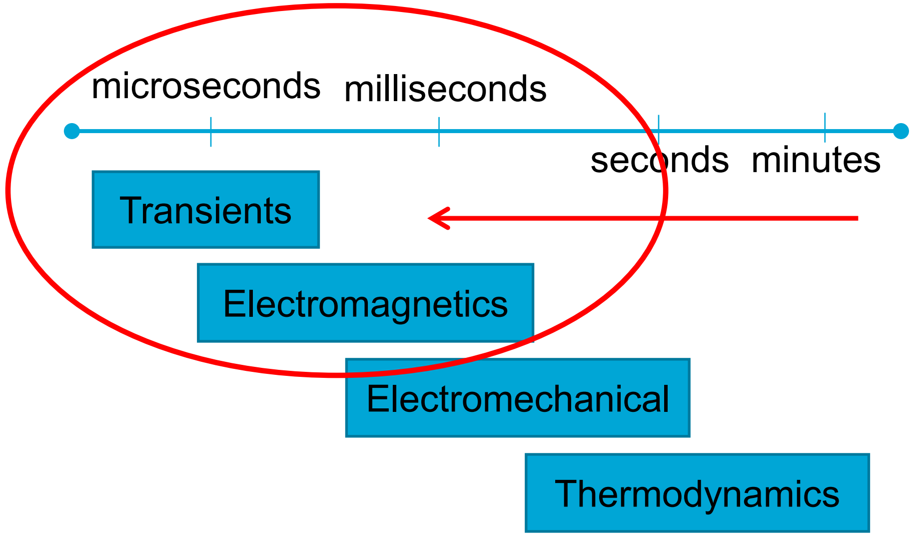
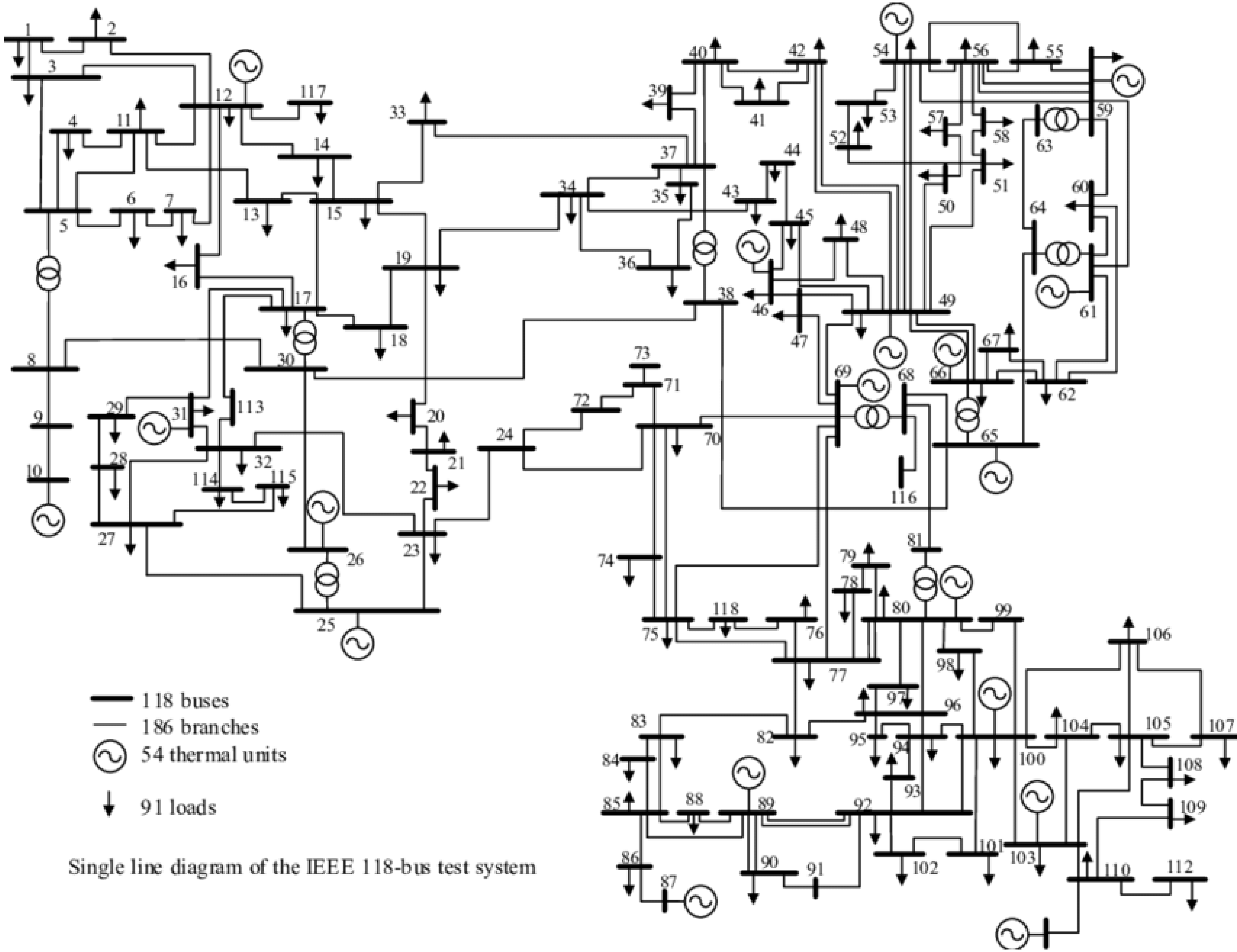
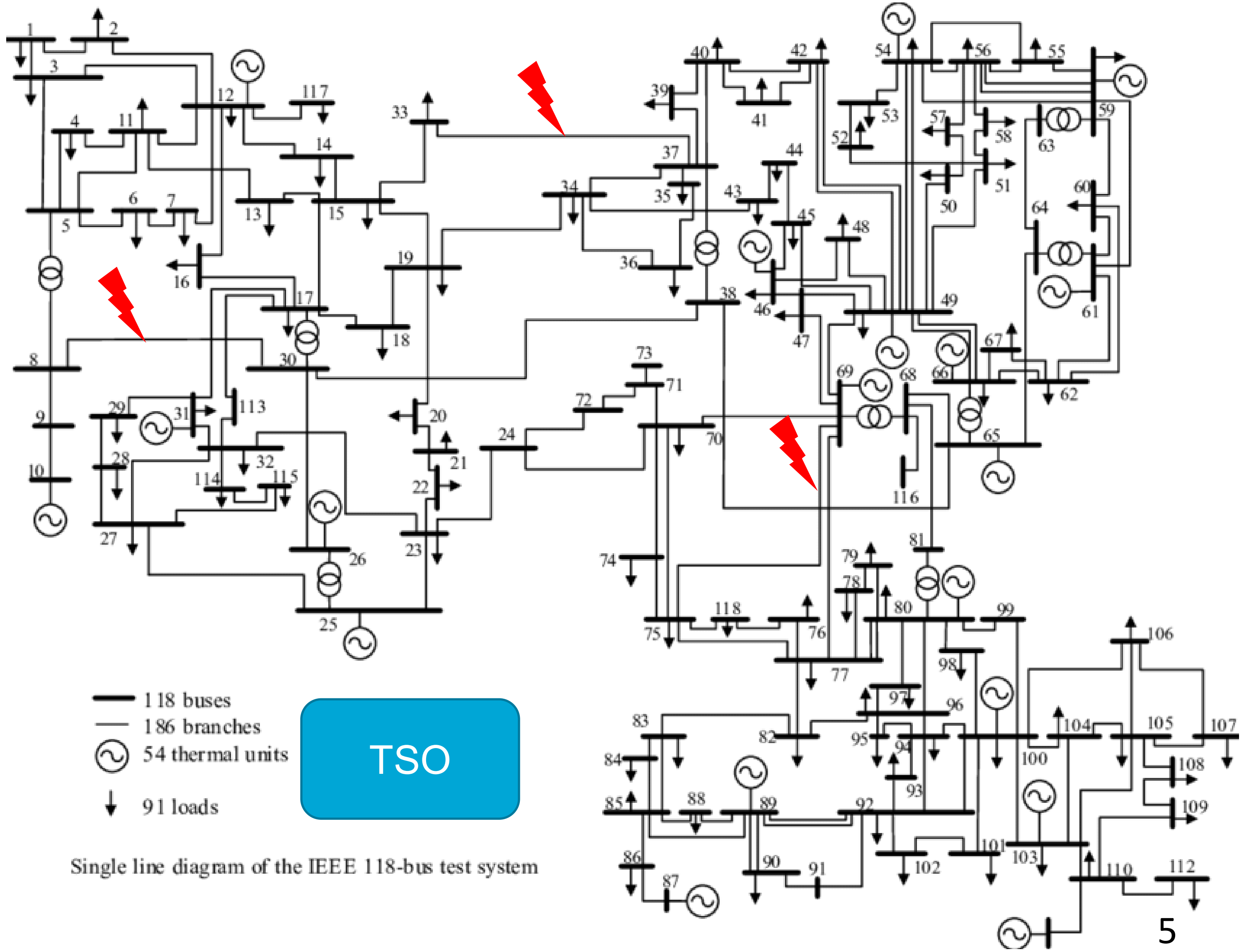




Single line diagram of the IEEE 118-bus test system

Computing Power System Dynamics

- Stability types: Frequency, voltage and rotor angle (transient).
- Dynamic system model in Differential Algebraic Equations (DAE).
- Identification of critical disturbances.
- Run simulations to evaluate possible scenarios.



Single line diagram of the IEEE 118-bus test system

Dynamic Security Assessment (DSA) – The conventional approach

Data generation with RMS simulations.

- Operational conditions
- Topological conditions: Network configuration and equipment status.
- Disturbance: Type, duration, continuation (permanent, temporary).

RMS simulations

- Solves high order DAE.
- Dynamic characteristic are captured
- Large number of states (internal and external)
- Highly accurate

- Computationally demanding
- Requires extensive system modelling
- Parameter tuning
- Not applicable in real time
- Challenging to model cascading events

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Dynamic Security Assessment (DSA) – Machine Learning

Machine learning classifiers to detect the future system label after post disturbance data.

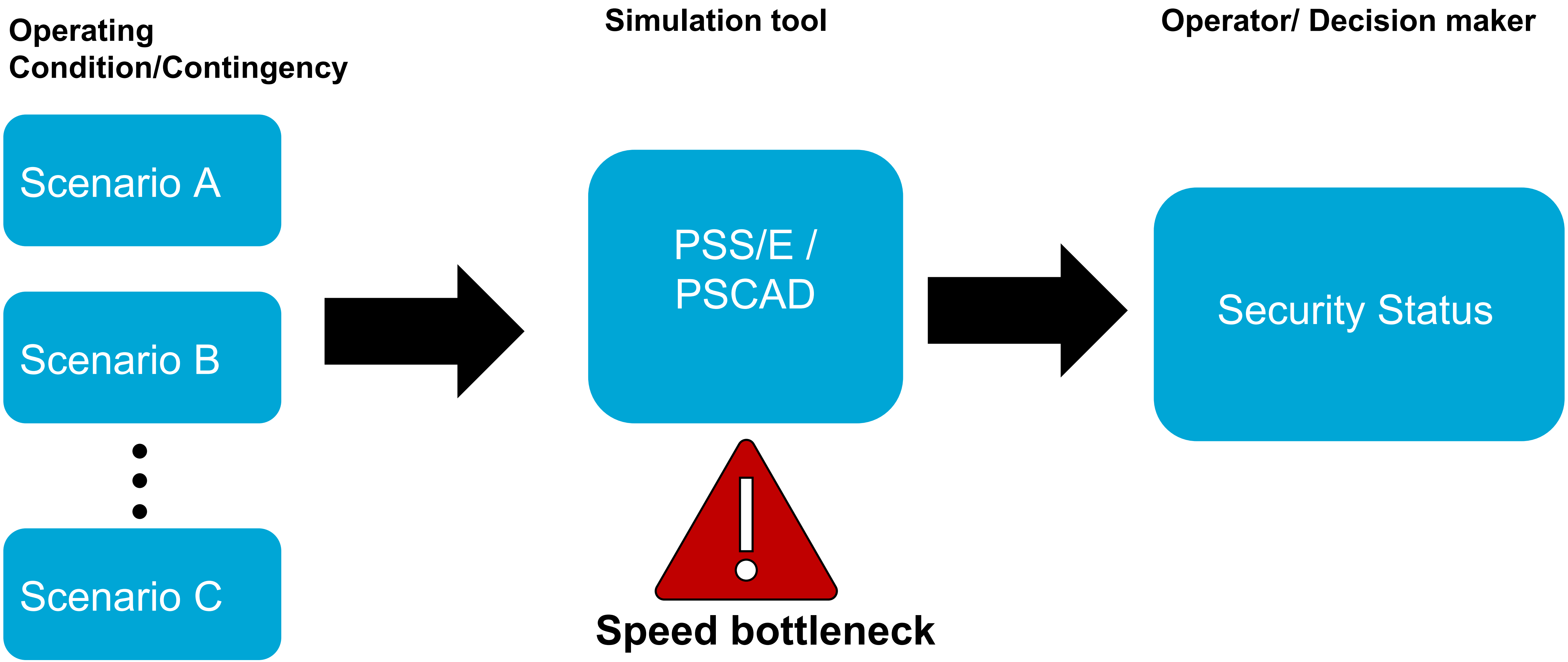
- Decision Tree, Random Forest, SVM, XGBoost, ANN. Single feed forward type models, no time element.
- RNN, ResNet, CNN, LSTM. Discrete time modelling, requires long training with large amount of data.

Machine Learning

- Prediction time is fast
- Applicable in real time
- Generalize unseen data
- Dynamics can be analysed

- Cascades cannot be captured
- Performance depends on the dataset
- Unseen new complex dynamics
- Adaptability against network changes

Real-time DSA bottleneck



Supervised Learning for Dynamics Surrogate

Notation: Power system s, model m, parameter x

Objective: assess $m(x) \rightarrow y$ **very** fast and **often**

Surrogate approach

1.Generate a training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^N$ where $y_i = m(x_i)$ from the full simulator

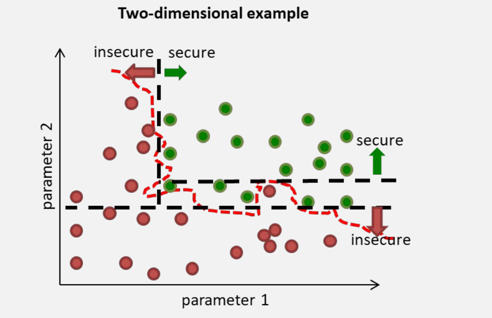
2.Train surrogate $f(x) \rightarrow \hat{y}$ with supervised loss $\sum_{i\in\Omega^T} \|y_i - \hat{y}_i\|$

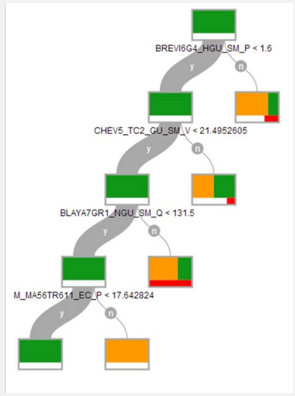
3.Use $f(x_j)$ for new j $\notin \Omega^T$

Benefit: speed at inference

Applications

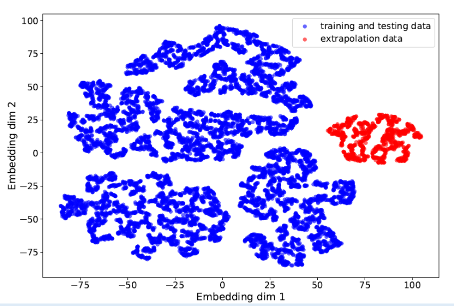
- Real-time dynamic security assessment ([1,2] and many others)





Challenges

- Out of distribution risks: What if s and m changes? e.g., topology changes
- What if the model is inaccurate $s \neq m$? e.g., inverter-based controls
- Need large, representative training data



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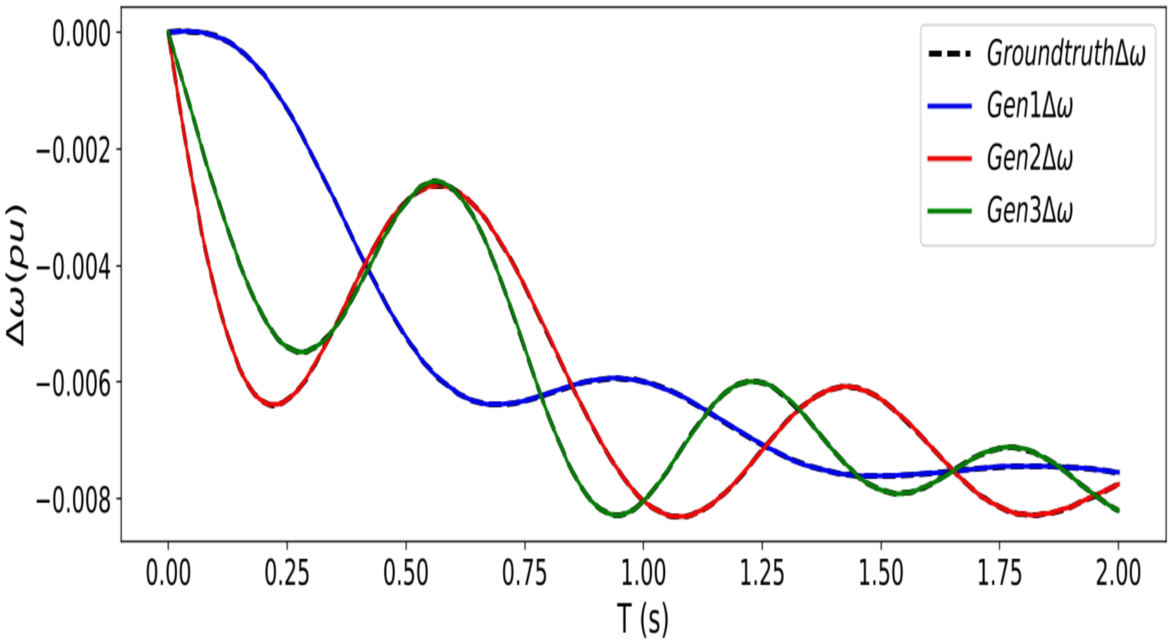
[1] Wehenkel, Louis, and Mania Pavella. "Decision trees and transient stability of electric power systems." *Automatica* 27.1 (1991): 115-134.
[2] Cremer, Jochen L., Ioannis Konstantelos, and Goran Strbac. "From optimization-based machine learning to interpretable security rules for operation." *IEEE Transactions on Power Systems* 34.5 (2019): 3826-3836.
[3] Olayiwola Arowolo, Jochen Stiasny, Jochen L. Cremer, “Exploring Extrapolation of Machine Learning Models for Power System Time Domain Simulation”, *Bulk Power System Dynamics and Control Symposium, 2025*

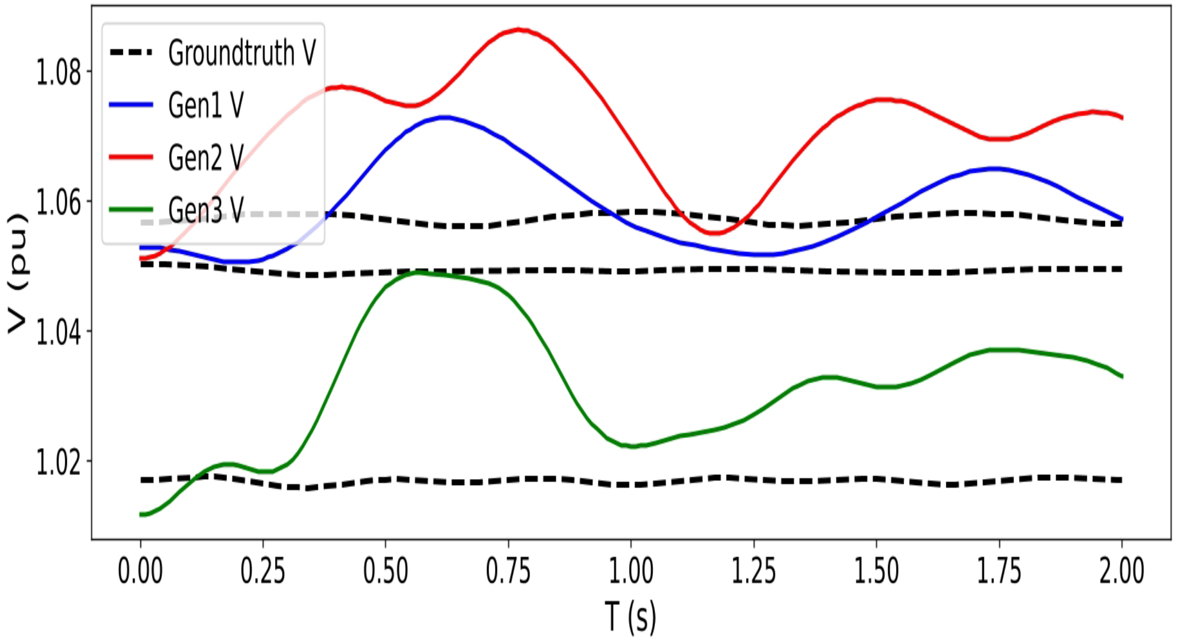
Extrapolation of ML Models in Transient Simulation

Olayiwola Arowolo

Model performs well for continuous disturbances within the training data distribution



Model fails to extrapolate for OOD discrete disturbances.



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[3] Olayiwola Arowolo, Jochen Stiasny, Jochen Cremer, "Exploring the Extrapolation Performance of Machine Learning Models for Power System Time Domain Simulations", 12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025

Physics-Informed Learning

Objective: surrogate learning enhanced with physics knowledge from model m

Idea: Incorporate physics residual (e.g. from a PDE or simulator) to guide learning and improve generalization

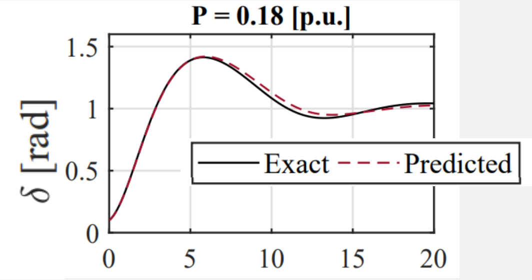
Physics-informed approach

1. Generate offline training dataset $\Omega^T = \{(x_i, y_i)\}_{i=1}^N$ with $y_i = m(x_i)$
2. Train surrogate $f(x) \rightarrow \hat{y}$ on composite loss $\sum_{i \in \Omega^T} \|y_i - \hat{y}_i\| + \mathcal{L}_{phys}(f(x_i), m)$
3. Use $f(x_j)$ for new j $\notin \Omega^T$

Benefits: Better generalisation performance with **fewer training samples**

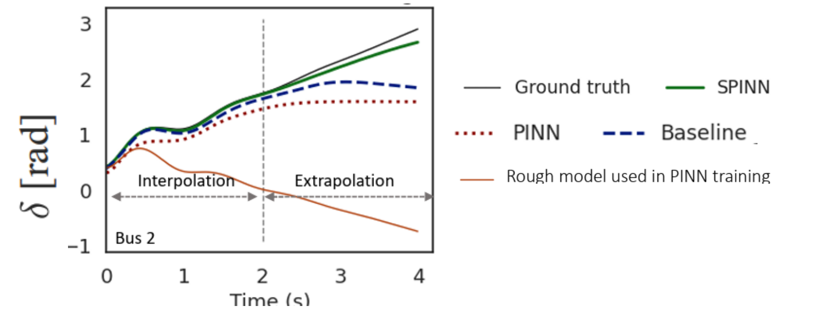
Applications

- Extrapolation in time-domain for dynamic analysis in power systems



Challenges

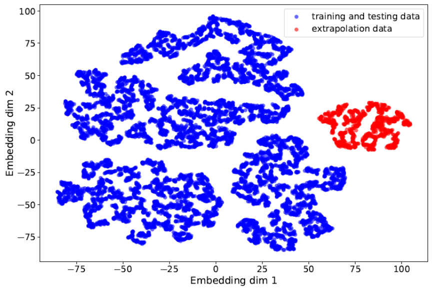
- Model inaccuracy $s \neq m$
- Changes in s or m
- Data sparsity
- Multi-loss scaling causes training instability
- Scaling issues to many physical loss terms in power systems



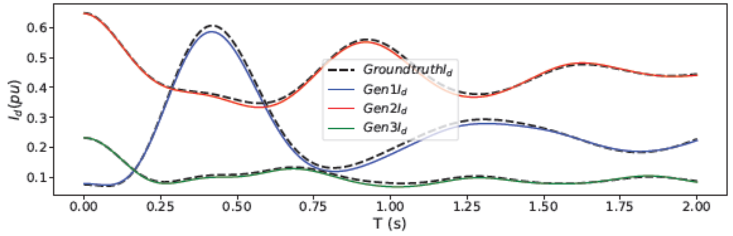
[4] Misyris, George S., Andreas Venzke, and Spyros Chatzivasileiadis. "Physics-informed neural networks for power systems." In *2020 IEEE power & energy society general meeting (PESGM)*, pp. 1-5. IEEE, 2020.
[5] Jochen Stiasny, Spyros Chatzivasileiadis, Physics-informed neural networks for time-domain simulations: Accuracy, computational cost, and flexibility, Electric Power Systems Research, Volume 224, 2023
[6] Xie, Haiwei, Federica Bellizio, Jochen L. Cremer, and Goran Strbac. "Regularised Learning with Selected Physics for Power System Dynamics." In *2023 IEEE Belgrade PowerTech*, pp. 1-7. IEEE, 2023.

Shared limitations

1. Generalisation to changes in s or m

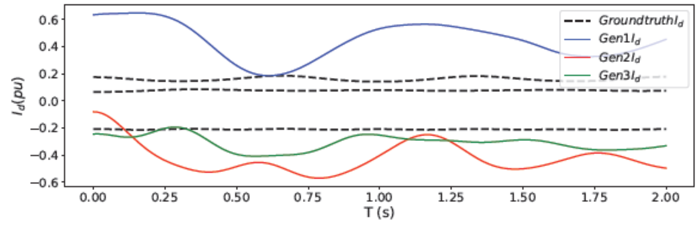


Continuous domain



(a) I_d current trajectory

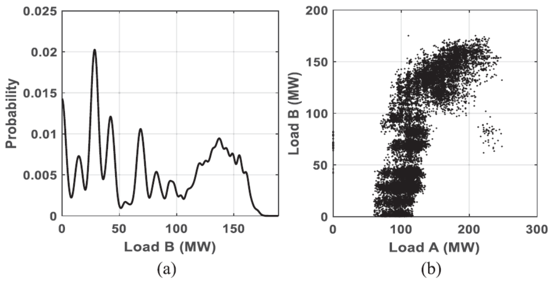
Nonlinear domain (discrete)



(a) I_d current trajectory

2. Data inefficiency

Sampling synthetic data & use real-data



3. Model inaccuracy $s \neq m$ (data quality issues)

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Dynamic Security Assessment (DSA) – Machine Learning

Solution

Train a machine learning model in real time to predict the dynamic states occurred after a disturbance to assess the system stability.

Mert Karaçelebi

Neural Ordinary Differential Equations (NODE)

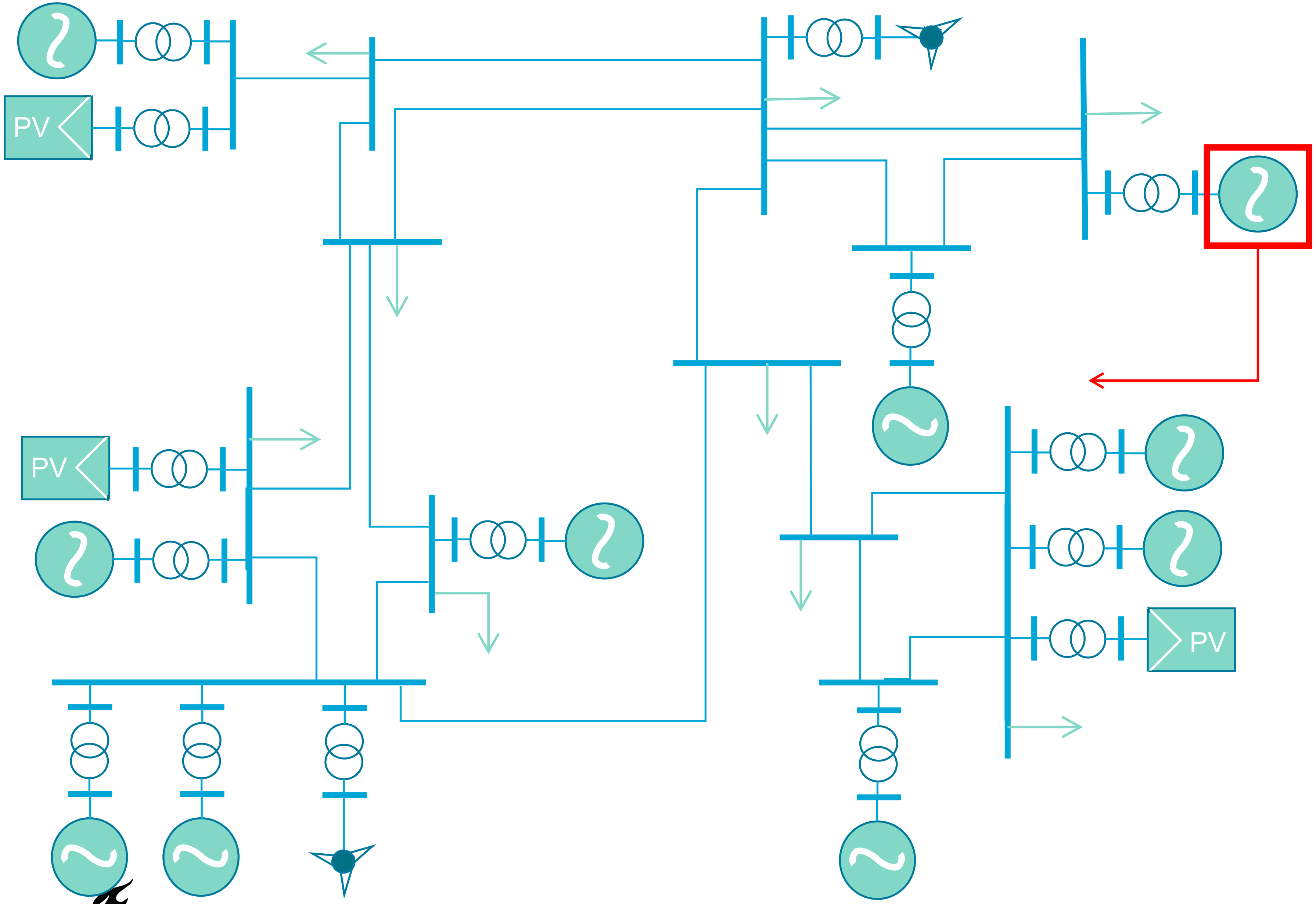
Machine Learning

- Prediction time is fast
- Applicable in real time
- Generalize unseen data
- Dynamics can be analysed

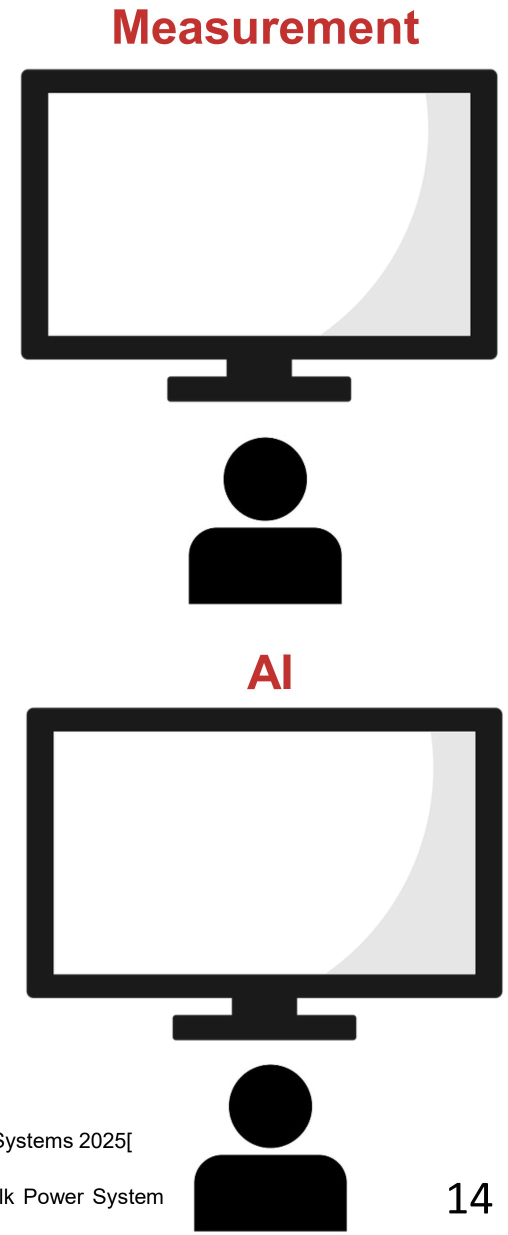
- Cascades cannot be captured
- Performance depends on the dataset quality
- Unseen new complex dynamics
- Network changes require replacement of the training dataset and retraining

[7] Mert Karaçelebi, Jochen L. Cremer "Online Neural Dynamics Forecasting for Power System Security", International Journal of Electrical Power & Energy Systems 2025[

[8] Mert Karaçelebi, Jochen L. Cremer, "Power system frequency monitoring and emergency control with neural ordinary differential equations", 12th Bulk Power System Dynamics and Control Symposium and Sustainable Energy, Grids and Networks Journal, 2025



Control Room



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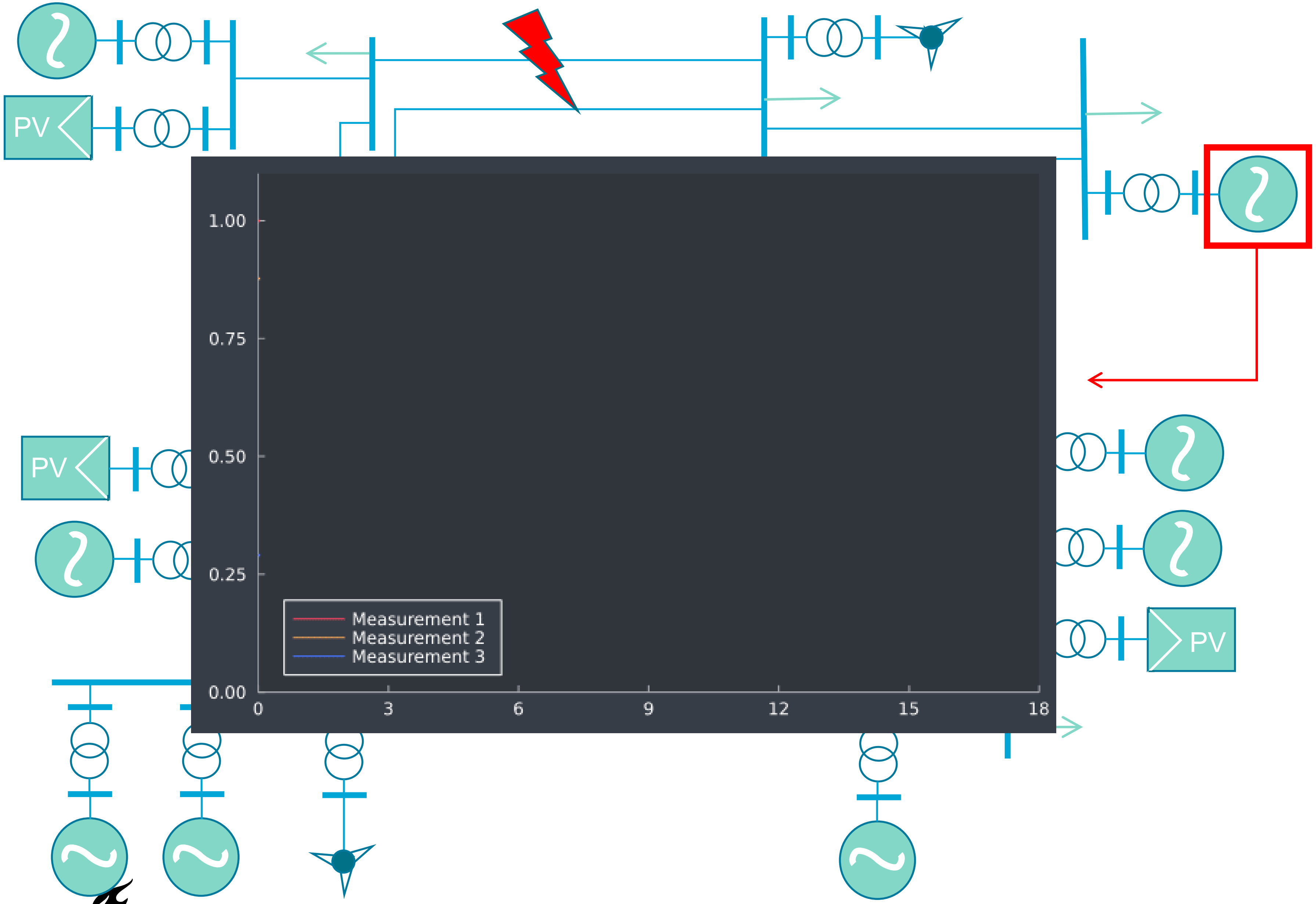

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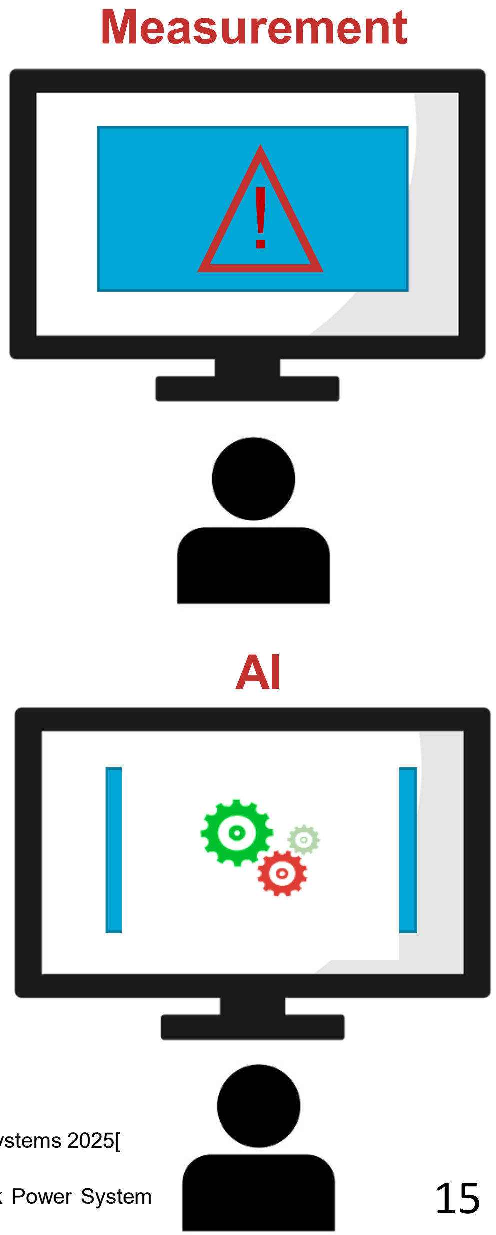

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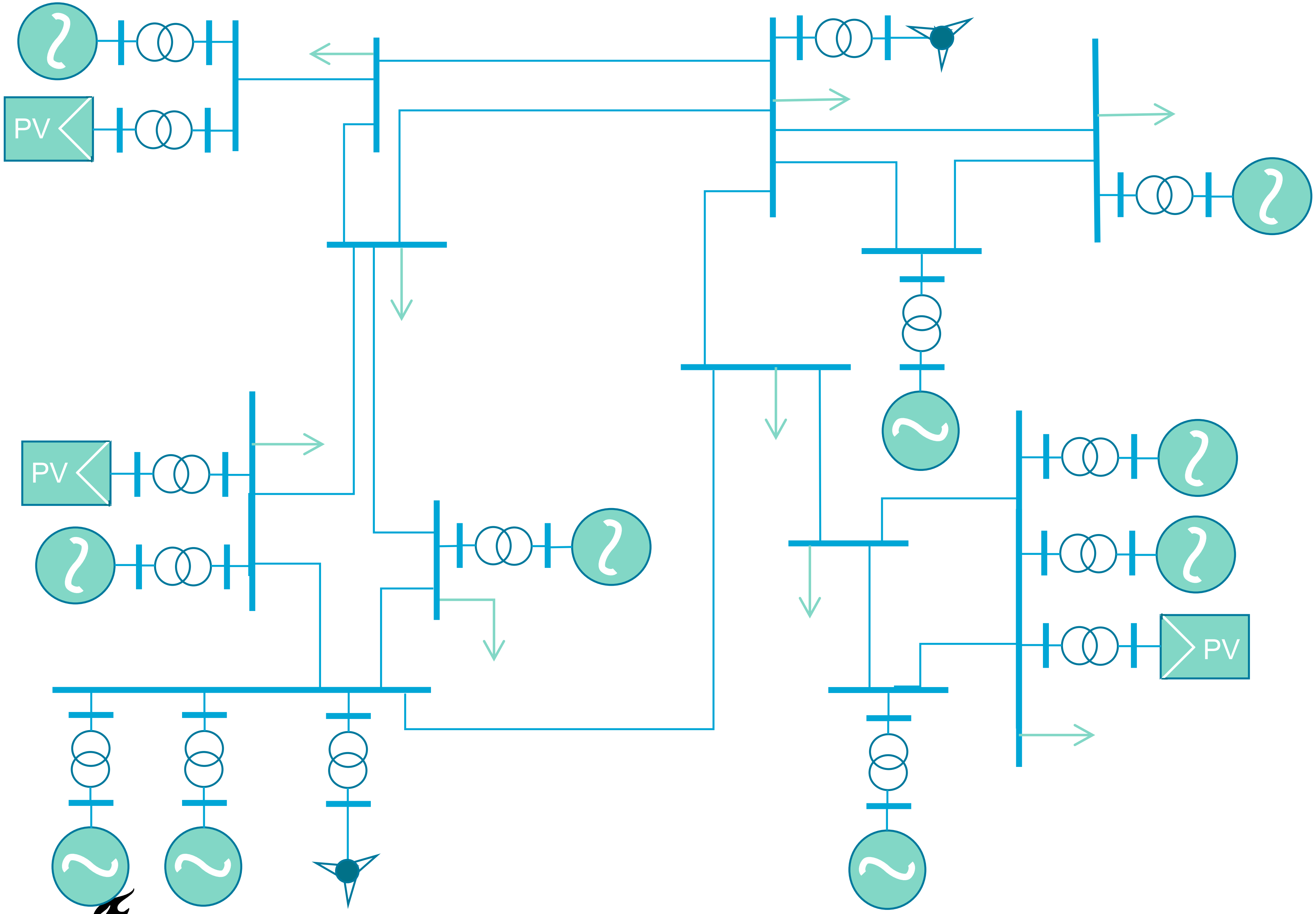
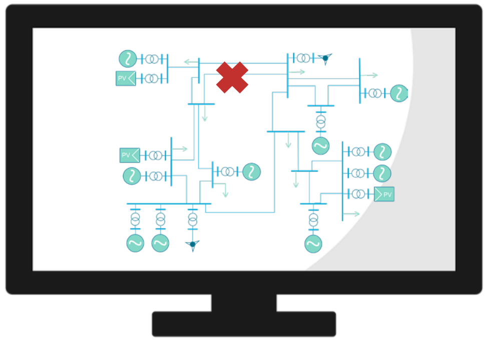
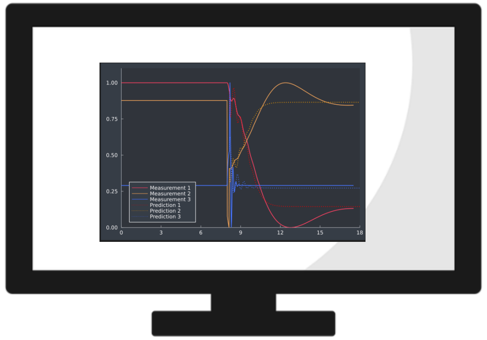


Measurement



AI



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Neural Ordinary Differential Equations (NODE)

- Continuous time domain train/prediction
- Neural networks can parametrize the ordinary differential equation (ODE) to evaluate hidden unit dynamics f.

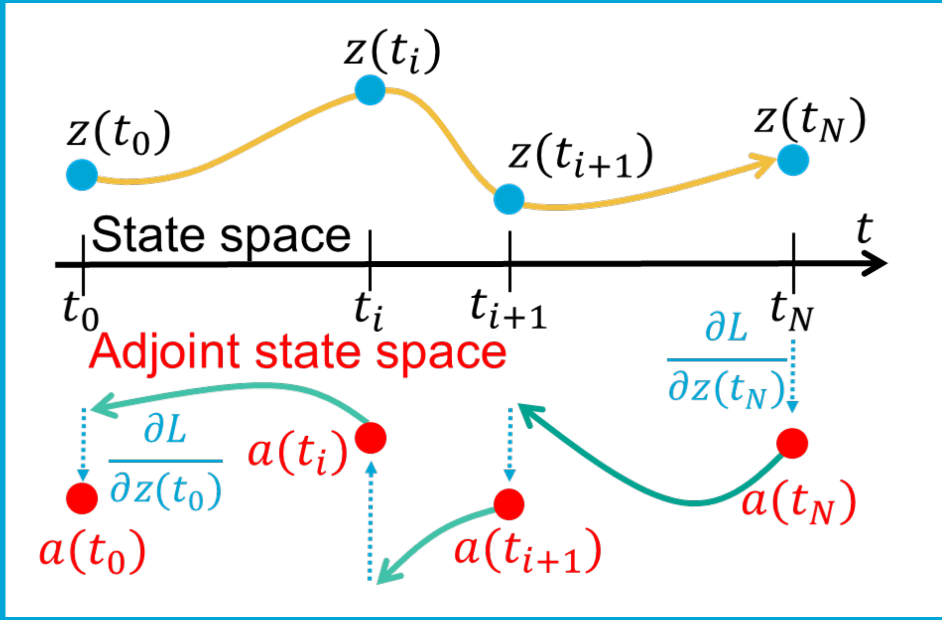
$$\partial z(t)/\partial t = f(z(t), t, \theta)$$

- ODE solver is used to train a recurrent layer.
- Memory efficient, adaptive computation, scalable.

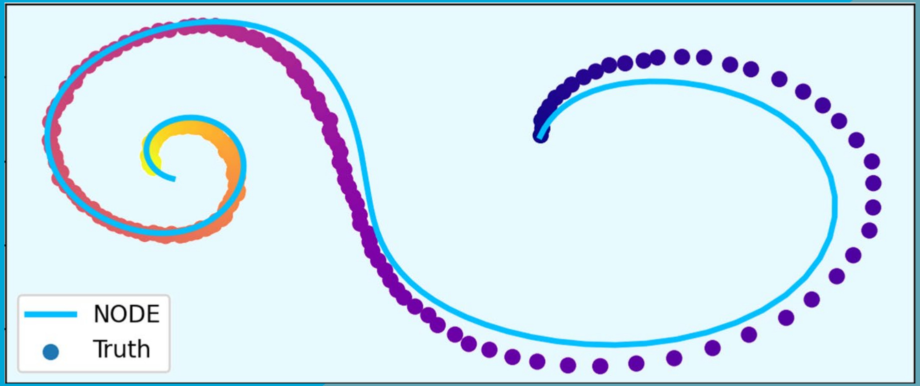
RNN $$z_{t+1} = z_t + f(z_t, \theta_t)$$

NODE $$z(\tau) = \mathrm{ODESolve}(z_0, f, t_0, \tau, \theta)$$

$$= z(t_0) + \int_{t_0}^{\tau} f(z(t), t, \theta)dt$$



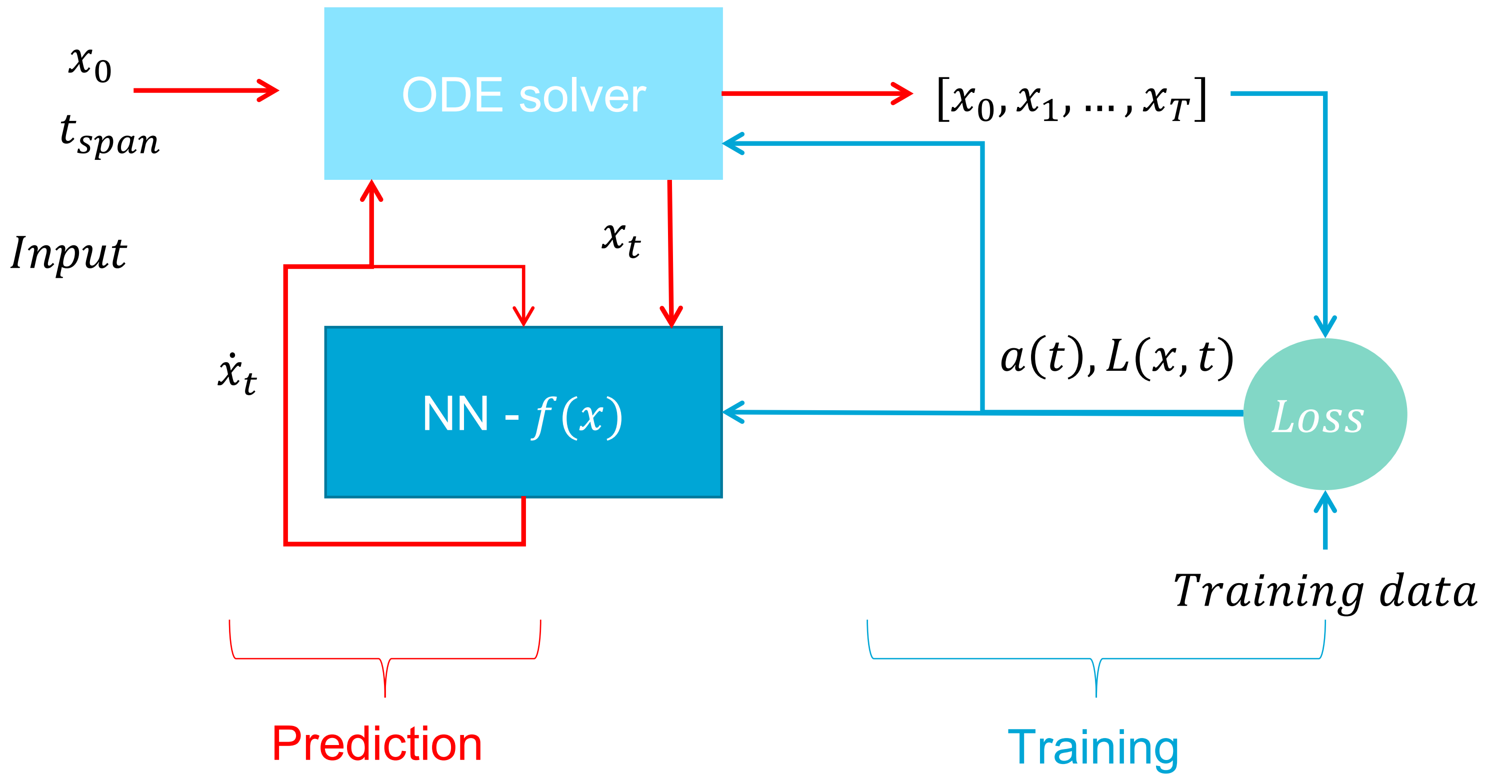
$$a(t) = \frac{\partial L}{\partial z(t)} \qquad \frac{da(t)}{dt} = -a(t)^T \frac{\partial f(z(t), t, \theta)}{\partial z}$$

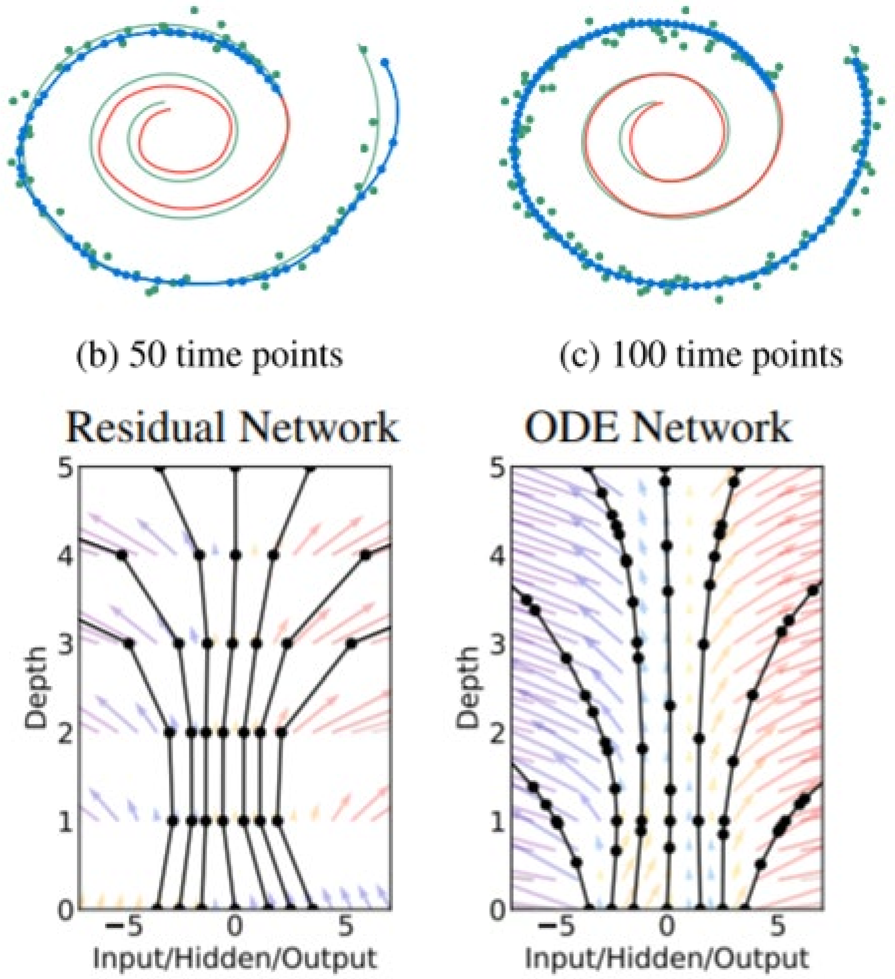


Source: Knauf, A. (2018). Ordinary Differential Equations. *UNITEXT - La Matematica per Il 3 Piu 2*, *109*(NeurIPS), 31–60.

Neural Ordinary Differential Equations (NODE)

How does it work?





Source:Chen, R. T. Q., Rubanova, Y., Bettencourt, J., & Duvenaud, D. (2018). *Neural Ordinary Differential Equations*. *NeurIPS*.

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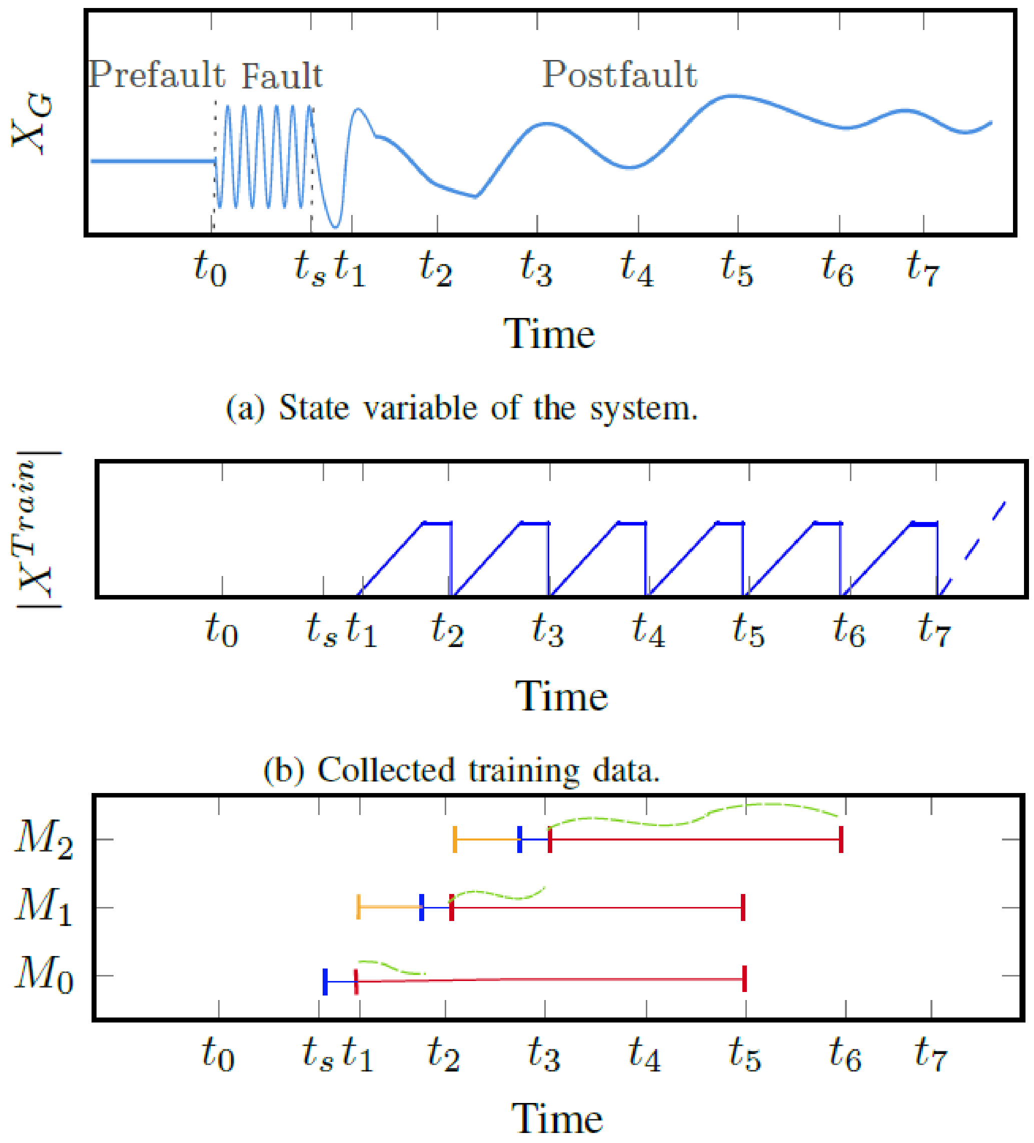
Real Time Training

- Following a disturbance training started.
- Linearly growing training dataset
- Moving window approach to capture changing dynamics
- Limited training ensured with limited training data size.
- Fast validation with the latest measurements.



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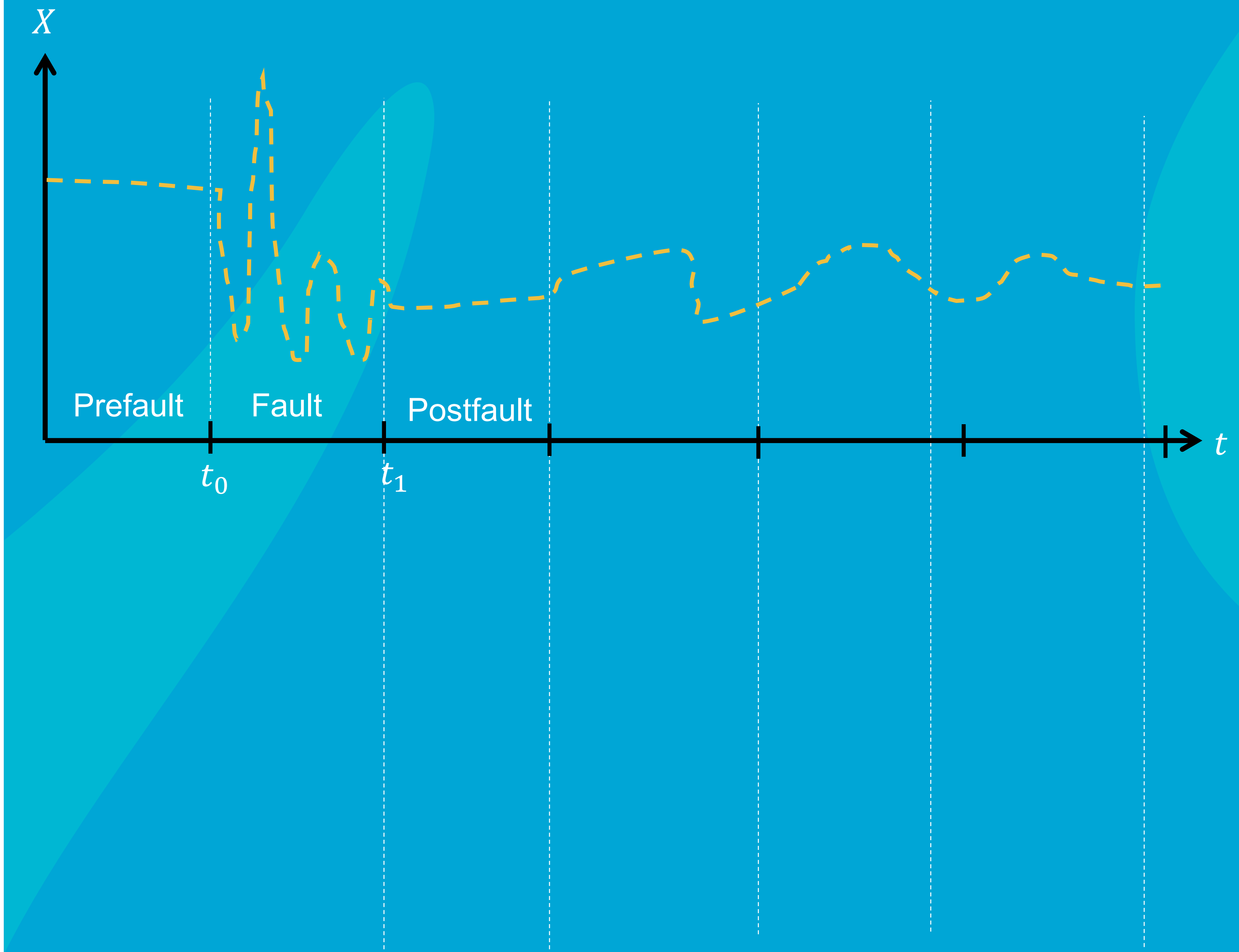
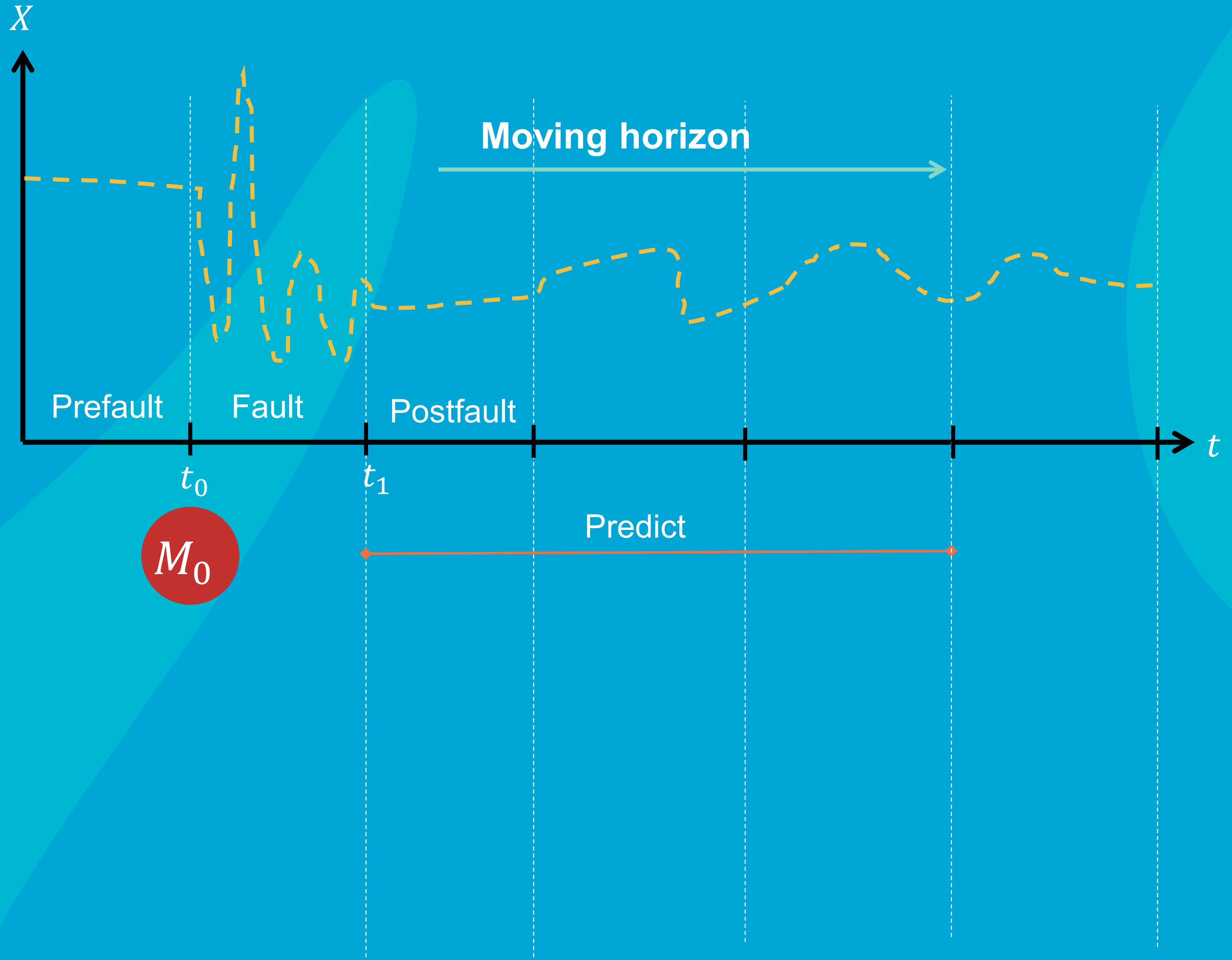
Real Time Training

- Disturbance occurs at t_0



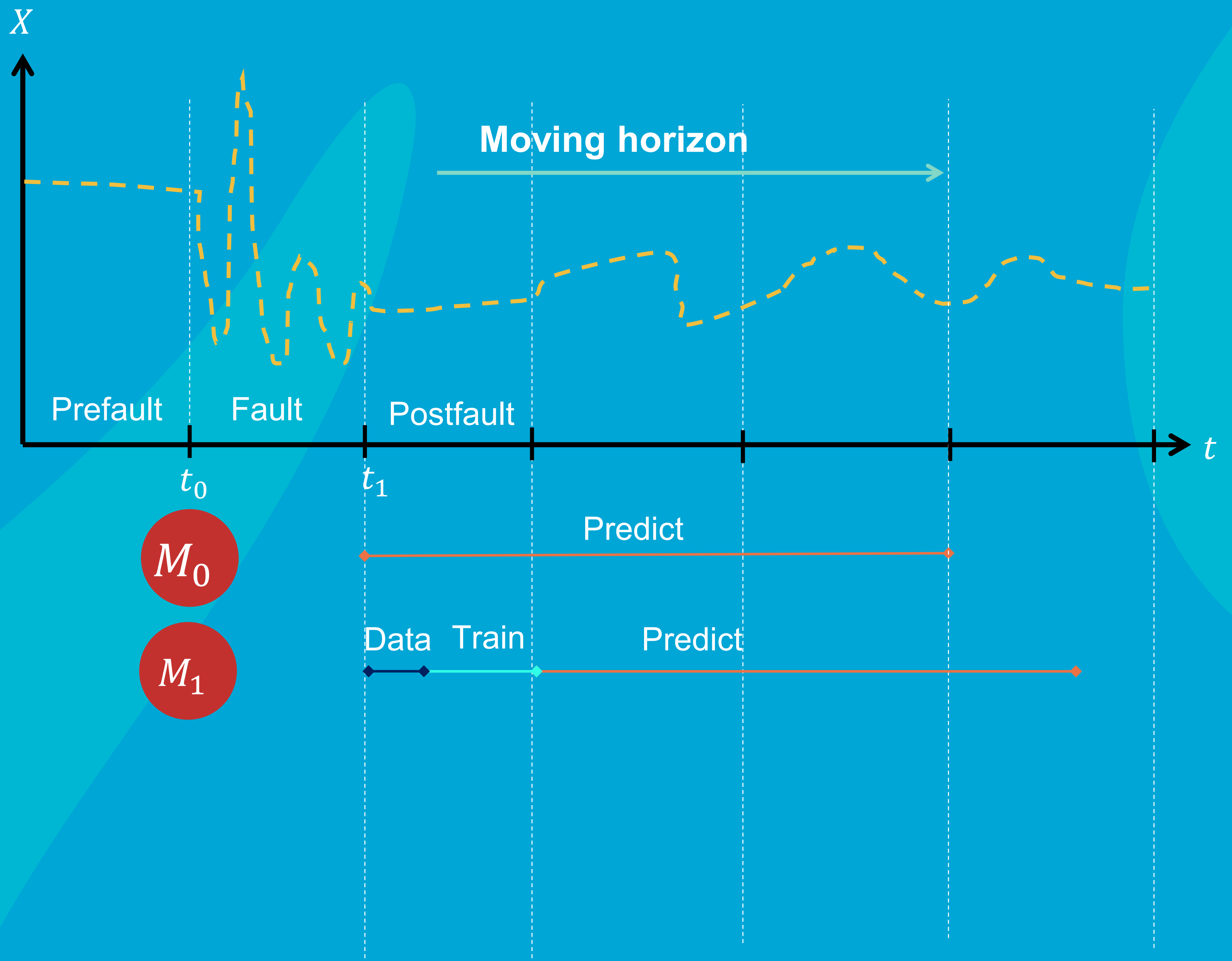
Real Time Training

- Disturbance occurs at t_0
- M-0 predicts system trajectories at t_1.



Real Time Training

- Disturbance occurs at t_0
- M-0 predicts system trajectories at t_1.
- M-1 starts training after initial dynamics have already occurred.



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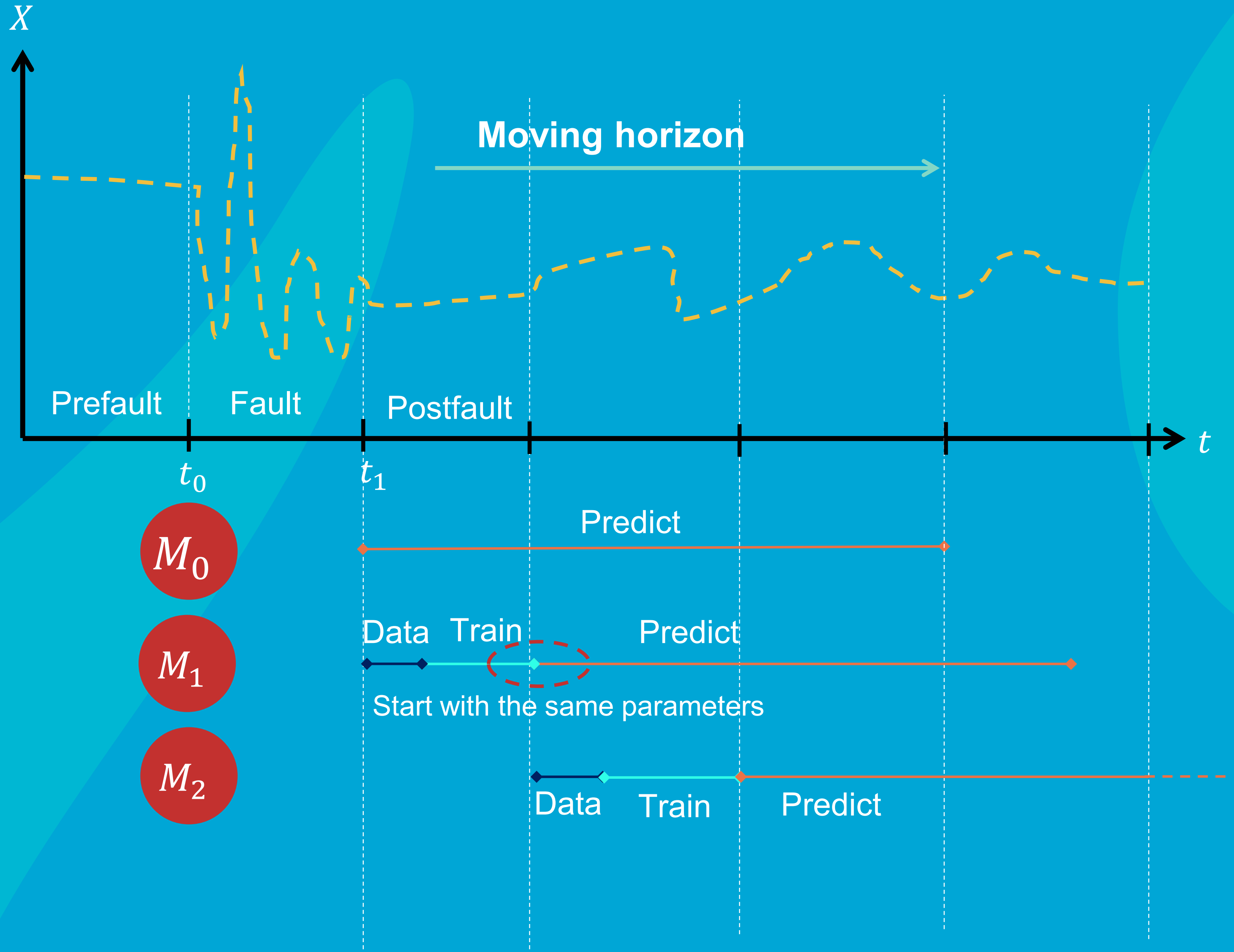
Real Time Training

- Disturbance occurs at t_0
- M-0 predicts system trajectories at t_1.
- M-1 starts training after initial dynamics have already occurred.
- M-2 starts training with new dynamics.



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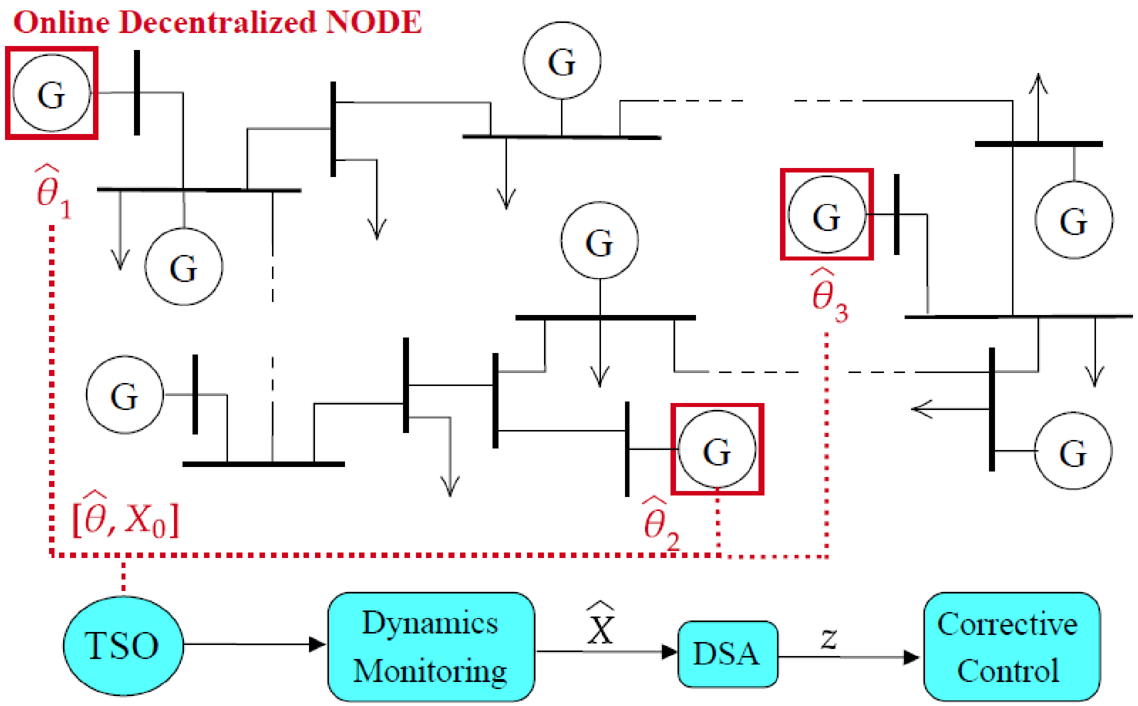
Decentralized Training Centralized Assessment

- Instead of measurements, transfer only the initial conditions and weights of the neural network.
- Transferred data size is independent of the recorded period.
- The same ODE system is solved in the control centre.
- System operators can acknowledge the training loss, hence the accuracy of the actual trajectories.
- Efficient, fast and detailed way to monitor actual dynamics.



- Other features of the approach:
  - Collocation based irregular down-sampling to identify time points with higher errors
  - Discrete Frechet Distance preserves temporal coherence while sensitive to the shape of the trajectory

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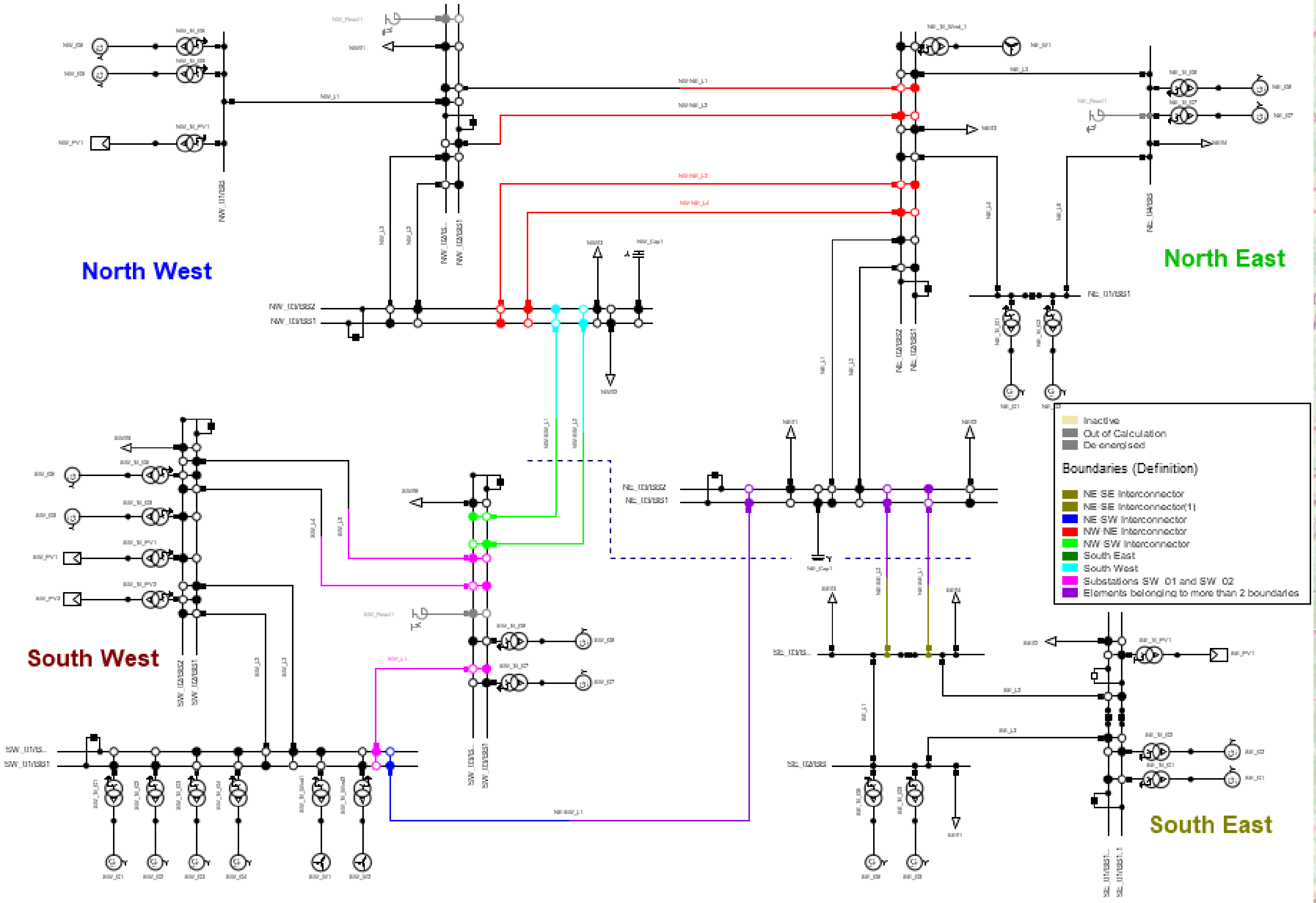
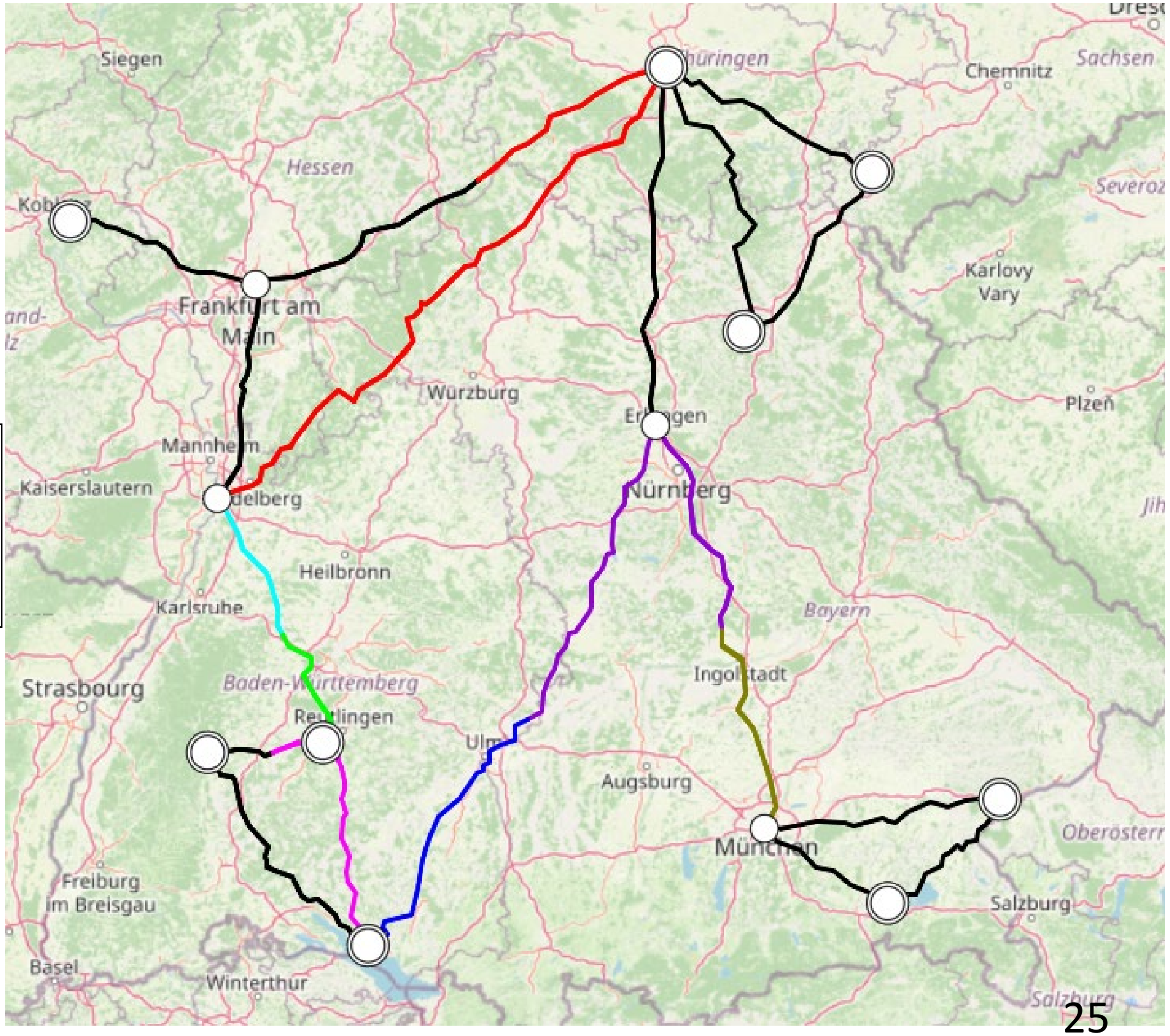
Case Study on Transmission System Example





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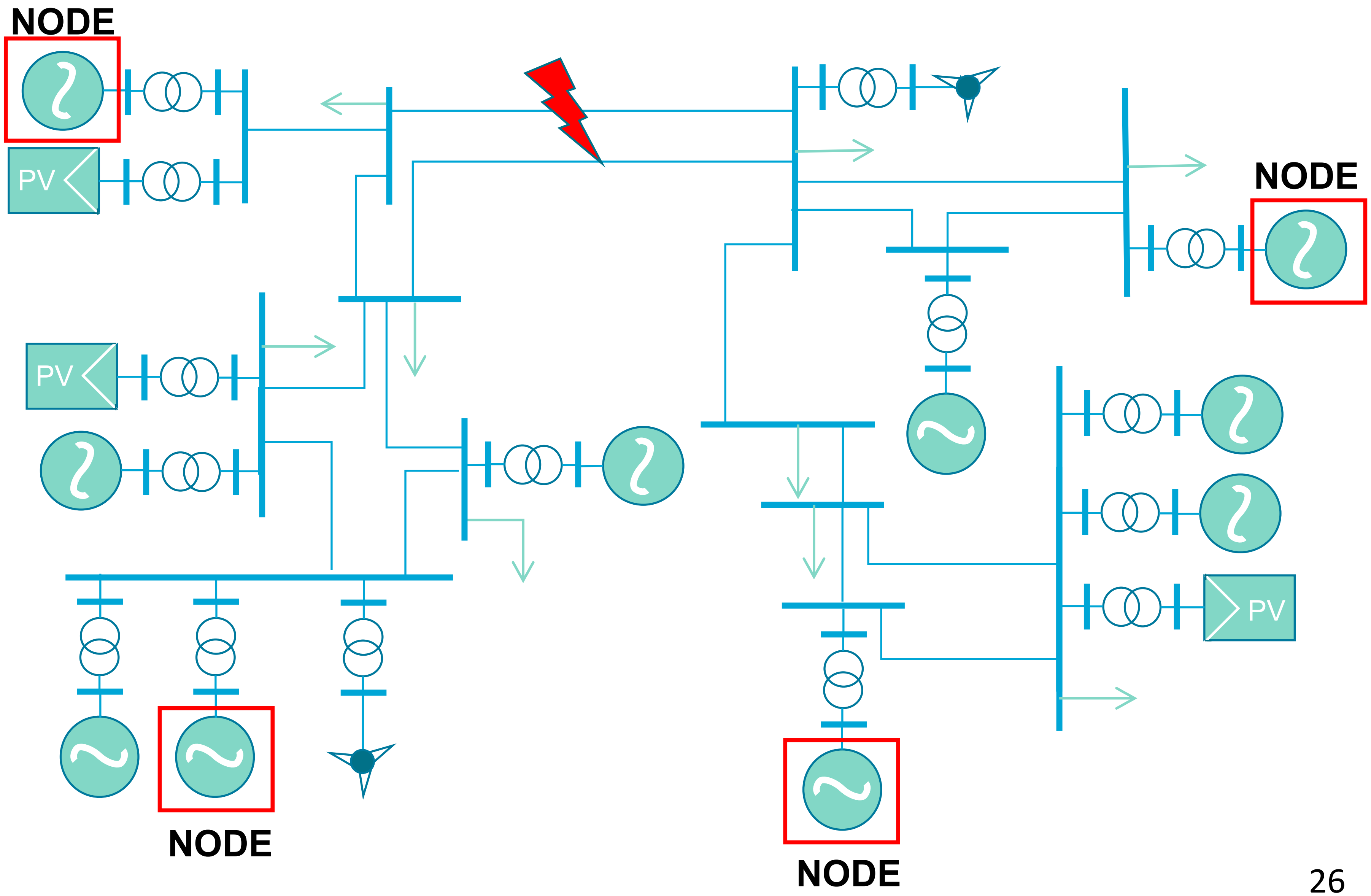
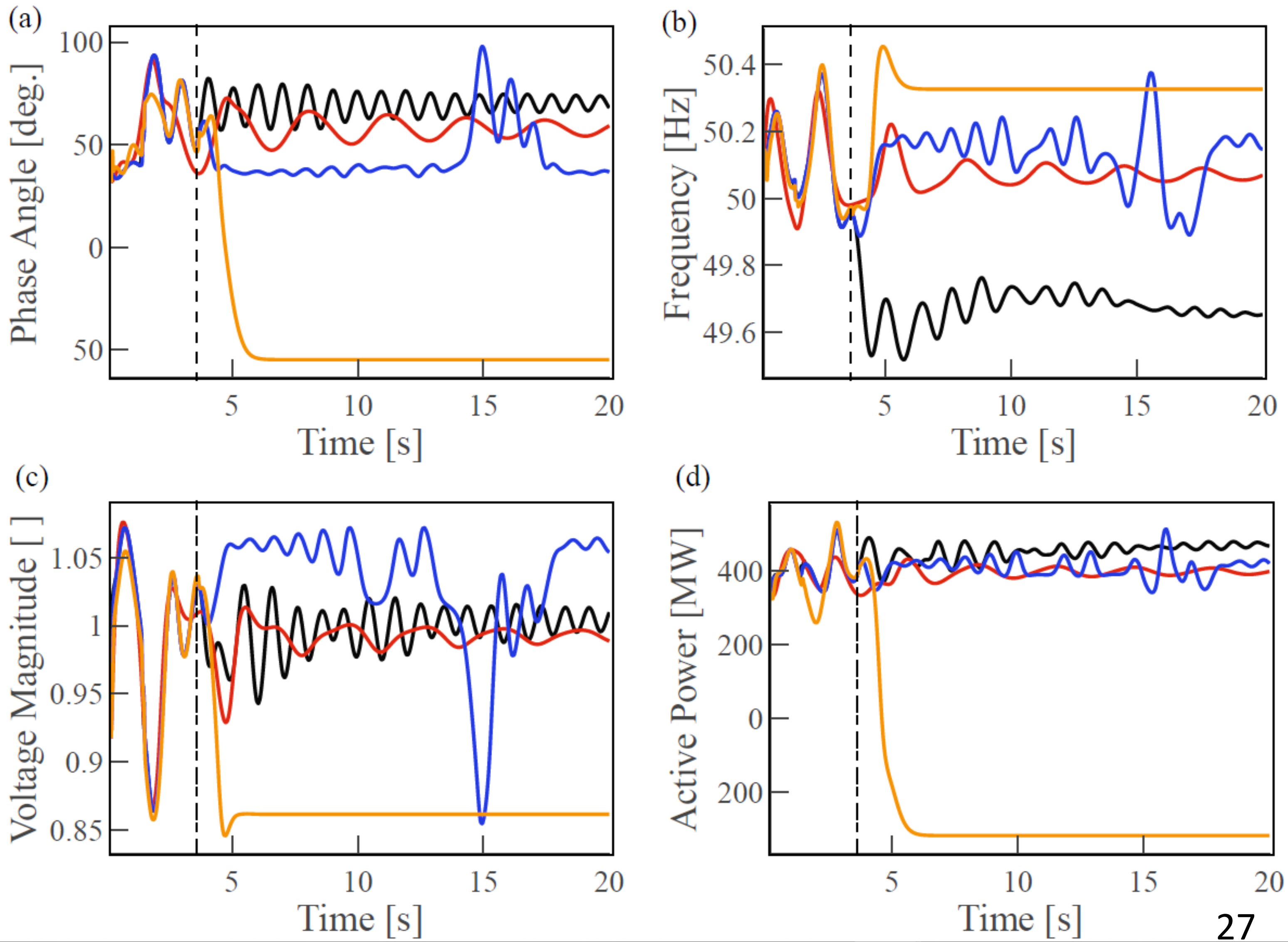
Case Study

- Assign NODE model for large generation units.
- Pretrain models using RMS.
- Re-train models with the postfault measurements.
- Assess the system security centrally using the decentralized predictions.

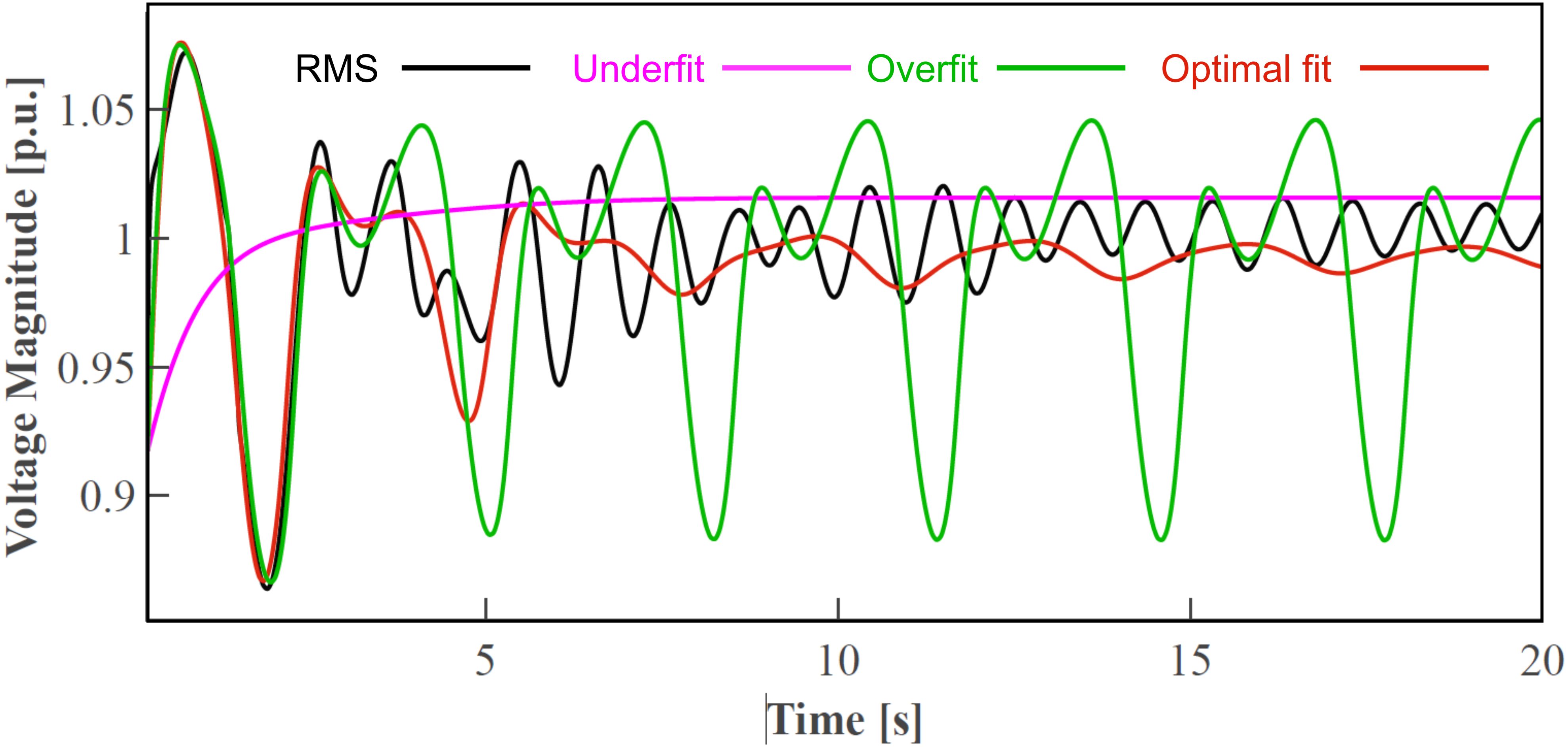


Regression Performance

- Black: RMS
- Red: NODE
- Blue: SVM-RBF
- Yellow: ANN



Fitting characteristics



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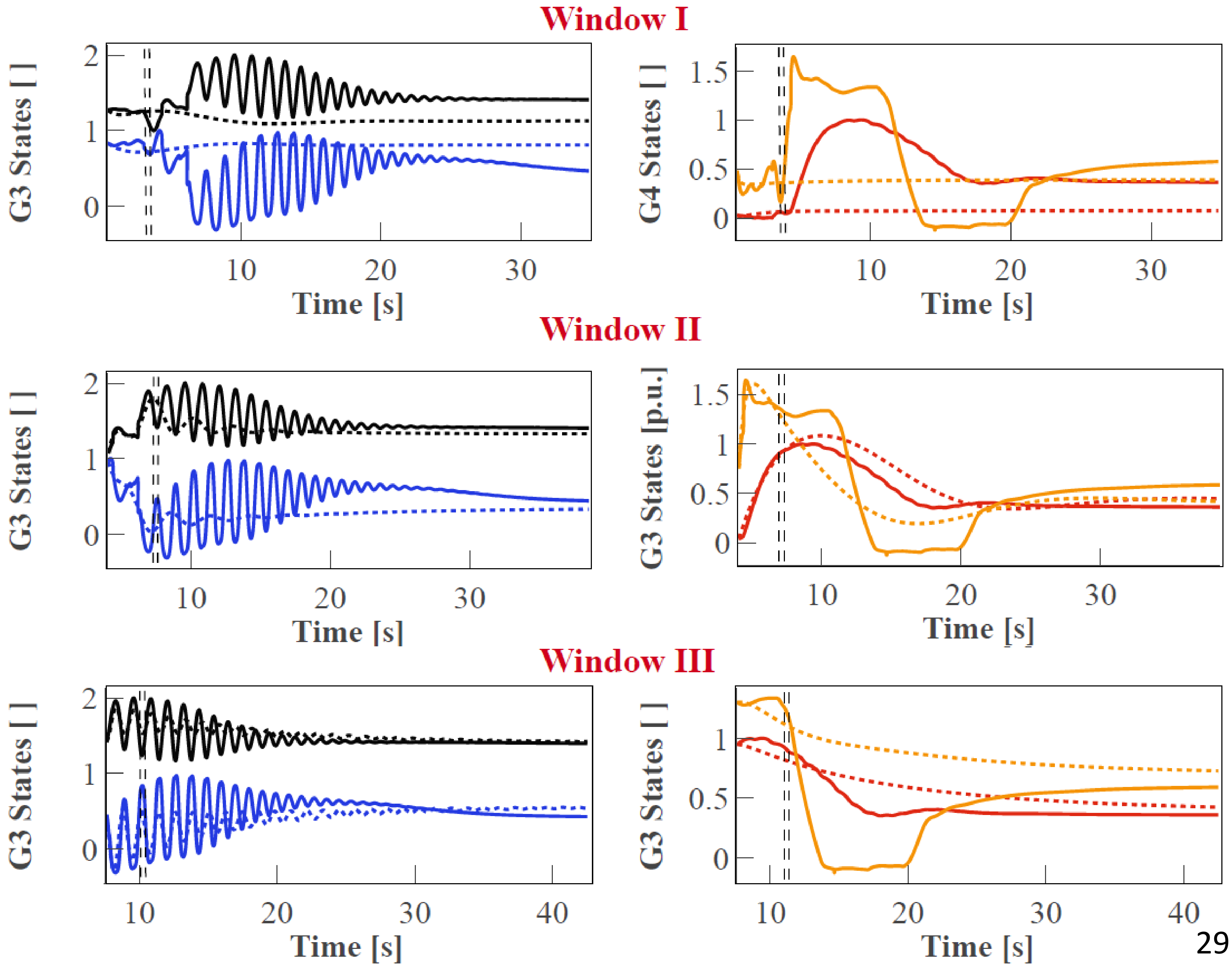
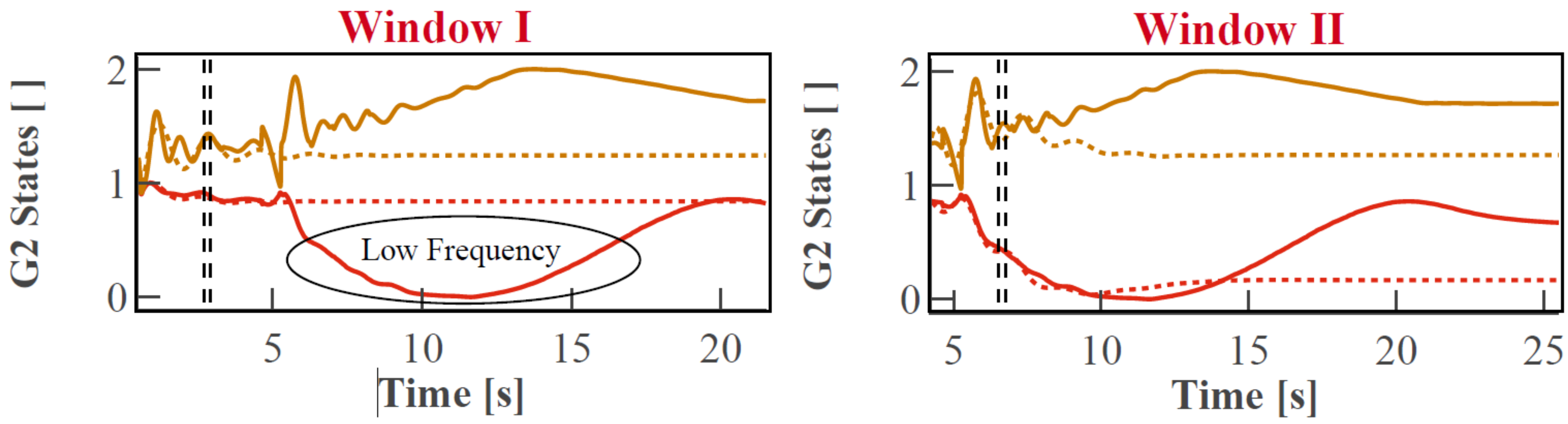
Regression - Cascading events

Solid lines: RMS
Dashed lines: NODE

Black: Rotor angle
Blue: Voltage magnitude
Yellow: Voltage magnitude
Red: Frequency



Regression -Cascading events



Solid line: RMS
Dashed line: NODE
Orange: Active Power Generation
Red: Frequency

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Conclusion

- NODE-approach can predict power system dynamics to some extent
- Approach can overcome barriers in ML for DSA: Generalization & data inefficiency
- Currently no alternative to predict dynamics in near realtime

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Future work

Scientific

- Identification of the optimal window size and sampling ratio for real power systems.
- Impact of the number and location of PMU units on DSA performance.
- Classification and activation of the optimal corrective control actions.
- Disturbance location estimation
- Investigation of the fast transient events (EMT domain) for inverter-based generation units.
- Online solver adjustment to handle stiff system responses.
- Pretraining based on the type of stability problem and system conditions (topology, dispatch).

Research & Development

- Development of the dynamics database with the existing simulation results and/or historical events.
- Implementation and tuning of the algorithm using the dynamics database.
- Analysis for the suitable processing unit near the substation (Microcontroller, FPGA, PC, etc.).
- Online testing of the trigger, training and forecast with the real system dynamics.
- Scenario construction and time study for corrective control actions considering the dynamics and training time scales.

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Thank you!

Speaker

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Associate Professor IEPG, TU Delft

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