



Machine Learning to Prevent Blackouts in Power Systems

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Session: Application of Big Data and AI/ML in monitoring, operations, planning and protection

Credits



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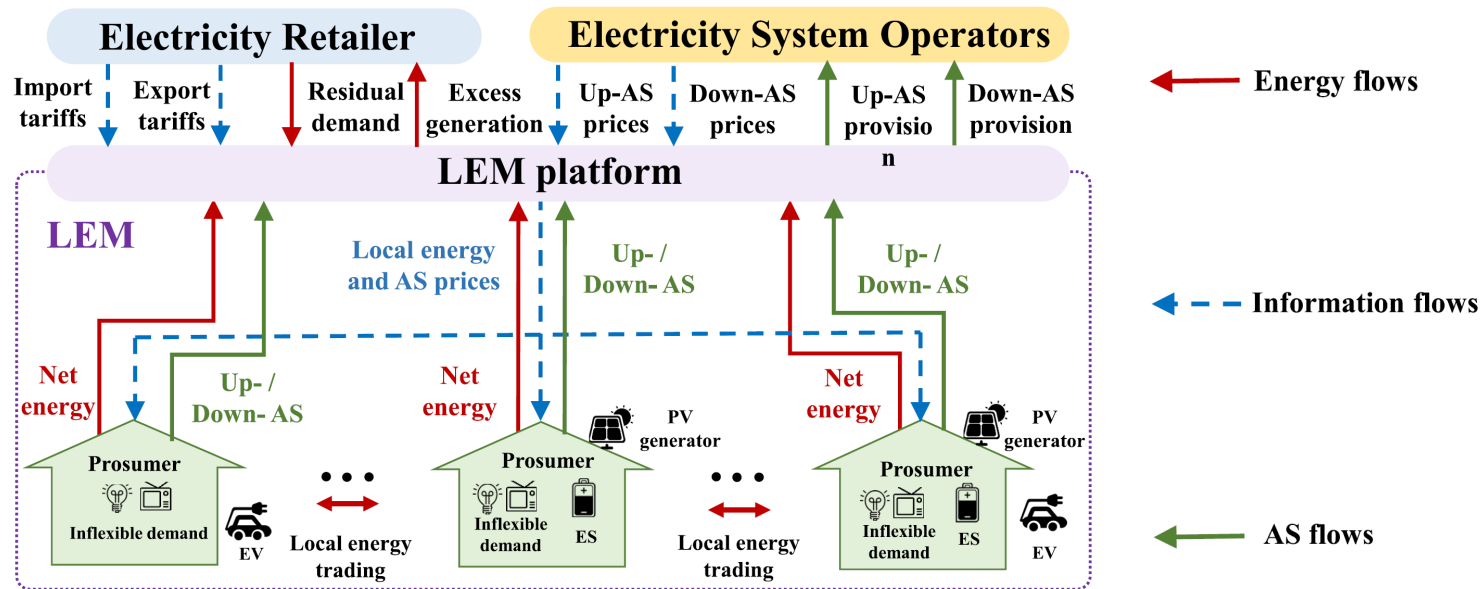


Fei Teng



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Cyber and physical risks for blackouts

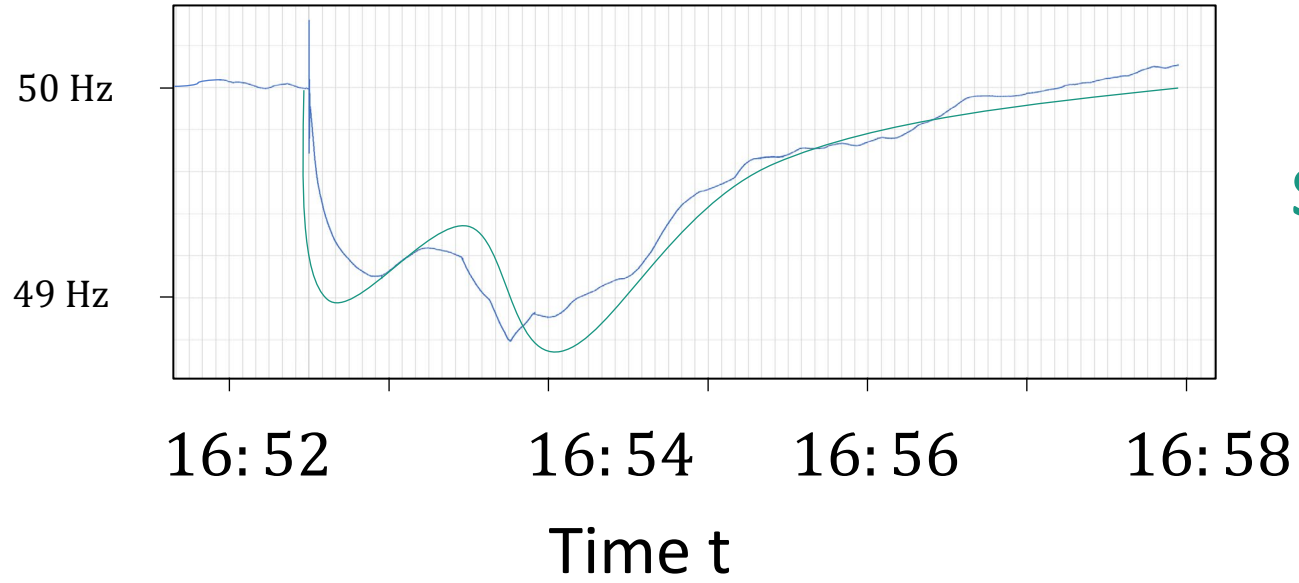


1. How to support dynamic security?
2. How to reduce cyber-security risks?

- Federica Bellizio, Wangkun Xu, Dawei Qiu, Yujian Ye, Dimitrios Papadaskalopoulos, Jochen L. Cremer, Fei Teng, and Goran Strbac. "Transition to Digitalized Paradigms for Security Control and Decentralized Electricity Market." *Proceedings of the IEEE*, 2022,
- Federica Bellizio, Al-Amin Bugaje, Jochen L. Cremer, and Goran Strbac. "Verifying Machine Learning Conclusions for Securing Low Inertia Systems." *Sustainable Energy, Grids and Networks*, 2022, 30, 100656.

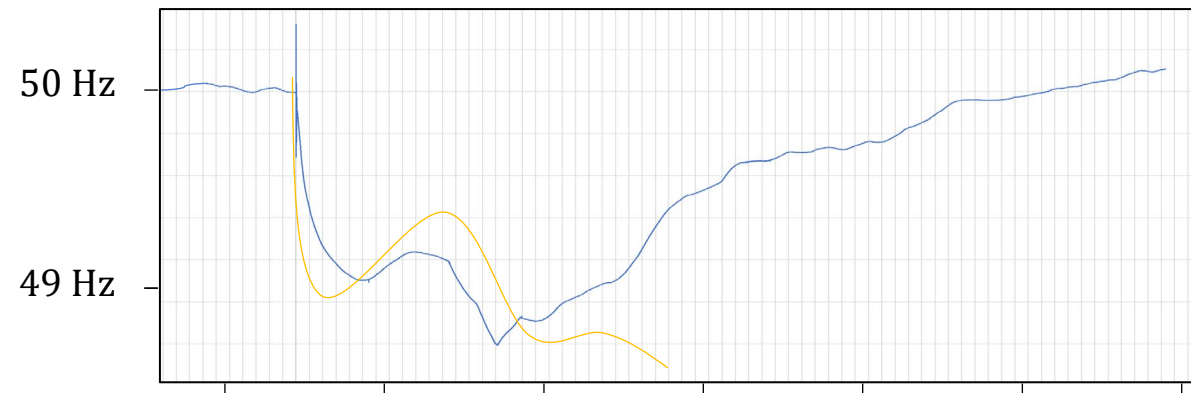
Real-time security in power systems

System frequency (Hz)



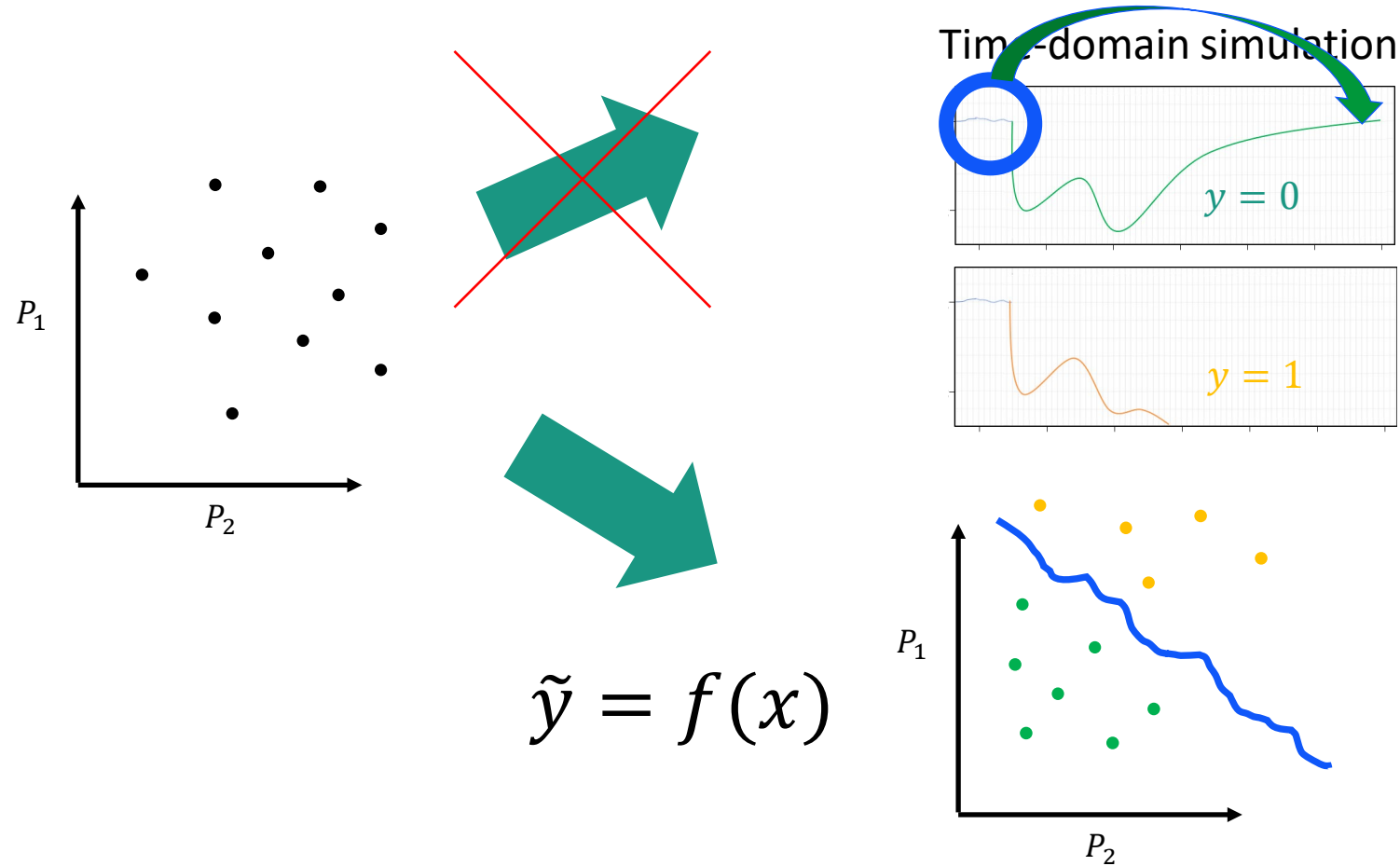
secure

$$y = 0$$



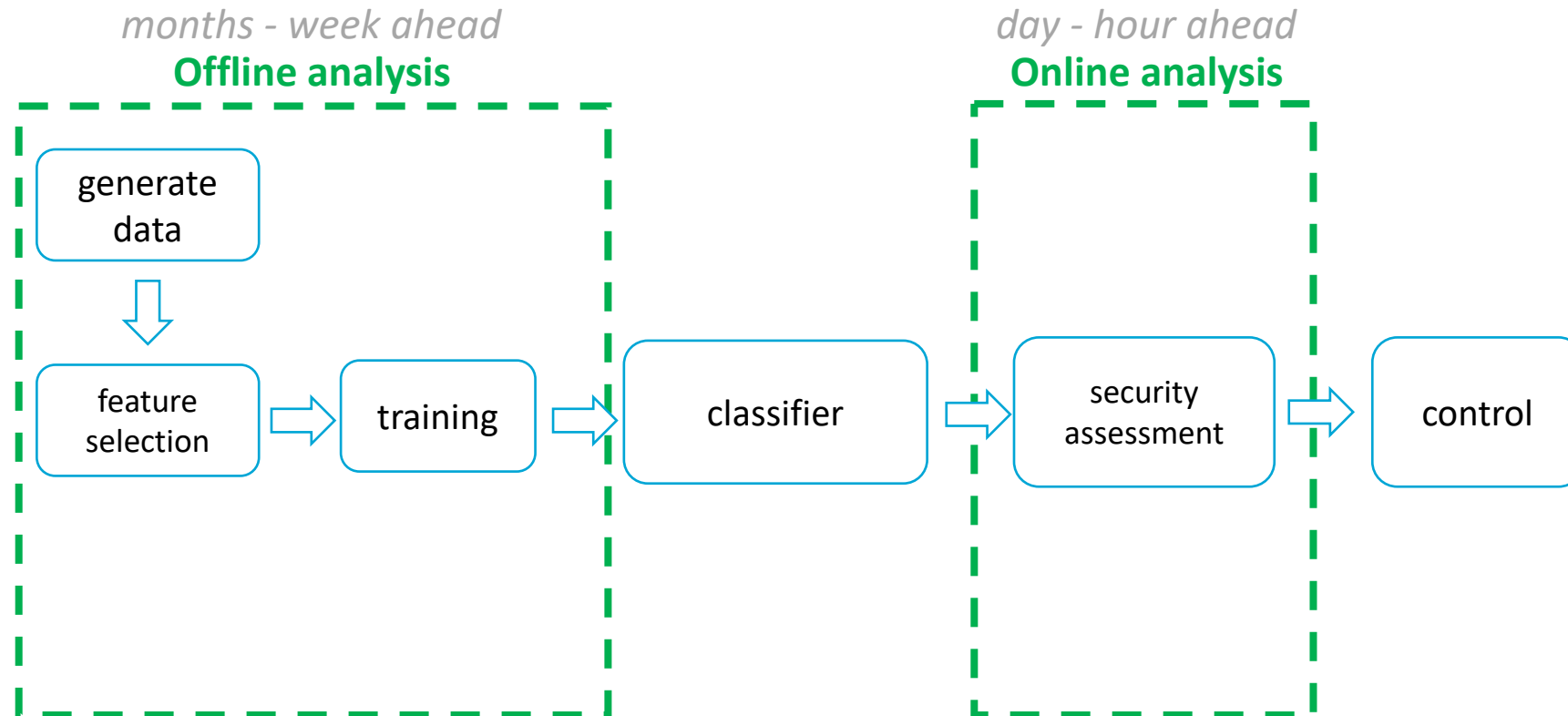
insecure $y = 1$

Machine learning for real-time DSA



How to train and use f ?

ML-based prediction and control



Supervised learning approach

Operating condition $\mathbf{x}_k = [\mathbf{x}_k^L, \mathbf{x}_k^G, \mathbf{x}_k^V]$

Assessment $f_a: (\mathbf{x}, B) \longrightarrow y_a = \begin{cases} 0 & \text{secure (negative)} \\ 1 & \text{insecure (positive)} \end{cases}$

Control $f_c: (\mathbf{x}^L, B) \longrightarrow \mathbf{y}_c = (\mathbf{x}_{OPT}^G, \mathbf{x}_{OPT}^V)$

Supervised learning

The ML approach learns approximation functions

$\tilde{f}_a: (\mathbf{x}, B) \longrightarrow \tilde{y}_a$

$\tilde{f}_c: (\mathbf{x}^L, B) \longrightarrow \tilde{\mathbf{y}}_c = (\tilde{\mathbf{x}}_{OPT}^G, \tilde{\mathbf{x}}_{OPT}^V)$

such that

$\|\mathbf{y}_a - \tilde{\mathbf{y}}_a\|_p, \|\mathbf{y}_c - \tilde{\mathbf{y}}_c\|_p$ are minimised

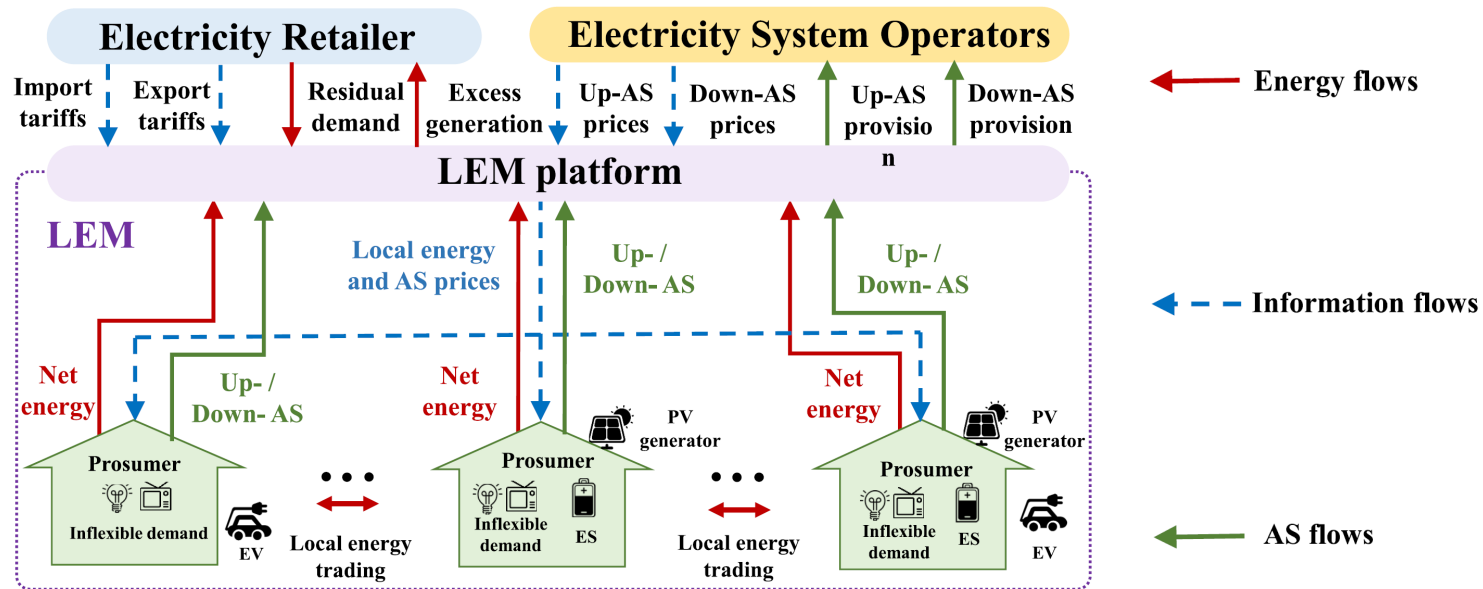


Highly nonlinear -> difficult to find, evaluate in real-time



Requires a large training database to create many (\mathbf{x}, B)

Cyber and physical risks for blackouts



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Cyber: False Data Injection (FDI) attacks on DSA

- Consider the power flow equations as $\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{e}$. The state estimation:

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \left\| \mathbf{R}^{-\frac{1}{2}} (\mathbf{z} - \mathbf{h}(\mathbf{x})) \right\|_2^2$$

- An FDI attack can be formulated by directly injecting on the estimated state:

$$\mathbf{a} = \mathbf{h}(\hat{\mathbf{x}} + \mathbf{c}) - \mathbf{h}(\hat{\mathbf{x}})$$

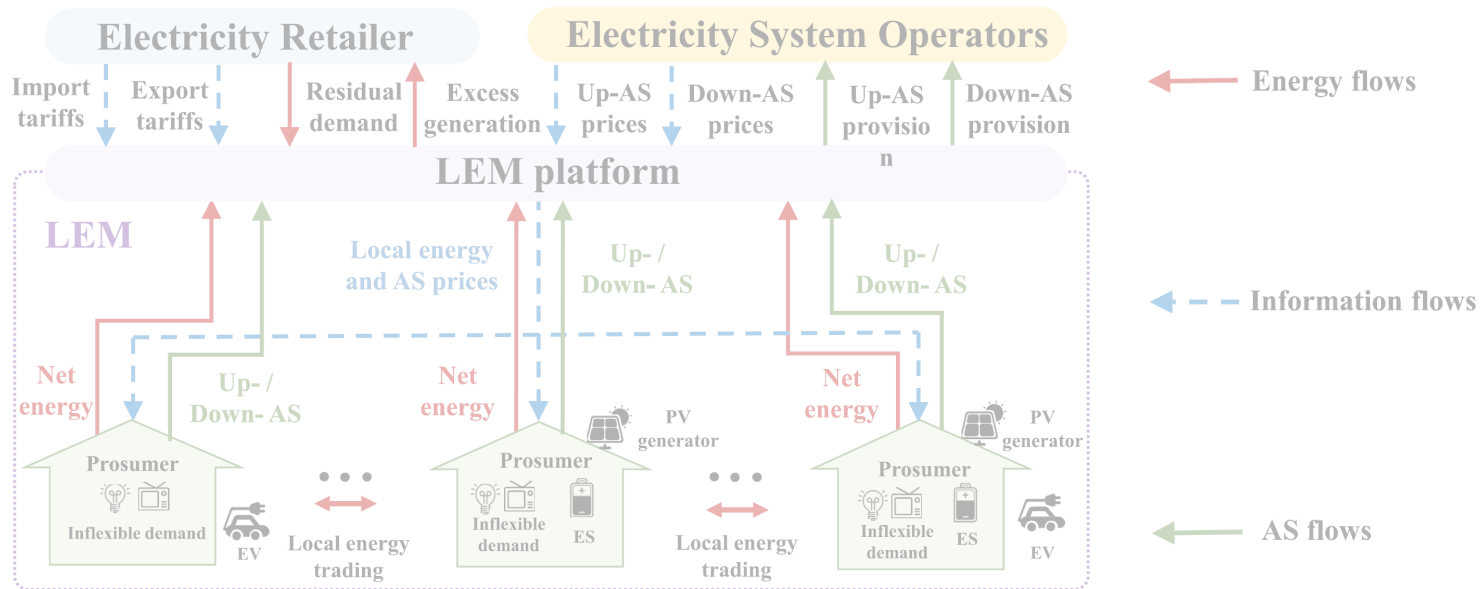
- This attack cannot be detected due to the unchanged residual

$$\begin{aligned} \gamma_a &= \left\| \mathbf{R}^{-\frac{1}{2}} (\mathbf{z}_a - \mathbf{h}(\hat{\mathbf{x}}_a)) \right\|_2^2 \\ &= \left\| \mathbf{R}^{-\frac{1}{2}} (\mathbf{z} + \mathbf{h}(\hat{\mathbf{x}} + \mathbf{c}) - \mathbf{h}(\hat{\mathbf{x}}) - \mathbf{h}(\hat{\mathbf{x}} + \mathbf{c})) \right\|_2^2 \\ &= \gamma \end{aligned}$$

Defense on the attack

- **Moving target defence (MTD):** the system operator can proactively change the grid's parameter (e.g., reactance) so that the attacker cannot launch a perfect attack.
- Data-driven approach builds a detection model based on normal measurement. An attack alarm is raised if the residual is higher than the predefined threshold.
- A combined data-triggered MTD is proposed
 - High TPR and low FPR can be achieved

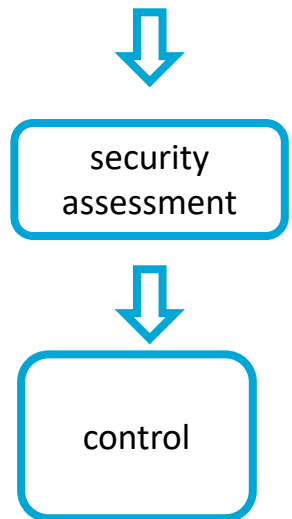
Case studies



1. Support dynamic security
 - A. in low-inertia systems
 - B. with LEMs
2. Reduction of cyber-security risks

Dynamic security with corrective LEM

IEEE 9 bus system, security of four control approaches, 25% wind power, Integral Square Generator Angle index (ISGA), $ISGA \leq 0.5$



Supervised learning

$$\tilde{f}_a : (\mathbf{x}, B) \longrightarrow \tilde{y}_a$$

$$\tilde{f}_c : (\mathbf{x}^L, B) \longrightarrow \tilde{\mathbf{y}}_c = (\tilde{\mathbf{x}}_{OPT}^G, \tilde{\mathbf{x}}_{OPT}^V)$$

$$\tilde{f}_c : (\hat{\mathbf{x}}_{a1}, B) \longrightarrow \tilde{\mathbf{y}}_c = (\tilde{\mathbf{x}}_{OPT}^G, \tilde{\mathbf{x}}_{OPT}^V)$$

$$\tilde{f}_c : (\hat{\mathbf{x}}_{a2}, B) \longrightarrow \tilde{\mathbf{y}}_c = (\tilde{\mathbf{x}}_{OPT}^G, \tilde{\mathbf{x}}_{OPT}^V)$$

Approach	Insecure OCs
No control	928/1000
Centralised control with LEMs	95/1000
Attacked centralised corrective	204/1000
Attacked decentralised corrective	148/1000

Reducing cyber-security risks

- **Issue:** Attacker launches FDI attacks on the voltage magnitude to mislead the security assessment.
- **Approach:** A combined data-triggered MTD

	Data-Driven Detector	Data-Triggered MTD
TPR	98.9%	97.5%
FPR	0.71%	0.12%

High TPR and low FPR

Conclusions

- Neural networks can predict dynamic security using estimated operating conditions but require lots of training data (**limitation**)
- **Corrective control improves dynamic system security**
- Cyber-attacks **can make the system 2-times more dynamically** insecure
 - Centralised attacks are worse than decentralised attacks
 - Attacks on local measurements can influence prosumers

Contact & references

Speaker



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Collaborators



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- Xie, H., Bellizio, F., Cremer, J.L. and Strbac, G., 2023. Regularised Learning with Selected Physics for Power System Dynamics. IEEE PES Belgrade Powertech, 2023.
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Thank you!

Dynamic security in low-inertia systems

IEEE 14 bus system, transient stability, 40% renewable generation, data: 10.000 OCs, train/test = 70%/30%



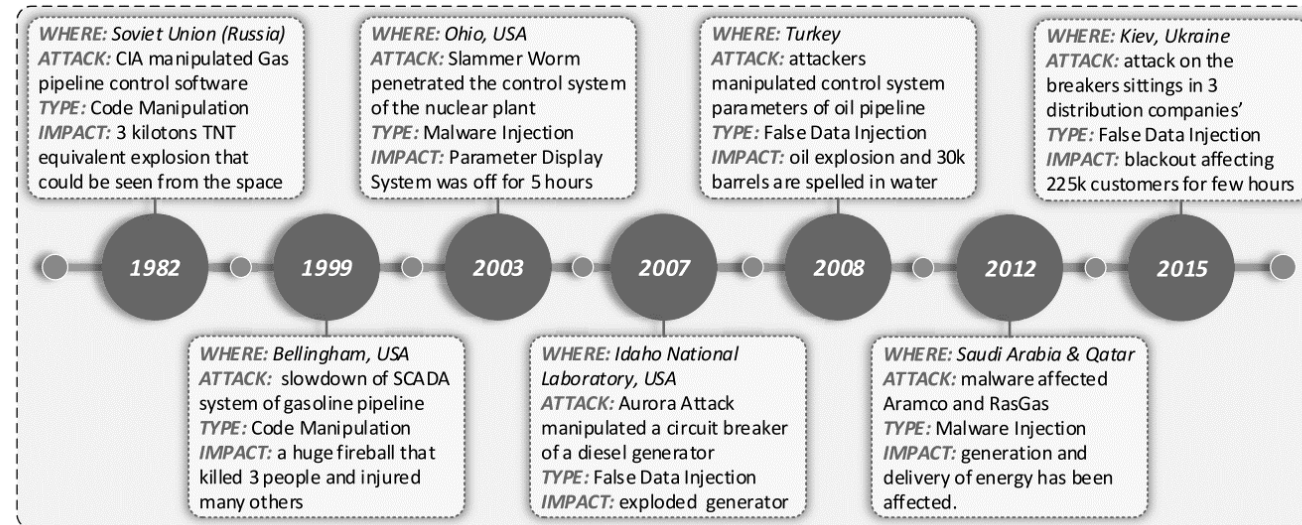
Features		Power generation s	Power loads	Voltage angles	Voltage magnitudes
HI system	F1-score	65%	46%	43%	43%
	$I(X; Y)$	0.5	0.5	0.6	0.5
LI system	F1-score	99%	97%	93%	96%
	$I(X; Y)$	1.7	2.4	4.7	1.6

Model types	DT	SVM	XGBoost	ANN
HI system	59%	55%	63%	63%
LI system	99%	97%	99%	99%

Scores	$\frac{N^+}{N^+ + N^-}$	$I(X; Y)$	Accuracy	F1-score
HI system	0.7	2.1	75%	59%
LI system	0.2	10.4	98%	99%

Cyber security

- Advances in computation and communication have transformed the power system into a compound cyber-physical system (CPS).
- This new trend raises concerns about CPS vulnerability.



1. False data injection (FDI) attacks against dynamic security assessment
2. Attacks on the local energy market.