Physics-aware Machine Learning for the Operation of Electric Power Systems

Louis Wehenkel

Institut Montefiore,
Department of Electrical Engineering and Computer Science,
Université de Liège, Liège, Belgium.

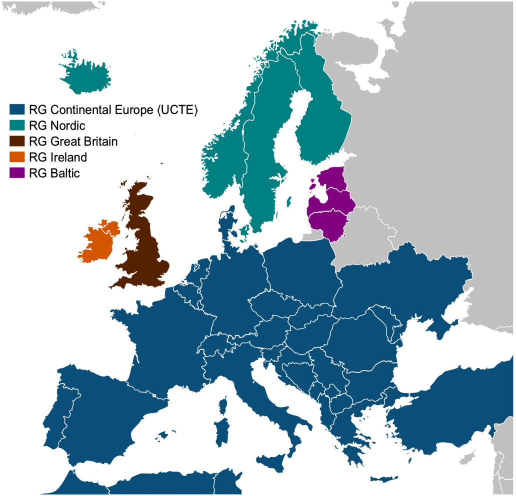
Academia Europaea Workshop on AI Challenges for European Research and Academia, Imperial College, London UK, September 4-5, 2024

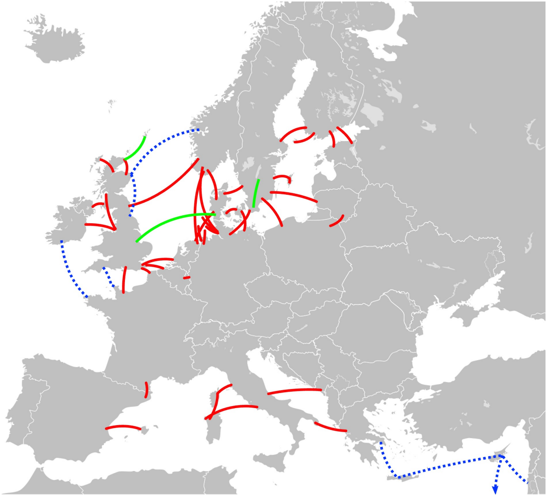
Overview

- Background & Motivations
- Methodology & Implementation
- Case study on the French transmission system (RTE)

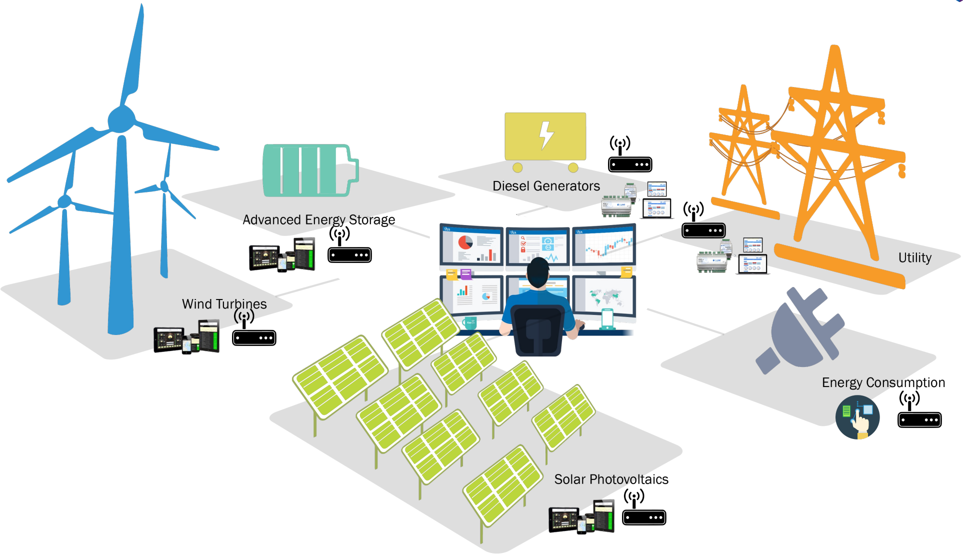
Background & Motivations

Large-scale electric power systems are in rapid transition...

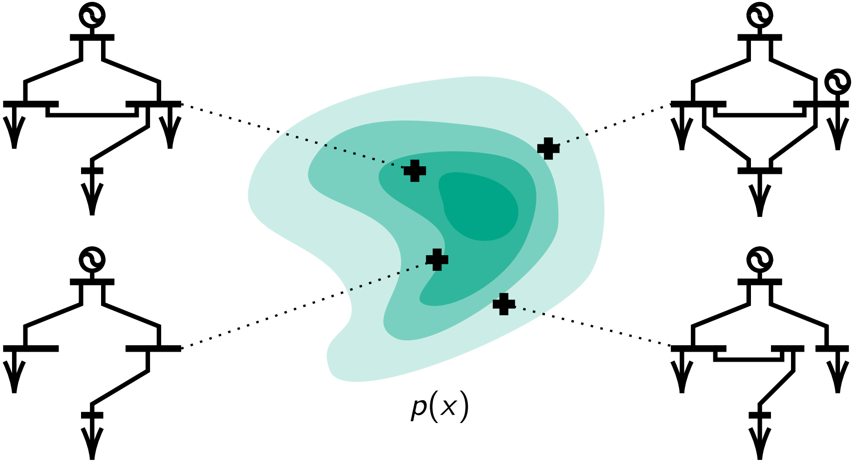




... and they are more and more cyber-physical



Electric power systems have a highly variable topology



Electric power systems have a highly variable topology

The topology changes significantly over time because of the following reasons:

- **Exogenous:** generator dispatch driven by weather conditions and market clearing mechanisms; automatic protections that open breakers to clear faults induced by weather storms, human errors, or adverse attacks; new generators and new customers becoming connected to the grid

- **Endogenous:** planned grid component outages for maintenance activities; operator actions aiming to improve system security; new grid components being put in operation

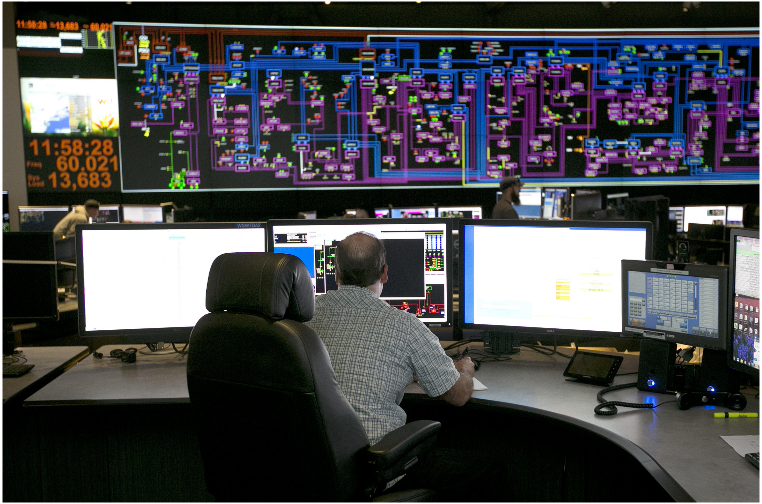
NB: Together with the loading level of the different components and the settings of their control devices, the topology defines the **power system operating condition** x.

Electric power systems have extremely high reliability requirements

- Avoid blackouts, maximise resilience, meet QoS standards
- Redundant system architecture, operated so as to be fully robust w.r.t. to the failure of any single component
- Hierarchical control structure
  - **Primary:** plant level, automatic, fast (milliseconds), protect equipment
  - **Secondary:** zonal level, automatic, slower (seconds), coordinate primary controls
  - **Tertiary:** system level, human operator in the loop, even slower (minutes), optimise settings of secondary and/or primary controls, and modify grid topology

NB: in France 7 regional control centres and 1 national control centre; in Europe about 40 'national' control centres.

Target of this work: leverage modern AI techniques to support EPS operators (tertiary control)



Building on available resources from the EPS world

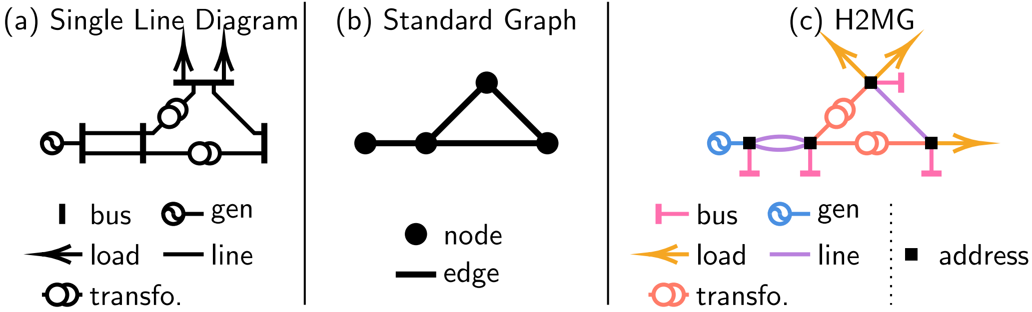
- Rich and real (but private) observational datasets:
  - Snapshots of actual operating conditions collected in real-time, e.g. every 5 seconds
  - Forecasts of operating conditions used by operation planners, e.g. every 60 minutes
- Strong physical models:
  - A variety of well documented static and dynamic physical models
- Tools:
  - Simulation and optimisation software and high performance computers
  - Simplified and artificial (but public) benchmark datasets
- Human expertise:
  - Operators, planners, R&D

Meeting actual needs

- Operator friendlyness
- Incorporation of all kinds of available physical knowledge, models, and data
- Proposing all kinds of suitable control decisions to operator
- Robustness w.r.t. all kinds of topology changes
- Adaptability to the profound changes induced by the energy transition
- Transportability to different classes of systems and decision and control problems

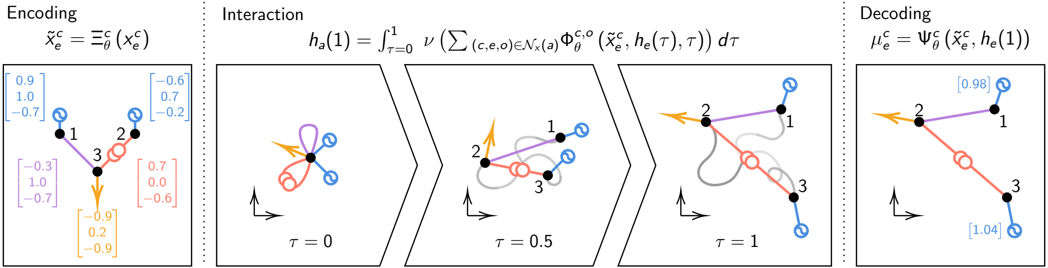
Methodology & Implementation

Data model: Hyper-Heterogenous Multi-Graphs (H2MG)



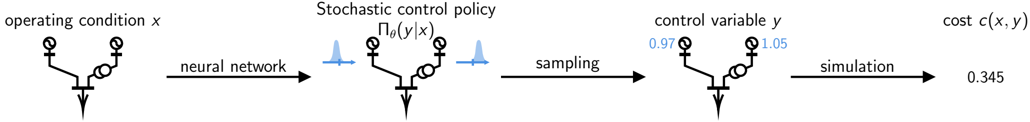
Standard graphs are made of nodes and edges, and require to aggregate together objects of different natures, while our proposed H2MG formalism allows for a seamless representation of power grid operating conditions; addresses are used to connect ports of hyper-edges.

Inference model: H2MG-NN with NODE coupling layer



The feature vectors of all hyper-edges are embedded into a latent space using class-specific encoders Ξ_θ^c. All addresses are associated with latent coordinates initialised at zero, and then follow a trajectory defined by a differential system whose second member involves couplings born by hyper-edges and defined by neural networks. Addresses interact until $\tau = 1$. Finally, hyper-edges exploit the final locations of their addresses to produce a meaningful prediction thanks to class-specific decoders Ψ_θ^c.

Machine learning approach: REINFORCE algo



A power grid operating condition x is passed as input to a H2MG-NN model which outputs a probability distribution $\Pi_\theta(y|x)$ for the vector y of control variables. Values for y can thus be sampled, and passed to the cost function $c(x, y)$ evaluated by a physical simulation.

At each iteration of the REINFORCE algo, several physical simulations with different (x, y) combinations allow to estimate a gradient descent direction w.r.t. θ to improve the control policy $\Pi_\theta(y|x)$, i.e. to search for

$$\theta^* \in \arg\min_{\theta \in \Theta} \mathbb{E}_{\substack{x \sim p(\cdot) \\ y \sim \Pi_\theta(\cdot|x)}} [c(x, y)] \, .$$

Summary

The proposed machine learning framework has a strong physics-awareness:

- Rich data model, allowing to encode at the input and output of the H2MG-NN all the physically relevant features for the problem under consideration
- 'Near optimal' control policy learning based on a sample of physically meaningful operating conditions, representative of the life of the system in terms of exogenous and endogenous sources of variability
- Learning and validation based on the use of already existing simulators faithfully modelling the physical phenomena for the problem of concern
- The overall approach is free of any 'smoothness' assumptions (not explained in this talk) and therefore applicable to discrete and continuous controls and non-differentiable physics simulators

Scientific Publication

For further details about the methodology and simulations results on a public benchmark power system model, please see:

Topology-aware Reinforcement Learning for Tertiary Voltage Control
Donon, B.; Cubélier, F.; Karangelos, E. et al. *Proc. of PSCC*, 2024

https://hdl.handle.net/2268/315490

Case study on the French transmission system (RTE)

Tertiary voltage control in the Toulouse Region

- South-West part of France
- About 1200 buses, 1600 branches
- Dataset of 15000 day-ahead planning snapshots collected over 2 years
- Topology dependent continuous and discrete control variables:
  - up to 70 Shunts (on/off)
  - up to 70 Transfo set-points (discrete)
  - up to 7 Secondary Voltage Control set-points (continuous)
- Use of cloud computing and RTE in-house physics simulator
- **First results are very promizing**

Ongoing work

- Strengthening the methodology and its implementation
- Application to other practical problems
- Towards industrialisation

Acknowledgements

This work was carried out through a research collaboration between ULiège and RTE-France, by a team composed of

B. Donon, F. Cubélier, E. Karangelos, and L. Wehenkel, from ULiège
and
L. Crochepierre, C. Pache, L. Saludjian, and P. Panciatici, from RTE-France

The authors would like to thank Vincent Barbesant and Florian Benoit for insightful discussions about the tertiary voltage control problem, Rémy Clément and Marc Schoenauer for their help in formalising the H2MG approach, and the operators of the Alan GPU cluster at the University of Liège.