

## Scientific background

In the context of smart buildings in smart cities, the growing spread of ICT (Information and Communication Technologies) and IOT (Internet Of Things) technologies is enabling the collection of a huge amount of building related-data. Consequently, the energy management in buildings is becoming more and more a data-centric task also considering the effectiveness of novel **data analytics technologies** in driving the development of ready-to-implement energy conservation measures in such a complex systems. In this framework, my research activity is aimed at exploiting the way in which a data analytics based approach is changing the paradigm of energy management leading to a significant reduction of energy consumption and energy wastes during the building operation. Even though some applications are well developed in the literature (e.g., Fault detection and diagnosis), the diversity of data analytics techniques and their combination still remain challenging to be handled in the building physics sector. The effective coupling of building physics and data science needs significant contributions aimed at exploring robust and generalizable analytical frameworks.

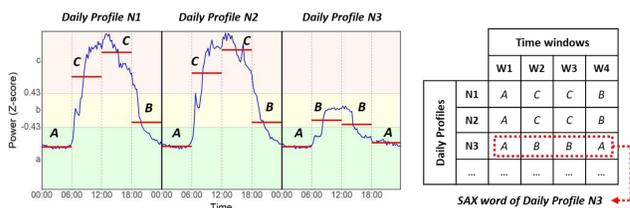
## Temporal data mining in buildings

In last years, particular attention has been devoted to the branch of **time-series analytics** for describing and modeling energy dynamics in buildings and systems during their real operation. This kind of analyses, based on the ensemble of data mining and machine learning algorithms, are of a paramount importance in harvesting valuable information from data preserving their chronological relation. In fact, the temporal discovery process makes it possible to extract useful knowledge in the time domain on the actual relations between outdoor disturbances, indoor conditions and energy demand.

The great advantage of this data driven approach is related to its potential capability in learning and characterizing building energy dynamics features for unforeseen systems without a-priori knowledge of their configuration.

Algorithms related to (i) Sequential and recurrent Pattern Mining (ii) Causality Analysis (iii) Time series similarity proved to be flexible in their combination and effective in addressing emerging issues in building energy management such as energy demand prediction, Fault Detection and Diagnosis, **anomalous energy trend recognition**.

Most of these techniques rely on **temporal abstraction** as a preprocessing stage for knowledge extraction. Temporal abstraction consists in transforming time series from numerical sequences to discrete state sequences by means of the reduction and the transformation of data.



**Symbolic Aggregate approxImation** (i.e., SAX) is one of most promising technique available to discretize a time series, without losing temporal key information. It is based on the reduction of the time series through a piecewise technique and on its transformation into a symbolic string.

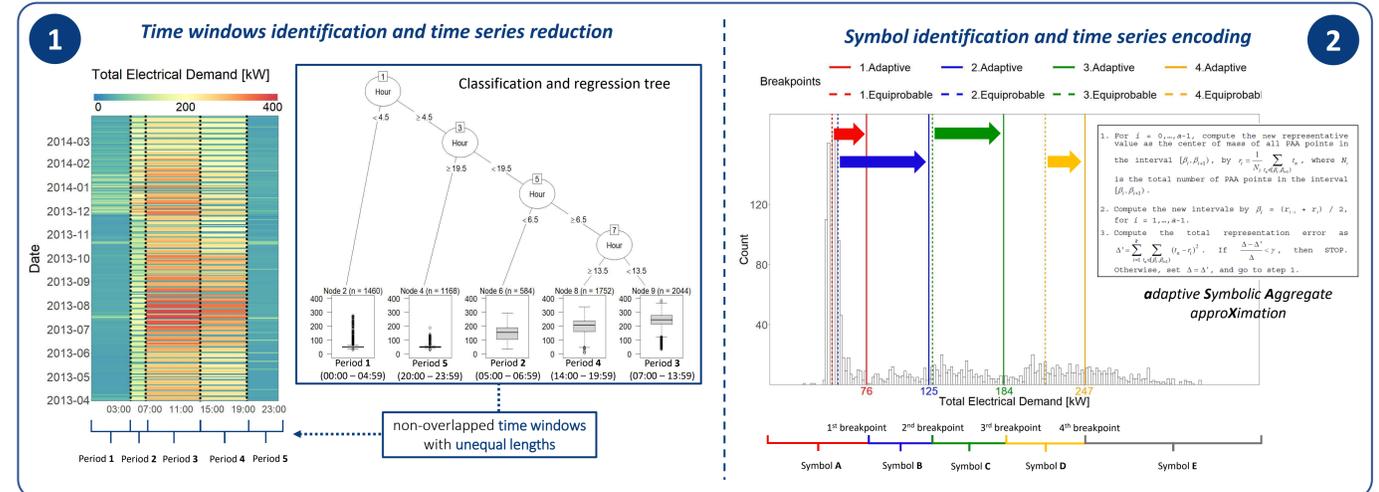
The symbols are associated to discrete states of the time series in non-overlapped time windows of equal length. The subsequent step consists of chunking the entire string into a set of N symbolic sub-strings, called SAX words.

Those words represent then the abstraction of the sequence of events during a reference period.

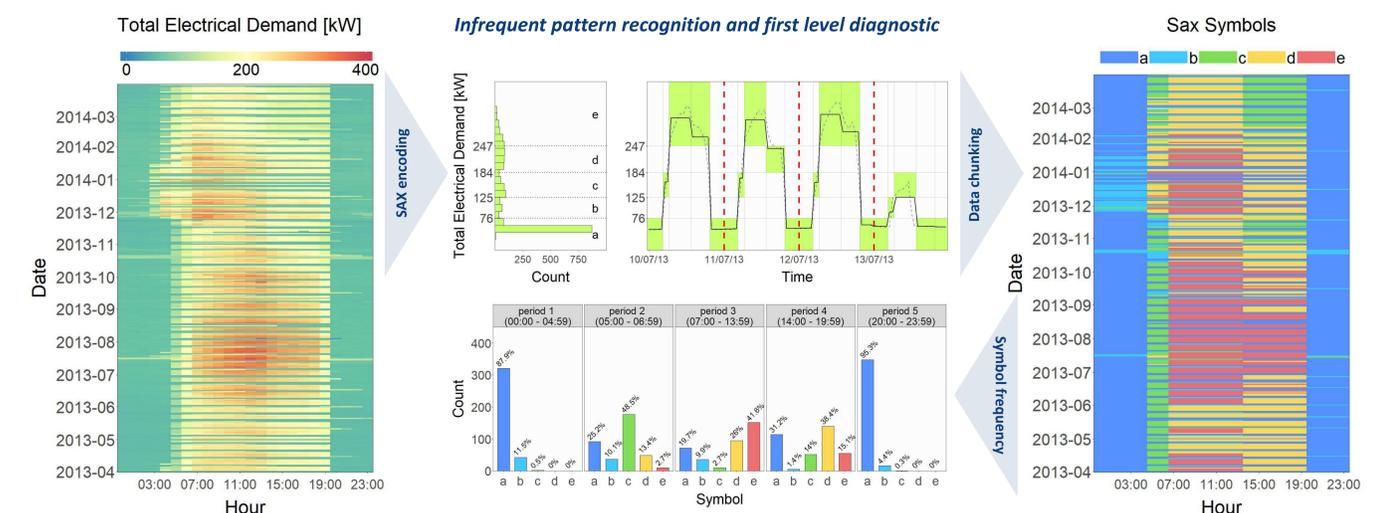
## Anomalous energy trend detection in buildings<sup>1</sup>: methodology

The first stage of the analysis is aimed at transforming the energy consumption time series by implementing an enhanced SAX process. In detail, two preliminary hypotheses are formulated in different ways from the classic SAX implementation:

- (i) **unequal time window lengths** can be identified to conduct a finer discretization,
- (ii) **rejection of equal probability of the symbols** in order to encode each approximated constant segment on the vertical axis.



After the data transformation, the entire time series encoded in a unique string is chunked into N sub-strings of a daily length (i.e., T = 24 hours) in order to obtain constant time-scale based sequences. The N symbolic sub-strings are made up of a certain number, W, of time windows encoded in alphabetic symbols and organized in a **NxW matrix**. In this way, each daily load profile is represented by a **SAX word** that is then used as the input for the successive anomaly detection analysis.



At this stage, the **probability of each symbol** occurring in each time window, under specific boundary conditions, is evaluated by means of a classification tree, which is based on additional explanatory variables (e.g., external temperature, internal temperature, day type, month). In this way, if the occurrence probability estimated with the classification tree and associated with a symbol is very low, it is likely that the energy consumption in the corresponding sub-daily time window is abnormal.

Furthermore, the post-mining stage of the analysis is performed using additional datasets in order to further support the **preliminary diagnosis of detected anomalies**. In this perspective, the proposed methodology represents a very useful tool that can be used to support the **implementation of advanced targeted anomaly diagnosis** in a specific time window of the entire time domain.

