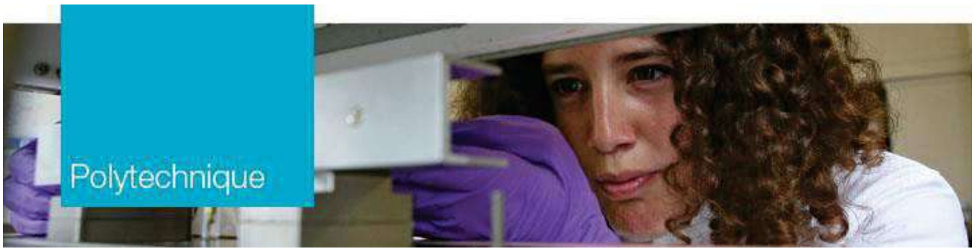
Public PhD thesis defense

24/11/2022



Data based Modelling of LV electrical networks :
Application for monitoring and predictive maintenance of the infrastructure

………………

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Jean-Paul GAUBERT, Université de Poitiers

Headlines

1. Introduction

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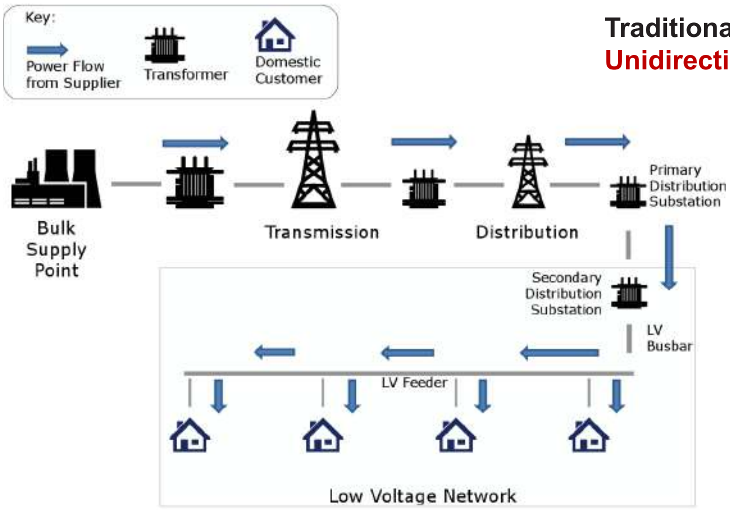
❑ Electrical networks : consumers are end stakeholder



Traditional electrical network : Unidirectional electricity flow

❑ Voltage constraints

✓RMS voltage (averaged over 10 minutes) at the connection point must remain at all times within a range of ± 10% around the nominal voltage (standard EN 50160)

✓Before connecting an user, DSO need to check that the voltage variation between the MV / LV transformer and any point of the LV network does not exceed preset values

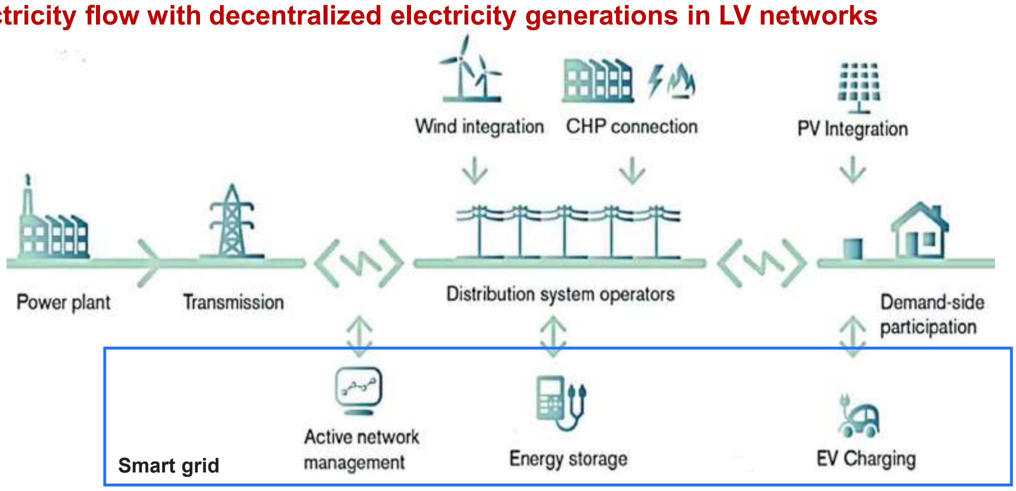
1.2. European sustainable policies involved in LV network

Nowadays

EU policy :

20-20-20 targets (Reduce emissions by **20%**; produce **20%** of the energy from renewable sources; consumed **20%** less energy)

Bidirectional electricity flow with decentralized electricity generations in LV networks



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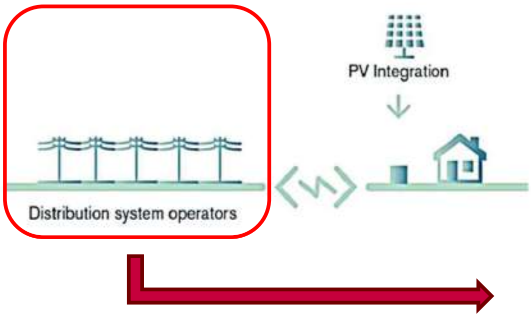
New requirements: Increase the control and the management of the LV network

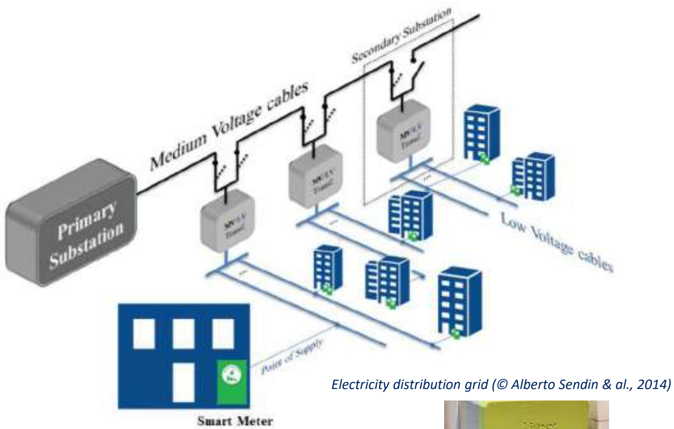
- To do this we need to know accurately and dynamically the state of the network
  => therefore to measure
  => therefore to develop advanced metering systems

1.2. European sustainable policies involved in LV network

In 2009, European Directive:

Intelligent measurement systems to promote the participation of consumers in the electricity supply market





Electricity distribution grid (© Alberto Sendin & al., 2014)

Implementation of individual communicating Smart Meters (SM) :
Sources of temporal and localized information about the flow of electricity transited within the network

Sources of data		Targets
* Characteristics of network equipment * Consumption and production data	**Modelling and computations** → **Time-based Voltage profiles**	* **Detection** of degradations (and maybe a critical situation) * **Decision help** of underground sections to be reinforced

1.2. European sustainable policies involved in LV network

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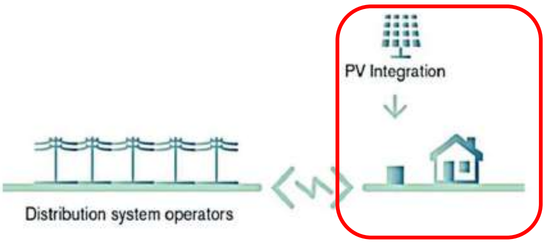

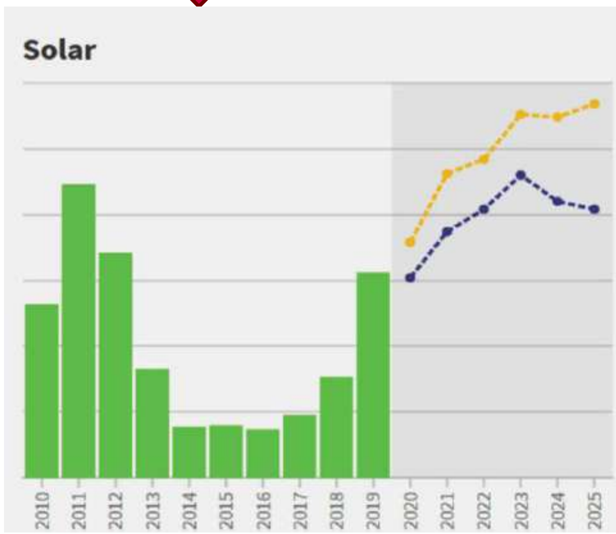

Hosting new PV connections challenge :

- modification of the voltage reference point is exceptional (manually and exclusively when the power is off)

- intermittency of most renewable energies connected to distribution networks

Annual capacity increase of solar installations in European Union

1.3. Challenges and Smart Grid opportunities

News users problems :

- ✓ New consumption profiles (electric vehicles, heat pumps, …)
- ✓ Need of more dynamical regulation process due to the increased variability of the power flows
- ✓ Need of quick reactivity (short response time)

Infrastructure problems :

- ✓ Local failures can lead to a possible collapse (partial blackouts).
- ✓ Ageing of materials (under more stress) and the climate change

Technologies problems :

- ✓ Need of more intelligence for the network management because of new technologies : distributed storage, dispatchable loads, …

Voltage control problems :

- ✓ Risk of over-voltages in the area close to the DGs
- ✓ Risk of voltage dips in case of faults (degradation, leakage current)

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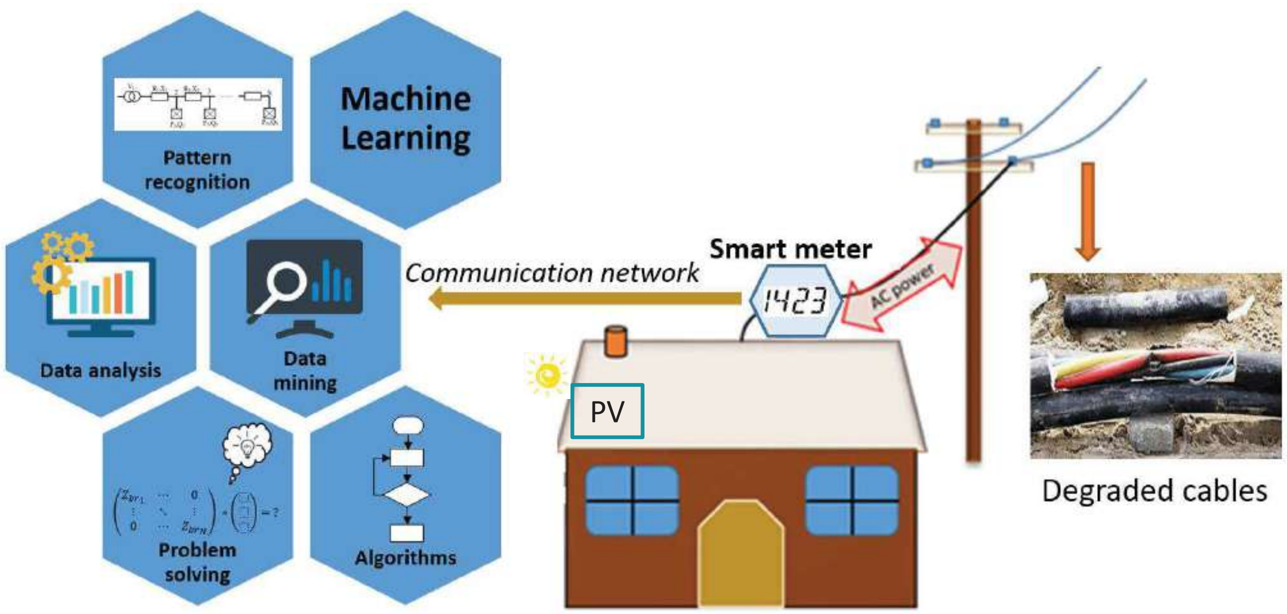
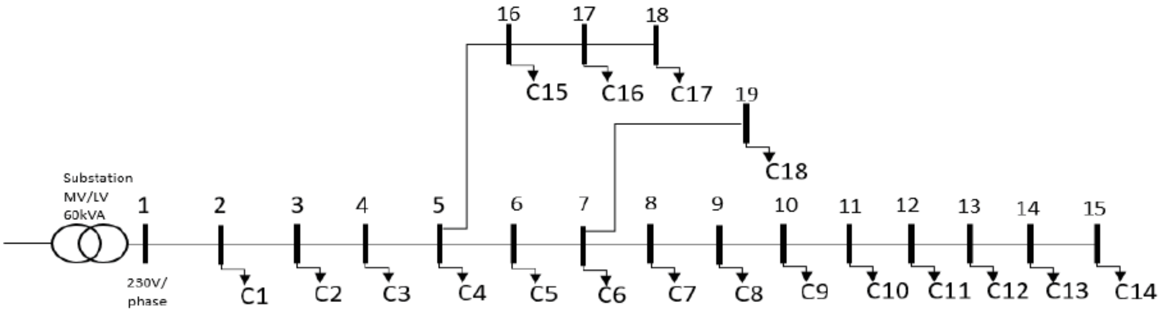
2. Problem formulation

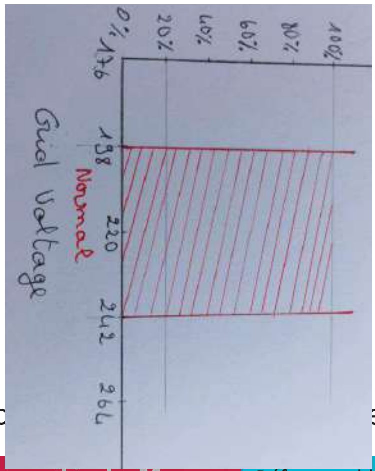
2.1. Objectives

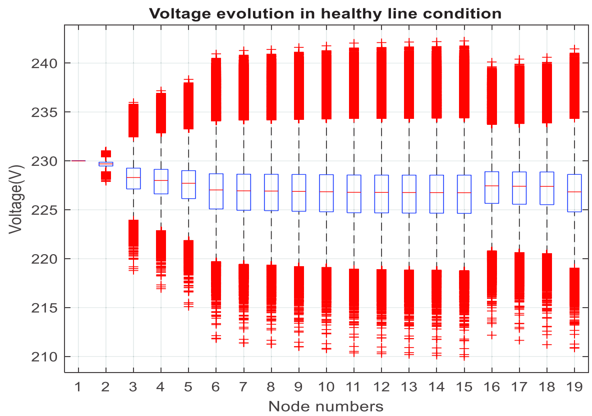


- ✓ Impact analysis of temperature variations onto voltage variations
- ✓ Modelling of the network within integration of the cable degradation
- ✓ Comparison of various Machine Learning (ML) techniques for condition assessment of LV networks

Low-Voltage network and related working hypotheses :





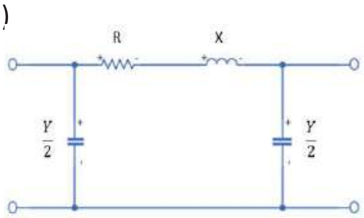


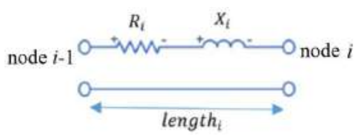
Impc es

Hypotheses :

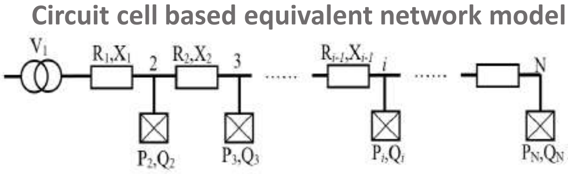
✓Overhead line : regarding reactive power Q consumption, capacitive effects can be neglected from the PI-segment model

✓Underground cable : Due to the short length, shunt admittances (capacitive phenomenon) can be neglected (0,0013pu increase of the slight voltage per 0,75km length which equal to 0,3 Volts in this application case)





Circuit cell based equivalent network model



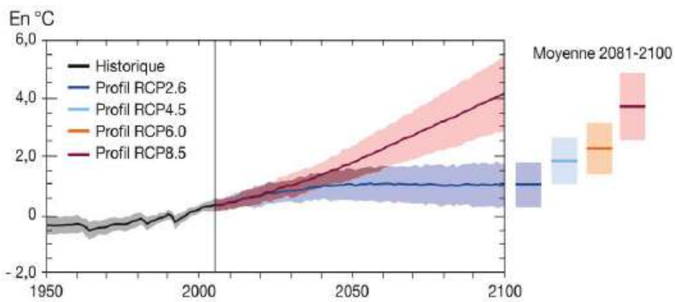
3. Contributions

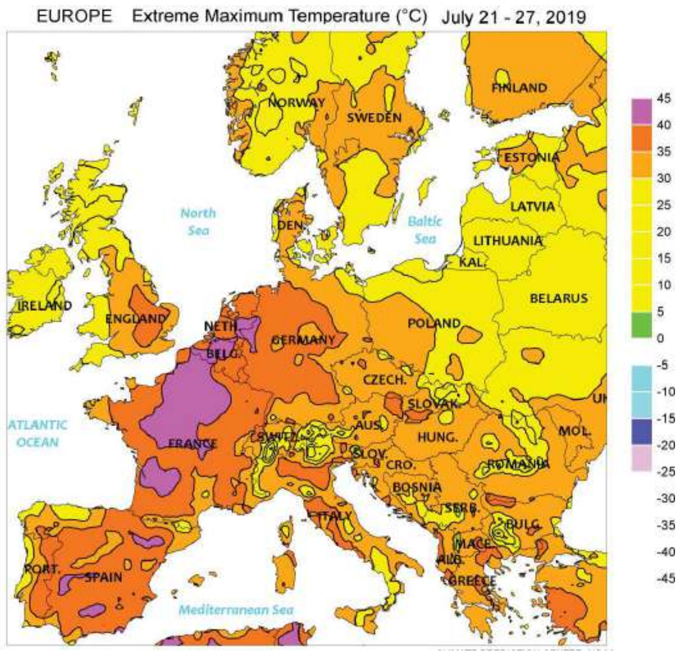
Motivation of the study

✓ Facts :

- Higher ambient temperature limits the cooling of overhead lines and damage conductors and insulators
- In permanent warming condition, the ground also heats up
  => induce the heating of underground cables
  => a power derating may be scheduled (as during summer 2003 in France)

✓ Unfortunately, the future various considered scenarios by the GIEC shows up a significant temperature increase





✓ The line **safety temperature** guaranteed up to an outside temperature of **40°C** was exceeded in many places during the heat waves of June and July 2019 (as well as 2022)

Assumptions on the temperature, adopted a few decades ago when sizing LV electrical networks, do not offer now a sufficient margin of safety with the global warming

3.1. Temperature based model of the resistance distribution

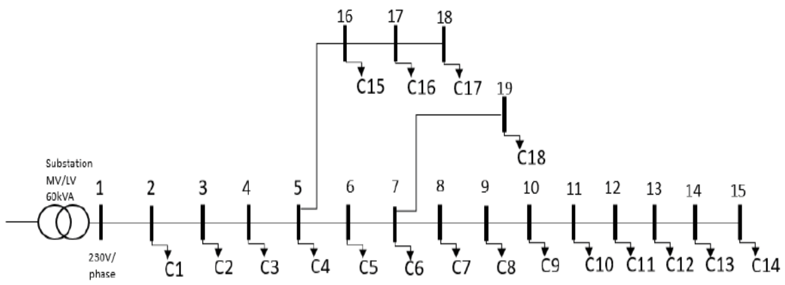
Study the effect of the temperature onto the operation of LV networks

$$Resistance = function \text{ (Steady state temperature)}$$

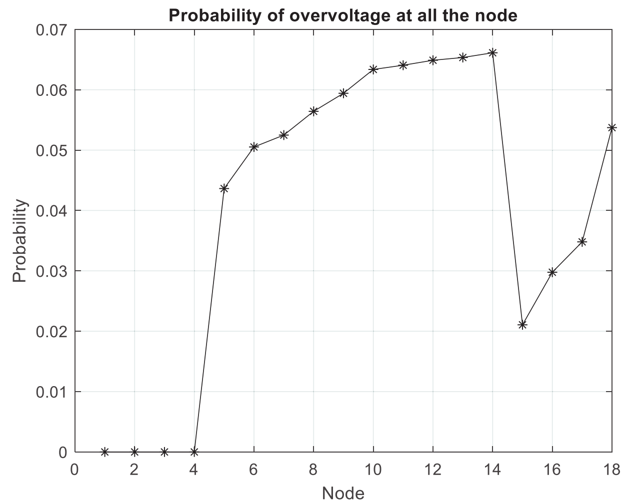
✓ Model the variations of the impedance in a year **as a temperature based variable**

✓ Show how and when the effect of the temperature variation influences the voltage profile

❑ Annual probabilities for all voltage nodes



	Summer	
	Overvoltage	Dip
Fixed R annual	**10.6 %**	**0 %**
Fixed R Winter	**13.9 %**	**0.001 %**
Sampled R Winter	**12.4%**	**0 %**



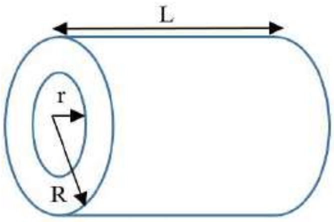
❑ Main findings

- ✓ The last node is the most critical node, in each study : the overvoltage passes through whole lines in the downward direction to the end of the feeder while
- ✓ Enable the detection of critical nodes

❑ Emerging issues and problem formulation

- ✓ Need to consider the **uncertain nature of the location and criticity of the insulation wear** as a lost of thickness of the insulation material
- ✓ Need to build a new model for evaluating impacts of insulation degradation of cable lines on the nodal voltages

- ✓ Cable with a **total radius *R*** and a **conductor radius *r*** : radius of the insulating material is *R-r*
- ✓ With a degraded insulation, the leakage current flows radially outwards from the center towards the surface of cable along the cable length *L*
- ✓ For an elementary section of a cylindrical cable of radius *x* and the thickness *dx :*



$$\boxed{Resistance = function \text{ (total cable raduis \{R\} and conductor radius \{r\})}}$$

1. Uncertainty modelling of insulation thickness

Represent the uncertainty of the insulation radius variation

2. Propagate the uncertainty onto AC voltages

Random sampling of the insulation thickness in order to cover all the possible scenarios

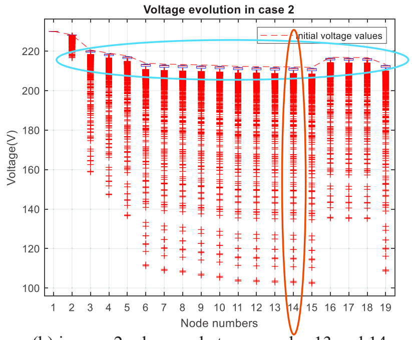
3. Construct the Voltage profiles of the network

Monte Carlo simulations including a Load Flow calculation

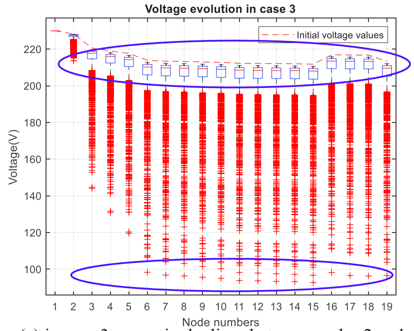
Determination of the nodal voltage variations regarding the insulation wear and the network working point

▪Working point in heavy load (85%) – light PV (0%) generation conditions :

- Important voltage variations
- Extreme scenarios of the case 2 : voltage drops to -115 volts
- nodal voltage variations are noticeably enlarged with respect to the ones in cases 1 and 2 ; voltages can go down to 90 volts



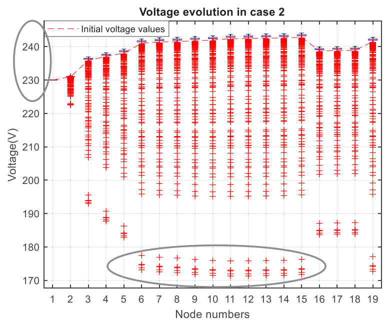
(b) in case 2 : damage between nodes 13 and 14



(c) in case 3 : wear in the lines between nodes 2 and 3, 8 and 9, 14 and 15, as well as, 17 and 18

▪Working point in low load (13%) – high PV (80%) generation conditions :

- Extreme scenarios of the case 2 : the nodal voltages can reach 170 volts
- Case 3 : the nodal variations become larger, and the voltages drop to around 140 volts



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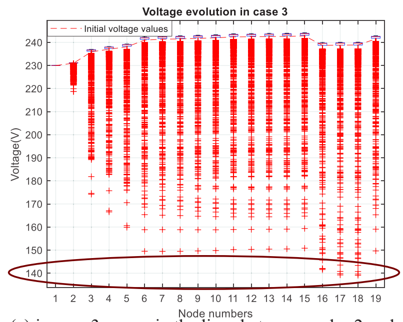


(c) in case 3 : wear in the lines between nodes 2 and 3, 8 and 9, 14 and 15, as well as, 17 and 18

❑ Main findings

✓ Less they are damaged lines in the feeder, less the insulation wear impacts the nodal voltage variations

✓ Due to the leakage current passing through entire lines in the upward direction of a degraded line, the closer that line is to the end of the feeder, the higher the voltage drop is

❑ Emerging issues and problem formulation

Establish the cable diagnosis (healthy or degraded) with the use of Machine Learning classifier and Smart Meter measurements

✓ Need to build a **synthetic database** of **nodal voltage variation signatures** according to the studied network condition (healthy or degraded) : model-based knowledge

✓ Need to detect the **LV cable condition** from available data i.e. voltage variations and Net demand profiles

Task : Early detection of cables degradations before breaking

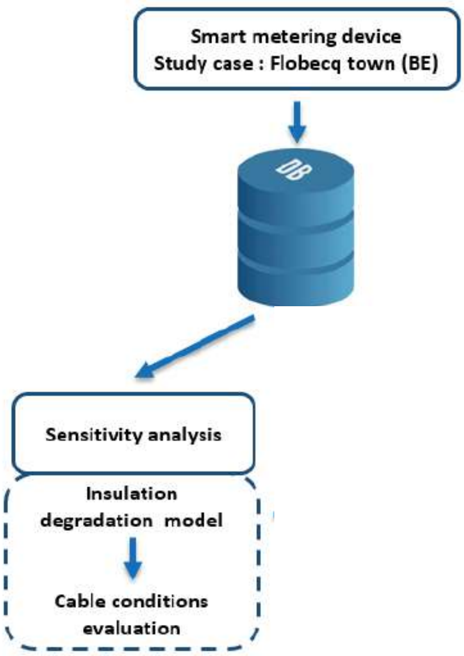
- Build a generic Learning-based identification / classification framework for an entire LV network : classification into multi classes of all electrical lines

- Evaluate the impact of PV generation onto the ML performances

Why Supervised Machine Learning (ML) ? :

Previous approach

Present approach

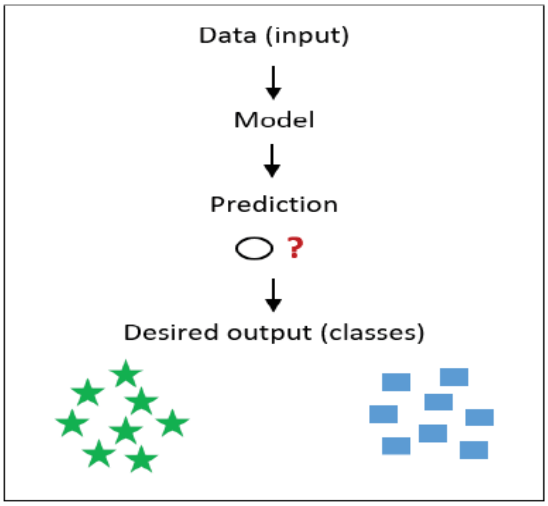


Classification methods = construction of predictive models our discrete responses

- Classification methods : dispatch the input observations in categorical groups
  Lead to the construction of predictive models

  - generate automatically knowledge rules (so-called the **Model**) from a database containing "samples" of inputs (so-called the **Data**) with the corresponding outputs

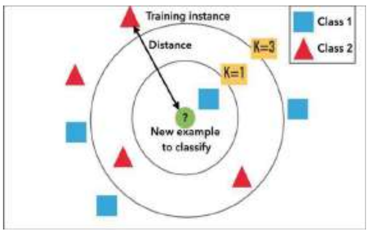
  - new input data (represented by the **circle** symbol) can be predicted into two classes (represented by the **star** and **square** groups)



- Objective of a classification : derive a rule or set of rules, which determine the class each input data (the test data set)
  The rules must be determined from another set of data (the training data set), whose class values are known.

k-nearest neighbors (kNN)

Each new observation is compared to existed ones by using a distance calculation and a number of nearest neighbors



Mostly used for fault detection and classification but also for power quality classification

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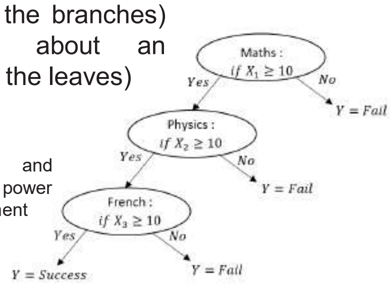
Decision Tree (DT)

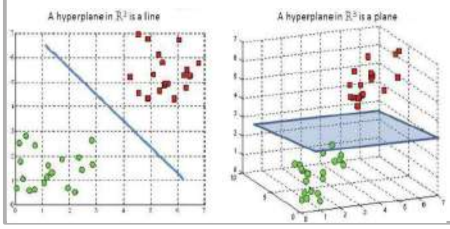
Recursive process, going from the properties (as seen in the branches) to the conclusions about an observation (as seen in the leaves)

Used for Preventive and corrective control, for power systems security assessment



Support Vector Machine (SVM)

The purpose is to learn a linear function in the feature space of input data that deviates from the learning outputs by at most a prescribed distance

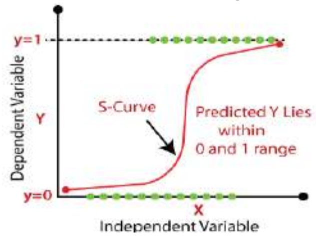


One-vs-One : For the N-class instances dataset, N*(N - 1)/2 binary classifier models have to be generated.

One-vs-All : For the N-class instances dataset, N-binary classifier models have to be generated.

Logistic regression (LR)

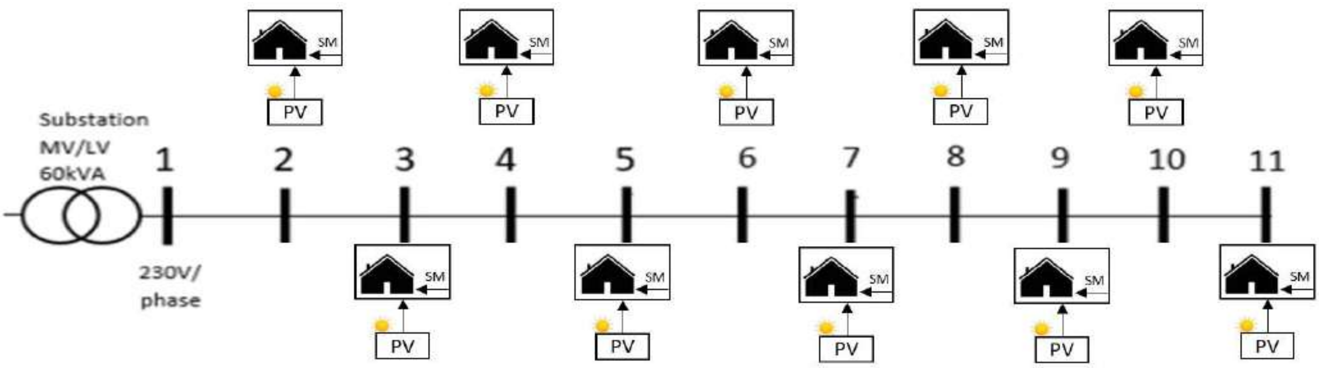
Predict the probability $h_\theta(x)$ of a new observation x to be classified into a given class y



Used for electricity monitoring, visualization and prediction, fault detection in renewable energy production

$$\begin{cases} If\, h_\theta(x) \geq 0{,}5 : predict\ 1\ (healthy\ cable\ line\ class) \\ If\, h_\theta(x) < 0{,}5 : predict\ 0\ (degraded\ cable\ line\ class) \end{cases}$$

Electrical network overview and new resulting labels



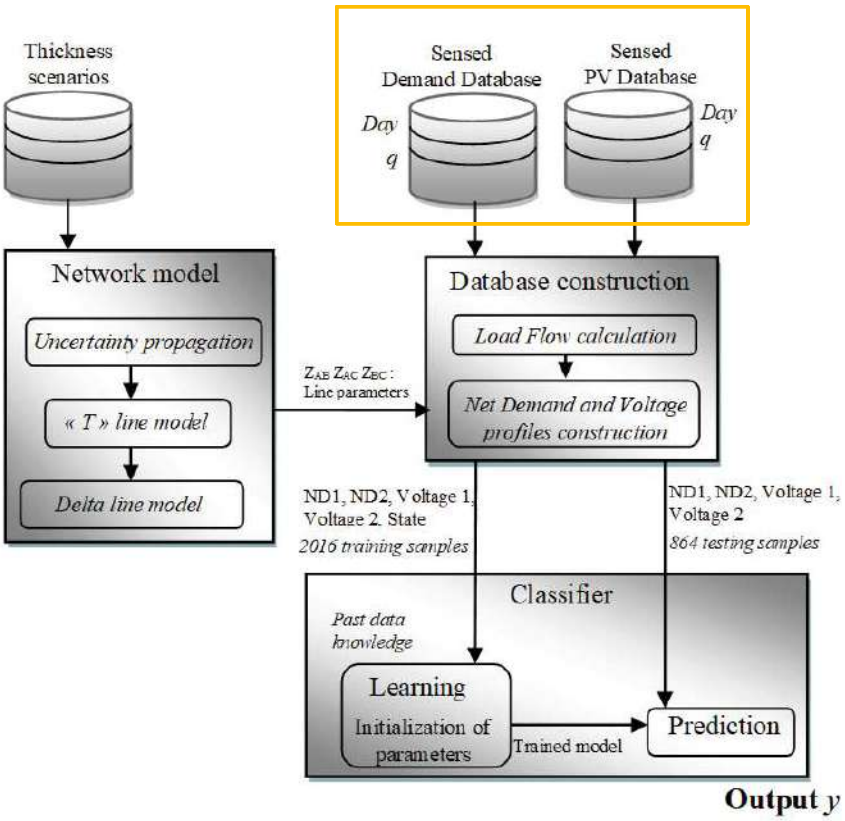
Defined classes	H	A	B	C	D	E	F	G	I	J
Length (m)		46	273	62	63	194	26	11	25	21

❑ Challenges :

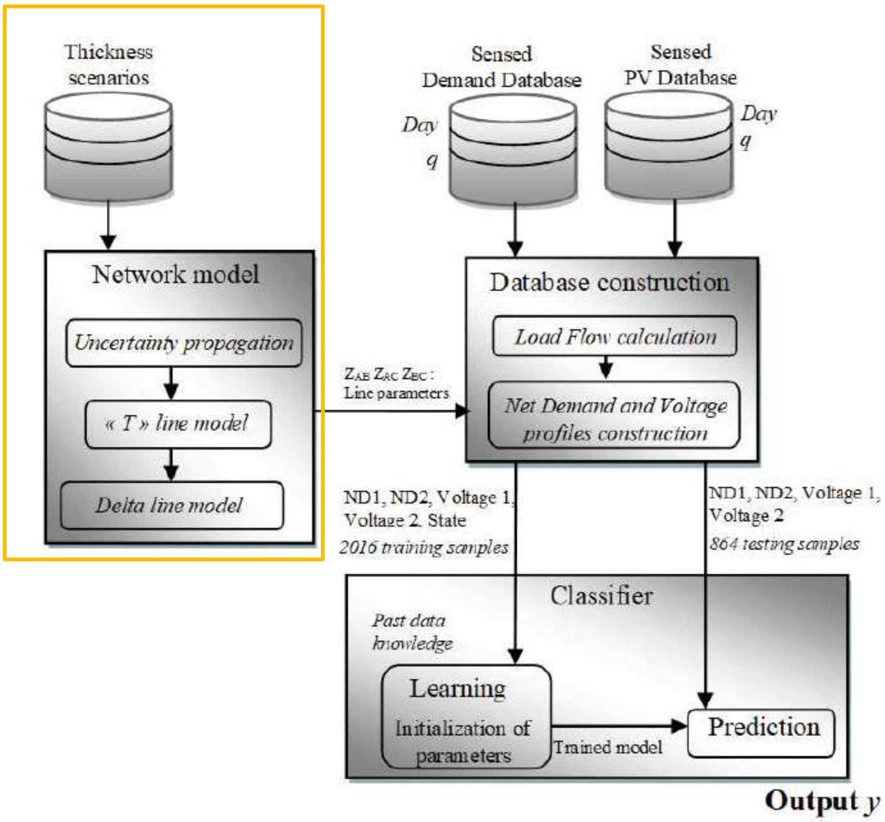
Detecting the degradation somewhere in the network with all the data

More complex because of the number of class is increasing

Multi-class classification problem



3.3. Machine Learning-based detection



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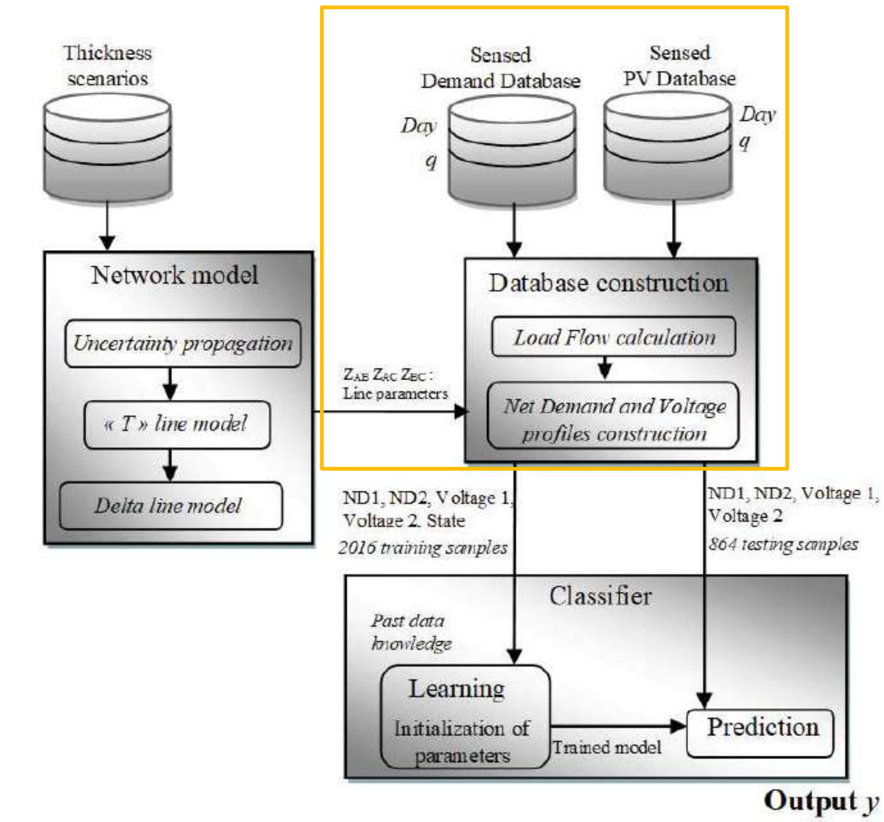
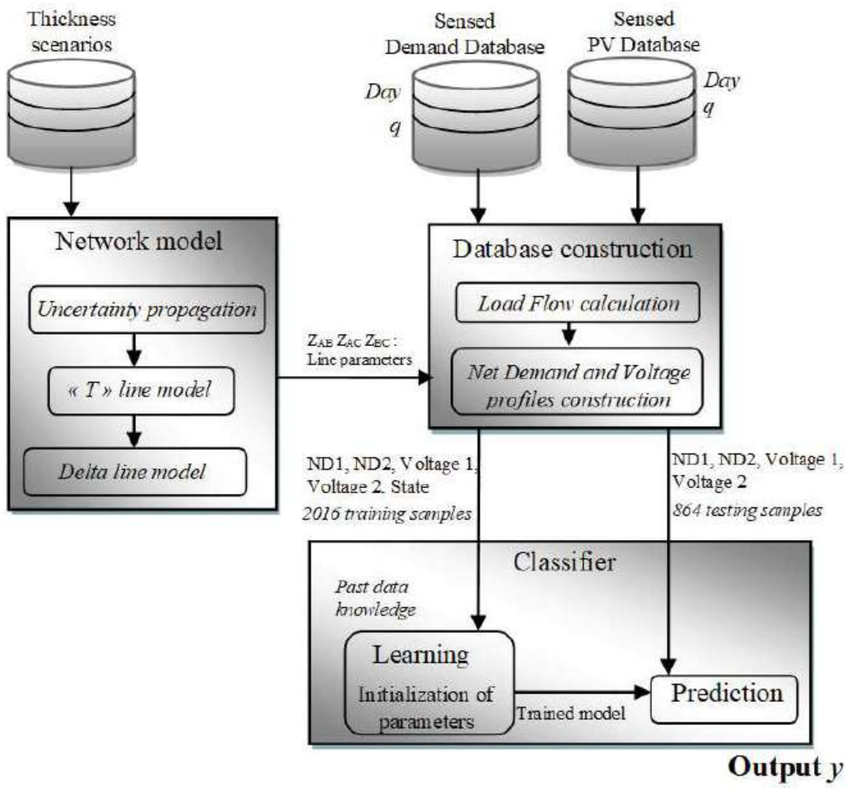
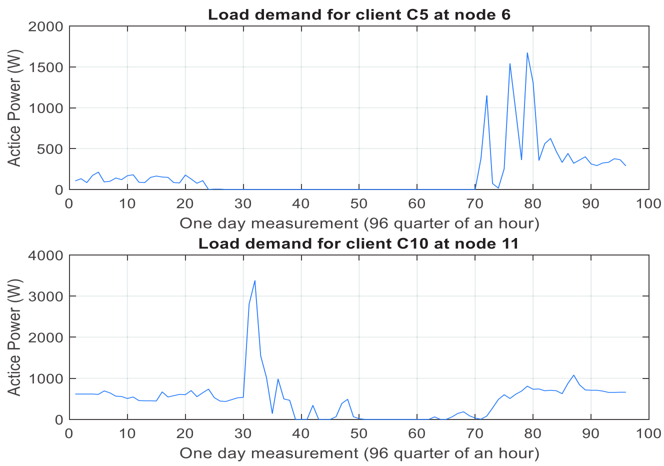


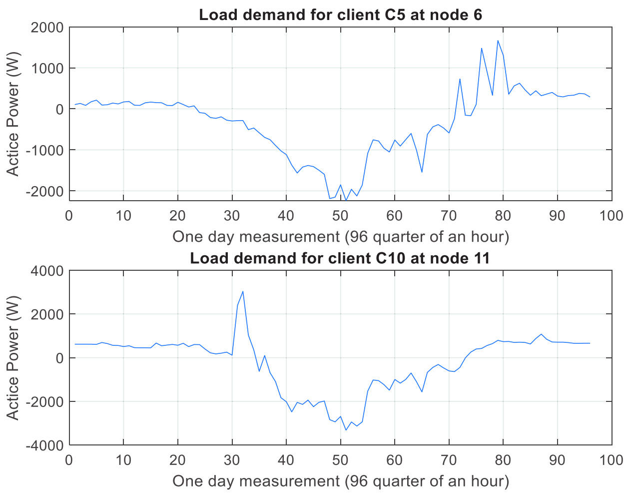


Database	Percentage	Samples
Working database	100%	11532
Training subset	70%	8072
Test subset	30%	3560

Performance analysis of ML techniques according the line degradation severity



Impact of PV generation onto performances of ML techniques



Performance analysis of ML techniques according the line degradation severity

LR

Output Class \ Target Class	H	A	B	C	D	E	F	G	I	J	
H	346 10.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
A	0 0.0%	346 10.0%	1 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	99.7% 0.3%
B	0 0.0%	0 0.0%	333 9.6%	35 1.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90.5% 9.5%
C	0 0.0%	0 0.0%	11 0.3%	311 9.0%	6 0.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	94.8% 5.2%
D	0 0.0%	0 0.0%	0 0.0%	0 0.0%	340 9.8%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
E	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	294 8.5%	14 0.4%	0 0.0%	0 0.0%	0 0.0%	95.5% 4.5%
F	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	52 1.5%	330 9.5%	0 0.0%	0 0.0%	0 0.0%	86.4% 13.6%
G	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	2 0.1%	345 10.0%	0 0.0%	0 0.0%	99.4% 0.6%
I	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	217 6.3%	64 1.9%	77.2% 22.8%
J	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	128 3.7%	281 8.1%	68.7% 31.3%
	100% 0.0%	100% 0.0%	96.5% 3.5%	89.9% 10.1%	98.3% 1.7%	85.0% 15.0%	95.4% 4.6%	100% 0.0%	62.9% 37.1%	81.4% 18.6%	**90.9%** **9.1%**

Target Class

Accuracy and mis-classification rate :

Correctly classed in green and incorrectly classified in red

True positive rate and false negative rate :

Belonging to each class that are correctly in green and incorrectly classified in red

1. Introduction 2. Problem formulation **3. Contributions** 4. Conclusion
3.3. Machine Learning-based detection

Impact of PV generation onto performances of ML techniques

LR

Output Class \ Target Class	H	A	B	C	D	E	F	G	I	J	
H	346 10.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
A	0 0.0%	346 10.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
B	0 0.0%	0 0.0%	340 9.8%	72 2.1%	3 0.1%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	81.9% 18.1%
C	0 0.0%	0 0.0%	5 0.1%	273 7.9%	25 0.7%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	90.1% 9.9%
D	0 0.0%	0 0.0%	0 0.0%	1 0.0%	317 9.2%	20 0.6%	4 0.1%	1 0.0%	0 0.0%	0 0.0%	92.4% 7.6%
E	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.0%	121 3.5%	101 2.9%	58 1.7%	17 0.5%	1 0.0%	40.5% 59.5%
F	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	205 5.9%	225 6.5%	135 3.9%	30 0.9%	5 0.1%	37.5% 62.5%
G	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	15 0.4%	128 3.7%	94 2.7%	41 1.2%	46.0% 54.0%
I	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	16 0.5%	48 1.4%	105 3.0%	28.4% 71.6%
J	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	1 0.0%	7 0.2%	156 4.5%	193 5.6%	54.1% 45.9%
	100% 0.0%	100% 0.0%	98.6% 1.4%	78.9% 21.1%	91.6% 8.4%	35.0% 65.0%	65.0% 35.0%	37.1% 62.9%	13.9% 86.1%	55.9% 44.1%	**67.6%** **32.4%**

Target Class

Accuracy and mis-classification rate :

Correctly classed in green and incorrectly classified in red

True positive rate and false negative rate :

Belonging to each class that are correctly in green and incorrectly classified in red

4. Conclusion

4.1. Highlights

- Integration of the resistance distribution in a seasonal probabilistic tool
  - Affect the collected reliability indices up to 10.4% depending on the season
- Characterization and modelling of LV line in degraded conditions
  - Interesting information about probability of appearance of voltage variations at customer connection points
- Combination of SM measurement data and data analysis tools
  - Construction of a knowledge database for the customer voltage profiles
- Setting up of a data-driven tool approach for the cable condition assessment in a perspective of optimal predictive maintenance strategies
  - Maintaining the network
  - Enlarge the hosting capacity (increase in demand for households, new consumers and renewable sources)
  - Enable the cost-effective planning of reinforcement upgrades by identifying weaker parts of the network

1. Condition assessment for any large ramified LV feeders :
   - Cross Nodal Learning to enable the learning between the models of each line section or cables
   - Ensemble learning process using multiple learning algorithms to get better predictions

2. Model generalisation by integrating an early step for filling the cable characteristics for models generalisation :
   - Voltage measurements for the effectiveness of SM data (rather than estimations from power flow calculations)
   - Transformer voltage and coupling characteristic to improve the quality and accuracy of the database

3. Additional inputs : type of cable, PV production, …
   - Provide adequate and complementary knowledge through more pertinent data inputs
   - Research track to improve the accuracy of ML classifiers by

Thanks for your attention

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