

INDIVIDUAL ELECTRICITY DATA APPLIED TO ENERGY DEMAND MANAGEMENT AND CUSTOMER KNOWLEDGE

Sophie Lamarche EDF R&D

10/2017

For the whole document : Icons made by freepik from www.flaticon.com

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# Sedf

#### The presentation

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 ☆ The Challenges
 ☆ Laboratories of the future
 ☆ R&D studies and Demande-side management

The studies cited were commissioned by various EDF Group entities. The data is from different sources, based on who commissioned the study and the issue addressed.

### ENERGY AT LOCAL LEVEL



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### A GLOBAL EVOLUTION

- Changes in EDF's businesses
  - New customer expectations and environmental concerns
  - Development of competition
  - New data
  - Increasingly local issues and players
- Changes in the research industry
  - Transformation of the businesses
    Rollout of R
- Changes in methods
  - Computational performance
  - Move to scale
- Quid Big Data ?





### SPECIFIC ISSUES

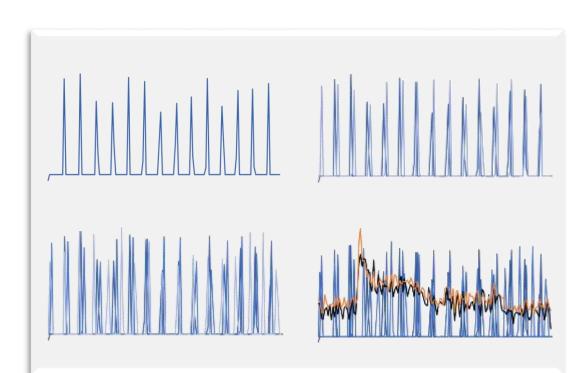
- Errors and other discrepancies
  - Selection of model
  - Likeness between two curves

#### Aggregate vision

- Addition of curves
- Addition of days
- Atypical points

#### Simulation

- Understand curves to be able to reproduce them: simulation using statistical or physical model
- Advantages of aggregate curve vs. individual load curve, need to look closely at individual curve as well



Curve of heat pump over one day, two days, three days, and aggregates over 30 and 100 days.





### FORGET ME NOT

... because solving problems requires asking the right questions.



### Quel consommateur d'énergie êtes-vous ?

#### PREPARING FOR THE FUTURE: DEMONSTRATORS

COMMENCER ICI

Illustration : SEL

EDF R&D

### SMART GRID PROJECTS

- Key challenges of projects EDF is involved in
  - Load management, demand flexibility
  - Introduction of local RES generation
  - Grid management
  - Equipment for metering and tracking, data management platform
  - Involvement of individual customers and companies
  - Economic issues
  - Evaluation of solutions tested



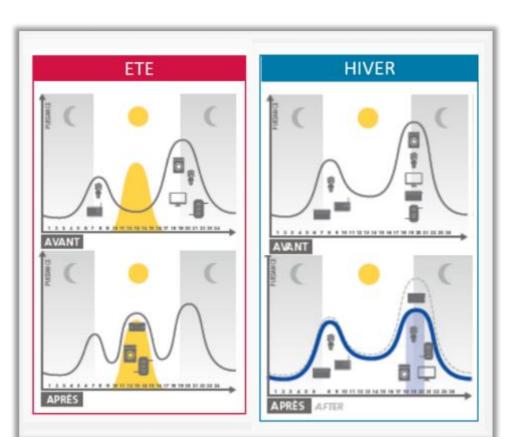
Map: Energies Renouvellables.org



## NICE – CÔTE D'AZUR



- Situation in Côte d'Azur
  - "Electric peninsula"
  - RES generation
- Key challenges for Nice Grid
  - Storage
  - Solar generation
  - Load reduction, monitoring
  - Islanding



NiceGrid: Principle of load monitoring, summer vs. winter

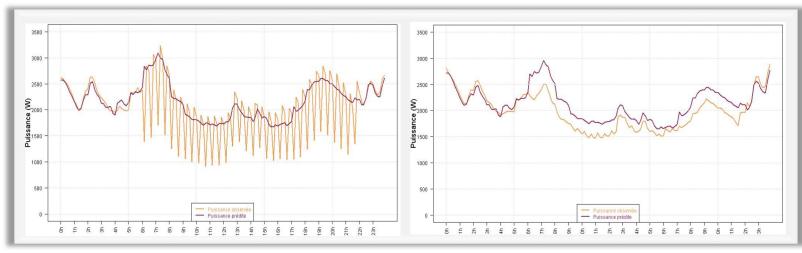
PROJECT MANAGER, R&D BENOÎT CHAZOTTES

### BRITTANY

- 'Une Bretagne d'avance'
  - Energy issues facing an electric peninsula
  - Testing different types of demand response for heating

### Challenges

- Remote management techniques
- Characteristics, efficiency of demand response, challenges
- Sociological aspects



Left: Behaviour (actual in orange) of a group of customers to which requests were sent for ten minutes of load reduction. Right: Results across all groups

PROJECT MANAGER, R&D ISABELLE DEBOST\*

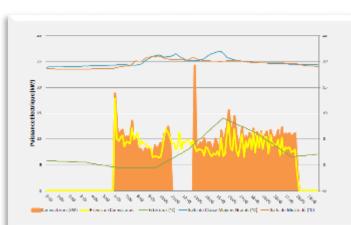
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\*Nouveau contact : Philippe Charpentier

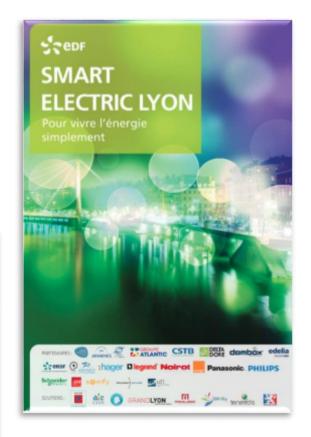
## Une Bretagne d'avance

### LYON

- EDF launched Smart Electric Lyon in 2012
- Broad consortium, followed by ADEME
- Challenges:
  - □ LRT (local radio transmitter)
  - Demand response and adoption by consumers
  - Impact of renovation
  - Use in B2C and B2B
  - Validation of IS chains
  - Validation of statistical methods and models







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PROJECT MANAGER, R&D SYLVIE PERRIN

Individual load curve with load reduction

86 -62 21 -56 -42 -88 68 -52 -99 -98 8 -73 -96 -42 92 22 -17 -70 53 10 40 79 -41 -89 28 44 -69 14 71 -93 -37 -81 -25 -78 60 69 9 76 -86 -59 -66 -37 56 -52 -90 -80 -66 -60 55 -95 2 2 -51 -84 65 -20 -28 -79 88 -13 40 78 -97 16 -36 -74 -29 69 -83 -84 25 45 -4 31 15 -15 1 -47 -8 81 -92 7 -55 -75 46 -39 88 18 -42 -6 -97 86 -1 4 40 27 87 75 74 72 15 83 78 20 12 68 90 42 88 72 58 56 42 -63 77 -66 7 59 54 -63 -51 -11 -68 -37 -5 17 -60 57 67 -2 5 87 -69 -55 -96 16 -76 51 -52 32 39 26 -97 59 -95 -80 -88 34 1 81 27 37 88 75 24 48 -24 -99 88 16 23 -20 12 21 47 -6 -48 89 5 5 9 23 47 -5 -82 74 -17 -6 81 -17 -50 -14 91 -39 32 90 -59 -30 1 15 60 -96 25 -7 -77 23 49 18 38 58 -97 -23 90 -66 -56 -7 -19 83 6 -46 59 87 90 -40 -11 62 -15 19 1 -41 -86 -56 -54 -11 -9 -24 11

| 82    -2    78    69    -13    1    -5      59    -73    17    -58    -55    -7      32    35    -19    88    -52    10      2    -62    77    5    -86    44    37      4    93    9    -93    -94    -29    14    7      55    -1    12    -76    1    -61    53    -4      51    73    -70    17    -56    99    -19      -27    93    -45    -93    9    23    -32 | R&D STUDIES | 47 46 -48 -95 -16 70<br>-24 -63 -1 26 0 24<br>-67 63 -97 -43 98 5<br>47 9 24 88 -32 -67<br>6 -33 3 70 24 -71 -21 4<br>) -72 -13 2 -6 -26 36 -75<br>99 -80 51 79 76 -20 -85<br>4 -14 79 EDFR&D#70/20174 -85 - |
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Illustration : S.Lamarche 26 42 29 91 29 -36 25 72 -98 31 -63 -44 6 60 -61 89 57 88 -2



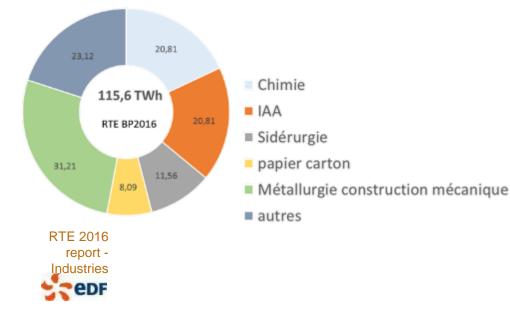
Annual data is the basis of customer knowledge.

It is the basic data for portfolio composition.

It tells us a good deal about residential customers, since it is representative of their usage. It is a stratifying variable for overall load curves.

It is crucial profiling data for RecoFlux.

It can be read remotely or manually (before Linky).



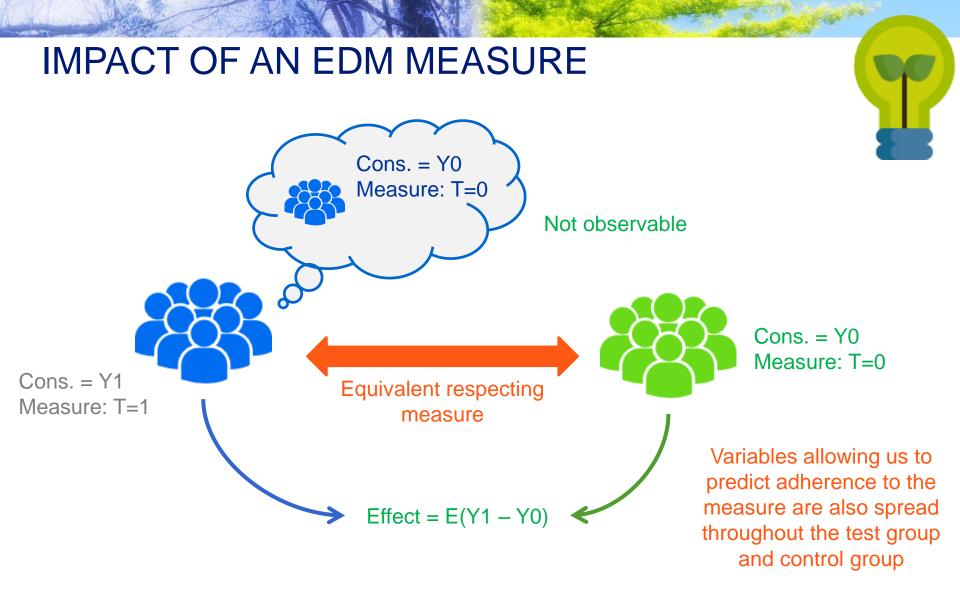


e.quilibre screen

### IMPACT OF AN EDM MEASURE

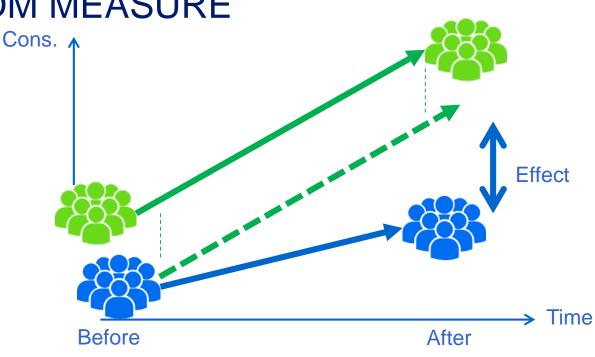


LAURENT BOZZI PHILIPPE CHARPENTIER



### IMPACT OF AN EDM MEASURE

- Use of customers' historical data, taking into account external factors
- Differences in differences method



Principle of differences in differences method

- Find an upper bound:
  - A linear model provides a confidence interval
  - A random forest analysis helps identify the most receptive subpopulation





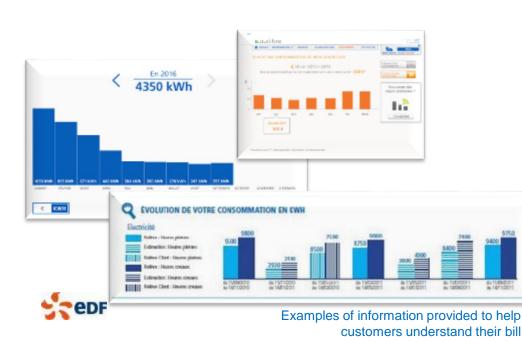


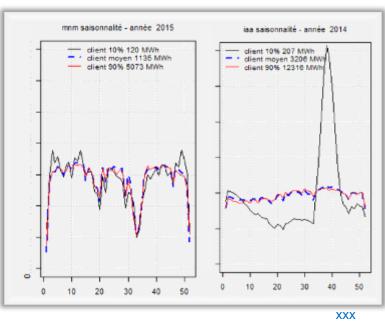
Monthly data is used for billing and summaries.

Structuring the yearly progress, it provides early indications of temperature sensitivity and consumption patterns.

Customers receive a bill every month, making this a good basis for tailored services.

Monthly data is collected through smart meters.





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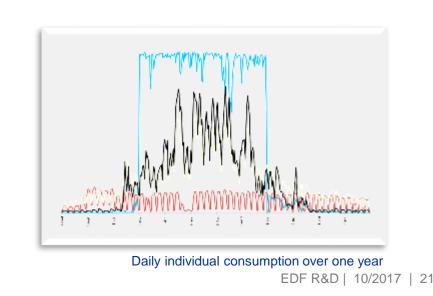
This is the most granular of the non-granular steps in the process.

Daily data provides initial insight into the customer's behaviour: temperature sensitivity, weekend and holiday effects, load reduction days.

It provides fairly accurate ideas of uses, based on the load curve rather than simply on reported usage.

Daily data is collected through smart meters. With Linky, it is the new basic data to which everyone has access, which is why it is being used to create new services: it is making scale-up possible.







### HOURLY DATA

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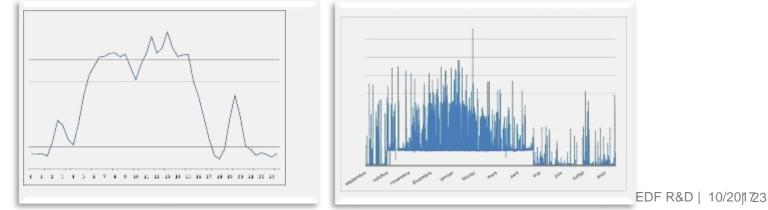


Hourly data (or half-hour or ten-minute increments) is usually what we refer to as the load curve.

This is the timeframe for supply and demand are balanced (load reductions, purchases, optimisation of generation, imbalance settlements, prices...). It provides an understanding of demand peaks, and allows us to get through the winter and decide on capacity levels. It is the data based on which values are assigned to products and services, where we also look at the dispersion of behaviours (idea of risk).

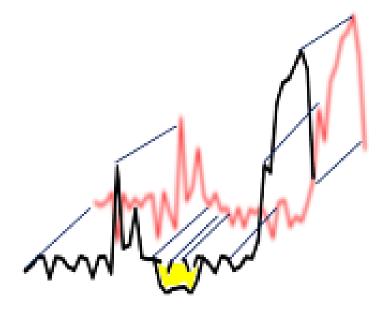
It gives us information about customer habits, is used to monitor usage and take advantage of off-peak hours, to estimate demand response or EDM levers, and to anticipate distortions in consumption. It is the data used by far the most often in studies.

It is read by Linky meters, accessible on demand and subject to customer approval.





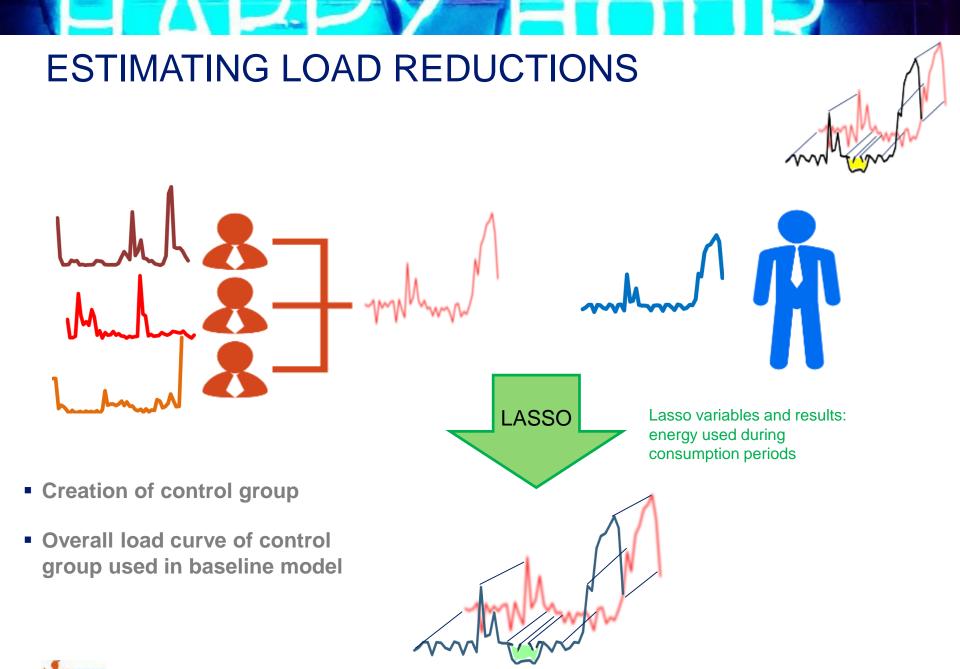


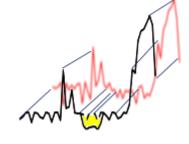


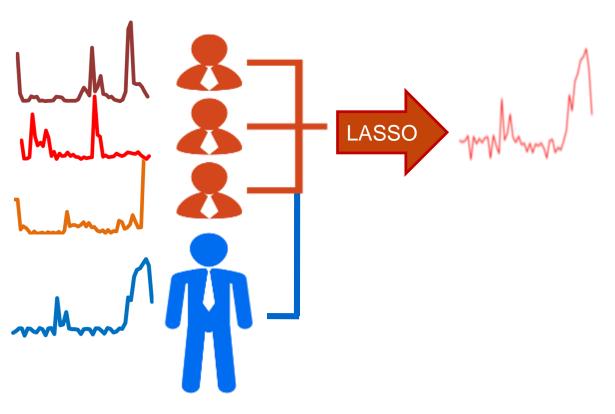
PHILIPPE CHARPENTIER

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Individual forecasting was initiated in Sophie Bercu's project

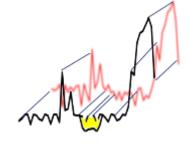


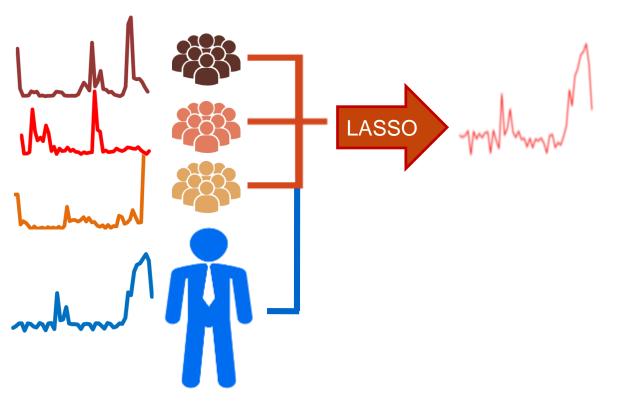




- Advanced method: Create a baseline curve for each customer
  - Optimisation of weighting coefficients with multilinear penalised regression applied to halfhourly load curves

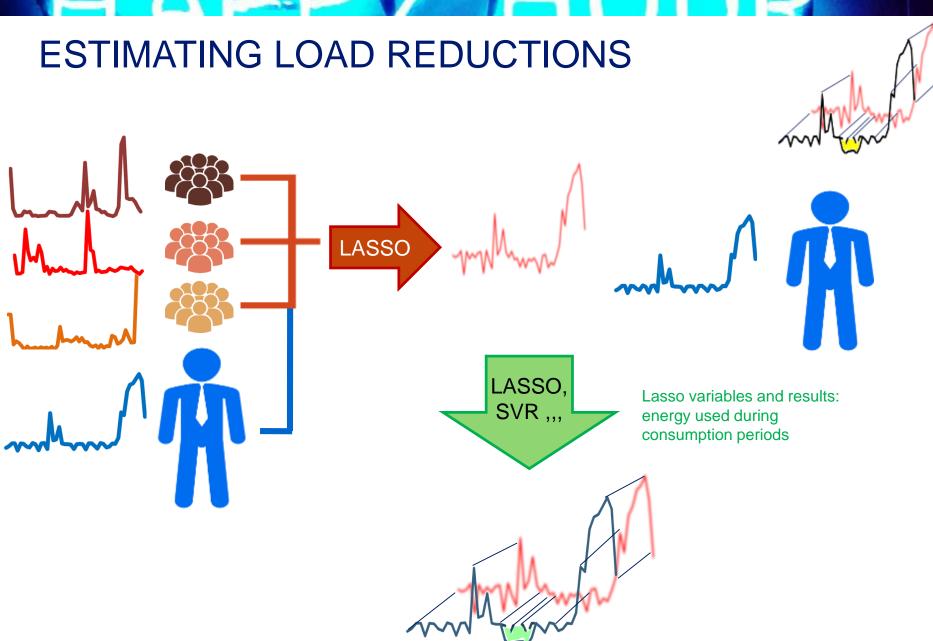




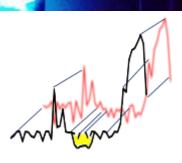


Advanced combined method: Start with an initial classification of control curves
 We use a HAC, preceded or not by a PCA, based on half-hourly data



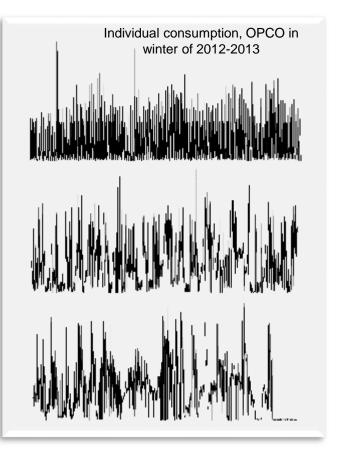






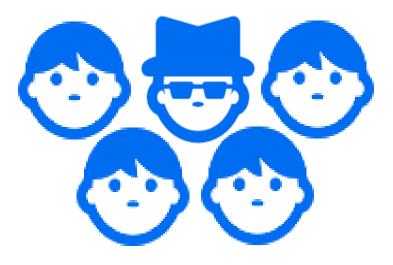
### Results:

- An algorithm with many parameters to test
- Benefits of advanced approaches with prior classification Median MAPE: 37% Min MAPE: 9% 3<sup>rd</sup> quartile MAPE: 61%
- Work under way today focuses on preparing data and the treatment of very short histories





### ATYPICAL INDIVIDUALS



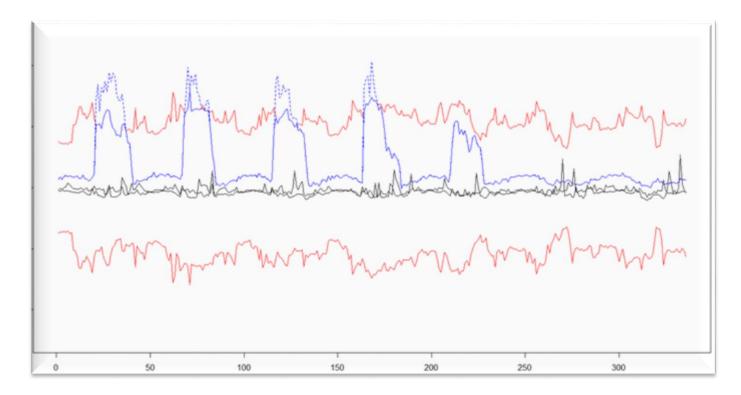
ANNE DE MOLINER

During her thesis with University of Burgundy, Presented to ERCIM

### ATYPICAL INDIVIDUALS

- What is an atypical individual?
- Detecting atypical individuals and limiting their influence
- Ad hoc vs. functional methods: impact on the result curve



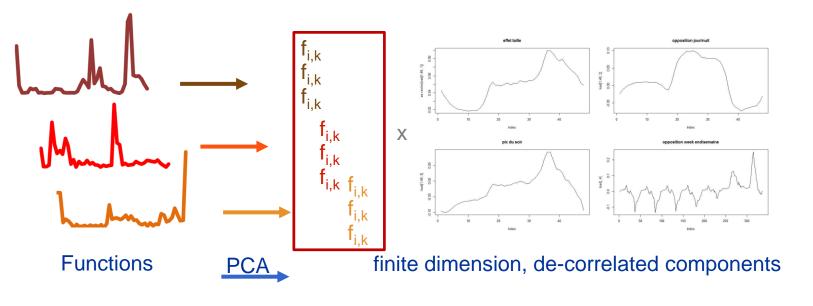




### ATYPICAL INDIVIDUALS A FUNCTIONAL METHOD



• An ad hoc method is applied to the components of the PCA.

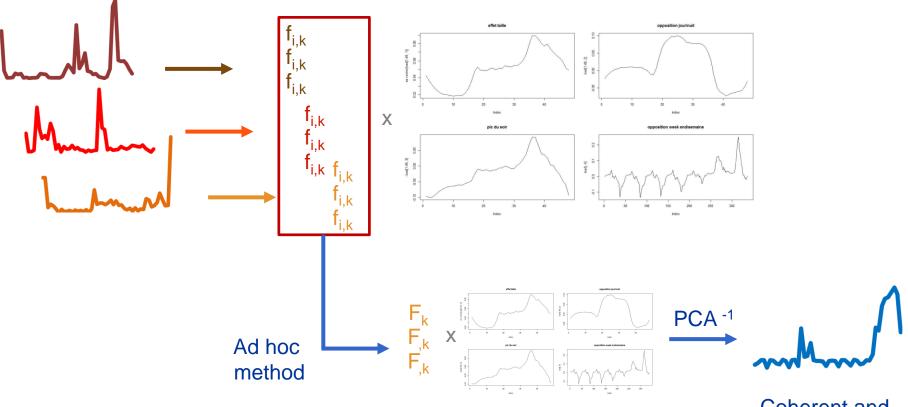




### ATYPICAL INDIVIDUALS A FUNCTIONAL METHOD



• An ad hoc method is applied to the components of the PCA.



Coherent and robust overall load curve





- Comparison of point process and functional methods
- Introduction of outliers: magnitude outliers, shape outliers, strata jumpers
- For the robust methods tested:
  - Strata jumpers adequately taken into account
  - □ Gain of 25% to 10% for populations of 40 to 200 individual curves





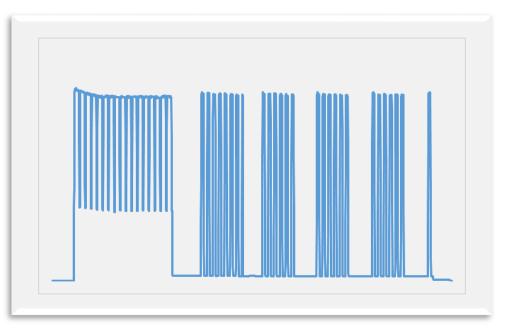


This is the data of the future, the data of the LRT meter.

It is on the basis of this data that we can begin to de-noise.

#### This data will allow a granular analysis of consumption.

It is real-time data.





Second-by-second load curve of an electric oven



### DISAGGREGATION THROUGH DEEP LEARNING

#### The context

#### D NILM

Acquiring data every second with a LRT

#### Disaggregation issues

- Detect when a usage begins
- Estimate the consumption associated with a usage
- Prior information

#### Methods

- Work of Jack Kelly (Imperial College)
- Deep learning methods



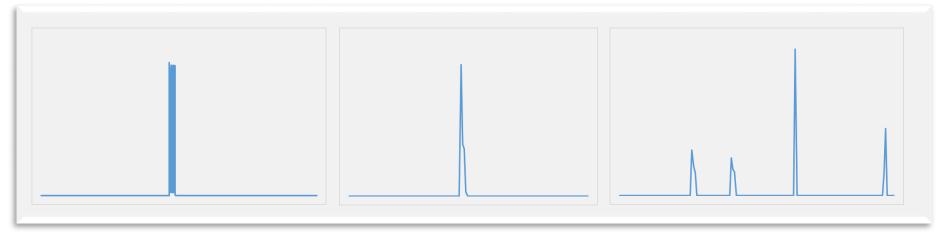


### DISAGGREGATION THROUGH DEEP LEARNING

- Usage detection study case of an electric oven
  - Industrial study contract with Centrale Supélec
  - Grid architecture studies

### Results

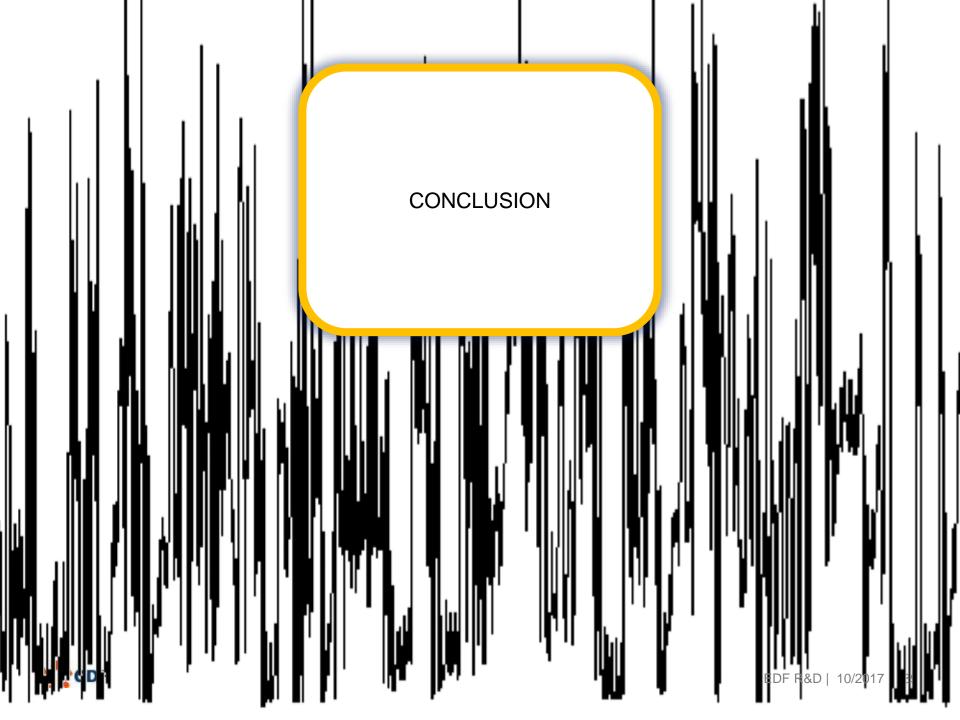
- Detection over a two-hour window
- Competitive results
- Accurate detection rate: 77%



Consumption by oven over one day at per-second and ten-minute intervals and over one week at one-hour intervals



PAUL KASSIS



#### 

- Challenges posed by energy demand management
  - □ For the system
  - For the environment
  - For the end customer
- Development of the local scale
  - Smart grids and local urban planning policies
  - Active consumers and generators
  - Close proximity to the customer



#### 

- Questions about relationship between local and overall
  - What an overall curve contributes to the local curve
  - Weak signals: granular characteristics of the local curve
- Statistical issues
  - Encoding
  - Metrics, readability
  - Functional methods
  - Real time
  - Working with limited historical data

#### Technical issues

- Measuring and processing data
- □ Managing data (in situ, on server, web services...)
- Industrialisation of codes, scaling up
- Data protection, privacy







