30/05/2018

Assisting control room operators with Artificial Intelligence

Antoine Marot – RTE R&D

AI & Power System

« Artificial Intelligence is the new electricity », Andrew Ng

Litterally, AI is an electricity
So, is Electricity already an AI ?
It is true that power systems are probably the most complex artificial systems on Earth!

But why are we talking of new **Smart Grids** to tackle the current Energy Transition ?
Surely we need to manage a more complex system with greater intelligence

Can AI be of any help here?

01

Rethinking control room Human-Machine Interfaces

OF THE POWER OF INTERFACES

Deep Blue beat Kasparov

Unlike the ancient Greek centaur, this centaur was coined ~ 20 years a

The story begins in New York City with a famous chess championship
Between IBM's Deep Blue supercomputer & chess grandmaster Garry

Centaur beats Gra

As it turns out, for the last decade, the world's best chess players have essentially become centaurs.
Since 2005, championships where grandmasters, supercomputers and Centaurs participate, have started being won by centaur players.
Centaurs are generally equipped with consumer PCs, not supercomputers.
By combining human intelligence with technological intelligence, these players tend to outplay either.

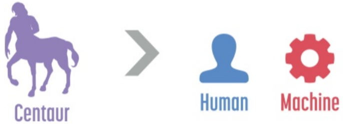
Amazon acts similarly when routing workers throughout their warehouse. The system has data on workers location through custom technology. Workers follow instructions on which isle to visit, or which robot to hand parcels over to. Amazon even measures the height of each employee to make sure they're optimized for each product pickup.

http://mentalfloss.com/article/61249/13-secrets-amazon-warehouse-employees

Kasparov: « machines still need human guidance to play better & … **eir interface** ».

operators to outperform a machine or

within
yers




Great Interface

scorpiopartnership

For better ….

Either, Human Only

Or… Machine only

+

Great Interface

CONTROL CENTERS TODAY

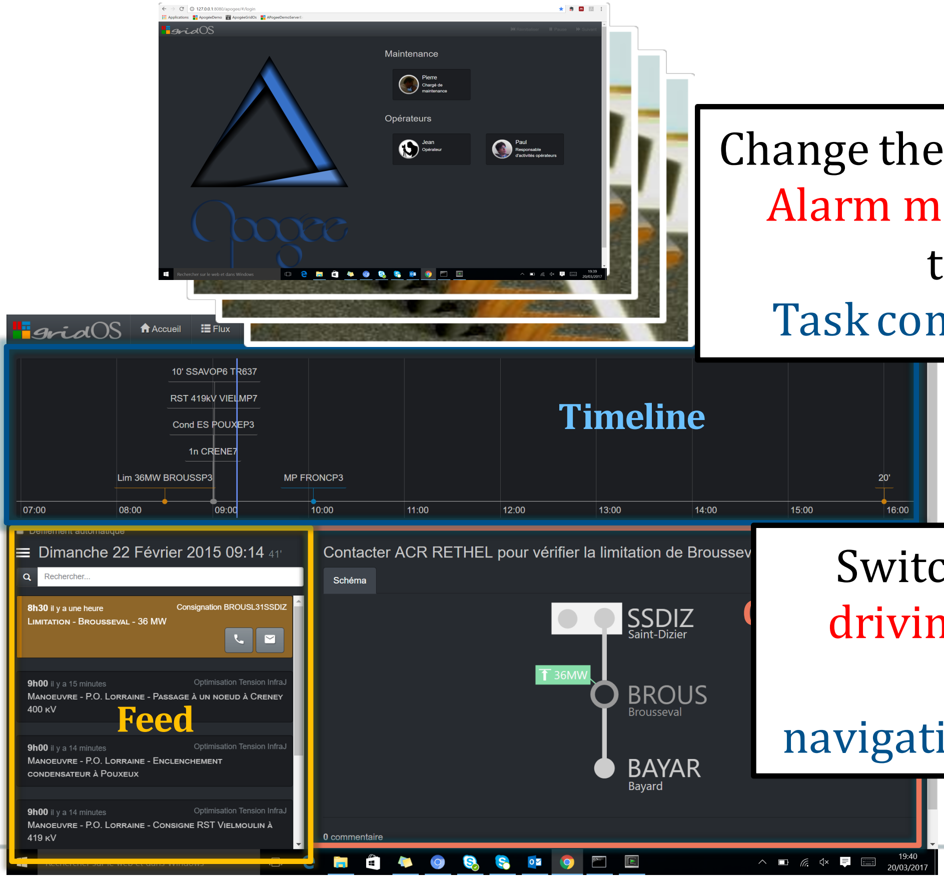
What about one more screen …?

AND TOMORROW ?

Yes, it is about thinking of a whole new interface …

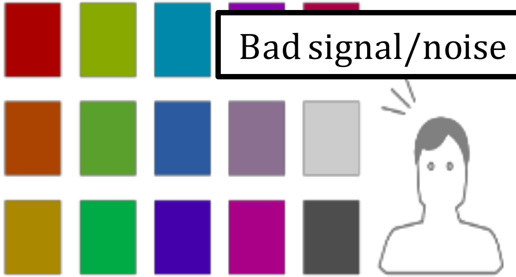
… But it is first a question of **strategic information management**

OUR PROJECT : APOGEE



Change the focus from
Alarm monitoring
to
Task completion !

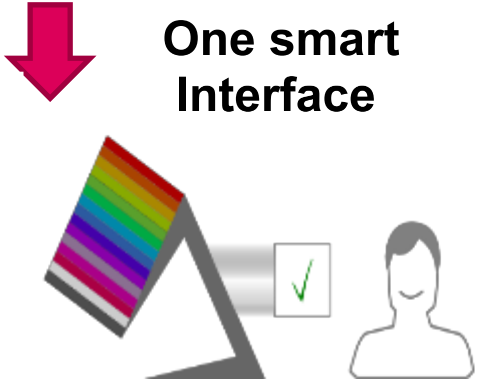
Supervision



Bad signal/noise ratio!

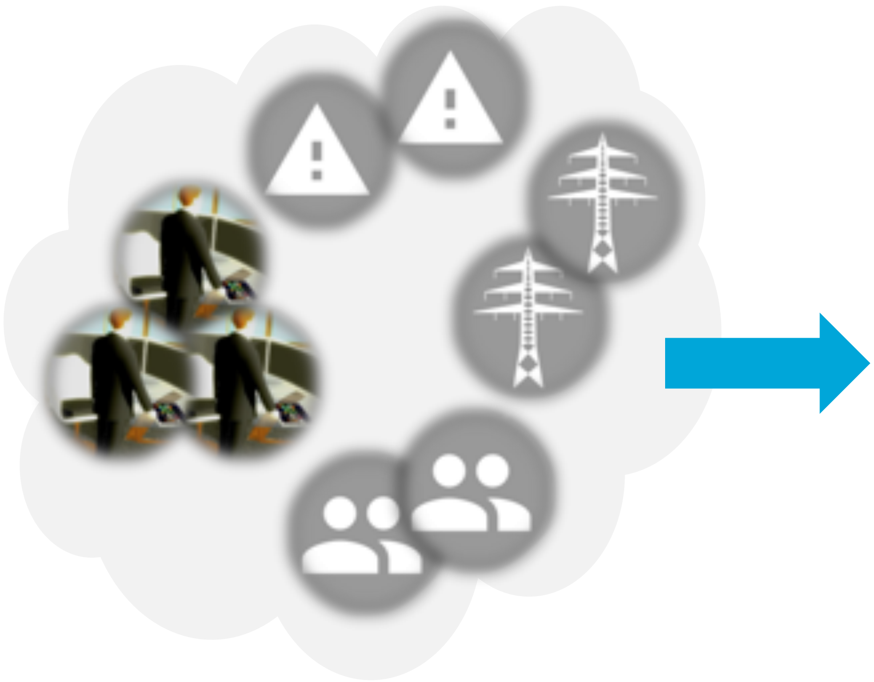
HYPERVISION

One smart Interface



Switch from
driving mode
to
navigation mode !

SEAMLESS INFORMATION & TRACEABILITY



ACTUAL SOURCES OF INSPIRATION

Personal assistant (Jarvis!)

Help you **plan** & make **suggestions**

Autonomous vehicle

Find your way and **pilot**

VS

plan your journey, **navigate** & coordinate

NB: On the grid, you still have to define your trajectory

Le réseau de l'intelligence électrique

OBJECTIVES SINCE 2014

REALIZE AND IMPLEMENT DEVELOPED CONTROL SYSTEM PROTOTYPES

Target 2018

In Real Time
In a control room

Hypervision

1 single tool on the Operator Station
Innovative interfaces
Contextual information and actions

Automation

Automatic coordinated actions
on the system

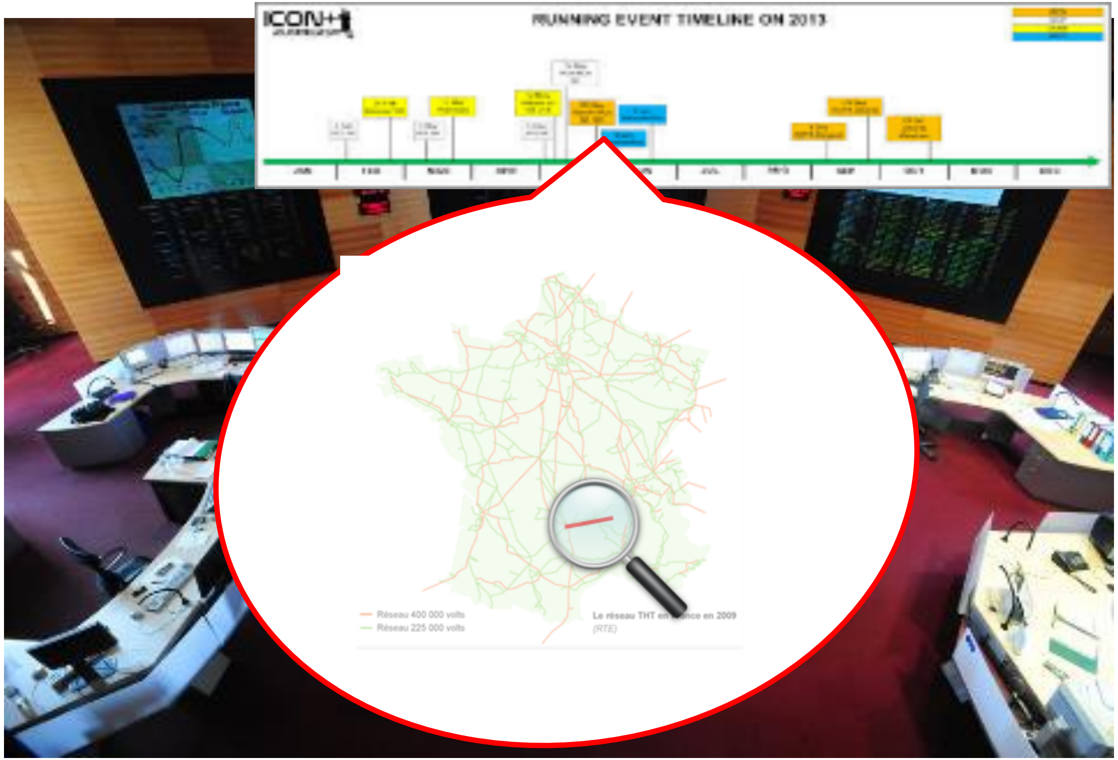
02

Problem statement
One day in control rooms

1 DAY IN CONTROL ROOM

How can we help our dispatcher:

- Anticpate and assess risks
- Makes sense of a situation
- Speed up his remedial action search



INTEGRATION IN REAL TIME OPERATIONAL PROCESS

Typical problem solving and decision making task

Problem identification

Solution search

Decision making

CURRENT REAL TIME OPERATIONAL PROCESS

Grid states Generation
= Forecast * contingencies

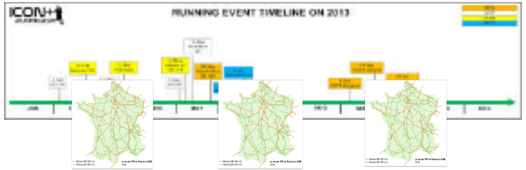
Operator
Tactic

Si

Constra

t

Limitations of only using physical model
- Only few representative snapshots studied per day (4am,9am,12pm,4pm,19pm)
- Lots of results to study but from lots of reccurent situations – no memory
- Risk study & assessment limited in depth
- Space of tactics limited in breatdh & depth
- No time to make overall strategies



How can we reach a better **Exploration-Exploitation** tradeoff near real-time ?
=> By capturing **reality** around our domain of operations and relying on **Prior Knowledge**

Selected Tactics

Unsecure grid detection

Action space search

Decision

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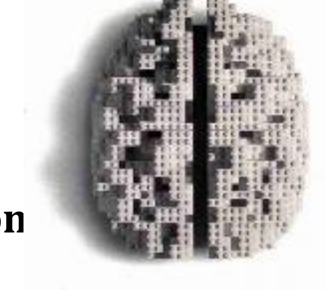
02

Next: AI in Apogee

TEASER: ARTIFICIAL INTELLIGENCE IN APOGEE



Data

- Generation
- Labelling
- Capitalization

Representation

- Modeling
- Contextualization
- Visualization

Learning

- Imitation
- Simulator

Adaptation

- Exploration
- Reinforcement
- Transfer

Any Question so far ?

CURRENT REAL TIME OPERATIONAL PROCESS

Grid states Generation
= Forecast * contingencies

Operator
Tactic

Si

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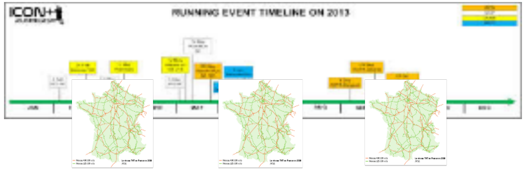

Constra

t

How can we reach a better **Exploration-Exploitation** tradeoff near real-time ?
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03

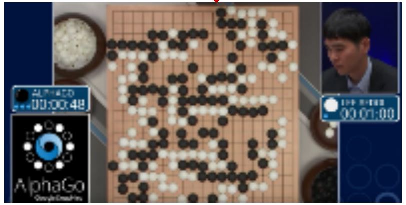
One key element: Learning!

IA: FROM EXPERT TO LEARNING SYSTEMS

Logic & Expert rules

Deep blue (Kasparovs vs Machine, échecs, 1997)
Gasparov: ~50 strategies consider at each move
Machine: >1 000 000 scenarios, 8 000 heuristics

Learning & reinforcement



Alpha Go (Lee Sedol vs Machine, Go, 2016)
Learning by expert imitation
Reinforcement by simulation

Towards industrial AI applications in an open and complex environment ?

BUILDING PRIOR KNOWLEDGE

Deep Blue

Expert System

Machine Learning

Alpha Go

Expert Systems (top-down) vs Machine Learning (bottom-up):

deduction induction

Expertize Formalization with symbolic and logical rules is hard

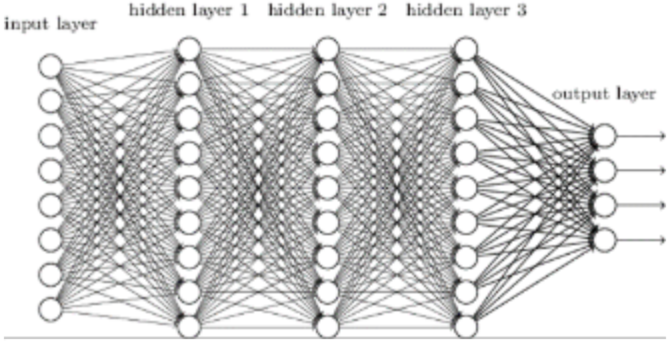
- Especially the most intuitive concepts

Learning approach to let the machine :

A key catalyst:

the advent of Deep Learning with Neural networks

=> powerful and flexible models for end-to-end learning



Introduce Machine Learning for power grid real-time operations

ALPHA GO INSPIRATION & RECIPE

Focus of our work today

1) Learning by imitation of expert moves

- With Deep learning
- Based on pure observations
- No objective formalization, or knowledge/expertise desc

=> Need labelled data

Imitation is good to build trust with operators !

2) A simulator to play and learn :

- To massively assess different states and actions for free

=> Need a fast and accurate simulator

3) An architecture to learn strategies and improve:

- Formalize **the objective** and model **the opponent**
- Generate an environment and explore scenarios with a prioris and a simulator
- Promote beneficial strategies, **revise your a prioris**

=> Need an environment generator and sufficient computational power

04

AI in Apogee

ARTIFICIAL INTELLIGENCE IN APOGEE

Data

Generation

Labelling

Capitalization

Representation

Modeling

Contextualization

Visualization

Learning

Imitation

Simulator

Adaptation

Exploration

Reinforcement

Transfer

OUR AI PROJECT TEAM

Apogee RTE researchers:

- Antoine Marot, Research Project Supervisor
- Rémy Clément, « Learning voltage control »
- Vincent Barbesant, « Forecasting grid states », control room operator previously

Managers:

- Benoit Jeanson, Apogee Project manager,
- Patrick Panciatici, R&D scientific advisor

PHDs:

- Benjamin Donnot, « Learning the Load-Flow with Deep Neural Nets », ending with INRIA
  - Co-advised by Isabelle Guyon and Marc Shoenauer
- Balthazar Donnot, « Learning to Run a Power Grid with Reinforcement Learning », beginning with INRIA. Data Challenge to come as well !
- Laure Crochepierre, « Interactive Machine Learning with expert users », beginning with LORIA

Master Thesis:

- Antoine Rosin, « Event detection and labelling in energy systems », 2018 with DTU

ARTIFICIAL INTELLIGENCE IN APOGEE

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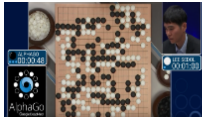
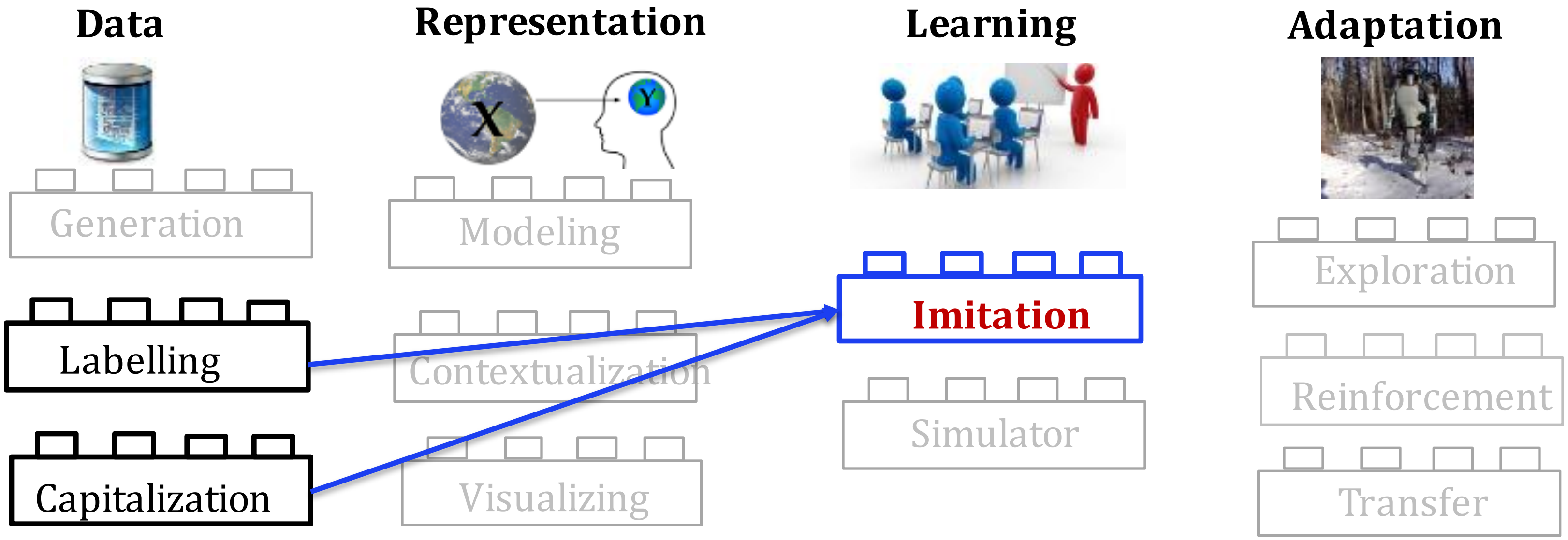
We Need:

1. Operator Decision Labelling to start learning
2. Need faster simulator for screening and exploration



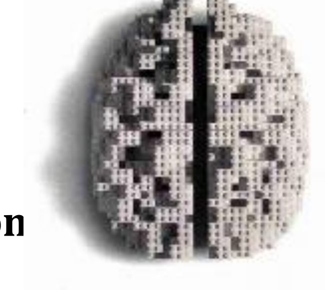
AI IN APOGEE: LEARNING

Some prerequisites



AI IN APOGEE: LEARNING

LEARNING A PHYSICAL MODEL: A CATALYST



Data

Generation

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Visualizing

Learning

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Simulator

Adaptation

Exploration

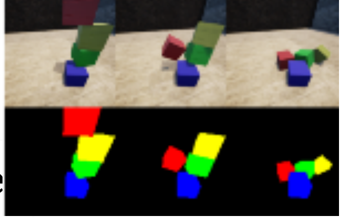
Reinforcement

Learn a lot from simulators based on physical models

05

Learning a fast proxy simulator

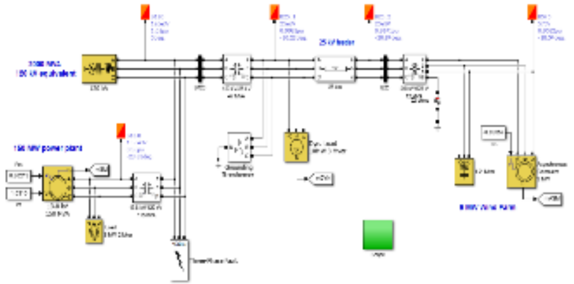
FAST PROXY SIMULATOR FOR REINFORCEMENT



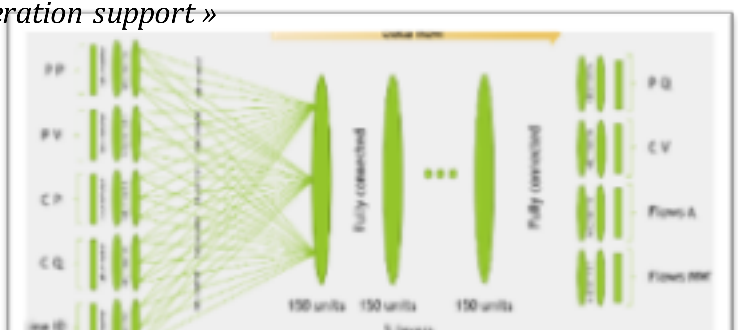
« Learning Physical Intuition of Block Towers by Example »

- We want to compute **millions of power flows for screening and exploring the action space**.
- Speed up of the computation is mandatory

« Introducing machine learning for power system operation support »



Physical model



Neural network model

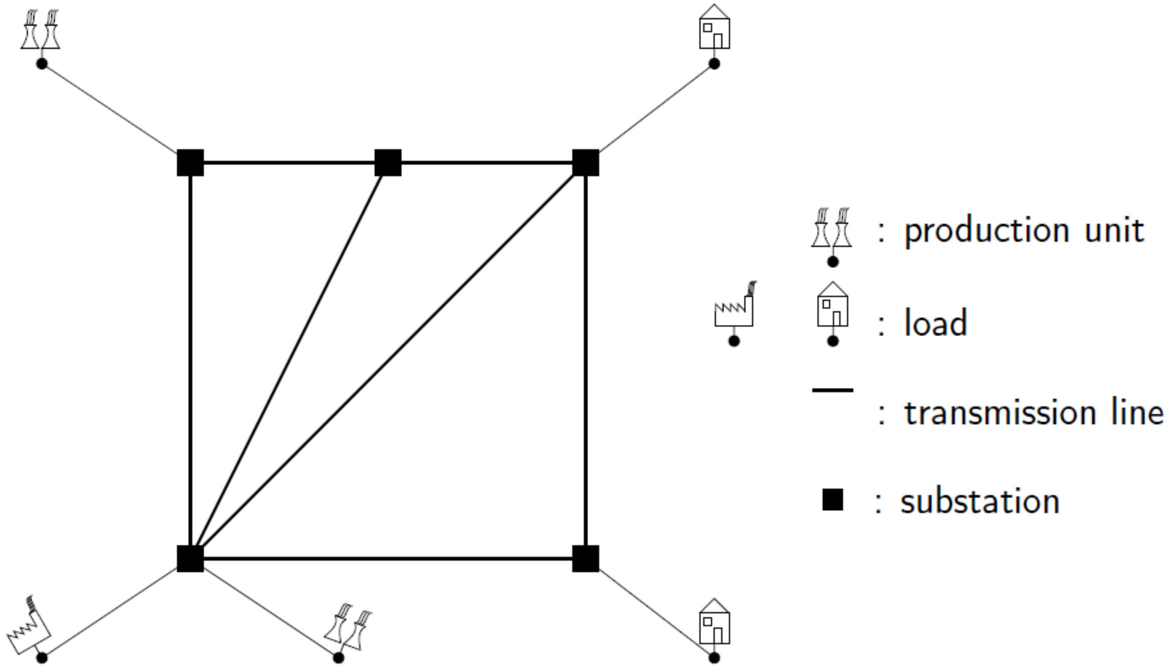
Very encouraging results (topologie fixe,118 nœuds vs 6000 RTE):

- **Accuracy loss of 2%** (DC approximation 5-10%)
- **Computation Gain *300**

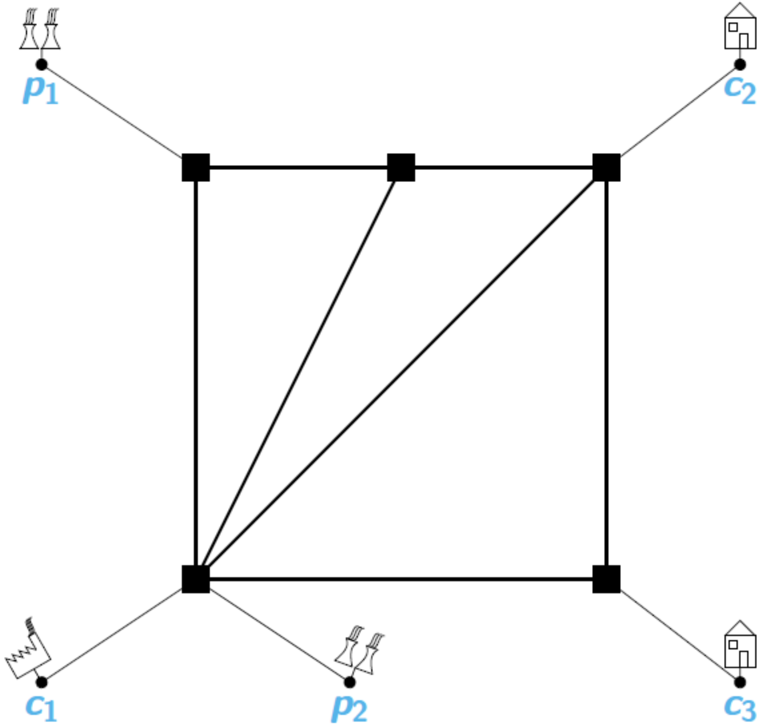
New neural network architecture to encode discrete topological modifications:

- « Guided dropout »

A TOY GRID EXAMPLE



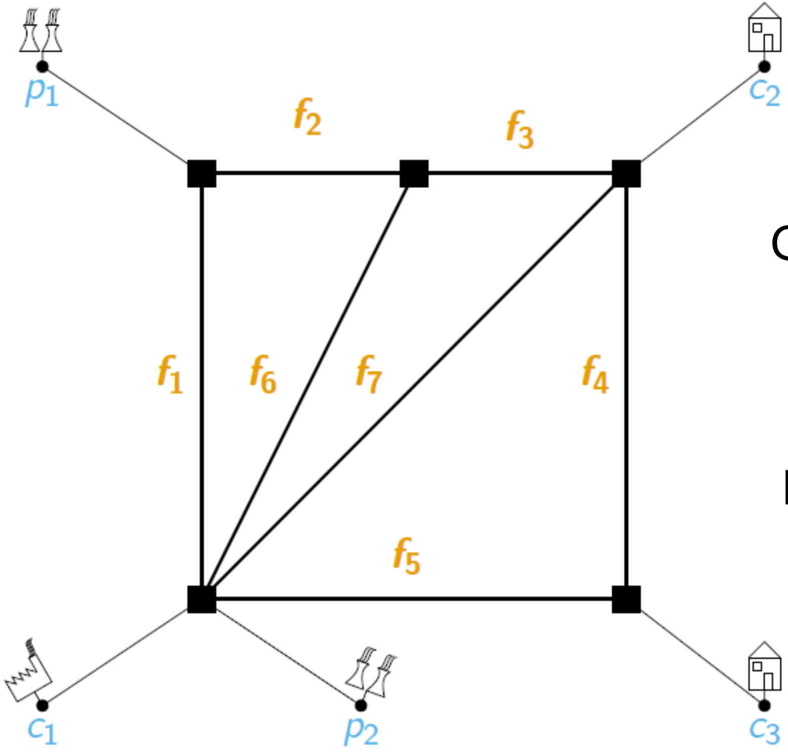
A TOY GRID EXAMPLE



Given productions & loads :

$\mathbf{x} \stackrel{\text{def}}{=} (p_1, p_2, c_1, c_2, c_3)$

A TOY LOAD-FLOW EXAMPLE



Given productions & loads :

$$\mathbf{x} \stackrel{\text{def}}{=} (p_1, p_2, c_1, c_2, c_3)$$

$$\mathbf{y} \stackrel{\text{def}}{=} (f_1, f_2, f_3, f_4, f_5, f_6, f_7)$$

Power Flows to compute

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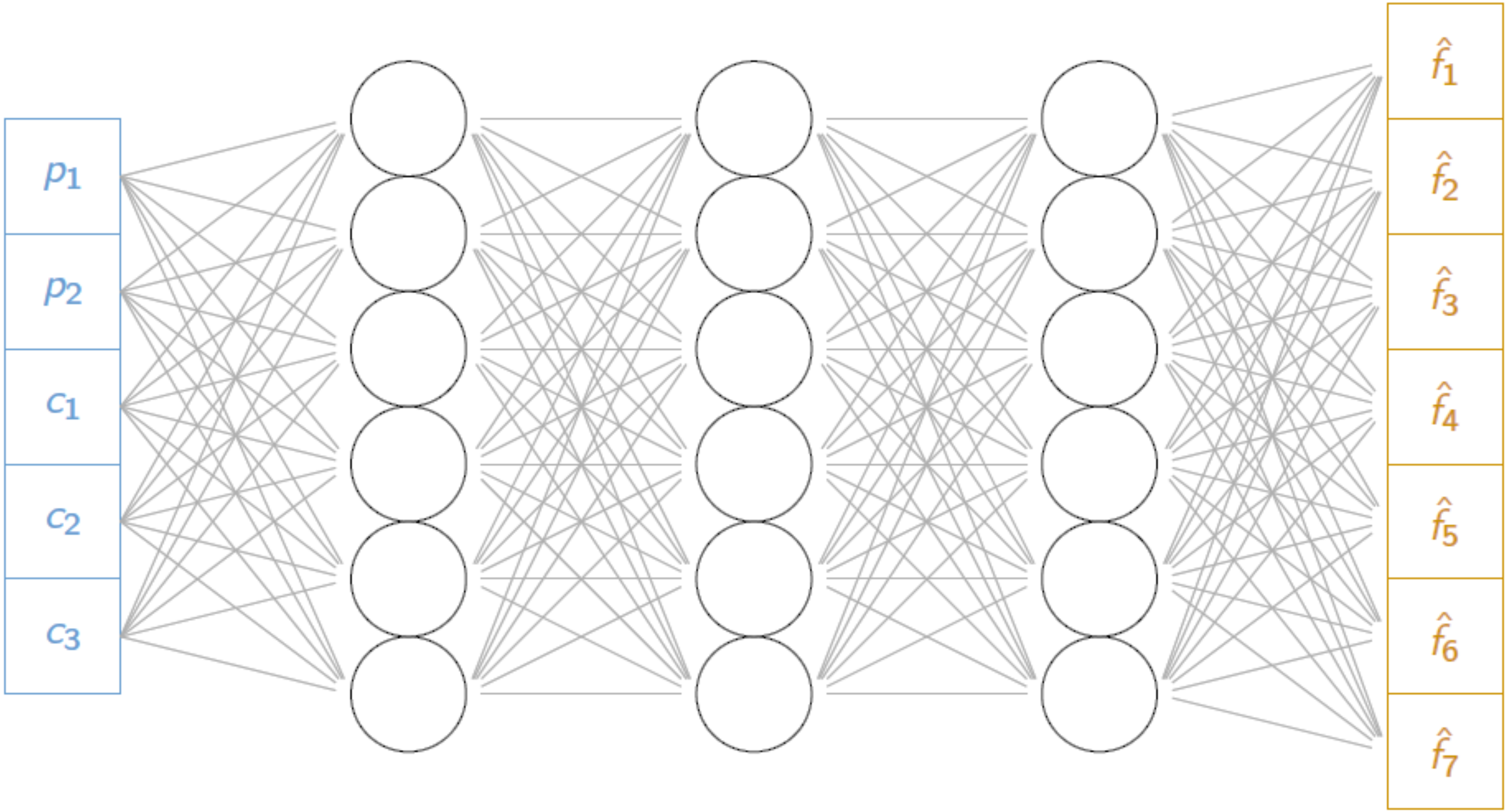
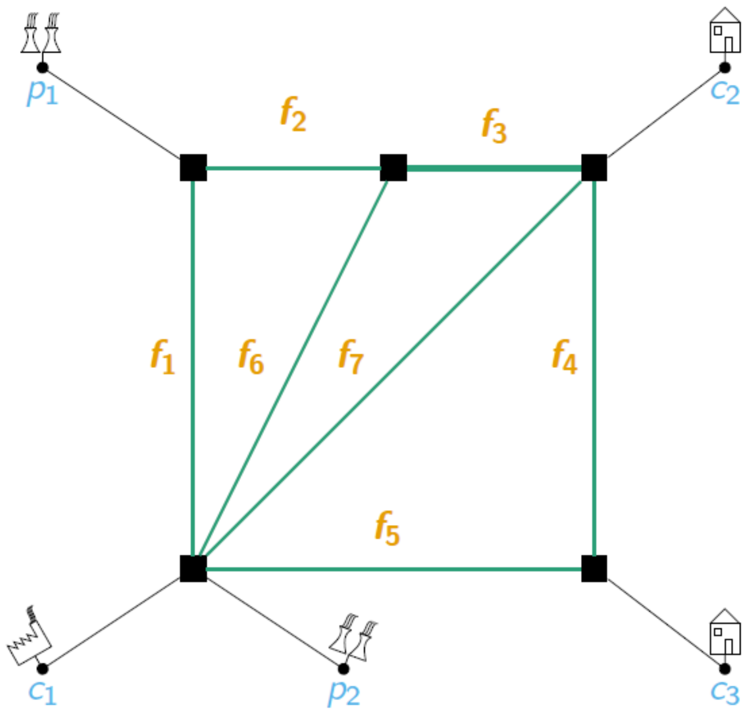
A NEURAL NETWORK TO LEARN IT



A TOY GRID EXAMPLE – CONTINUED



$$\mathbf{x} \stackrel{\text{def}}{=} (p_1, p_2, c_1, c_2, c_3)$$

$$\tau \stackrel{\text{def}}{=} (0, 0, \mathbf{0}, 0, 0, 0, 0)$$ **And for different topologies?**

$$\mathbf{y} \stackrel{\text{def}}{=} (f_1, f_2, f_3, f_4, f_5, f_6, f_7)$$

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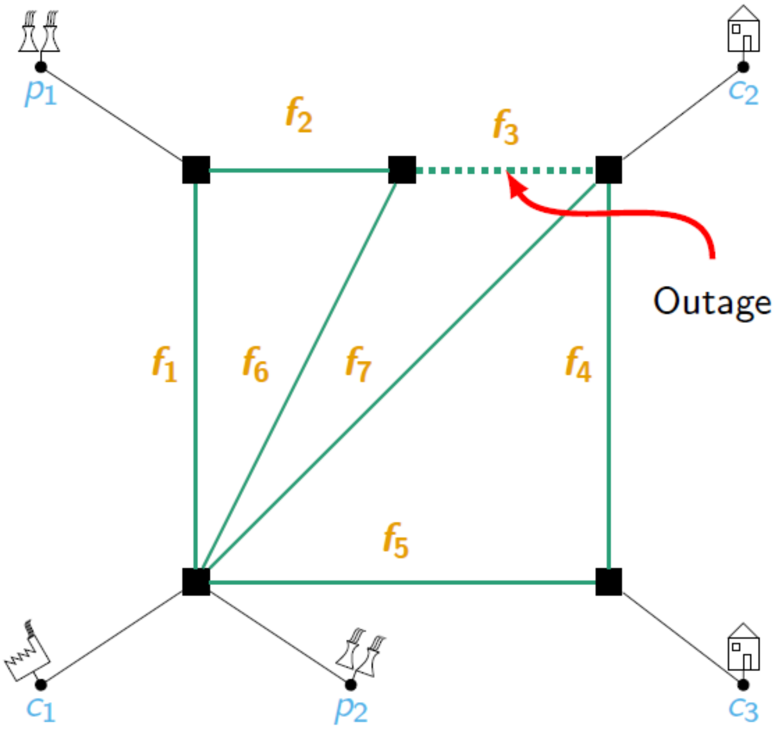
A TOY GRID EXAMPLE - CONTINUED

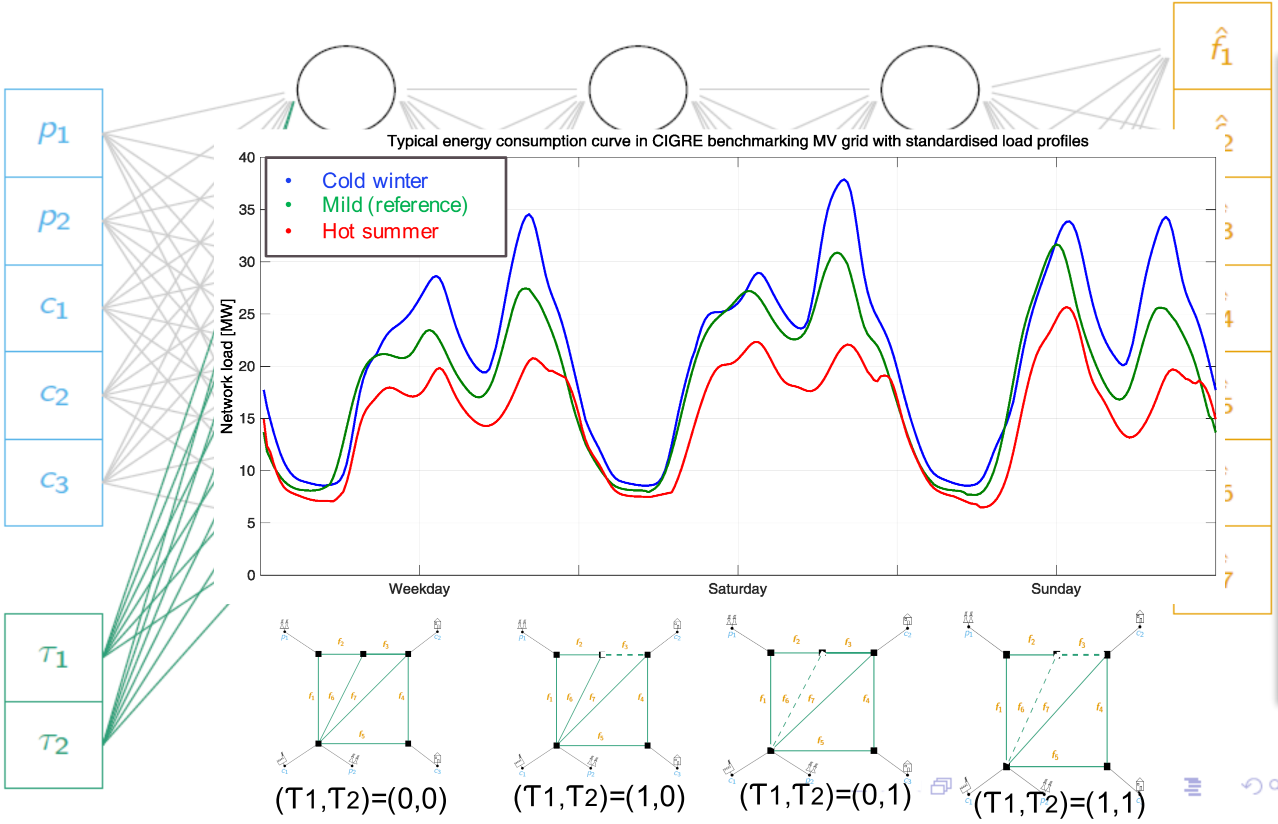


$$\mathbf{x} \stackrel{\text{def}}{=} (p_1, p_2, c_1, c_2, c_3)$$

$$\tau \stackrel{\text{def}}{=} (0, 0, \mathbf{1}, 0, 0, 0, 0)$$ Change in topology

$$\mathbf{y} \stackrel{\text{def}}{=} (f_1, f_2, f_3, f_4, f_5, f_6, f_7)$$

ONE HOT ENCODING



But the reference topology occurs a lot more often in reality.

In this setting we are not leveraging it:

- the reference topology is encoded in the same way as rare interventions.
- We are somehow learning *n* different models for *n* topologies.

⇒ Maybe we could **learn a reference model** and **modulate** its response for other rare conditions ?

GUIDED DROPOUT ARCHITECTURE

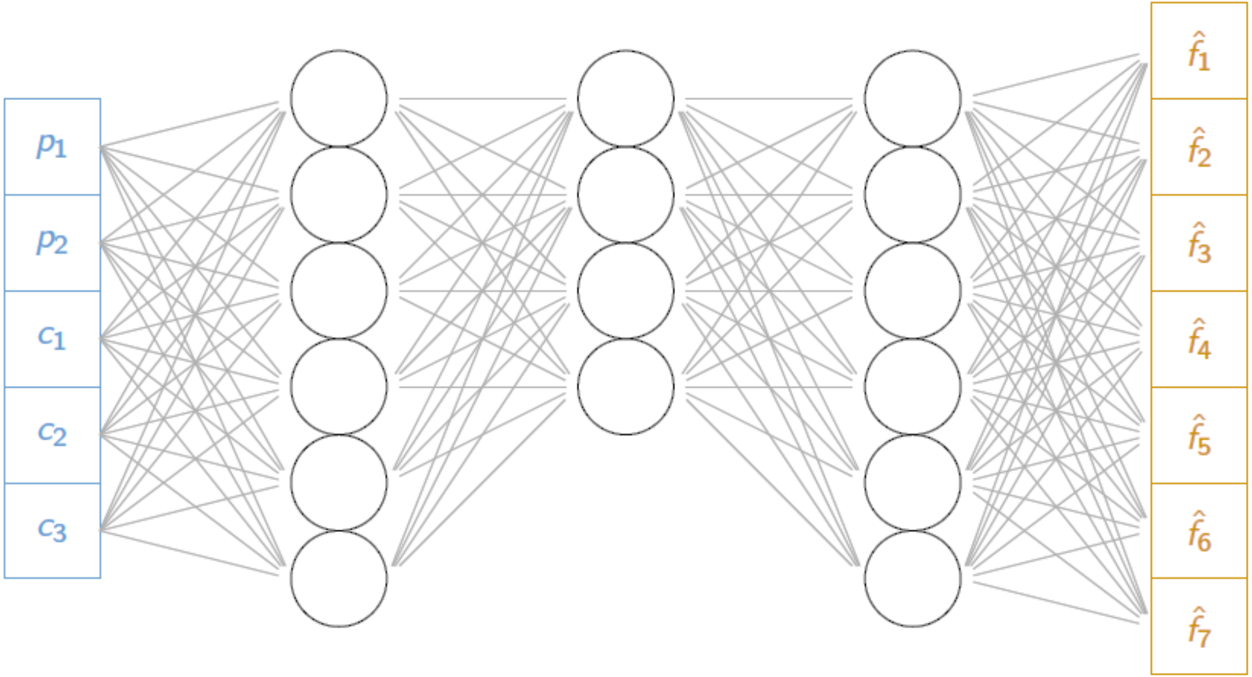
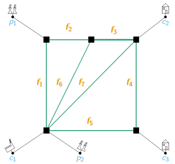


Figure: $\boldsymbol{\tau} = [0, 0, 0 \ldots]$: all the lines are connected

We are **learning a reference model**



(T1,T2)=(0,0)

GUIDED DROPOUT ARCHITECTURE

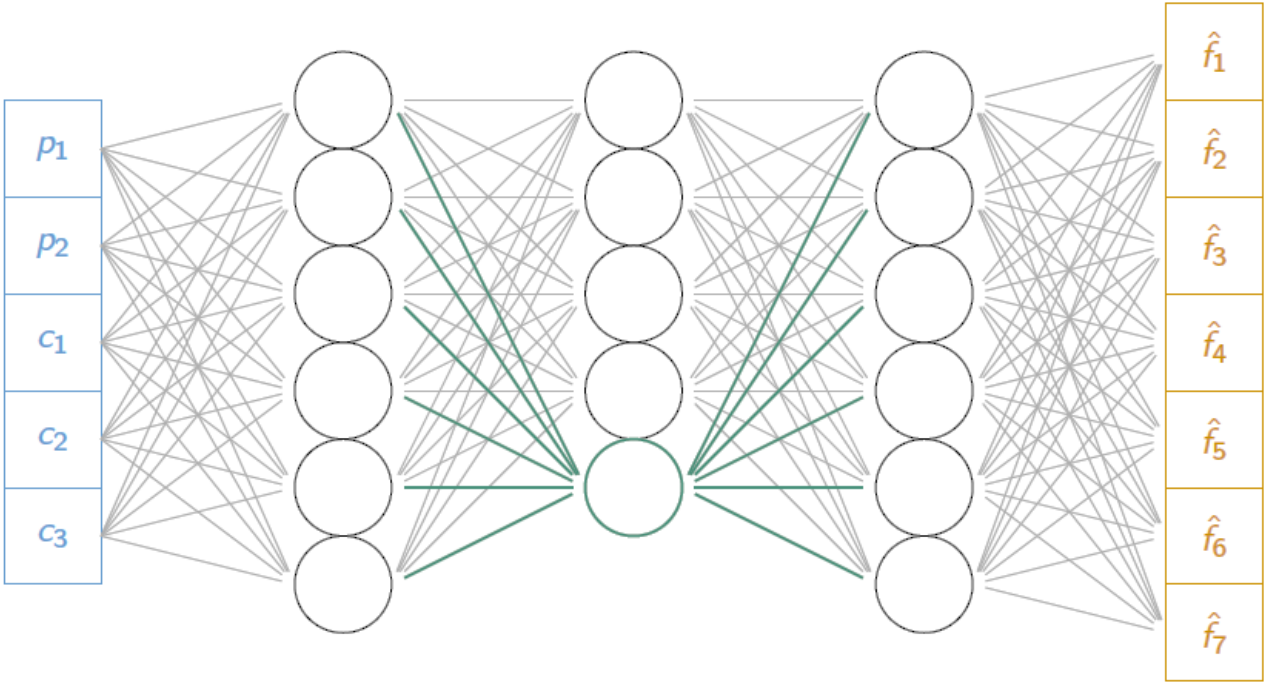
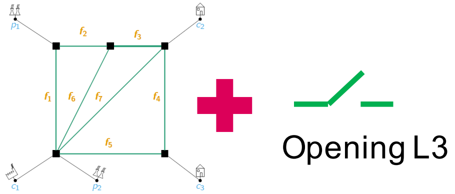


Figure: $\boldsymbol{\tau} = [1, 0, 0 \ldots]$: only line 1 is disconnected

reference model **modulation**



GUIDED DROPOUT ARCHITECTURE

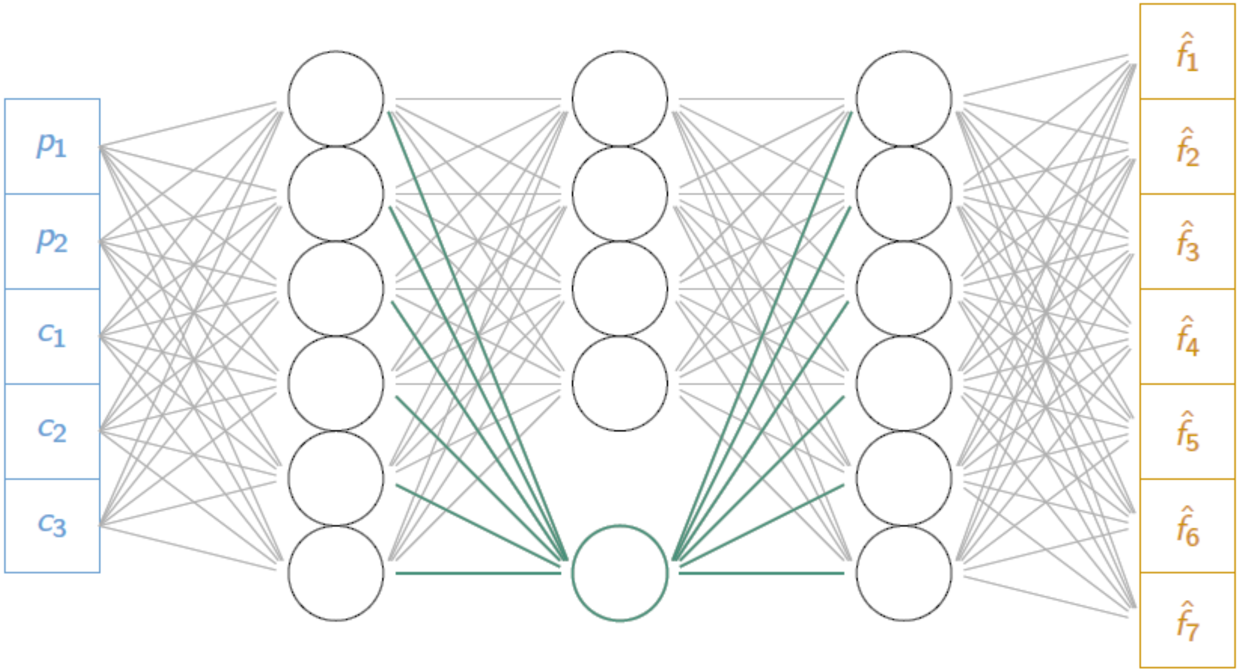
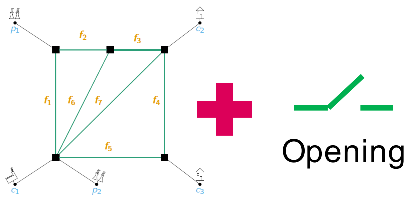


Figure: $\boldsymbol{\tau} = [0, 1, 0 \ldots]$: only line 2 is disconnected

reference model **modulation**



Opening L6

GUIDED DROPOUT ARCHITECTURE

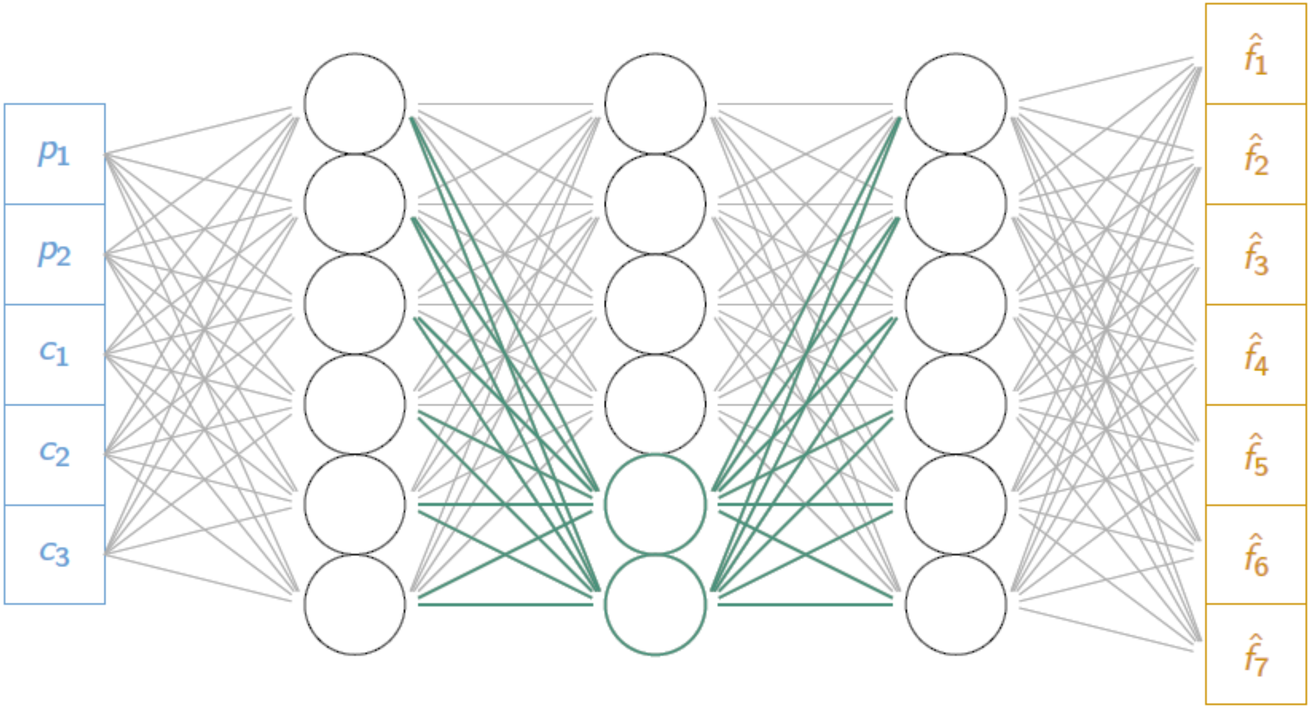
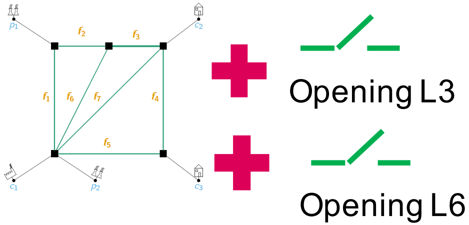
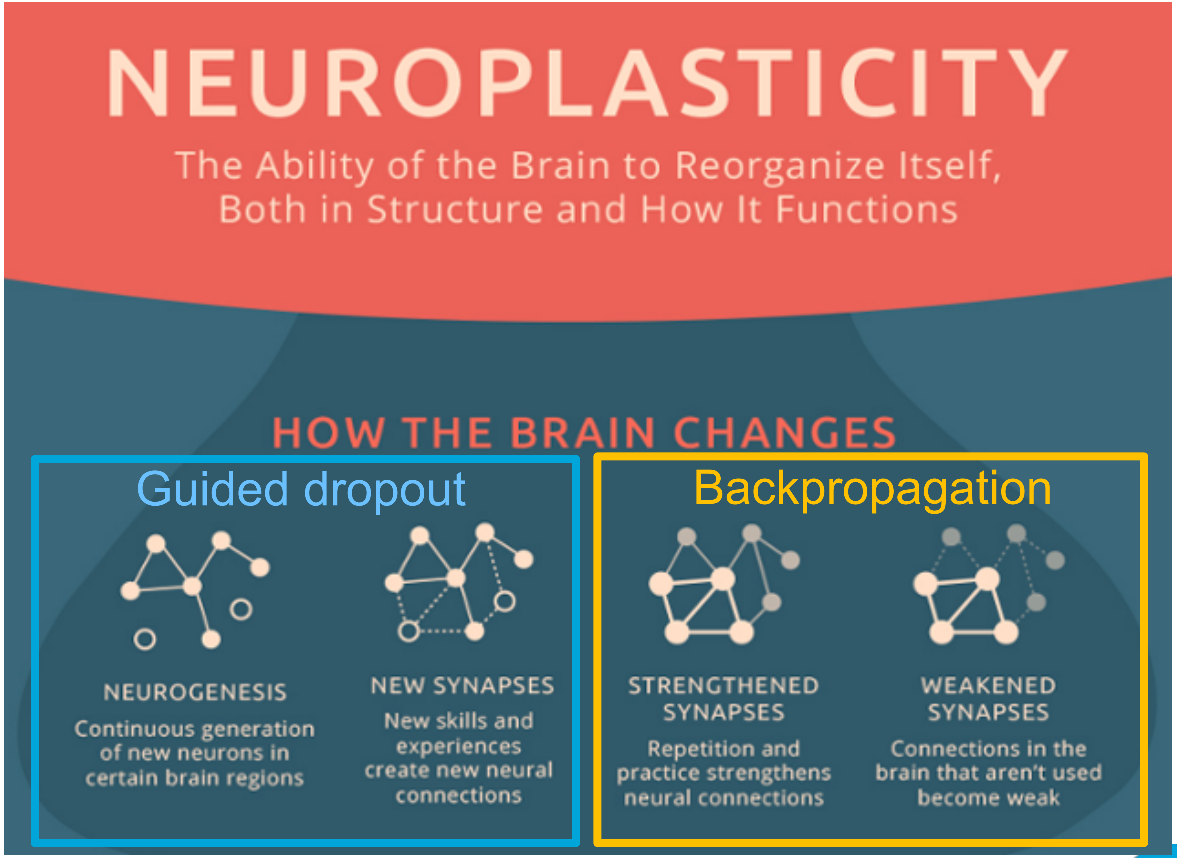


Figure: $\boldsymbol{\tau} = [1, 1, 0 \ldots]$: line 1 and line 2 only are disconnected

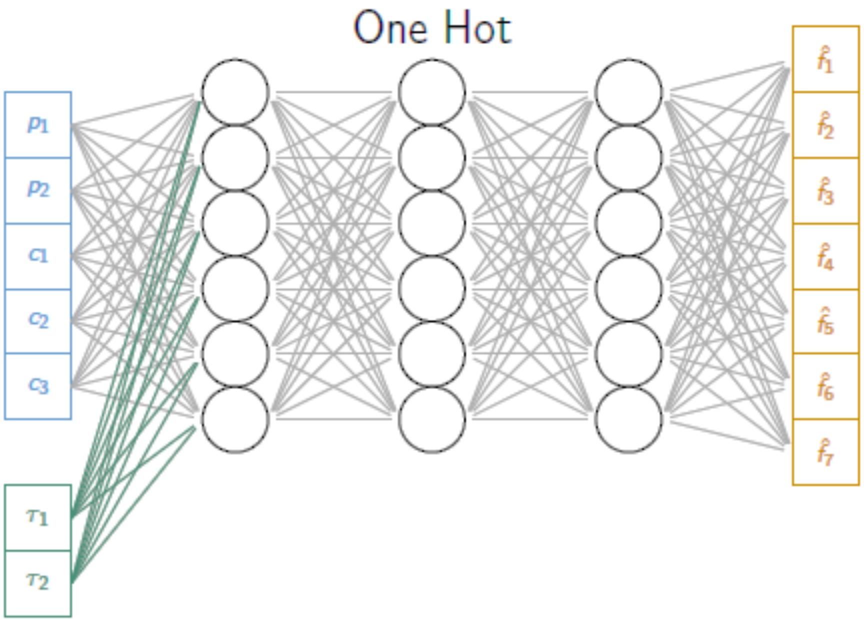
reference model **modulation**

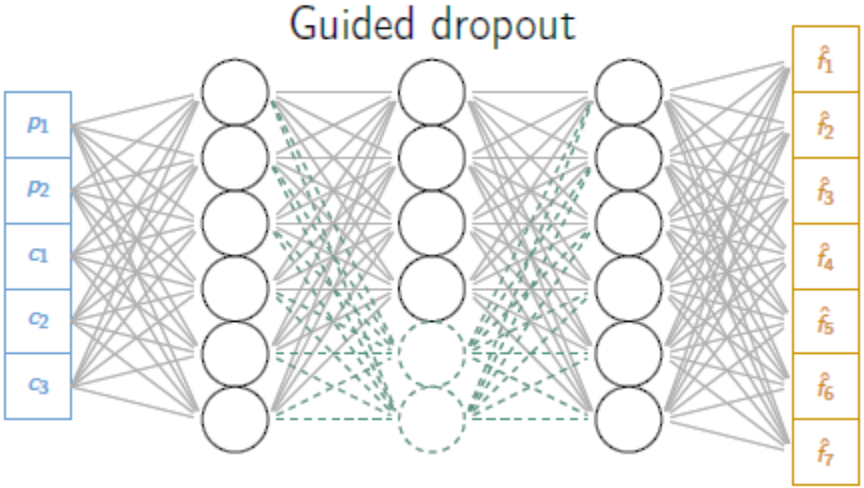


GUIDED DROPOUT = ADDITIONAL PLASTICITY



COMPARING ARCHITECTURES





06

Learning a fast proxy simulator: **Results**

EXPERIMENTAL SETTINGS

Training dataset

- Built training set by:
  - Sample $\boldsymbol{x}$ (injections)
  - Sample $\boldsymbol{\tau}$ (zero or one line disconnected $\sum \tau_i \leq 1$)
  - Run the physical simulator (Hades2) to get $\boldsymbol{y}$ (current flows)

Testing dataset (different from training)

$\boldsymbol{x}$: Same distribution as training

Test: Exactly one power line disconnected $\sum \tau_i = 1$

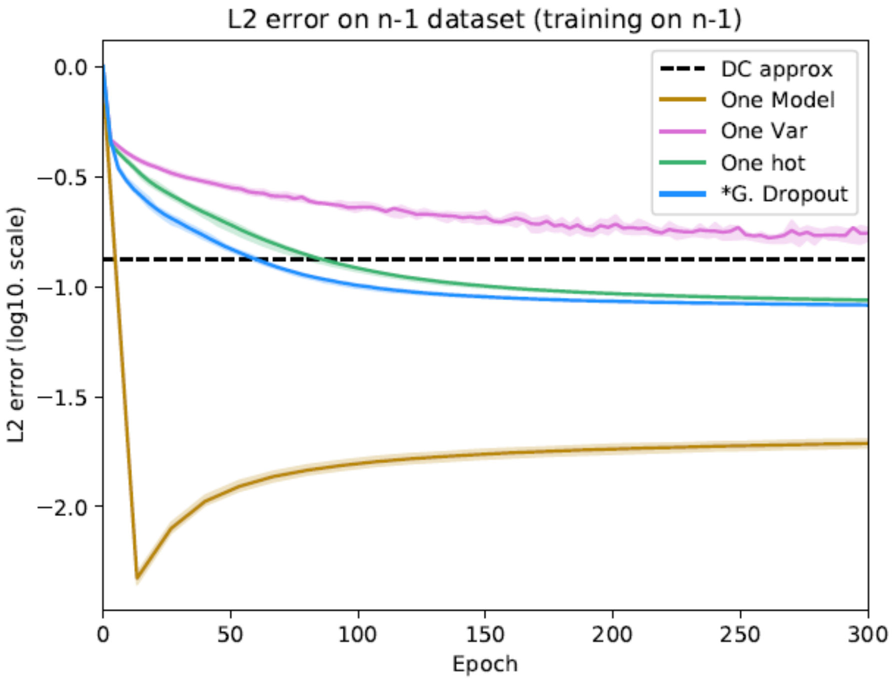
SuperTest: Exactly two power lines disconnected $\sum \tau_i = 2$

$\boldsymbol{y}$: Same simulator

NB: errors are always reported on data never seen during training

NB: the powergrid used is the case118 of Matpower

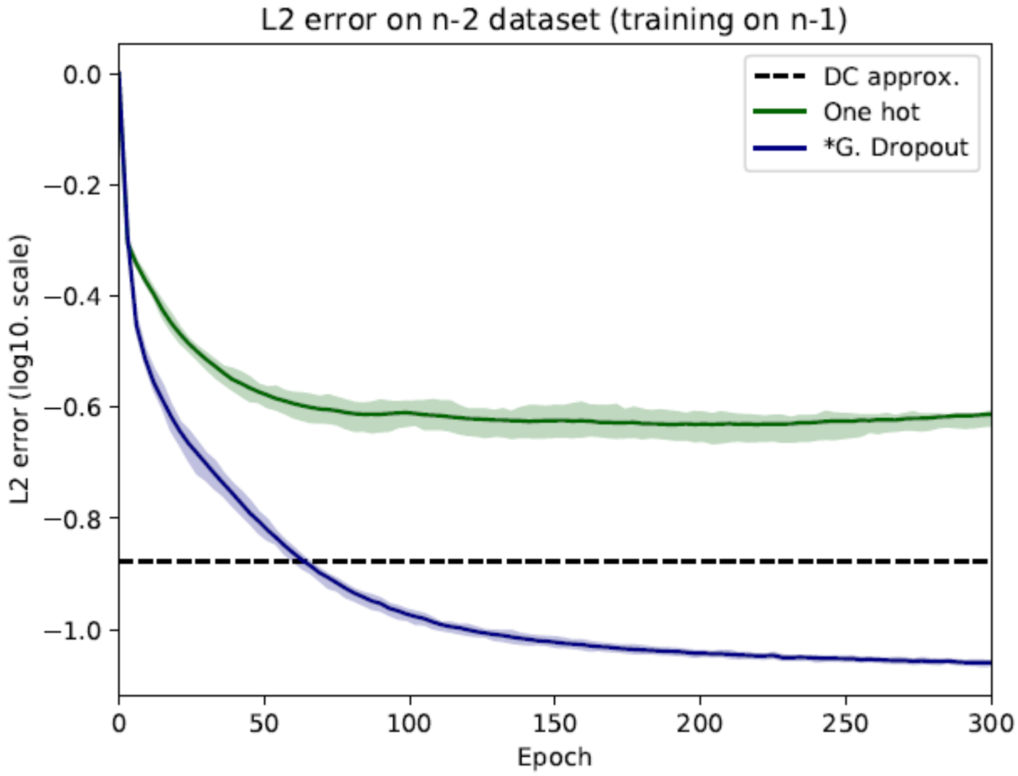
GENERALIZATION



(a) Test set: **Generalization**

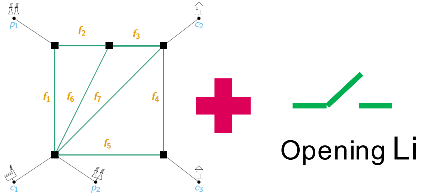
- One Hot & G.Dropout have similar accuracy
- Both do better than DC baseline (physical model approximation)
- G. Dropout requires less parameters (20%less)

SUPER GENERALIZATION

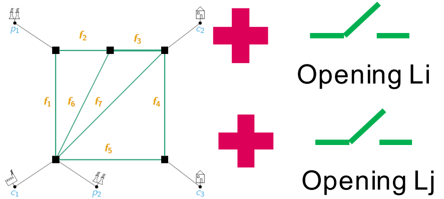


(b) "SuperTest" set: **SuperGeneralization**

Trained on N-1



Tested on N-2



G.Dropout super-generalize (not One-hot) => it is able to **extrapolate** beyond the distribution it knows

PERSPECTIVES

First Conclusions on guided dropout

- Train a single neural network to predict power flows for variants of grid topology
- $\simeq$ 300 times faster than the currently deployed AC power flow simulator for small grids (118 nodes)
- Up to 2 000 faster for larger grid (France EHV) for preliminary experiments

Possible applications

- Contingencies screening
- Risk evaluation / assessment

07

reConnecting the dots

TODAY’S REAL TIME PROCESS

Grid states Generation
= Forecast * contingencies

Simulator

Constraints to deal with

Unsecure grid detection

Operator Tactic

Simulator

Candidate solutions

Action space search

Validation by simulation

Optimization for best compromise

Selected Tactics

Decision

FUTURE REAL TIME PROCESS

Grid states Generation = Forecast * contingencies

Learnt Proxy Simulator

Constraints to deal with

Unsecure grid detection

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FUTURE REAL TIME PROCESS

Grid states Generation
= Forecast * contingencies

Learnt Proxy Simulator

Constraints to deal with

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Operator strategies

Learnt Tactics

Generated Tactics

Learnt Proxy Simulator

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Optimization for best compromise

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FUTURE REAL TIME PROCESS

Grid states Generation
= Forecast * contingencies

Learnt Proxy Simulator

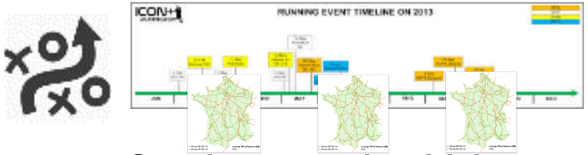
Constraints to deal with

Unsecure grid detection

Operator

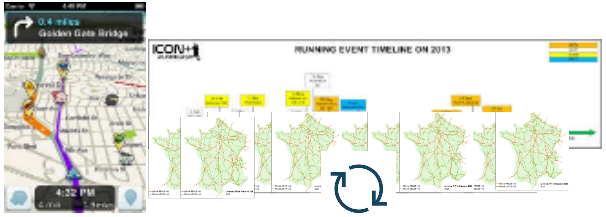
Learnt

Generated



Snaphsot reactive driving

Continuous anticipation & navigation



Action space search

Validation by simulation

Optimization for best compromise

Selected Strategies

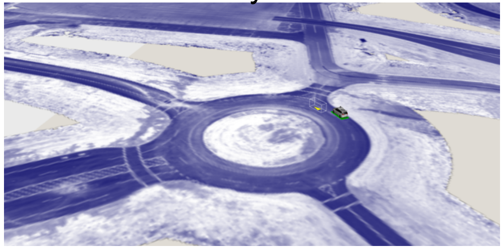
Decision

OF THE IMPORTANCE OF PHYSICAL MODELS

All our current AI developments are actually built on top of physical simulators

Some people say « **Data will eat the world** »
⇒ Do we only need to collect data we observe to make sense of the world?

Carcraft: Waymo's simultor



No **we also need theory and physics to build simulators in order to extrapolate to unseen distributions**.

Exemple of the most data driven company in the world, Google:
- WAYMO -> 20000 virtual vehicles in a physical simulator!
- ML to helps extract information from a maze of data

AI=ML+Simulator
Need to know the physics of your system & environment + model the behavior of other agents + make your own decisions

FUTURE REAL TIME PROCESS

Grid states Generation
= Forecast * contingencies

Learnt Proxy Simulator

Fast Security Analysis

Constraints to deal with

Unsecure grid detection

Operator strategies

Learnt Tactics

Generated Tactics

Learnt Proxy Simulator

Candidate solutions

Action space search

Validation by simulation

Optimization for best compromise

Selected Tactics

Decision

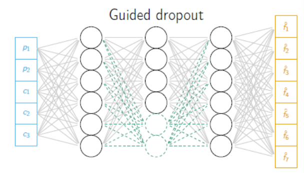
08

Fast Security analysis

CONTINGENCY SCREENING & RISK ASSESSMENT

Objectives

- Sort contingencies according to their dangerousness
- *Compute with an high end simulator only the most dangerous*
- Use neural networks as a pre-filtering proxy
- Benefits:
  - Reduce computation time
  - More complex contingencies taken into account
  - "N-2" security
  - or "N-1" but for probabilistic grid states



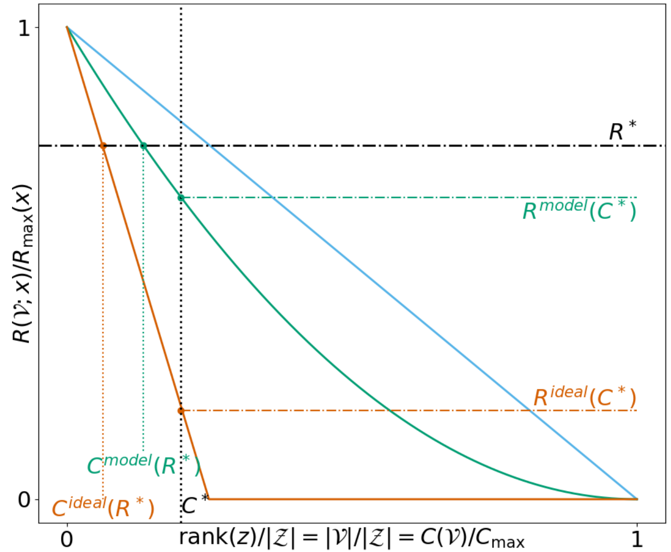
Key concept : Residual risk

- Risk of *NOT* computing a set $\mathcal{Z} - \mathcal{V}$ of contingencies

$$R(x; \underbrace{\mathcal{V}}_{\text{set of contingencies studied}}) \stackrel{\text{def}}{=} \sum_{z \in \mathcal{Z} - \mathcal{V}} \underbrace{p(z)}_{\text{probability of occurrence}} \cdot \underbrace{L(z; x)}_{\text{cost}}$$

Residual risk = risk we have not assessed yet

Residual risk after x simulated contingencies



R*: the maximum residual risk we are willing to accept.
C* the maximum computational budget we have

CONTINGENCY SCREENING & RISK ASSESSMENT

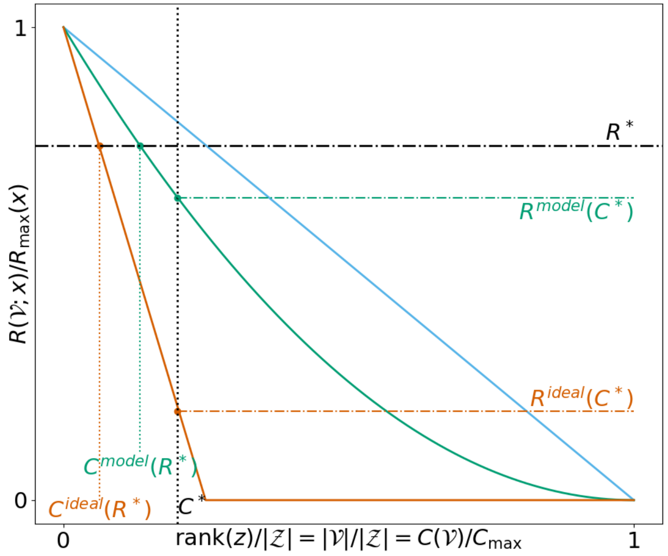
NN screening vs current N-1 operators methods

	Operators	G. Dropout trained n-1 only	G. Dropout	Ideal
Gini coeff.	0.41 $\pm$0.04	0.52 $\pm$0.04	0.95 $\pm$0.01	1.00
$\frac{R(\mathcal{V}*)}{R_{\max}}$	0.59 $\pm$0.04	0.58 $\pm$0.04	0.46 $\pm$0.03	0.44 $\pm$0.03
$C(R^*)$	186	3 $\pm$2	3 $\pm$2	3 $\pm$2

Summary of the pre screening

- Contingencies ranking:
  - Very accurate if trained on all topologies (not feasible in practice)
  - Pretty accurate if only 1% of the grids topologies it is tested on
- Always better than "N-1" strategy **[for simulated data]**
- Same level of risk than "N-1" with only 2% of budget **[once the training is done]**

Residual risk after x simulated contingencies



R*: the maximum residual risk we are willing to accept.
C* the maximum computational budget we have

09

Human Machine Collaboration

FUTURE REAL TIME PROCESS

Grid states Generation
= Forecast * contingencies

Learnt Proxy Simulator

Constraints to deal with

Unsecure grid detection

Operator strategies

Learnt Tactics

Generated Tactics

Learnt Proxy Simulator

Candidate solutions

Action space search

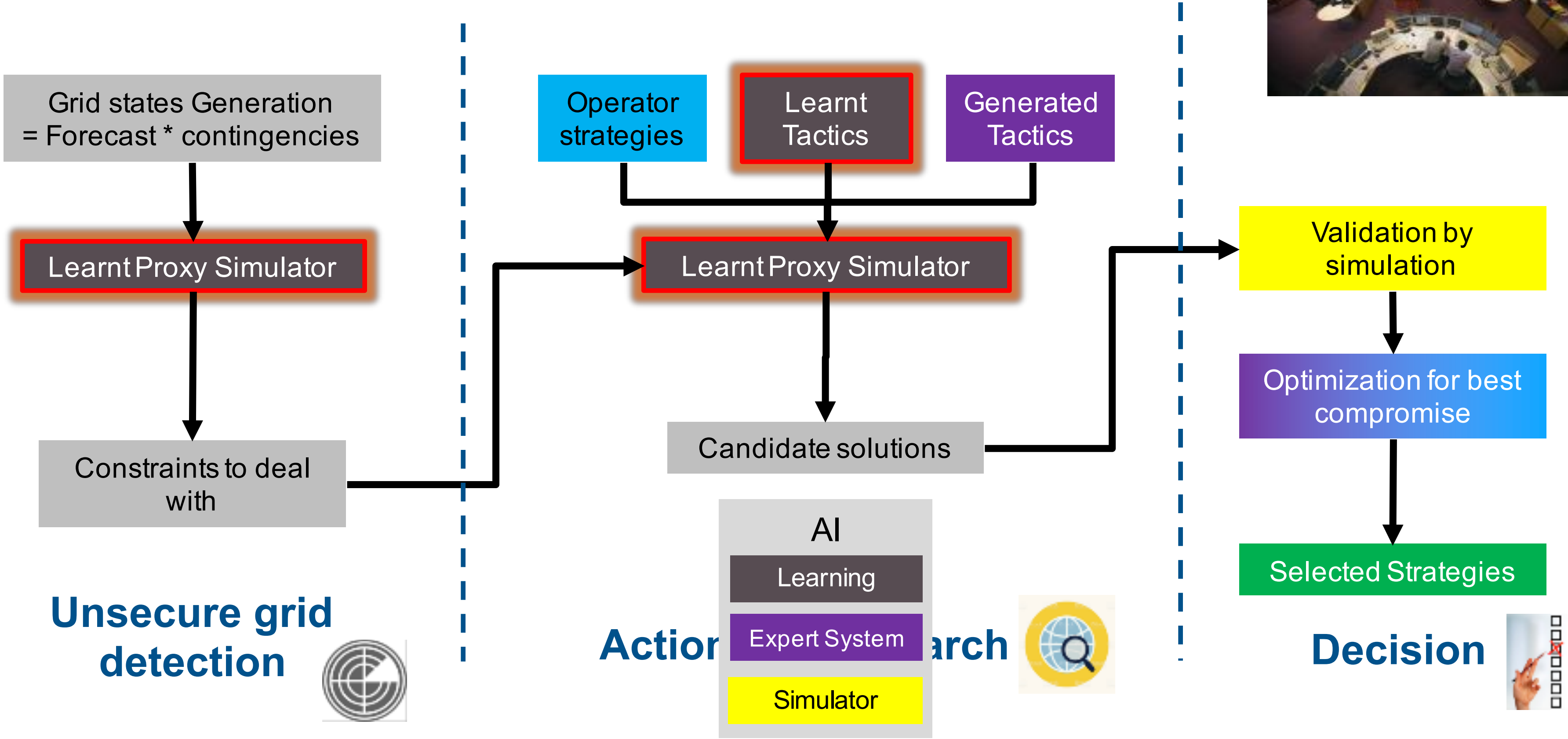
Validation by simulation

Optimization for best compromise

Selected Strategies

Decision

FUTURE REAL TIME PROCESS



FUTURE REAL TIME PROCESS

Grid states Generation = Futur * variability

Learnt Proxy Load flow

Constraints to deal with

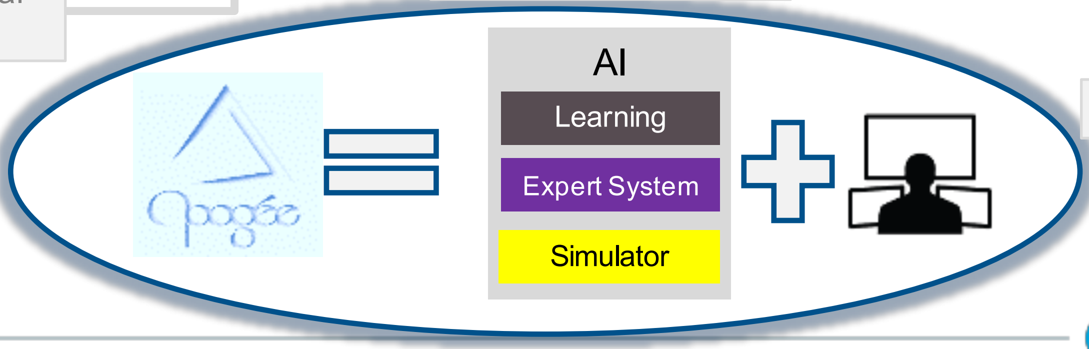
Operator strategies

Learnt Tactics

Generated Tactics

Learnt Proxy Load flow

A human-machine collaboration

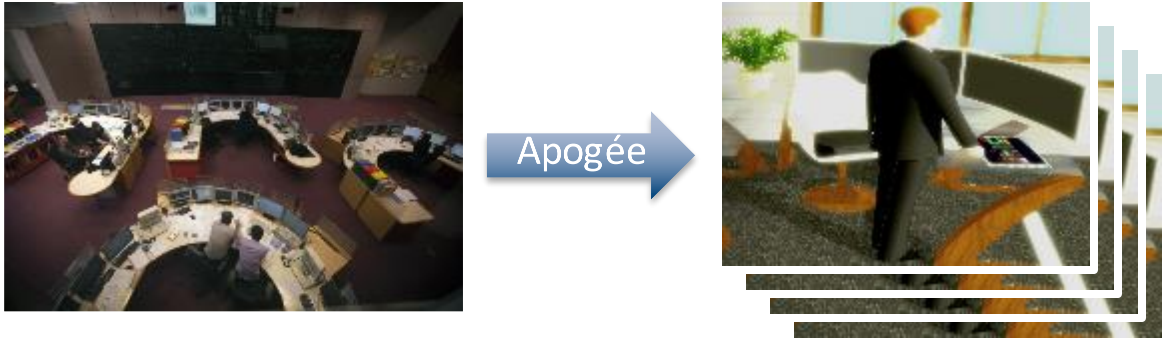


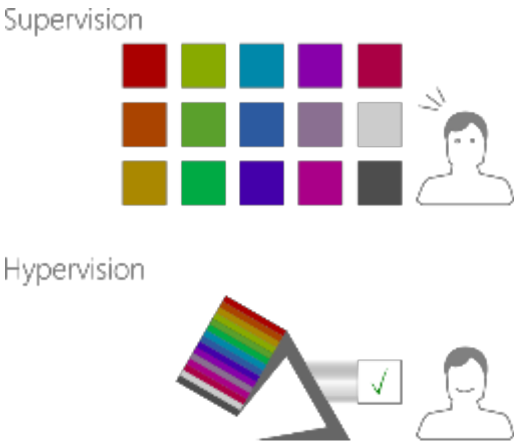
Validation by simulation

Optimization for best compromise

Selected Strategies

APOGÉE: ASSISTANT FOR CONTROL ROOM OPERATORS





gridOS

Cortana. Siri amazon echo Google now Facebook M Apogée

A personnal assistant for the operator

AI & Power System

« Artificial Intelligence is the new electricity », Andrew Ng

Litterally, AI is electricity
So, Electricity is already AI ?
It is true that power systems are the most complex artificial systems we have on Earth!

But why are we talking of new **Smart Grids** to tackle the current Energy Transition ?
Surely we need to manage a more complex system in a more proactive fashion

Electricity is about processing energy
while **AI** is about information processing !

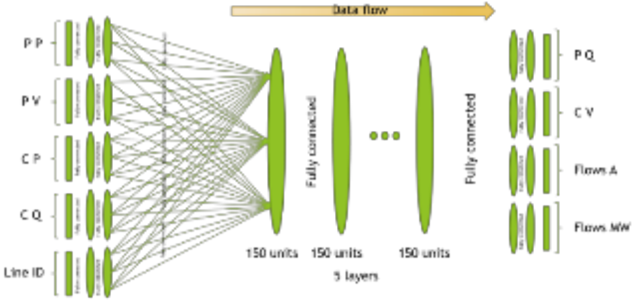
AI could be transformative for us, leading to a new efficient cyber-physical system
with properly entangled information and physics

OUR REFERENCES

Related work:

Accepted

- **IERP 2017: Introducing Machine learning for power operation support**
- **ESANN 2018: Fast Power system security analysis with Guided Dropout**
- **IJCNN 2018: Anticipating contingengies in power grids using fast neural net screening**



In review for **2018**

- **ISGT Europe: Optimization of computational budget for power system risk assessment**
- **ISGT Europe: Guided machine learning for power grid segmentation**
- **MedPower 2018: Expert System for topological remedial action discovery**

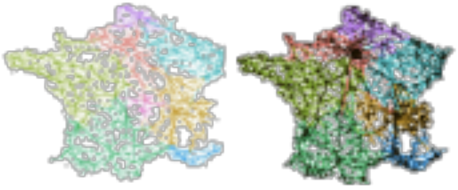


Fig. 7. Comparison of a) our French power grid segmentation with b) historical RTE regional segmentation.

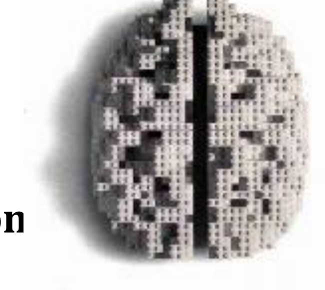
Thank You
For your attention !

antoine.marot@rte-france.com

10

Annexe

ARTIFICIAL INTELLIGENCE IN APOGEE



Data

Generation

Labelling

Capitalization

Representation

Modeling

Contextualization

Visualization

Learning

Imitation

Simulator

Adaptation

Exploration

Reinforcement

Transfer

ARTIFICIAL INTELLIGENCE IN APOGEE

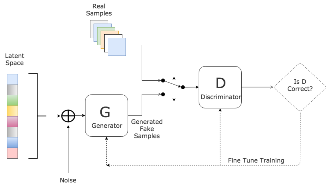
Generation

Contextualization

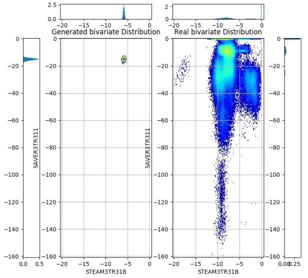
Labelling

Visualization

Generating multivariate production plans with **GANs**

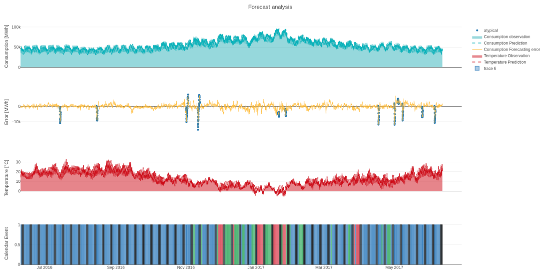


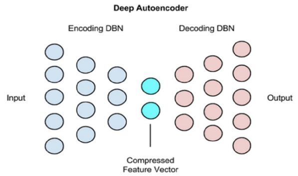
GAN architecture



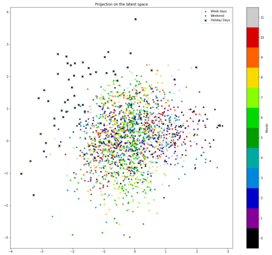
Learning complex joint distribution from 2 nearby productions

Predictive past **event detection** to look for interesting context to relabel

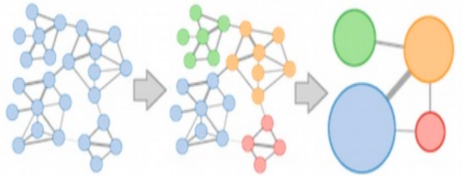




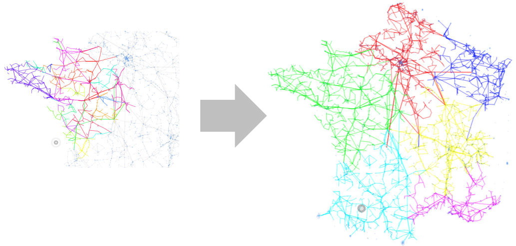
Latent space Deep autoEncoder



Hierarchical power grid segmentation for flexible representations



Infomap graph clustering algorithm



French power grid segmentation

AI IN APOGEE: DATA

Data

Generation

Labelling

Capitalization

Representation

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Contextualization

Visualization

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Imitation

Simulator

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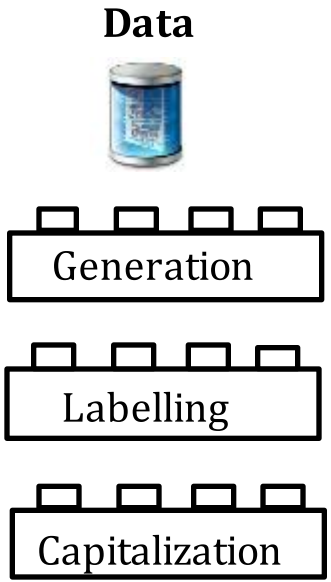
Reinforcement

Transfer

AI IN APOGEE: DATA



Data quality & volume is vital for today's AI

Current situation:

- Few interesting situations ever happen and are observable:
  - Generate realistic cases to learn from
- Decisions are not labelled: Why did we do something ?
- Studies are not stored to capitalize from

AI IN APOGEE: DATA

Generation

1. Simple historical **replay** with contingencies

2. Generation from learnt joint distributions with **GANs**

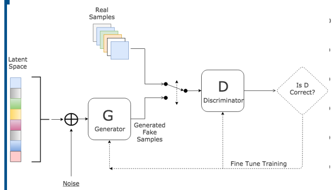


Fig.1: *GAN Architecture*

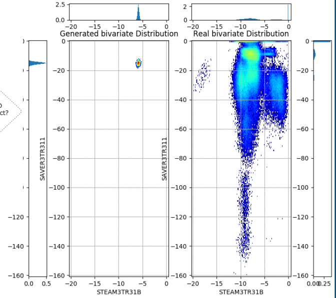
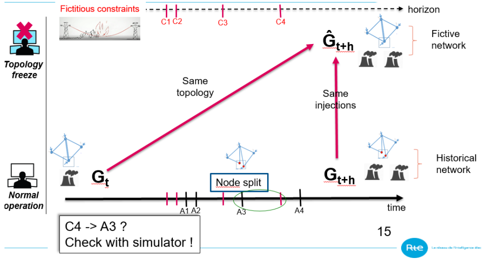


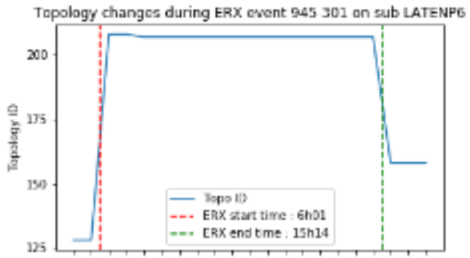
Fig.2: *Learn joint distribution from two productions*

Labelling

1. **Simulated counterfactual** reasoning (what if no operators?)



2. **Crossing** SCADA & Exploitation **databases**



Capitalization

1. Study and decision **traceability** in Apogee

2. Remedial Action **database**

AI IN APOGEE: REPRESENTATION

Data

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Representation

Modeling

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Transfer

AI IN APOGEE: ADAPTATION

Data	Representation	Learning	Adaptation
	 		
Generation	Modeling	Imitation	Exploration
Labelling	Contextualization	Simulator	Reinforcement
Capitalization	Visualization		Transfer

AI IN APOGEE: ADAPTATION

Adaptation

Exploration

Reinforcement

Transfer

To manage a system, it should continuously adapt in a coherent fashion:

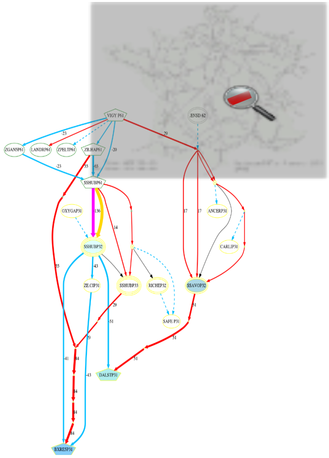
- For new context and new grid developments

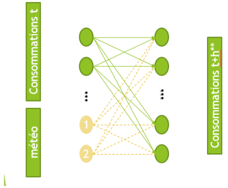
Current situation:

- **Expert system** to discover topological remedial actions with a physical simulator

- Reinforcement learning:
  => Academic challenge and thesis to start

- Transfer :
  => Extend Guided Dropout neural network architecture to transfer learning problems





Reference model + conditional neurons

AI IN APOGEE: RESEARCH STATUS

Data

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Labelling

Capitalization

Representation

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Contextualization

Visualization

Learning

Imitation

Simulator

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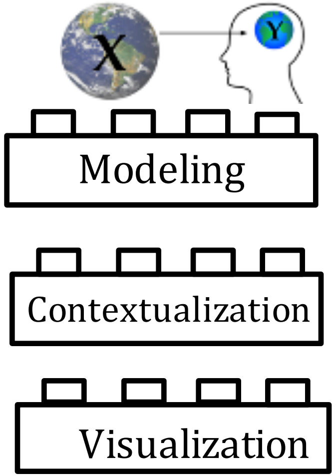
Transfer

AI IN APOGEE: REPRESENTATION

Representation

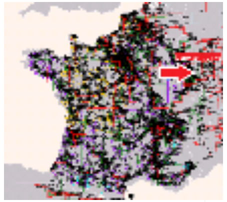


Proper representation is important to effectively learn

- Too much information kills information => need selection
- Wrong detailed data is worse than no data => need abstractions

Current situation:

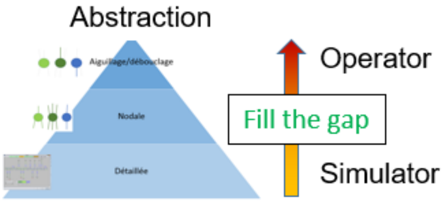
- Detailed deterministic physical modeling in study tools
  - Ineffective with uncertainties
- No relevant contextual indicator restitution
  => As complexity rises, context becomes important
- Static visual representation with interactive navigation
  =>Dynamic hierarchical and task specific visualization



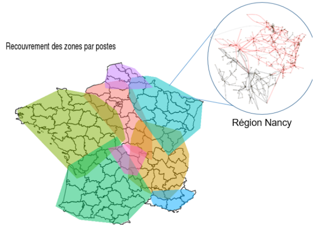
AI IN APOGEE: REPRESENTATION

Modeling

1. New **numerical object class** to model abstract information & action



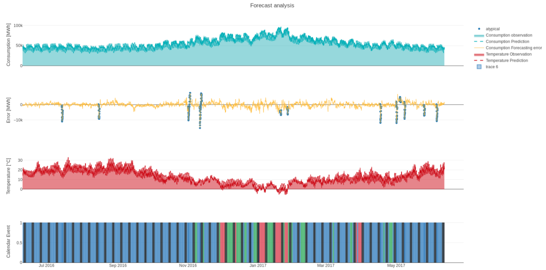
2. New **proxies**, learning hierarchical electrical segmentation



Clustering de toute la France (point figé 2012/01/19 :19)

Contextualization

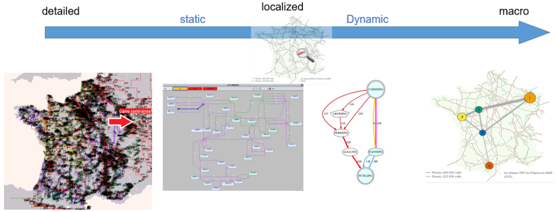
1. Predictive **event detection** to look for interesting context



2. New operator **indicators**

Visualization

1. Dynamic hierarchical and task specific visualization: **HYPERVISION**



AI IN APOGEE: LEARNING

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Transfer