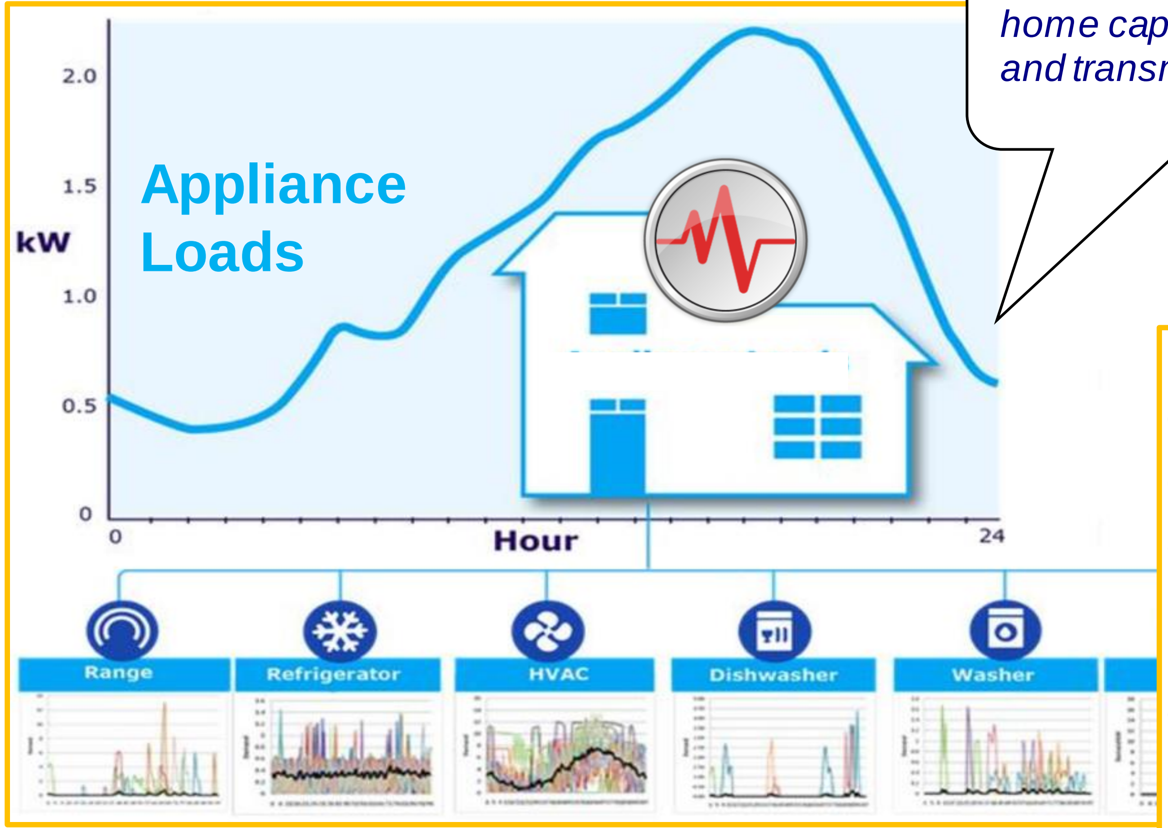
Challenge

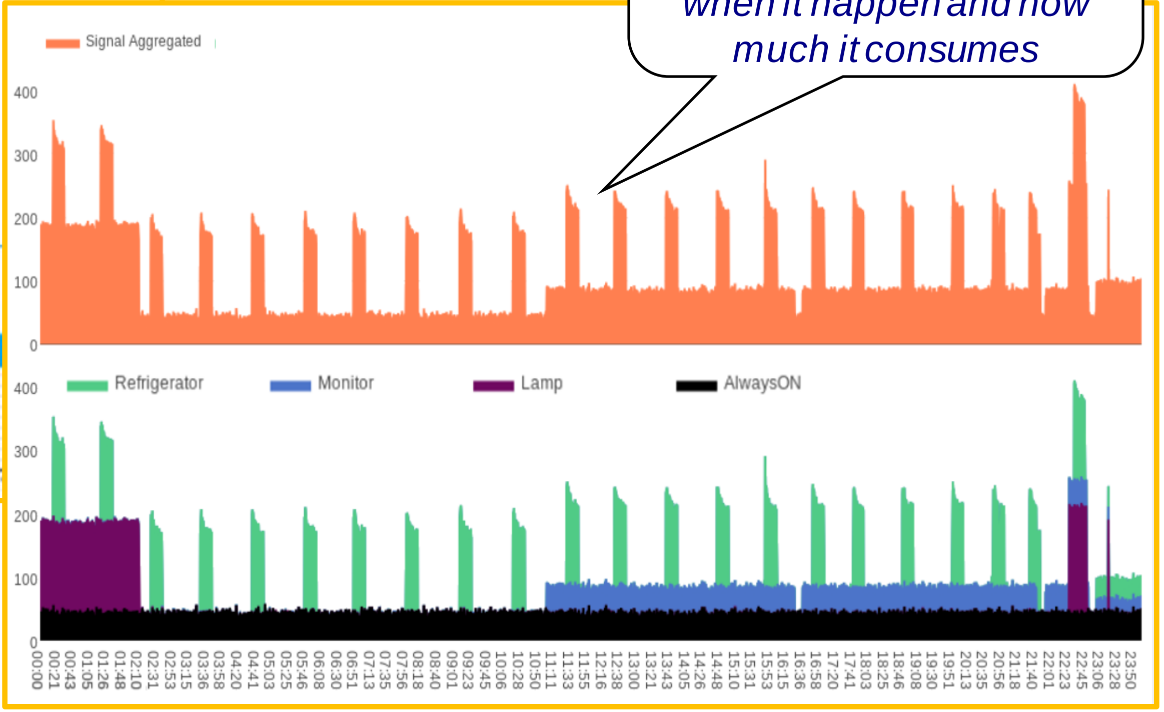
Not Intrusive Load Monitoring: problem

Analysis of aggregate energy consumption of a user to identify the devices present in a house, understanding their working cycles and drawing the consumption associated with them

a sensor at the user's home captures, transforms and transmits the electrical signal



remote algorithms disaggregate the signal: which device turns on / off, when it happen and how much it consumes



highly complex problem, hundreds of custom component algorithms

Not Intrusive Load Monitoring: approach

PROS

- While ILM requires one or more than one sensor per appliance to perform appliance load monitoring, NILM just requires only a single meter per house
- NILM has lower costs than ILM
- Unlike ILM which needs the configuration of multiple sensors, NILM only needs one sensor

CONS

- ILM is more accurate than NILM that estimates the energy consumption of individual appliances starting from the aggregate signal

Fundamentals of Artificial Intelligence 2022 – 2023

Master's Degree in Intelligent Systems Engineering

Challenge Engineering

NILM: on-off status classification of household appliances

Classification of the on-off status of three household appliances (washing machine, dishwasher, oven) based on the time series of electrical data sampled per second (power and harmonics of the current)

Consumption monitoring: importance and benefits

NILM
Non Intrusive Load Monitoring

PROVIDERS

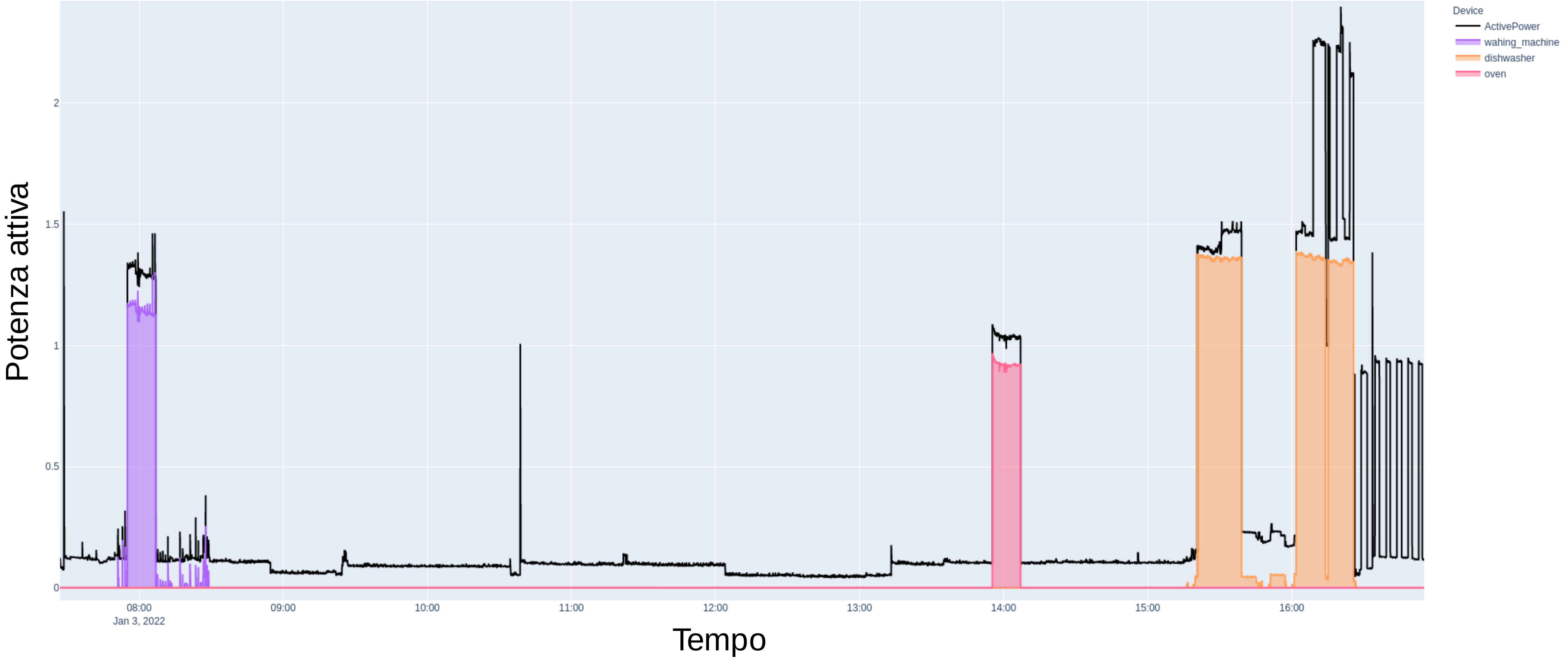
- Profiling consumers on the basis of consumption
- Offer personalized plans to consumers to increase loyalty
- Improve planning of energy generated/supply

CUSTOMERS

- Keep your expenses under control by monitoring energy consumption
- Optimize the use of devices by being able to track their consumption at the level of individual devices
- Identify equipment malfunctions through consumption analysis over time

Dati

The information provided refers to the consumption of an apartment for several days of collection (25) with sampling per second.
Among the data you have available not only the energy information of the entire apartment, but also the consumption details related to the three devices to be identified: washing machine, dishwasher and oven.



Obiettivo

Identify the operating moments of the three devices: washing machine, dishwasher and oven in a house with many other active devices using models equipped with memory:
To improve the classification on the generic instant T-Mo: RealTime
To adjust the classification at the end of the day: batch

DateTime	ActivePower	ReactivePower	Voltage	Current	harmonic1_Real	harmonic1_Imaginary	harmonic3_Real	harmonic3_Imaginary	harmonic5_Real	harmonic5_Imaginary	harmonic7_Real	harmonic7_Imaginary	wahing_machine	dishwasher	oven
2022-01-01 00:00:00	0,0248063	0,035852294	0,000164719	0,000253036	1,05E-05	-0,00027056	9,11E-06	-5,40E-05	-1,26E-05	-2,24E-05	-3,50E-06	-1,12E-05	0	0	0
2022-01-01 00:00:01	0,024941979	0,036632431	0,000164719	0,000254438	9,81E-06	-0,000273363	9,11E-06	-5,47E-05	-1,33E-05	-2,31E-05	-9,11E-06	-1,05E-05	0	0	0
2022-01-01 00:00:02	0,024667113	0,036640141	0,000164719	0,000251634	9,81E-06	-0,000268457	8,41E-06	-5,40E-05	-1,33E-05	-2,31E-05	-5,61E-06	-1,61E-05	0	0	0
2022-01-01 00:00:03	0,024667113	0,036636636	0,000164719	0,000251634	1,19E-05	-0,000268457	8,41E-06	-5,33E-05	-1,33E-05	-2,24E-05	-4,91E-06	-9,11E-06	0	0	0
2022-01-01 00:00:04	0,025079411	0,036645048	0,000164719	0,00025584	1,26E-05	-0,000276868	9,11E-06	-5,61E-05	-1,33E-05	-2,38E-05	-5,61E-06	-1,68E-05	0	0	0

The data are provided through CSV files in which the following features are present:

- DateTime: date and time of the event, therefore the instant to which the collected data refer;
- ActivePower: active power consumed;
- ReactivePower: reactive power;
- Voltage: electrical voltage;
- Current: current delivered;
- harmonick_Real: parte reale dell'armonica k-ma;
- harmonick_Imaginary: fictional part of the K-ma harmonica;
- k = 1, 3, 5, 7
- washing_machine: active power consumed by the washing machine in that instant of time;
- dishwasher: active power consumed by the dishwasher in that instant of time;
- Oven: active power consumed by the oven in the instant of reference time

* *link per scaricare il dataset*

Evaluation metrics

Average Recall	Average F1-score
3 points	3 points
2 points	2 punti
1 point	1 point

The value of each team will be calculated by adding the scores obtained on each metric.

Exceeding 4 out of 6 metrics adds another +1!

The challenge will be on 6 metrics plus 2 average metrics:

- ***Recall** per device and medium on devices*
- ***F1-score** per device and average on devices*

Riferimenti

Device	Recall	F1-score
Lavastovigle	94%	95%
Lavatrice	93%	94%
Forno	90%	75%
Media	92.33%	88%

Each group will receive a score for each average metric equal to its position in the ranking, according to the values indicated.

+2 points in the final vote

+1 Point to final vote

+0.5 Point to final vote

Further information

- *You will have to divide into groups of 2 or 3 people*

- *The experiments will be carried out in 10-fold-cross validation, the timestamps will be provided by the teachers*
    - *The data will be divided into 10 contiguous blocks, which in rotation will be the test set, and the remaining training sets*
    - *In the division into 10 blocks the days must not be broken: either they are in the training or in the test*
    - *The validation set can be extracted by you according to the policy that you decide from the training set*

- *You will have to deliver:*
    - *an analytical table of the performances evaluated on the basis of timestamps (recall mean and F1 average score per class of each fold, mean value and standard deviation for the 10 folds)*
    - *The commented code*
    - *a file containing instructions for running the code either in cross-validation mode or simply for testing*
    - *PowerPoint presentation of the pitch presentation of the adopted solution (pitch duration 7 minutes + questions)*

- *You will have to identify by mutual agreement a date for the pitch to be communicated to us by 30/5 pv*

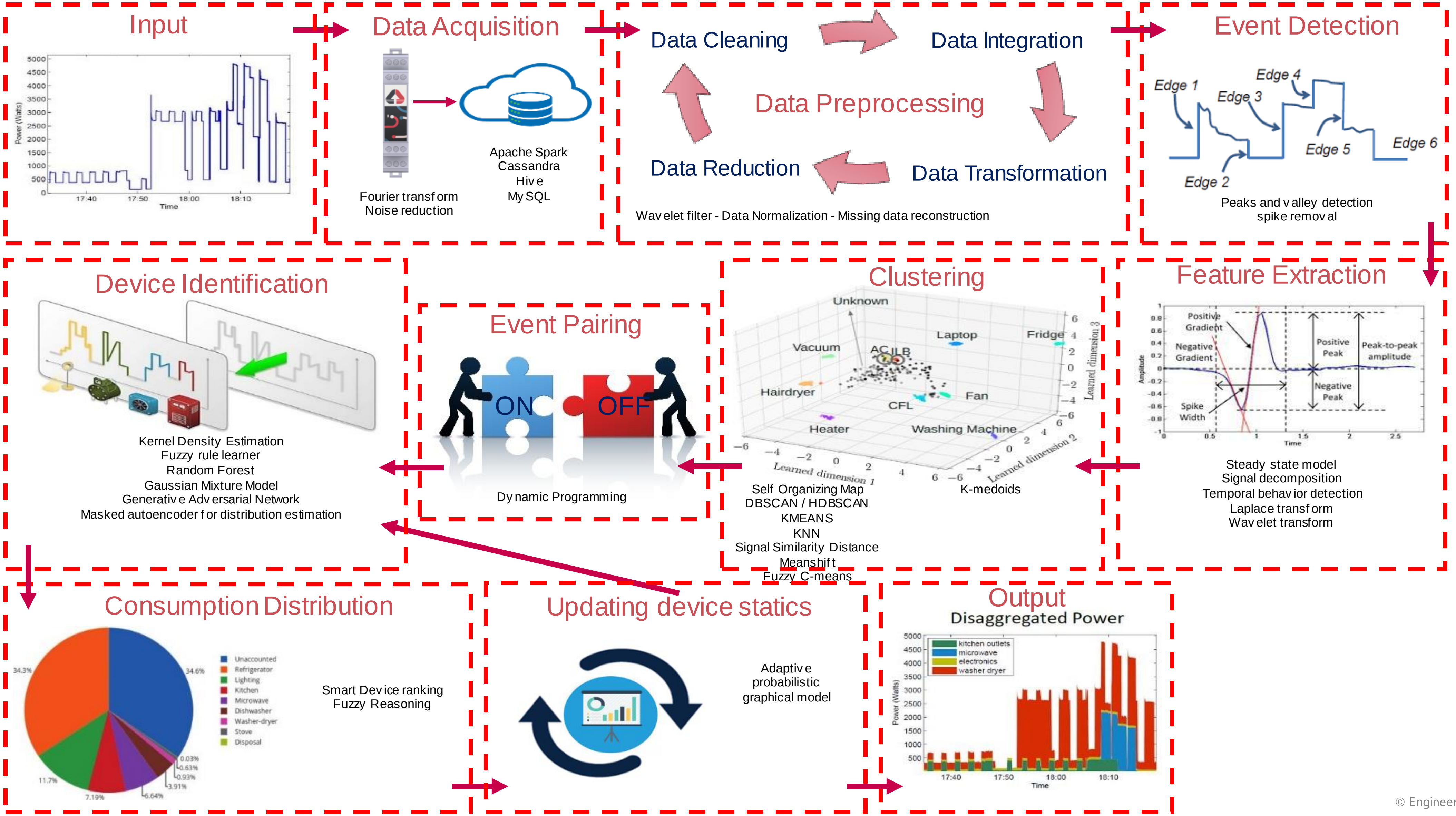
Home EnergIA

Innovative services on energy data

Some technical detail

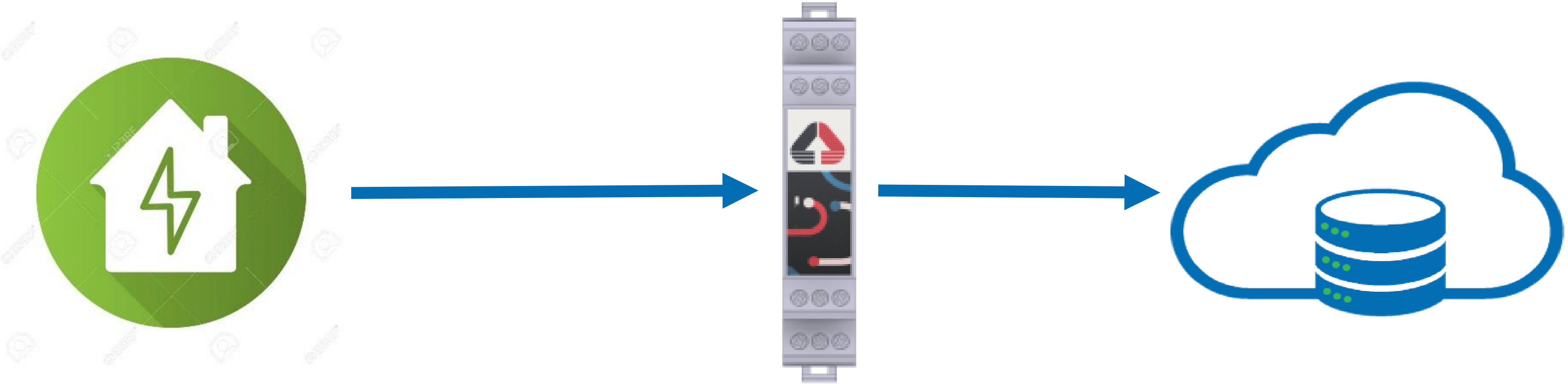
ENGINEERING HOMEenergIA

Solution: Algorithmic flow



Data Acquisition

Data acquisition is a stage of obtaining aggregated load measurements from the household at a given time interval so that distinctive load patterns can be identified. During this stage, voltage and current measurements are obtained and processed to produce power metrics (real power, reactive power and harmonic currents).



Data Preprocessing

It is a data mining technique that involves transforming raw data into an understandable format. Major tasks in Data Preprocessing are:

- Data cleaning
  - Fill in missing values, smooth noisy data, identify or remove outliers
- Data reconstruction
  - Integration of multiple databases, data cubes, or files
- Data transformation
  - Normalization and aggregation
- Data reduction
  - Obtains reduced representation in volume but produces the same or similar analytical results

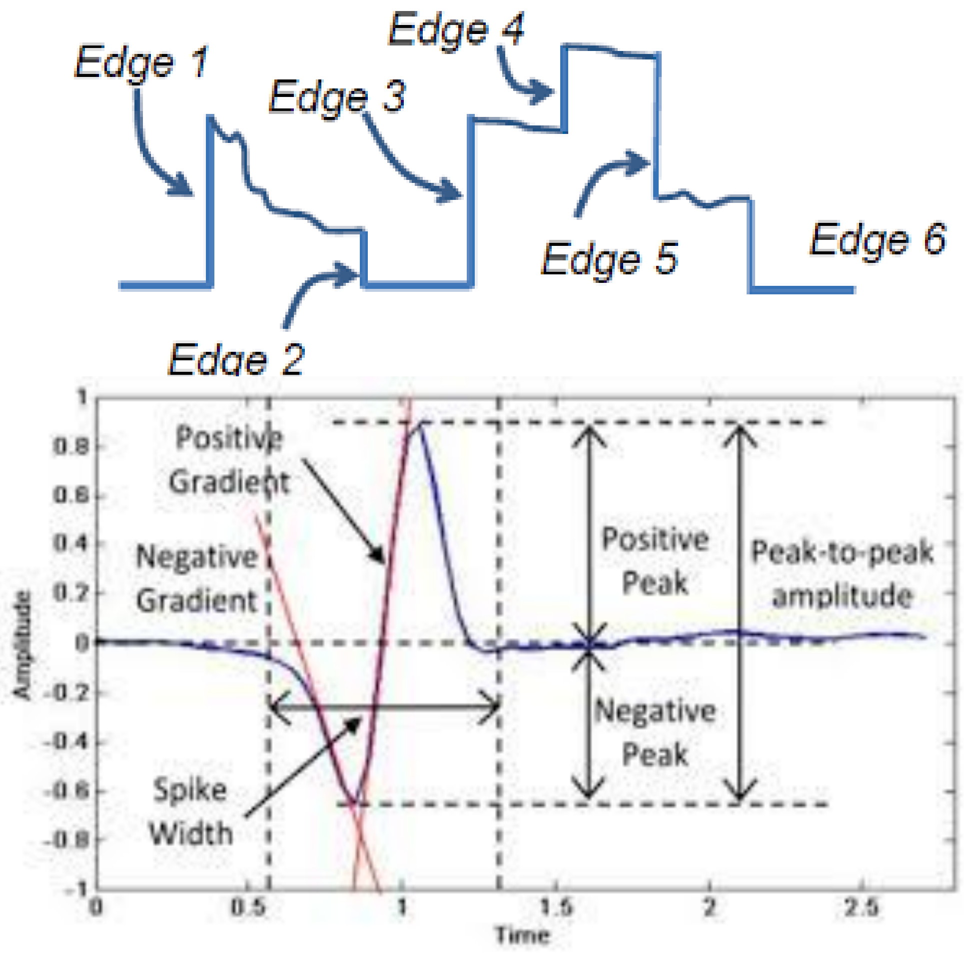
Features Engineering

Event Detection

In the event detection stage, the electrical signal is split up into contiguous and transient data points. (Wavelet)

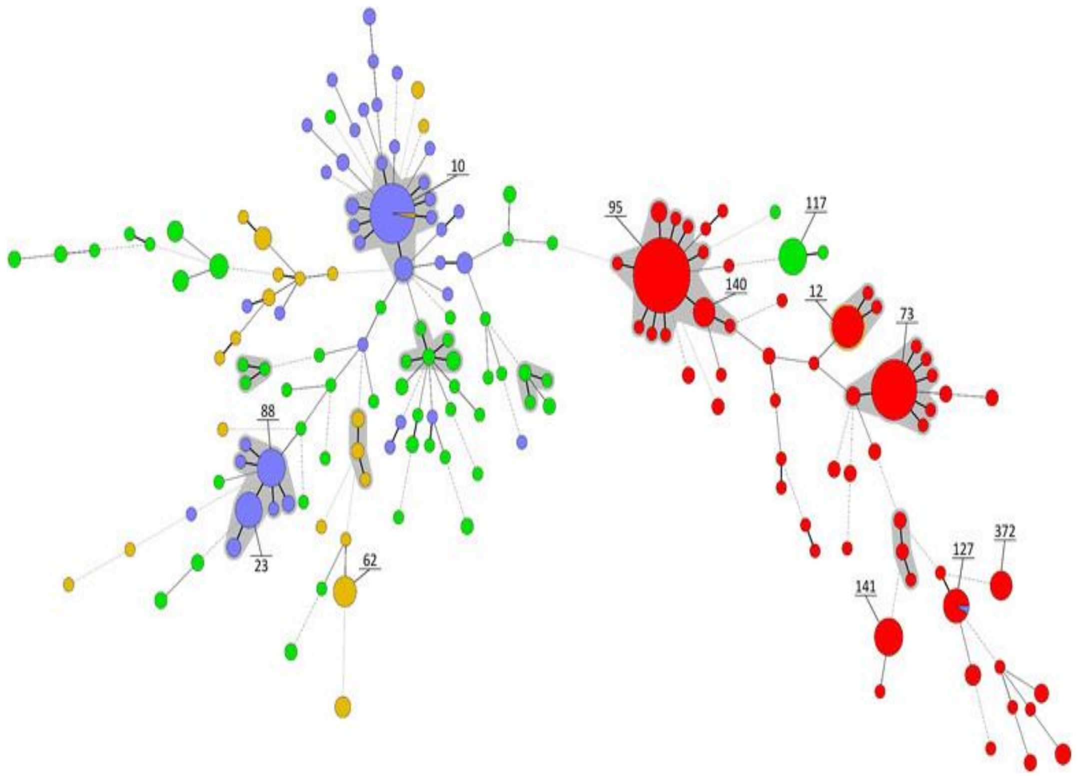
Feature Extraction

In this section, features are extracted from each transient portions of the original unfiltered signal. Relevant features are the power change Δ(P,Q), the geometric features of the transient spikes on both real and reactive power and the behavioral characteristics



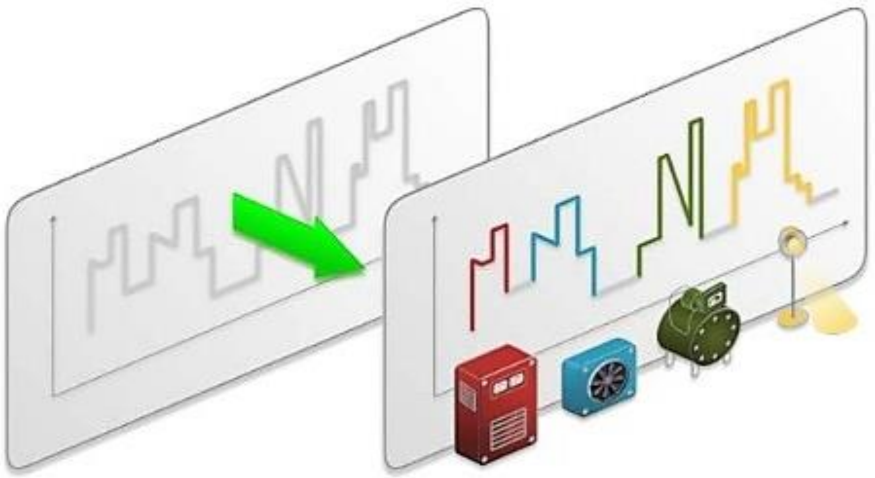
Clustering

In the clustering stage, events and coded dynamic behavior are grouped in separate clusters according to their extracted features. The clustering procedure should determine automatically how many clusters are in the data (corresponding to the number of different appliance state-transitions) and the centroid of these clusters (corresponding to the average power change for those transitions).



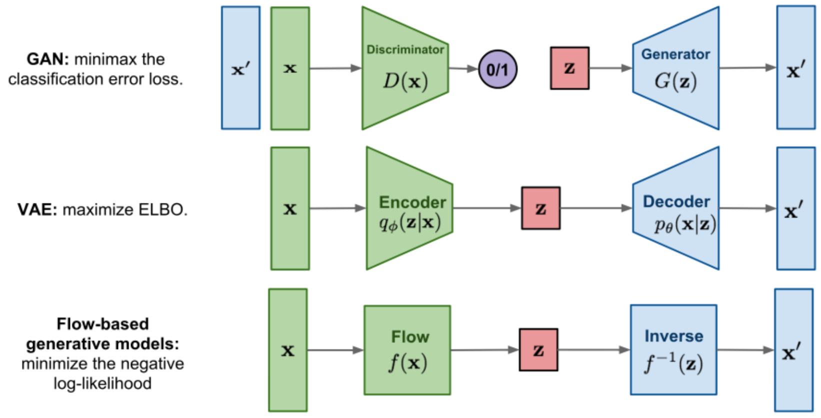
Event Pairing

In the matching process, all rising and falling events are checked for matching pairs to infer the usage interval of each appliance. The matching process is based on the background level detection and active window approach.



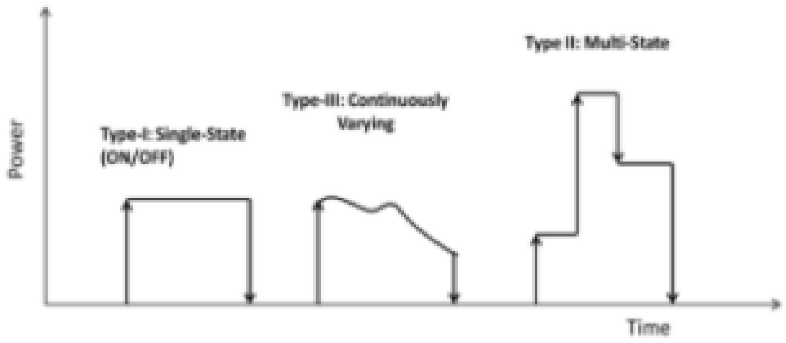
Device Identification

In this stage algorithms use advanced density estimator model (MADE) to find the MOST PROBABLE class (device) for a given instance (pair)



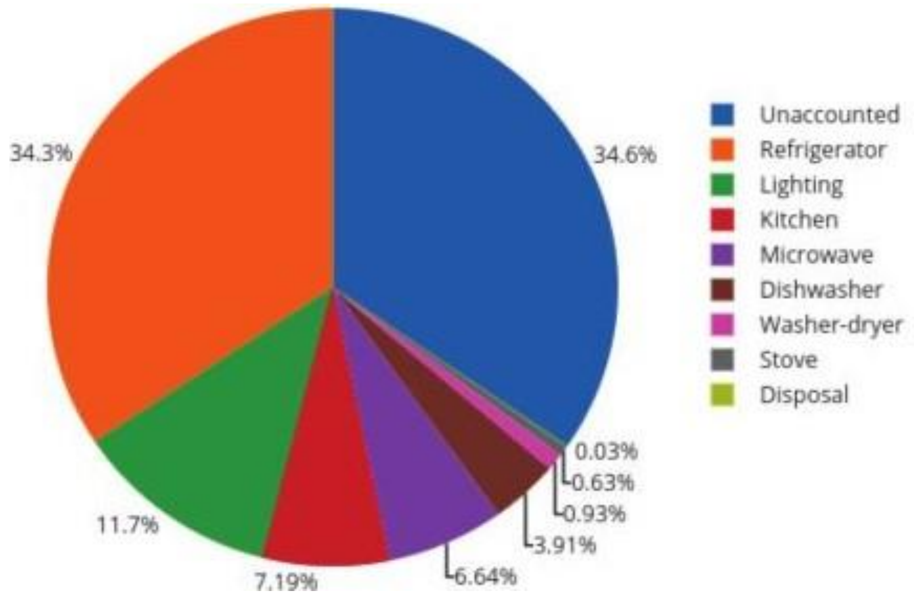
Consumer appliances can be categorized based on their operational states:

Type I	Only ON/OFF
Type II	Multi-State
Type III	Continuously Varying devices
Type IV	Permanent consumer devices



Consumption distribution

The total aggregate load is distributed among the various devices identified (Meta-learner)



Updating device statistics

The models containing the operating and behavioral characteristics are created/updated for each device identified to improve subsequent recognition (Bayesian reasoning)

Identified devices

Web dashboard

Knowage: Synthesis dashboard

Mean and Total Consumption

Consumption per device

Current expenditure and CO2 emission forecast

Percentage of consumption compared to the budget

Hours of greatest and least consumption

Percentage of consumption on weekdays and holidays

Percentage of day and night consumption

Web dashboard

Knowage: Detail dashboard of the selected device

Summary of device consumption

Energy class of the device

Consumption of the device by time slots

Percentage of device consumption on the total

Home EnergIA mobile app

HomeEnergIA App