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Machine Learning

Attractive and Powerful tools for Power Systems Applications

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Challenges in Power Systems

Particular difficulties

- Too much information (growing and growing)
  - Large interconnected system
  - Many assets and sensors
  - Many unsupervised agents, with independent behaviour
  - Interaction with other systems and environments
- Need to act fast
  - Fast flow of information
  - Prevent cascading failures
  - Corrective action in seconds
- Anticipation is key, the issue is generate time for decision
  - Weather forecast
  - Consumer response behaviour
  - Agents behaviour (market and generation)
- Uncertainty
  - Uncertainty in inputs, algorithm parametrization, change in behaviours
  - Expected value is not enough for risk based decisions
- Meaning and interpretability
  - Operators carry the responsibility, need a justification for the decision
  - We need AI to capture and aggregate the knowledge of operators (imitation learning)

ML applications in Power Systems

High value tools

- Renewable generation forecast (essential for control)
  - Wind generation forecast
  - Solar generation forecast
  - Hydro generation forecast
- Electricity price forecast (essential for profit)
  - Short term forecast (spot prices, day ahead)
  - Mid and long term forecast (futures, day-to-years ahead)
- Load forecast
  - Short term (consumer, substation, system level)
  - Long term (spatial load forecast)
- Generation dispatch optimization (profiling agent strategies)
- Consumer profiling and demand response
- State estimation and system control (deal with huge and uncertain data)
- Asset management (health and risk of failure, transformers, protections)
- Network fault risk prediction

ML applications in Power systems

Renewable generation forecast (wind, solar, hydro)

Objective // target

Forecast hourly generation for 7 days ahead, for each generation plant
Challenges: accuracy, long horizon, high resolution, uncertainty modelling

Data // Features

Chronological information (hour, month)
Future weather forecast (many features)
Historical weather data (many features)
Generation characteristics (engineering)
Availability plan (strategy, reliability)
Historical generation (himself, neighbour)
Real time generation (himself, neighbour)
Simulation time series (new plants)

Algorithms

- Classical Supervised Learning
  - Regression (function adaptation)
  - Kernel Density Estimation (probabilistic, parametrization)
- Neural Networks (time series problem)
  - Conventional (FFNN, RBF, ensemble)
  - Recurrent Neural Networks (LSTM, GRU)
- Deep Learning (? maybe not)
  - Problem based on physics (meteorology, engineering)
  - Week link with past, historical don't repeats
  - Highly chaotic process, high uncertainty

ML applications in Power systems
Electricity price forecast (spot, futures)

Objective // target

SPOT: Forecast hourly prices, for day ahead, for regional markets
FUTURES: daily, monthly, annual prices, for year(s) ahead, for markets
Challenges: behaviours, long horizon, uncertainty, identify features

Data // Features

Chronological information (hour, month)
Renewable forecast (short horizon)
Consumption forecast (short and long term)
Price forecast (renewables, thermal)
Availability plan (strategy, reliability)
Generation characteristics (engineering)
Agent bidding strategies (historical)
Prices of oil, gas, coal (different markets)
CO_2 prices (loop problem)
Market rules and restrictions

Algorithms

pre-processing, clearing, synchronization (80%)
Usual Classical Tools (function adaptation)
- Supervised Learning (Regression, KDE)
- Conventional NN (FFNN, RBF, ensemble)
- Dimension reduction (PCA, LSA,)

Dimensionality Reduction (complementary tool)
- Conventional (PCA)
- Unsupervised Learning (clustering, pattern search)
- NN encoders (AE, Variational AE, Denoising AE, SAE)

Reinforcement Learning (behaviour and environment adaptation)
- TD (Temporal Difference), SARSA, Q-Learning

ML applications in Power systems

Generation dispatch optimization and forecast

Objective // target

Identify patterns in hourly generation, for portfolio of generation units
Forecast hourly generation, for day ahead, for generation agents

Data // Features

Chronological information (hour, month)
Renewable forecast (short horizon)
Consumption forecast (short and long term)
Generation mix (renewables, thermal)
Availability plan (strategy, reliability)
Daily generation patterns (historical)
Market bidding actions (recent data)

Algorithms

Clustering (day dispatch profiling)
K-mean, Fuzzy c-mean, DBSCAN
Patter search (associated rule learning)
"sunday + summer + high renewables = pattern X"
Convolutional Neural Networks
"Transform generation data in motion 2D images and process with image CNN algorithms"

ML applications in Power systems

Network fault risk forecast

Objective // target

Forecast, for 7 days ahead, the risk of outage in the network lines, caused by meteorological events. The prediction of number and location of outages are used to plan preventive and corrective actions.

Data // Features

Meteorological forecast (7 days)
Historical meteorology (4 years)
- wind speed, direction and gust
- temperature, hourly and lag average
- precipitation and humidity

Fault events (4 years, 80000 km lines, 12000 events)
- fault duration, location and equipment

Fault cause (storm, wind, rain, other)
Geographic characteristics (100 m resolution)
- orography, vegetation, urban coverage

Power line characteristics
- age, length, type, voltage

Algorithms

Classical Supervised Learning (CSL)
- Regression (function adaptation)
- Kernel Density Estimation (good for rare events)

Classification (also a CSL)
- Naive Bayes inference (probability index)
- SVM, decision trees (yes, no)

Neural Networks (function adaptation)
- Conventional (FFNN, RBF, ensemble)
- Recurrent Neural Networks (LSTM, GRU)

Implementation Example
Network fault risk forecast

Bayesian Inference.

Explanatory Event V

Number of occurrences		V	$\bar{V}$	sum
Fault events E	E	E_K	$E_T - E_K$	E_T
	$\bar{E}$	$V_K - E_K$	$V_T + E_K - E_T - V_K$	$V_T - E_T$
	sum	V_K	$V_T - V_K$	V_T

Bayes Teoreme

$$P(E|V) = \frac{P(V|E) \cdot P(E)}{P(V)}$$

$$P(E|V) = \frac{E_K}{V_K} \qquad P(V) = \frac{V_K}{V_T}$$

$$P(V|E) = \frac{E_K}{E_T} \qquad P(E) = \frac{E_T}{V_T}$$

V Explanatory Event occurred (wind speed > 10m/s)

$\bar{V}$ Explanatory event don't occurred (wind <10m/s).

E Fault occurred independently of V

$\bar{E}$ Fault didn't occurred independently of V

E_T Total occurrences of faults

V_T Total occurrences of explanatory event

E_K Kernel density estimation for fault occurrence E, done for bin i in V

V_K Kernel density estimation for explanatory variable V, done for each bin i in V

Implementation Example

Network fault risk forecast

The Risk Index IR is the conditional probability P(E|V) normalized by the probability of occurrence of events P(E), in this modelling computed by the normalized density functions

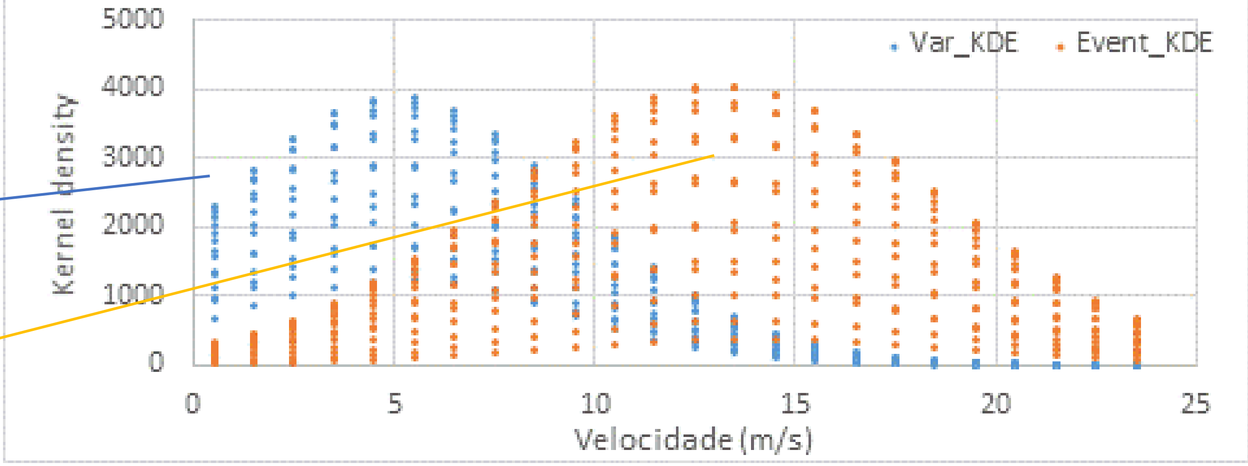
$$RI_i = \frac{P(E|V)}{P(E)} = \frac{E_{Ki}}{V_{Ki}} \cdot \frac{V_T}{E_T}$$

$$V_{Ki} = \frac{1}{nV \cdot |H|} \cdot \sum_{k}^{nV} K\left(H^{-1}(V_k - V_i)\right)$$

$$E_{Ki} = \frac{1}{nE \cdot |H|} \cdot \sum_{k}^{nE} K\left(H^{-1}(E_k - V_i)\right)$$

$$V_T = \sum_{i}^{ni} V_{Ki} \qquad E_T = \sum_{i}^{ni} E_{Ki}$$

Simple example, V_K e E_K for a univariate (wind)



$$\widetilde{IR}_i = \frac{P(E|V)}{P(E)} = \frac{1}{ni} \cdot \sum_{i}^{ni} \frac{E_{Ki}}{V_{Ki}} \cdot \frac{V_T}{E_T} = 1$$

Average Risk Index is 1

IR=1 is the reference value, normal situation

Implementation Example
Network fault risk forecast

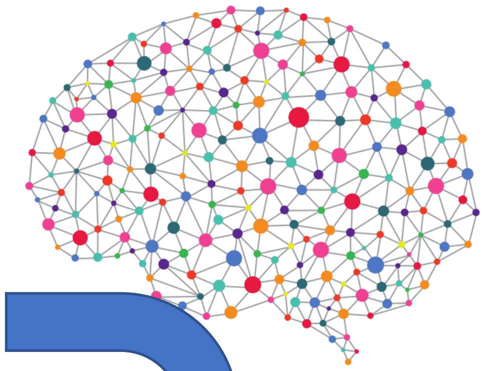
Explanatory Variables

(knowledge base with 47000 bins)

	VT	ET
sum->	4218423	1292055

Vh	Vh3	Vh6	T(ºC)	L(km)	VK	EK	IR
10	12	4	15	27	40,04508	157,3597	5,175265
2	6	8	15	27	406,2767	30,76772	0,099738
10	6	8	15	27	336,463	473,2143	1,852289
2	12	8	15	27	20,50657	6,053949	0,388807
10	12	8	15	27	127,5661	805,5669	8,316766
2	6	4	25	27	400,7429	6,959955	0,022873
10	6	4	25	27	111,3828	41,24414	0,487677
2	12	4	25	27	6,786934	0,428144	0,083081
10	12	4	25	27	9,168155	36,97147	5,31096
2	6	8	25	27	162,6946	5,006449	0,040527
10	6	8	25	27	78,62898	96,63353	1,618577
2	12	8	25	27	5,468109	1,044887	0,251664
10	12	8	25	27	19,44295	202,5768	13,72195
2	6	4	15	53	792,1719	29,41837	0,081005
10	6	4	15	53	287,2261	175,6224	1,333735
2	12	4	15	53	17,52777	1,769965	0,220268
10	12	4	15	53	40,04508	117,959	6,42533
2	6	8	15	53	406,2767	23,23488	0,124748
10	6	8	15	53	336,463	363,608	2,357271
2	12	8	15	53	20,50657	4,681737	0,497998

Train a FFNN
RI is the target



Input variables (weather forecast) for 7 days ahead

RI forecast for 7 days ahead, for asset X

Average fault rate for asset X

Probability of fault for asset X, ahead

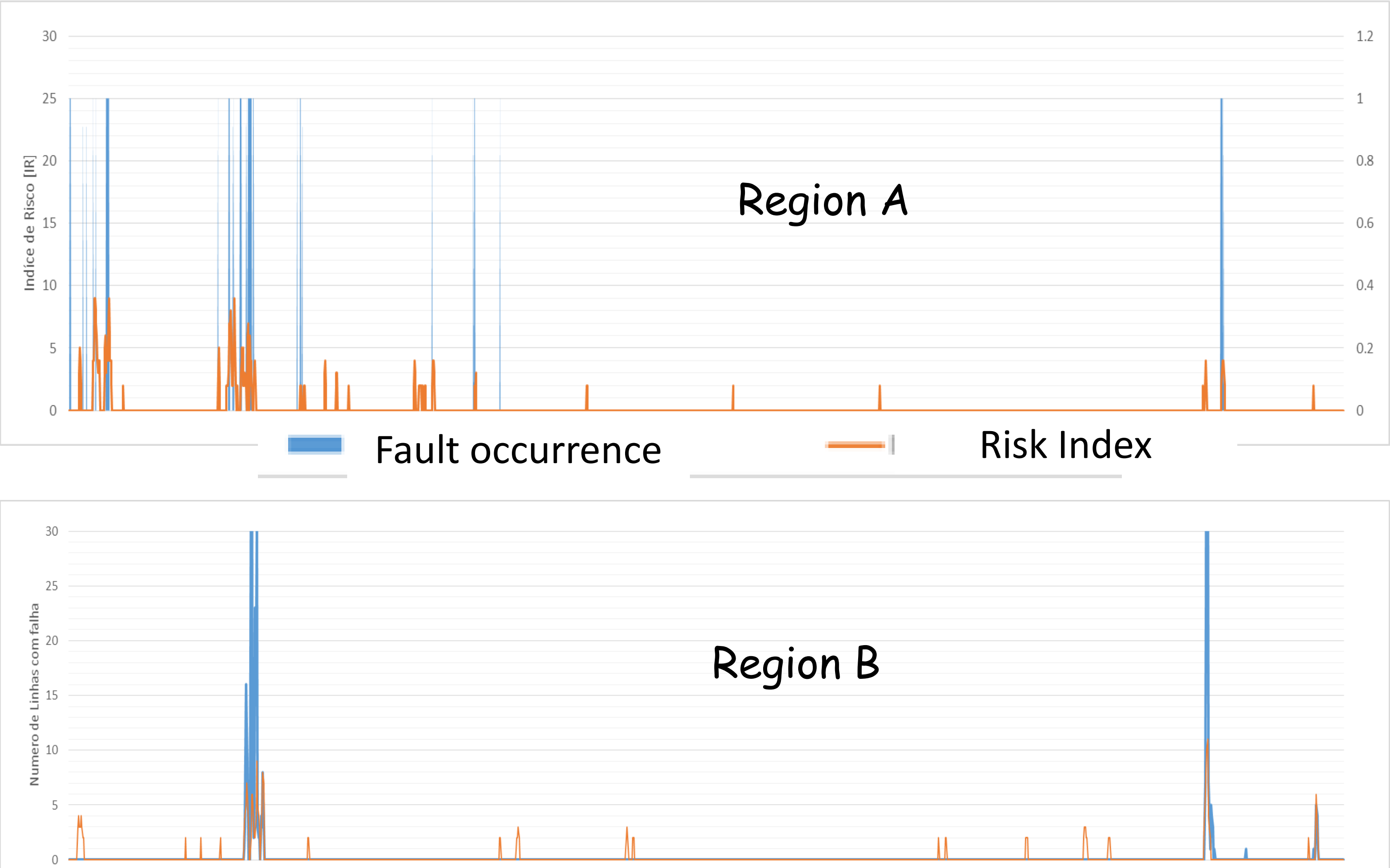
Geographical aggregation

Regional number and location of faults

Implementation Example

Network fault risk forecast

Results 6 month testing



Data	[0-5]	]5-10]	]10-15]	>15	Eventos
05/03/18 18:00	91%	7%	0%	2%	0
05/03/18 21:00	96%	4%	0%	0%	0
06/03/18 00:00	94%	5%	0%	0%	0
06/03/18 03:00	82%	9%	2%	8%	0
06/03/18 06:00	84%	8%	1%	7%	0
06/03/18 09:00	92%	6%	0%	1%	1
06/03/18 12:00	93%	6%	0%	1%	1
06/03/18 15:00	89%	7%	1%	3%	0
06/03/18 18:00	93%	6%	0%	1%	0
06/03/18 21:00	98%	2%	0%	0%	0
08/03/18 21:00	98%	2%	0%	0%	0
09/03/18 00:00	98%	2%	0%	0%	0
09/03/18 03:00	98%	2%	0%	0%	1
09/03/18 06:00	91%	8%	0%	1%	1
09/03/18 09:00	94%	6%	0%	0%	5
09/03/18 12:00	90%	8%	0%	2%	1
09/03/18 15:00	80%	20%	0%	0%	4
09/03/18 18:00	72%	28%	0%	0%	5
09/03/18 21:00	79%	12%	4%	5%	3
10/03/18 00:00	54%	9%	17%	20%	15
10/03/18 03:00	71%	23%	3%	3%	0
10/03/18 06:00	65%	20%	7%	8%	0
10/03/18 09:00	74%	18%	4%	5%	0
10/03/18 12:00	98%	1%	0%	1%	0
10/03/18 15:00	67%	4%	7%	22%	2
10/03/18 18:00	66%	14%	9%	10%	2
10/03/18 21:00	50%	23%	11%	16%	8
11/03/18 00:00	57%	12%	0%	31%	7
11/03/18 03:00	41%	50%	2%	7%	3
11/03/18 06:00	80%	4%	1%	14%	5
11/03/18 09:00	35%	49%	3%	13%	4
11/03/18 12:00	77%	16%	1%	6%	3
11/03/18 15:00	18%	60%	0%	22%	2
11/03/18 18:00	57%	20%	12%	11%	0
11/03/18 21:00	66%	21%	6%	7%	0
12/03/18 00:00	55%	22%	12%	10%	0
12/03/18 03:00	78%	21%	0%	0%	1
12/03/18 06:00	83%	8%	1%	7%	0
12/03/18 09:00	97%	3%	0%	0%	0
12/03/18 12:00	98%	2%	0%	0%	0
12/03/18 15:00	98%	2%	0%	0%	0
12/03/18 18:00	98%	2%	0%	0%	0
12/03/18 21:00	98%	1%	0%	0%	0

Tips to use machine learning in Power Systems

Powerful tool, but better if used by Power System experts

- Realize that 80% of the effort is pre-processing, clearing and synchronizing data
- Data structures and extremely important for efficient usage and reuse in multiple applications
- Realise that the same data could be used in different problems. Cascading of models is very usual in power system forecast.
- Most of the cases we need to integrate societal and environmental behaviour with physical laws, is not only a data analysis
- Study the characteristics of the problem and try to apply ML toll that best fits the objective and requirements
- If possible, do your own ML tools adapted to the problem you are solving

Thanks

Exploring the Past to be King in the Future

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Thank You!

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