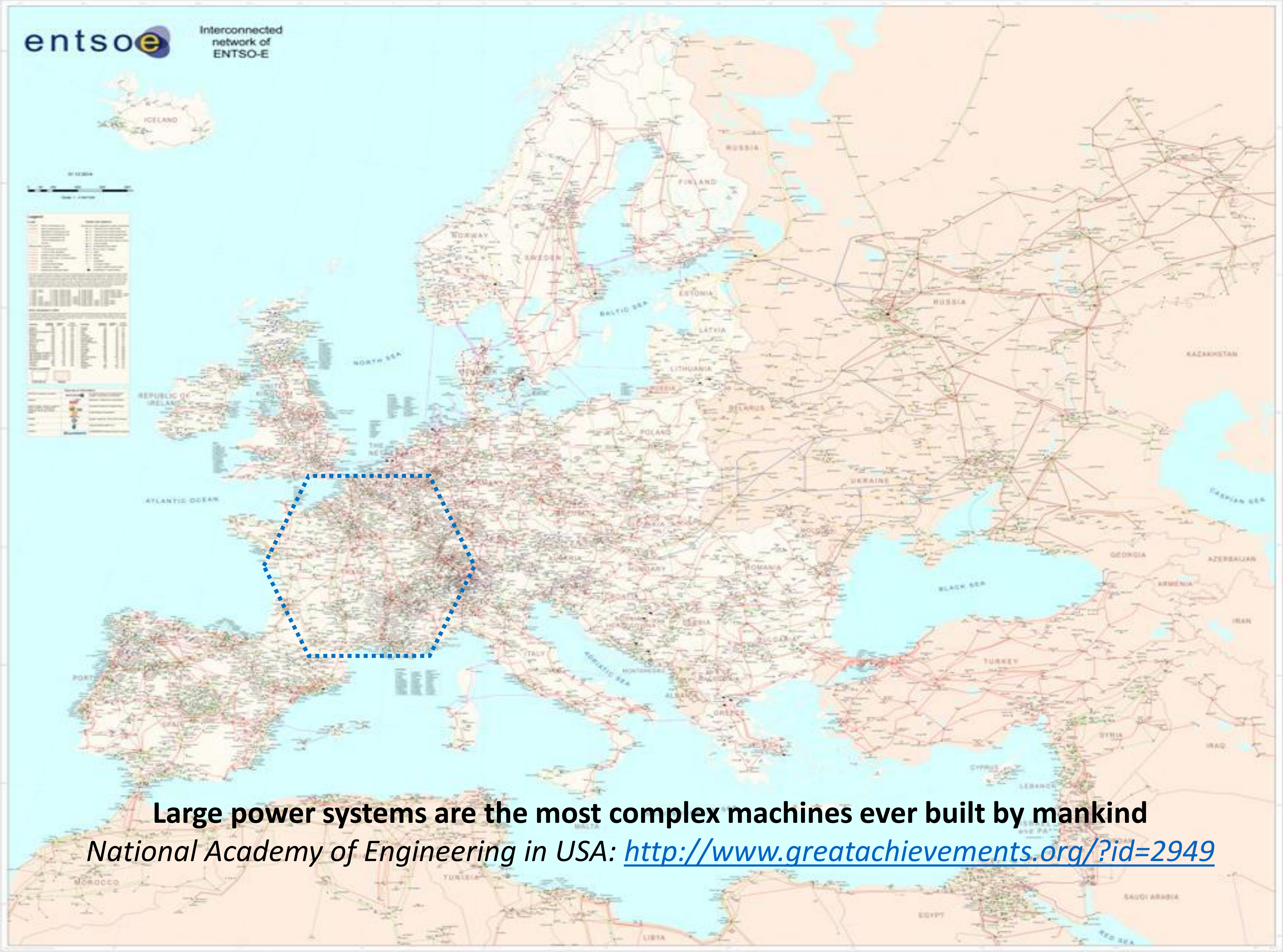
IEEE PES Power & Energy Society® | IEEE

Topology aware Machine Learning for Transmission System Operation

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

July 19th IEEE PES GM Orlando

Patrick Panciatici*, Balthazar Donon, Lucas Saludjian (RTE France)



Large power systems are the most complex machines ever built by mankind

National Academy of Engineering in USA: *http://www.greatachievements.org/?id=2949*

Energy Transition

➔ Increasing complexity

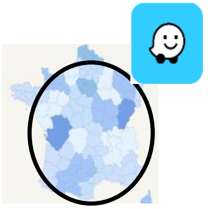
- Smaller distributed generating units connected to the grid through power electronics: new dynamic behavior, reduced observability and controllability
- Solutions: challenging our traditional assumptions *“inflexible load, no storage”*
  Active consumers (prosumers), electrical batteries, electrolyzers (H_2)? …

Our mission remains to keep the lights on in a large interconnection: balancing, congestion management, stability... with a required level of reliability defined by the regulatory authorities.

➔ Coordination of large population of devices/agents with some partial autonomy but still integrated with large generating units : Nuclear, Hydro, Offshore Wind and Interconnectors (AC, HVDC)

A new control Architecture

Cyber Physical System of Systems



Optimize

CENTRALISED CONTROLS – OPTIMIZATION
View : global & anticipative in control center room
Goals : anticipated set-points = coordination layer + preventive action and human in the loop!

Smart assistant

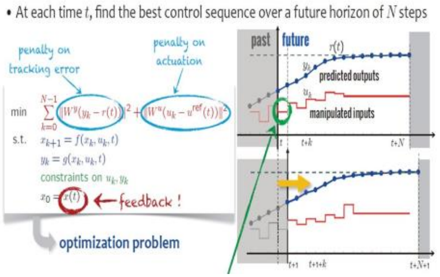
Control

Cyber Physical System

AREA CONTROLS

NEW

Autonomous Area : substations (~10)
Curative actions
Goals : closed loop control - using Model Predictive Control + applying actions while following set-points received from higher layer



Automatic actions

Protect

SUBSTATION PROTECTIONS
In a substation
Goals : ensure last resort equipment and person protection
Simple & Reliable

Top layer: Coordination

Optimal trajectory and setting: Very complex optimization problems

Decision making process: Preventive actions taking into account uncertainties but also all embedded controllers and last time to decide constraints while ensuring the required reliability level.

Last time to decide: time is needed to implement some actions

- Purchase reserves on market platforms (day ahead to few hours ahead)
- Postpone planned outages (cost ↑ when approaching real-time)
- Must run generators (mostly day ahead) ....

➔ *Machine Learning can help us to solve these optimization problems efficiently: assistant suggests actions to operators*

The grid topology is not static!

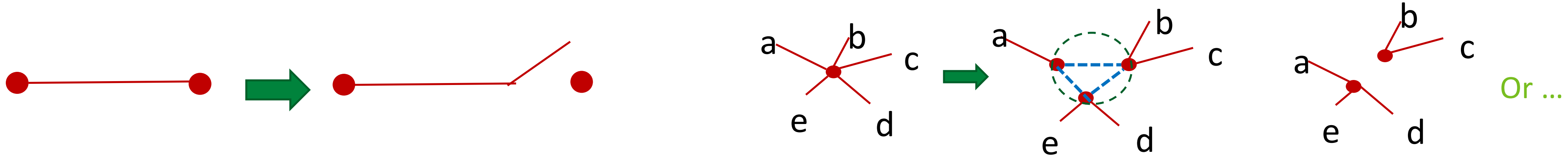
Efficient levers: Substation Reconfiguration and Optimal Switching

- The grid topology changes due to planned or unplanned (faults) outages!

✓ *Without knowledge of the grid topology ➔ wrong decisions*

- Moreover substation reconfiguration and optimal switching are efficient levers almost cost less actions, fast and easy to implement (for a TSO, Transmission Owner)

✓ *Without topological actions ➔ sub optimal decisions,*



➔ Any machine learning approach applied to power systems must take grid topology into account.

Topology aware Machine Learning

Limitations of fully connected neural networks !

- Too many papers don’t explain that the learning is done for one given grid topology and must be re-run in case of topology changes ➔ *impossible to use this kind of model for operating a real transmission system*

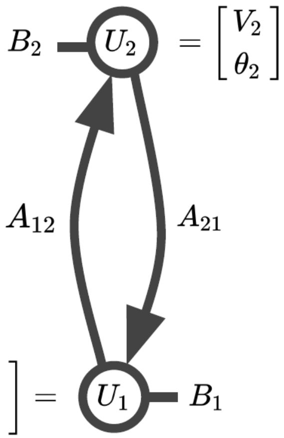
➔ Power grid model: Graph !

Inputs

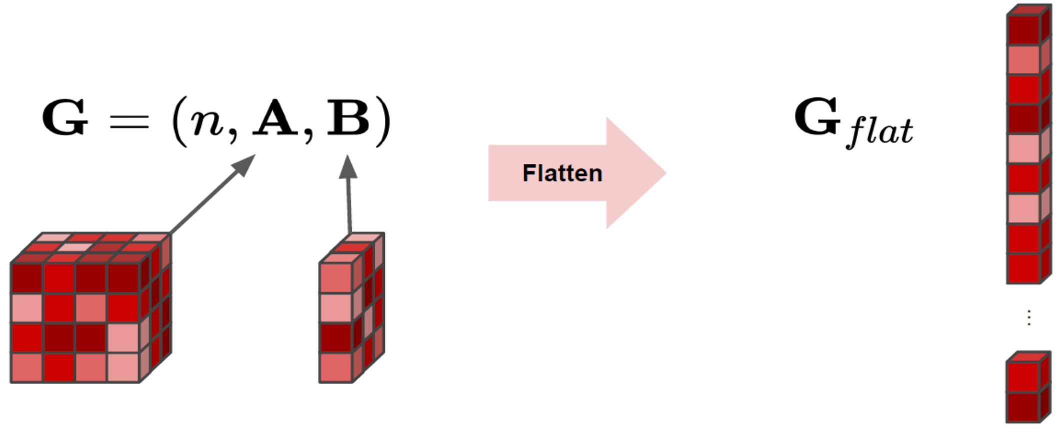
$$\mathbf{G} = (n, \mathbf{A}, \mathbf{B})$$

Outputs

$$\mathbf{U} = (U_i)_{i \in [n]} \qquad ; U_i \in \mathbb{R}^{d_U}$$



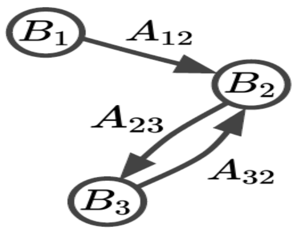
Fully connected neural networks only work on vectors



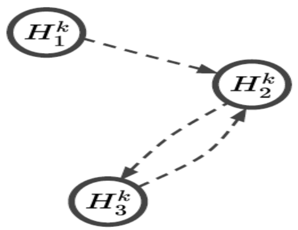
Graph Neural Network

Topology aware Machine Learning

$$\mathbf{G} = (n, \mathbf{A}, \mathbf{B})$$



Latent representation

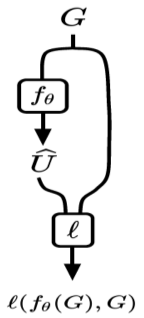


GNN(θ)

$$H_i^{k+1} = H_i^k + \Psi_\theta^k(H_i^k, B_i, \textstyle\sum_{j\in\mathcal{N}_i} \Phi_\theta^k(H_i^k, H_j^k, A_{ij}))$$ Message passing

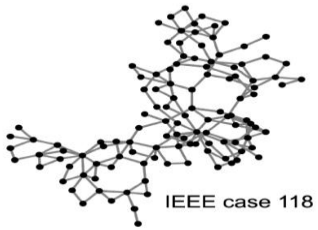
Where $\Psi_\theta^k, \Phi_\theta^k, \Xi_\theta$ are Neural Nets(θ)

$$\widehat{U}_i = \Xi_\theta(H_i^{\bar{k}})$$ Decoding



$$\theta^* = \underset{\theta\in\Theta}{\arg\min}\ \mathbb{E}_{\mathbf{G}\sim\mathcal{D}}[\ell(f_\theta(\mathbf{G}), \mathbf{G})]$$

Test case:
Proxy of power flow
Minimization of the violation of the laws of physics



- **Speed up : 2 or 3 orders of magnitude**
- **Acceptable accuracy**
- **Impressive generalization capabilities** *change of conditions but also addition/removal edges or vertices in the graph*

"Deep Statistical Solvers": B. Donon and Z. Liu, Zhengying, Liu, Wenzhuo, I. Guyon, A. Marot, Antoine, M. Schoenauer, Advances in Neural Information Processing Systems, Neurips 2020

Example of one ongoing work at RTE

Tertiary voltage control using topology aware ML

Collaboration with the University of Liège (Belgium).

Many types of voltage controls embedded in the system: *On Load Tap Changer, Static Var Compensator, Automatic Capacitor/Reactor Switching, Secondary Voltage Control controlling AVR ...*

➔ Improvement of the tertiary level which provides set points and/or initial conditions to the embedded controllers.

- *Voltage set points for OLTCs, SVCs, for pilot points of SVC-AVRs*
- *Limits for ACRS*
- *Initial state for Capacitor/Reactor banks (on/off)*

Approaches based on AC optimal power flow: not robust enough, not fast enough

➔ *Assistant based on topology aware (GNN) reinforcement learning*

My main take-away messages

to discuss today …

- Any machine learning approach applied to power systems must take grid topology into account.
- Graph Neural Networks seem to be good candidates to provide efficient solutions: a step towards “Physics informed Machine Learning”

➔ Thank you for attention: *Patrick.Panciatici@rte-france.com*