TEBE
TECHNOLOGY ENERGY BUILDING ENVIRONMENT

Politecnico di Torino
1859
Department of Energy "G.Ferraris"

BAEDA Lab
Building Automation Energy Data Analytics

BAEDA Lab experience in FDD and ADD in energy&buildings

Speaker

Prof. Alfonso Capozzoli

17 June 2021

BAEDA Lab

BAEDA is research lab in DENERG aimed at contributing to bridge the gap between building physics and data science supporting the transition toward novel paradigms of energy management in buildings and energy grids.

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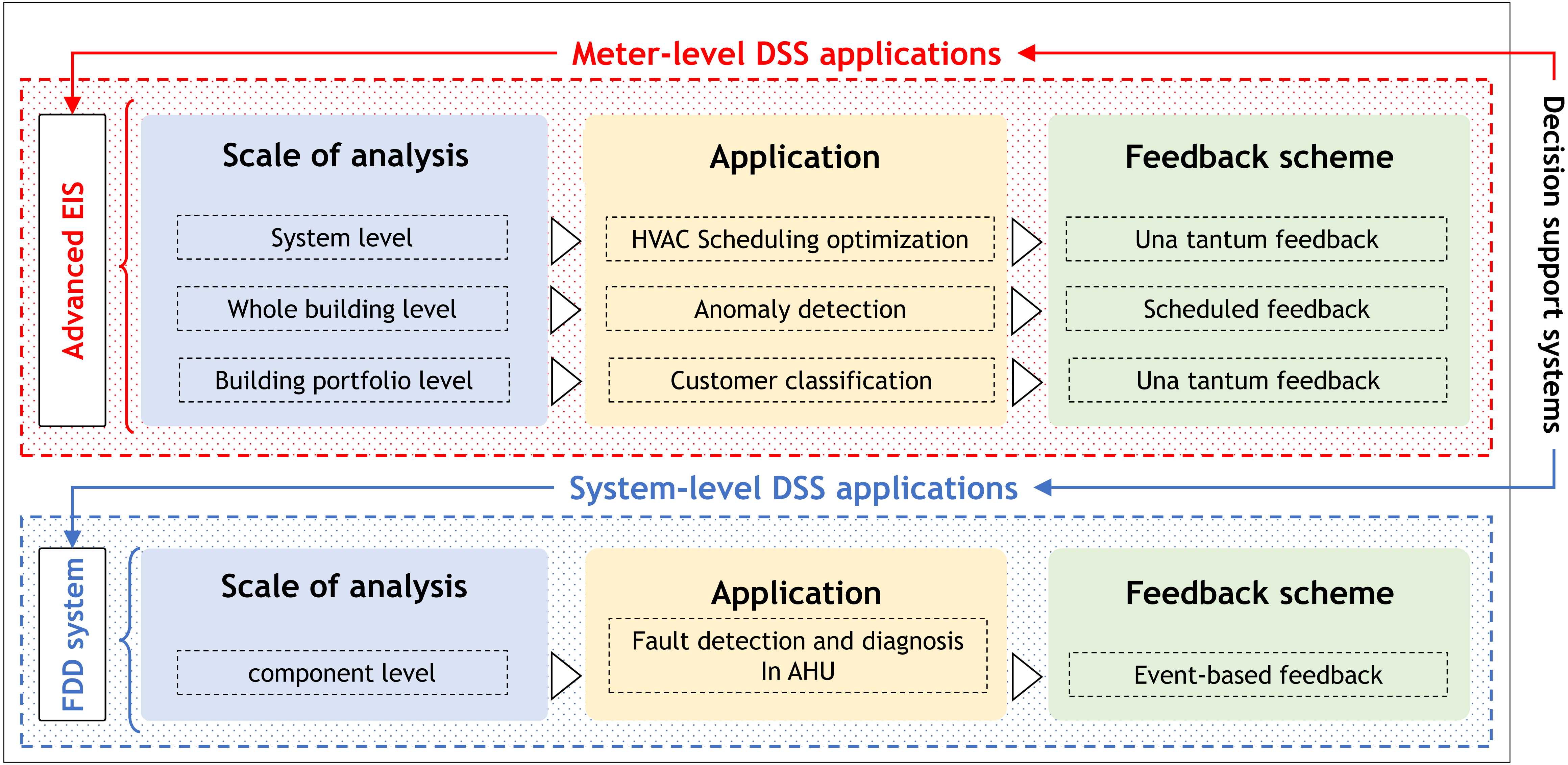
Post-doc researcher

BAEDA Lab
Building
Automation
Energy
Data
Analytics

Research outline: DSS application at meter and system level



DSS applications: main barriers and objectives

Kramer H, Lin G, Granderson J, Curtin C, Crowe E. Synthesis of Year One Outcomes in the Smart Energy Analytics Campaign Building Technology and Urban Systems Division. 2017

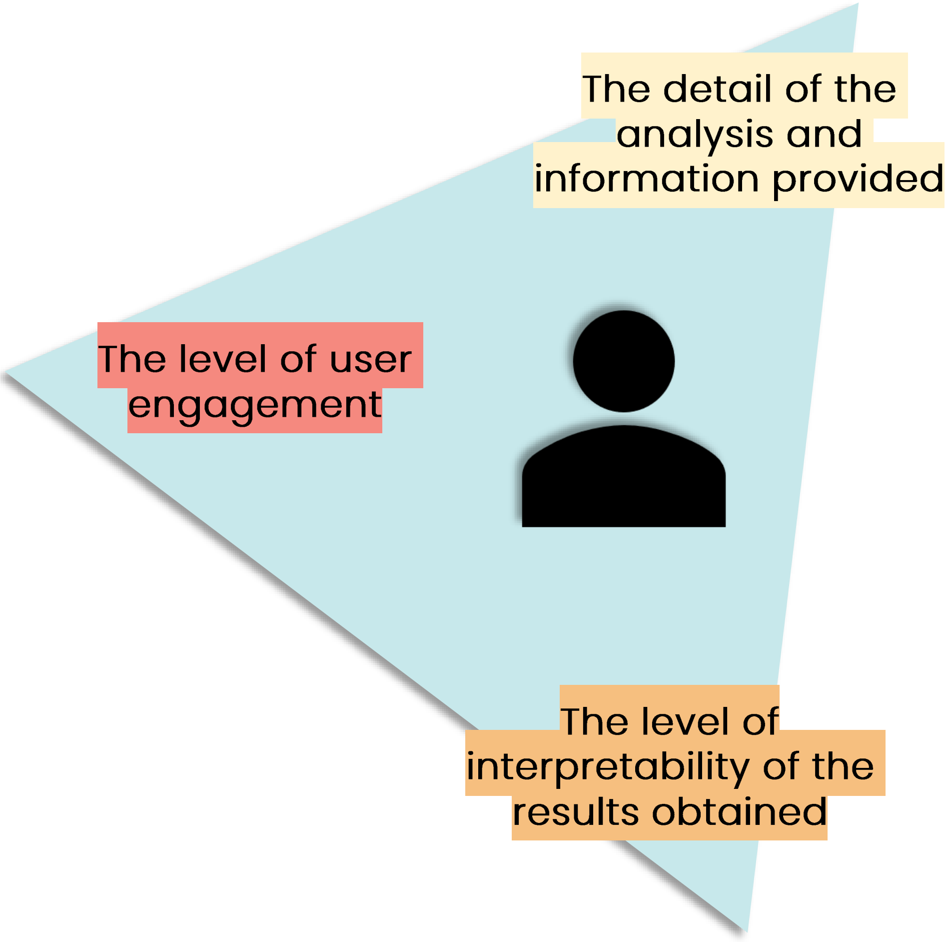
- Advancing research on DSS solutions represents the most effective way for strongly impact the building automation sector in the short term

- Address the emerging need of increased automation and robustness in data analytics-based procedures for the advanced characterization of the energy performance in buildings (i.e., from system component up to district level).

- Address the need of high interpretability of the analyses performed by data analytics based DSS tools.

- Rationalize and improve the quality of the feedback schemes especially for real time analytics processes.

The unfortunate triangle



Energy

Information

System

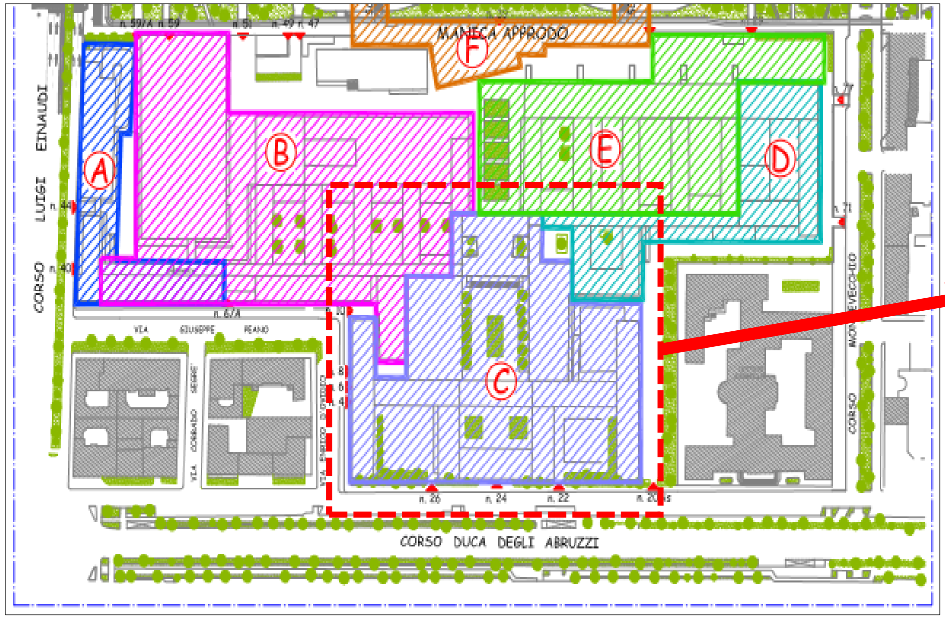
Application at whole building level

Anomaly detection in energy consumption time series

- in most of real cases, just few and aggregate variables related to the total energy consumption of the building are measured and stored.
- the developed EIS tool is capable to automatically detect anomalous energy trends in building energy consumption time series exploiting a small set of input variables.

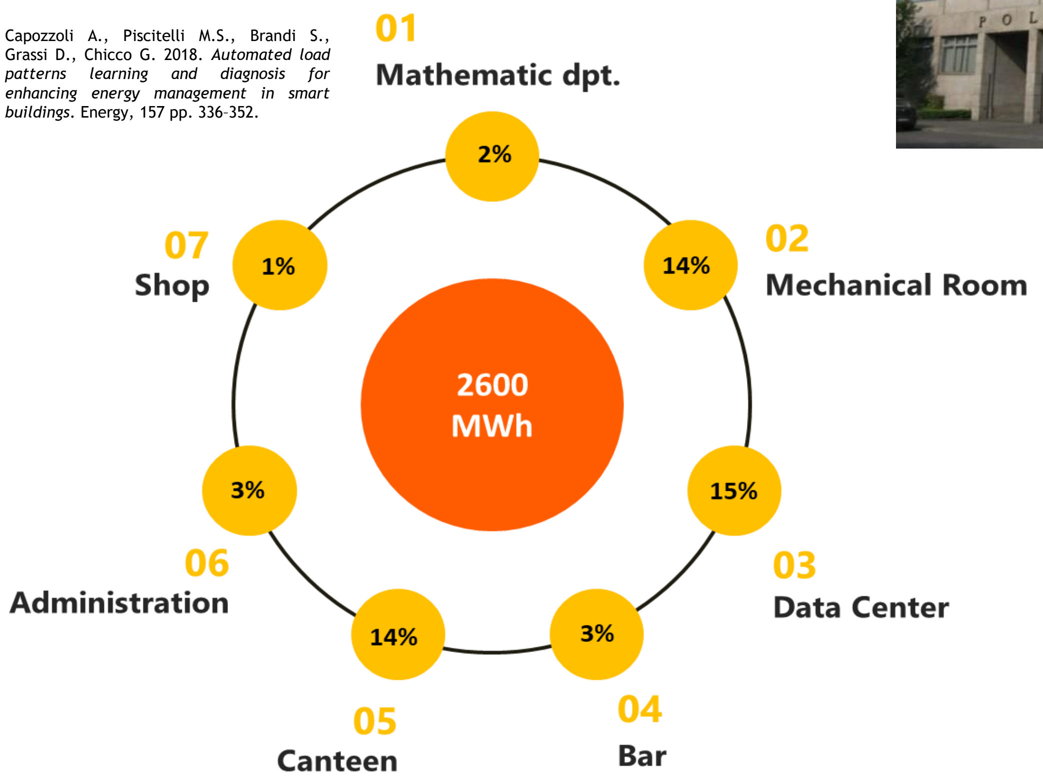
EIS tool for anomaly detection in energy consumption time series: Case study

- Spatial scale/final use -> Whole building (University campus)
- Sampling frequency -> 15 min
- Recording period length -> 1 year



Layout of the electrical substations of Politecnico di Torino

Capozzoli A., Piscitelli M.S., Brandi S., Grassi D., Chicco G. 2018. *Automated load patterns learning and diagnosis for enhancing energy management in smart buildings*. Energy, 157 pp. 336-352.



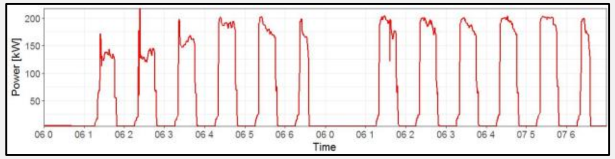
Type of data

- Building energy consumption
- Climatic data
- Number of occupants

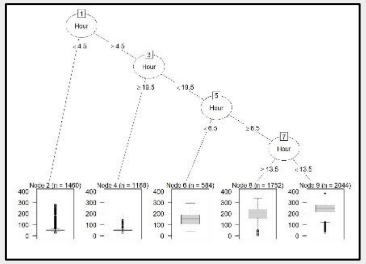
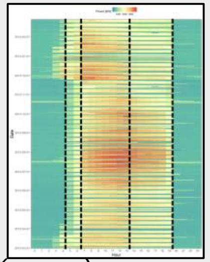
The campus is equipped with an electrical power station that is composed by a loop of ten transformer substations. In this case study the electrical energy consumption data of one substation is considered for the analysis.

Anomaly detection in energy consumption time series: Methodological framework

Building energy consumption data

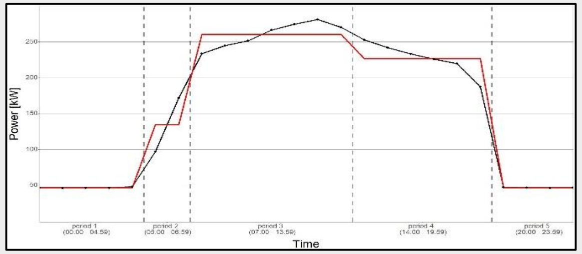


Time window Identification

Regression tree (CART)

Time series reduction

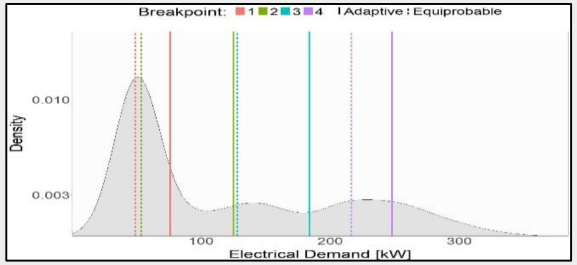


Constant approximation in time windows

Additional explanatory variables

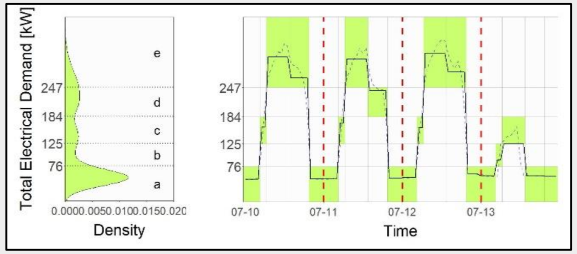
(e.g., external temperature, internal temperature, day type, number of occupants)

Adaptive breakpoint identification



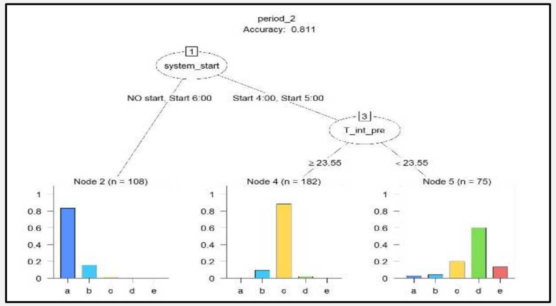
aSAX algorithm

Time series encoding in a symbol string



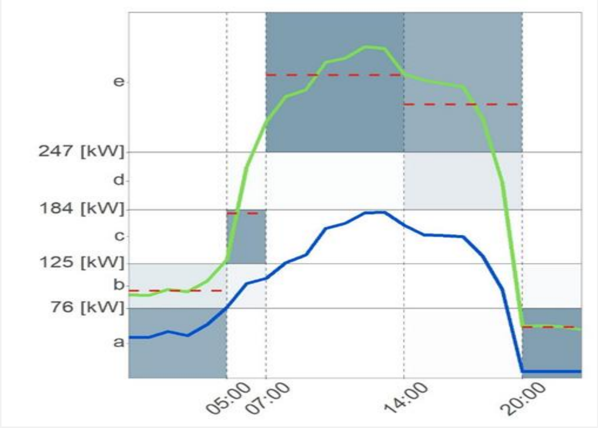
Symbolic aggregate approximation

Symbol prediction in each time window



Classification trees (CART)

Detection of anomalous patterns



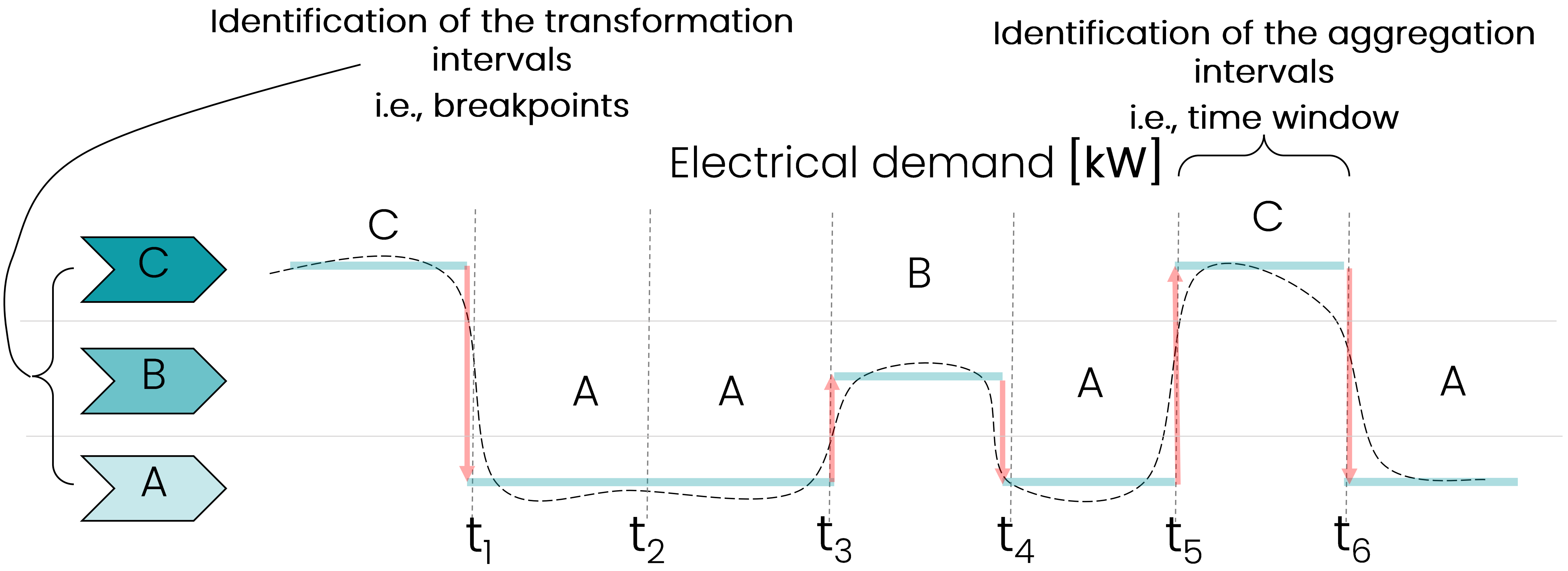
Preliminary diagnosis of the detected anomalies using energy consumption profiles of heating/cooling system equipment

Capozzoli A., Piscitelli M.S., Brandi S., Grassi D., Chicco G. 2018. *Automated load patterns learning and diagnosis for enhancing energy management in smart buildings.* Energy, 157 pp. 336-352.

Temporal abstraction of time series for knowledge extraction

Capozzoli A., Piscitelli M.S., Brandi S., Grassi D., Chicco G. 2018. Automated load patterns learning and diagnosis for enhancing energy management in smart buildings. Energy, 157 pp. 336–352.

Symbolic Aggregate approXimation (SAX) for reducing and transforming time series



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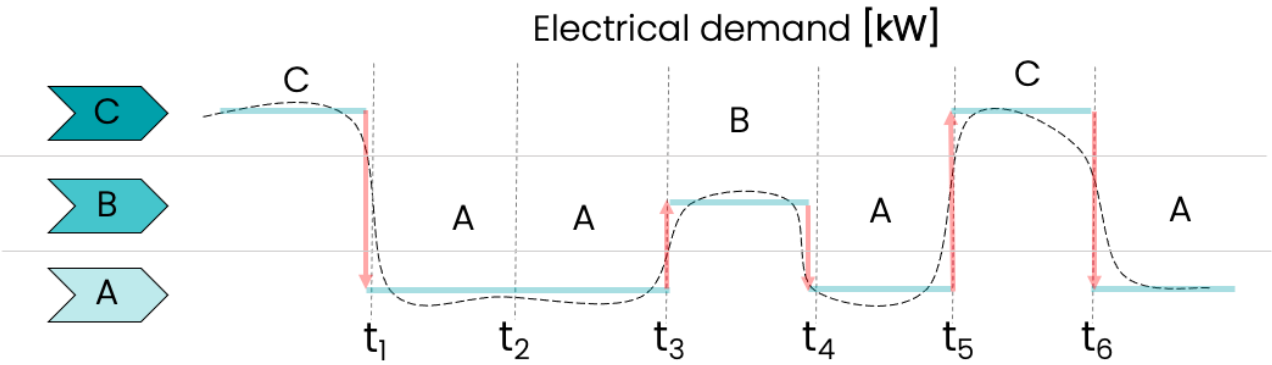
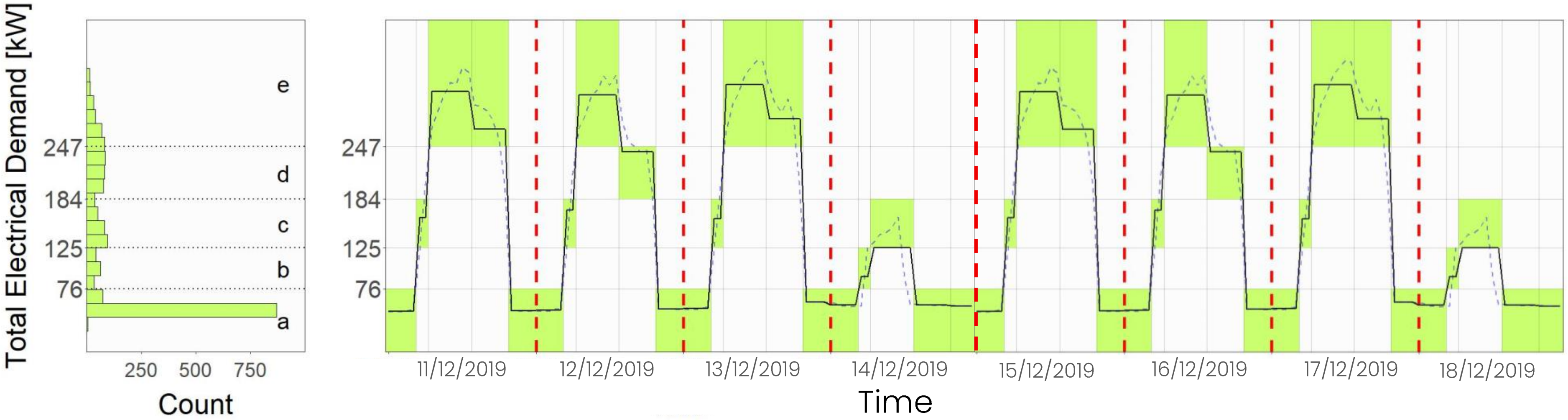


Enhanced SAX encoding of the total electrical demand of Substation C of Politecnico



Customized SAX transformation process: time series encoding

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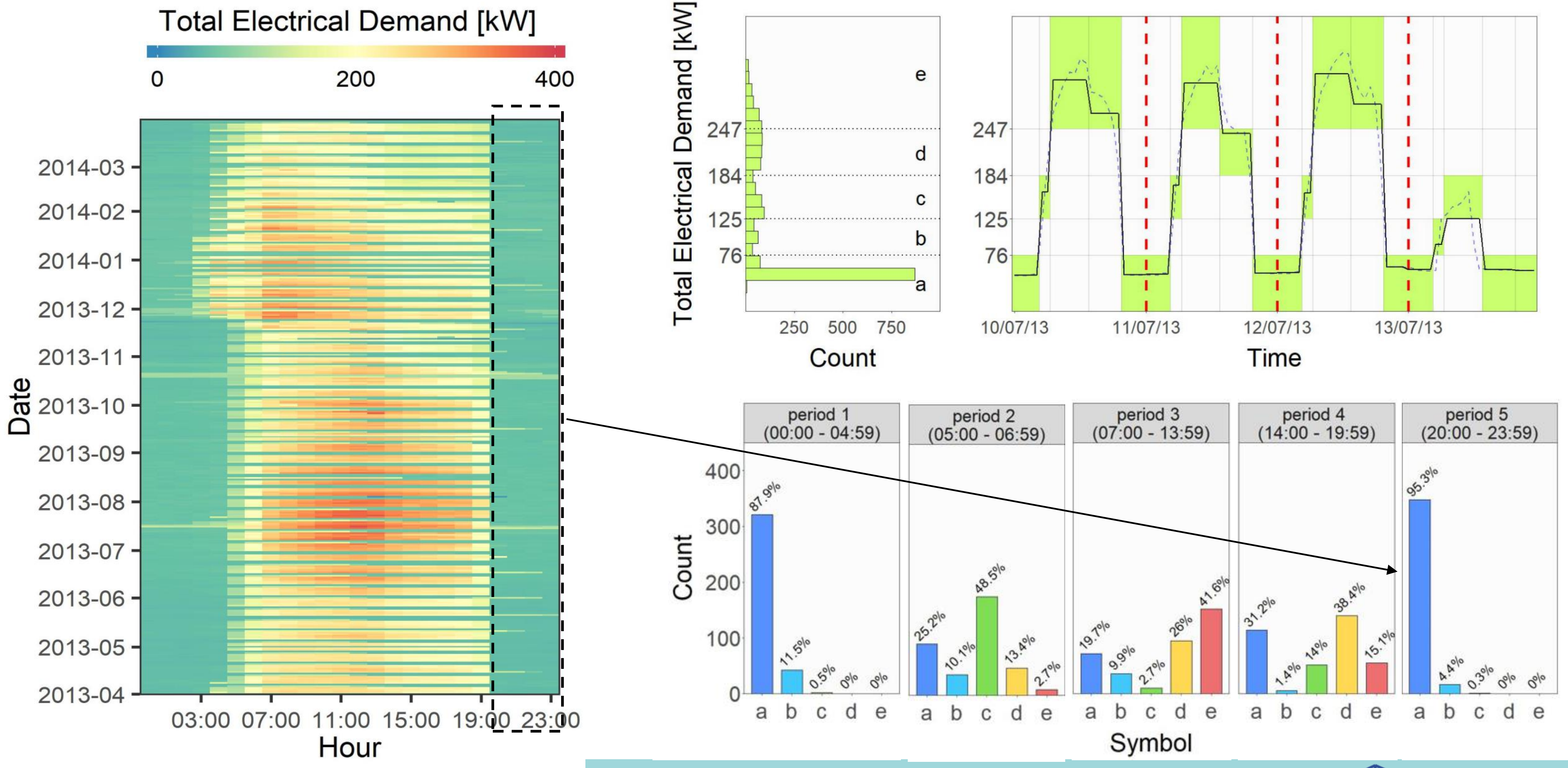

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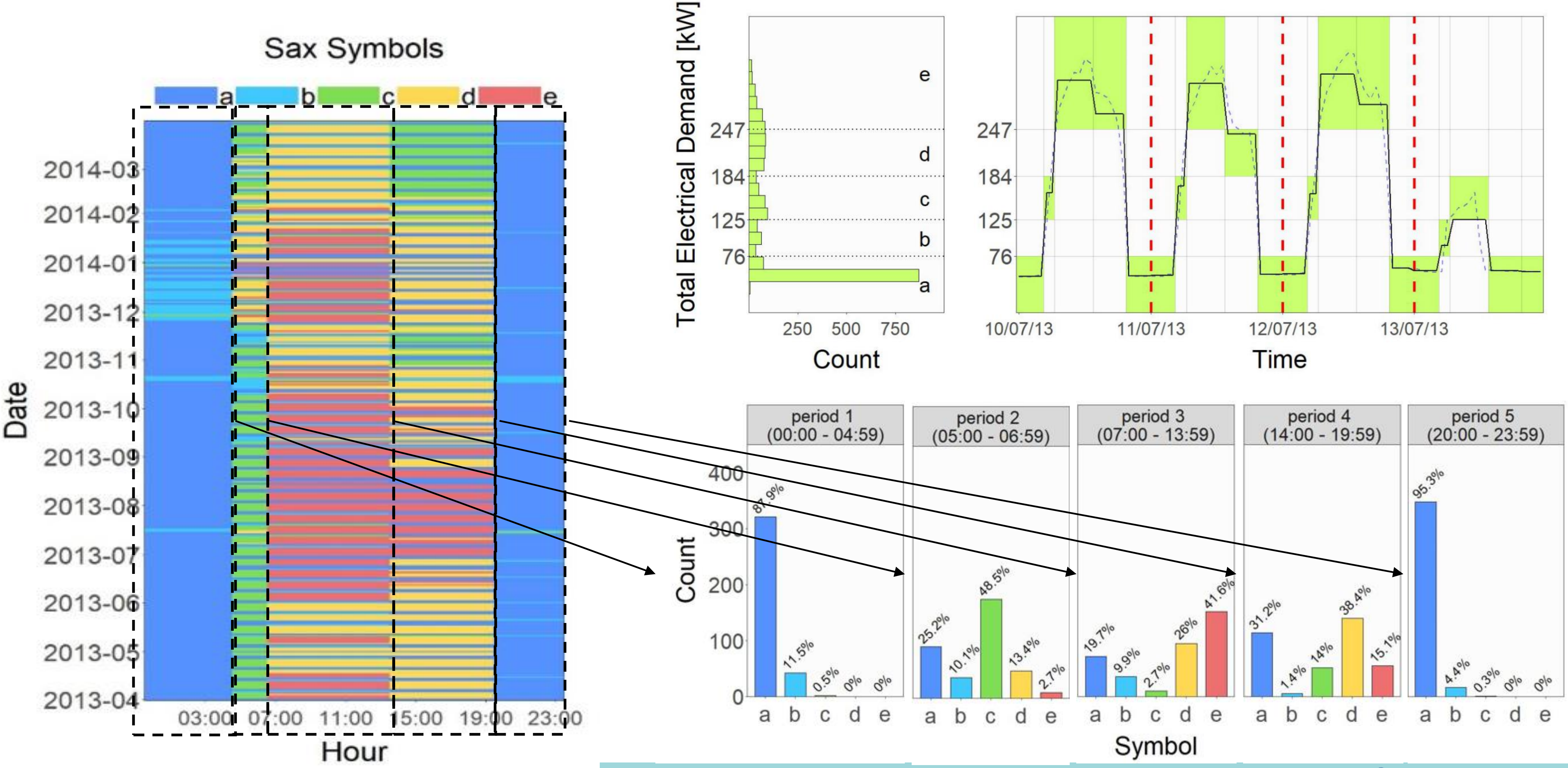
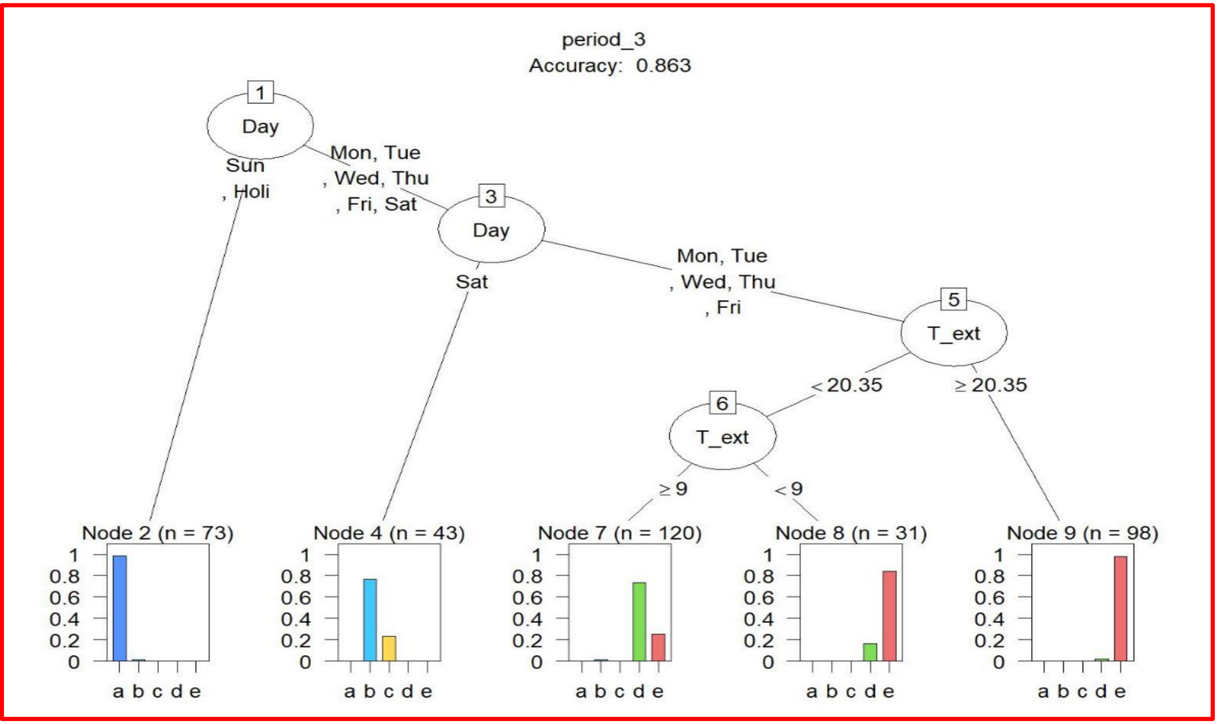


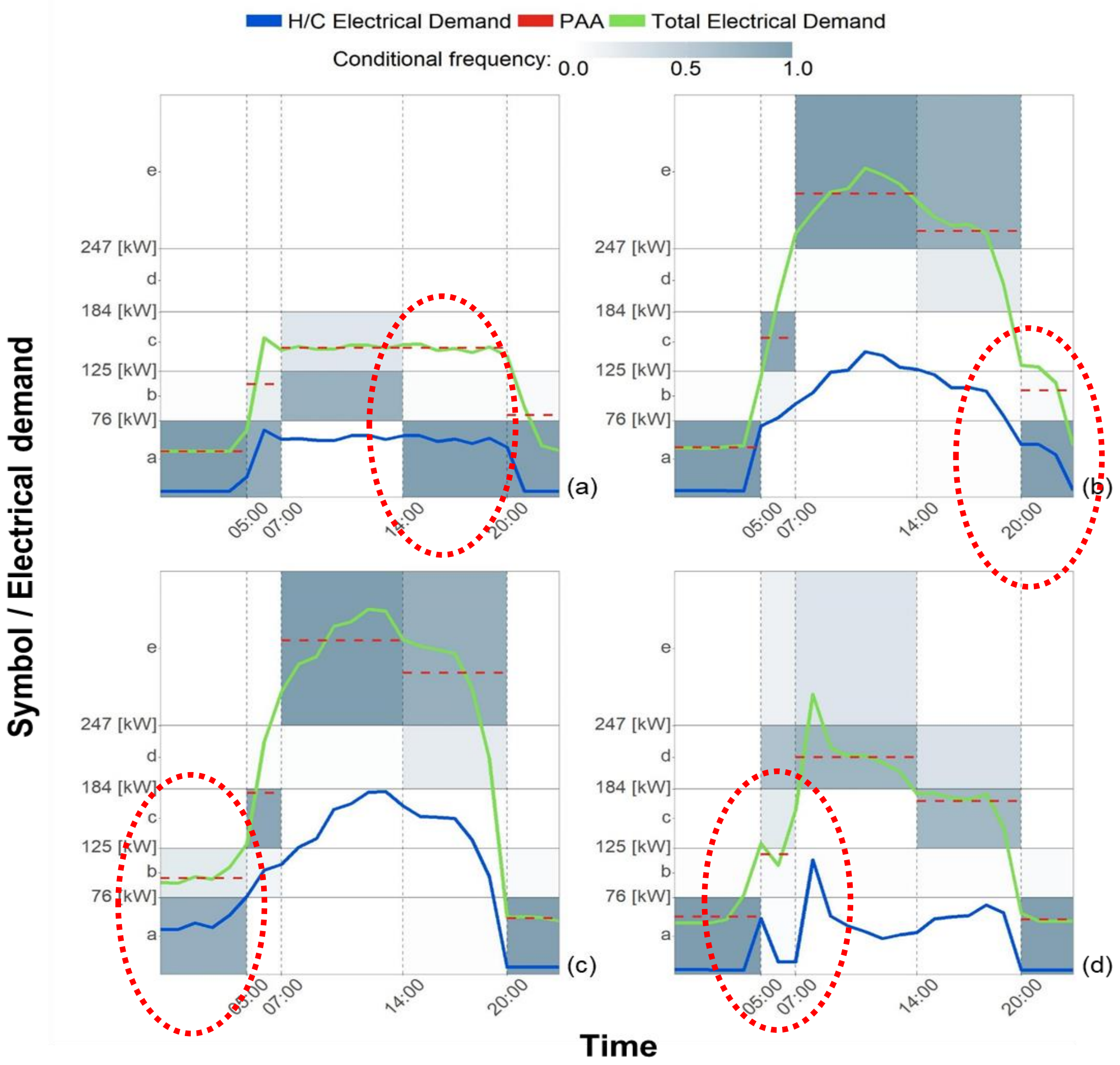
Estimation of typical energy patterns and identification of anomalies

Capozzoli A., Piscitelli M.S., Brandi S., Grassi D., Chicco G. 2018. *Automated load patterns learning and diagnosis for enhancing energy management in smart buildings*. Energy, 157 pp. 336-352.



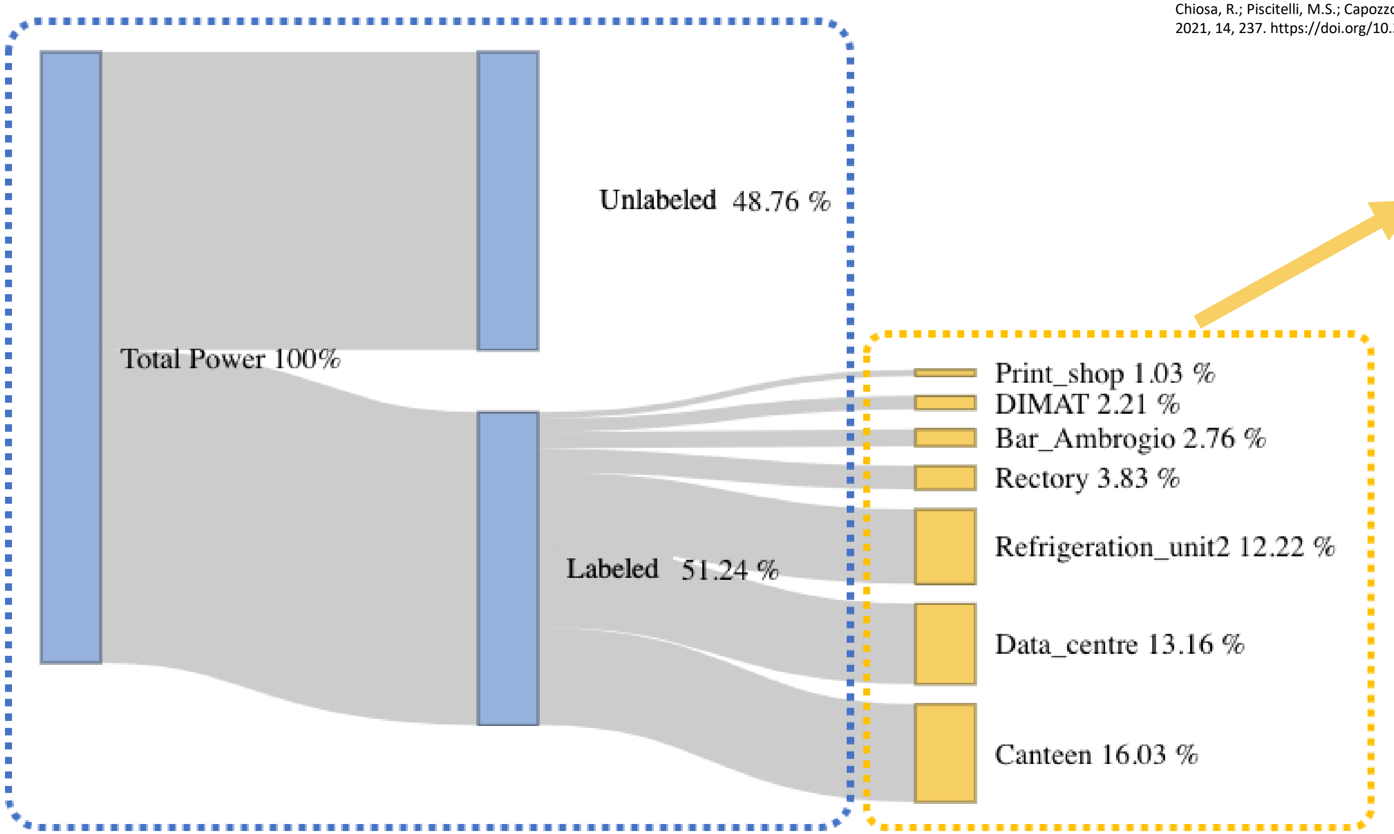
Decision rules for Case study 1.

Time window	Decision rules	Symbol	Accuracy
Period 1 (00:00–04:59)	IF ***system_start*** = is turned OFF	→ ***a***	98%
	IF ***system_start*** = is turned ON at 04:00 a.m. AND ***T_int*** ≥ 23,43 °C	→ ***a***	80%
	IF ***system_start*** = is turned ON at 04:00 a.m. AND ***T_int*** < 23,43 °C	→ ***b***	79%
Period 2 (05:00–06:59)	IF ***Day*** = Holiday OR Sunday OR Saturday	→ ***a***	83%
	IF ***Day*** = Monday OR Tuesday OR Wednesday OR Thursday OR Friday AND ***T_int_pre (period 1)*** ≥ 23,55 °C	→ ***c***	88%
	IF ***Day*** = Monday OR Tuesday OR Wednesday OR Thursday OR Friday AND ***T_int_pre (period 1)*** < 23,55 °C	→ ***d***	60%
Period 3 (07:00–13:59)	IF ***Day*** = Holiday OR Sunday	→ ***a***	99%
	IF ***Day*** = Saturday	→ ***b***	77%
	IF ***Day*** = Monday OR Tuesday OR Wednesday OR Thursday OR Friday AND 9 °C ≤ ***T_ext*** < 20,35 °C	→ ***d***	73%
	IF ***Day*** = Monday OR Tuesday OR Wednesday OR Thursday OR Friday AND ***T_ext*** ≥ 20,35 °C	→ ***e***	98%
	IF ***Day*** = Monday OR Tuesday OR Wednesday OR Thursday OR Friday AND ***T_ext*** < 9 °C	→ ***e***	84%
Period 4 (14:00–19:59)	IF ***Sym_pre*** = a OR b OR c	→ ***a***	96%
	IF ***T_ext*** < 24,1 °C AND ***Sym_pre (period 3)*** = "d" AND ***T_int*** < 25,55 °C	→ ***c***	69%
	IF ***T_ext*** < 24,1 °C AND ***Sym_pre (period 3)*** = "d" AND ***T_int*** ≥ 25,55 °C	→ ***d***	75%
	IF ***T_ext*** < 24,1 °C AND ***Sym_pre (period 3)*** = "e"	→ ***d***	94%
	IF ***Sym_pre*** = "d" OR "e" AND ***T_ext (period 3)*** ≥ 24,1 °C	→ ***e***	79%
Period 5 (20:00–23:59)	–	→ ***a***	95%



Diagnosis of anomalies using sub-loads information and Association Rule Mining

Chiosa, R.; Piscitelli, M.S.; Capozzoli, A. A Data Analytics-Based Energy Information System (EIS) Tool to Perform Meter-Level Anomaly Detection and Diagnosis in Buildings. Energies 2021, 14, 237. https://doi.org/10.3390/en14010237

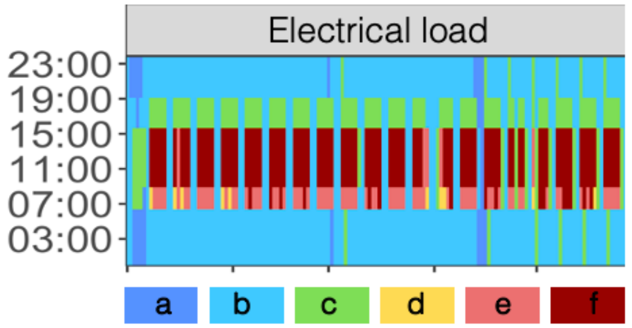


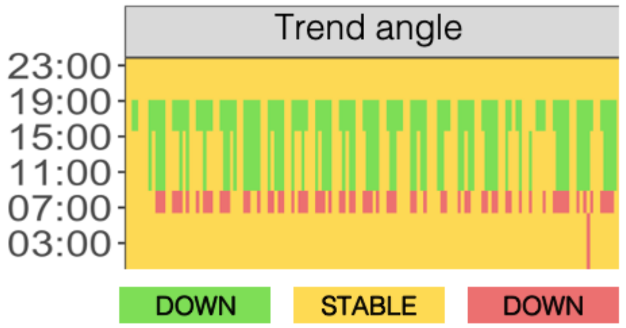
Meter-level total load

Meter-level sub-load

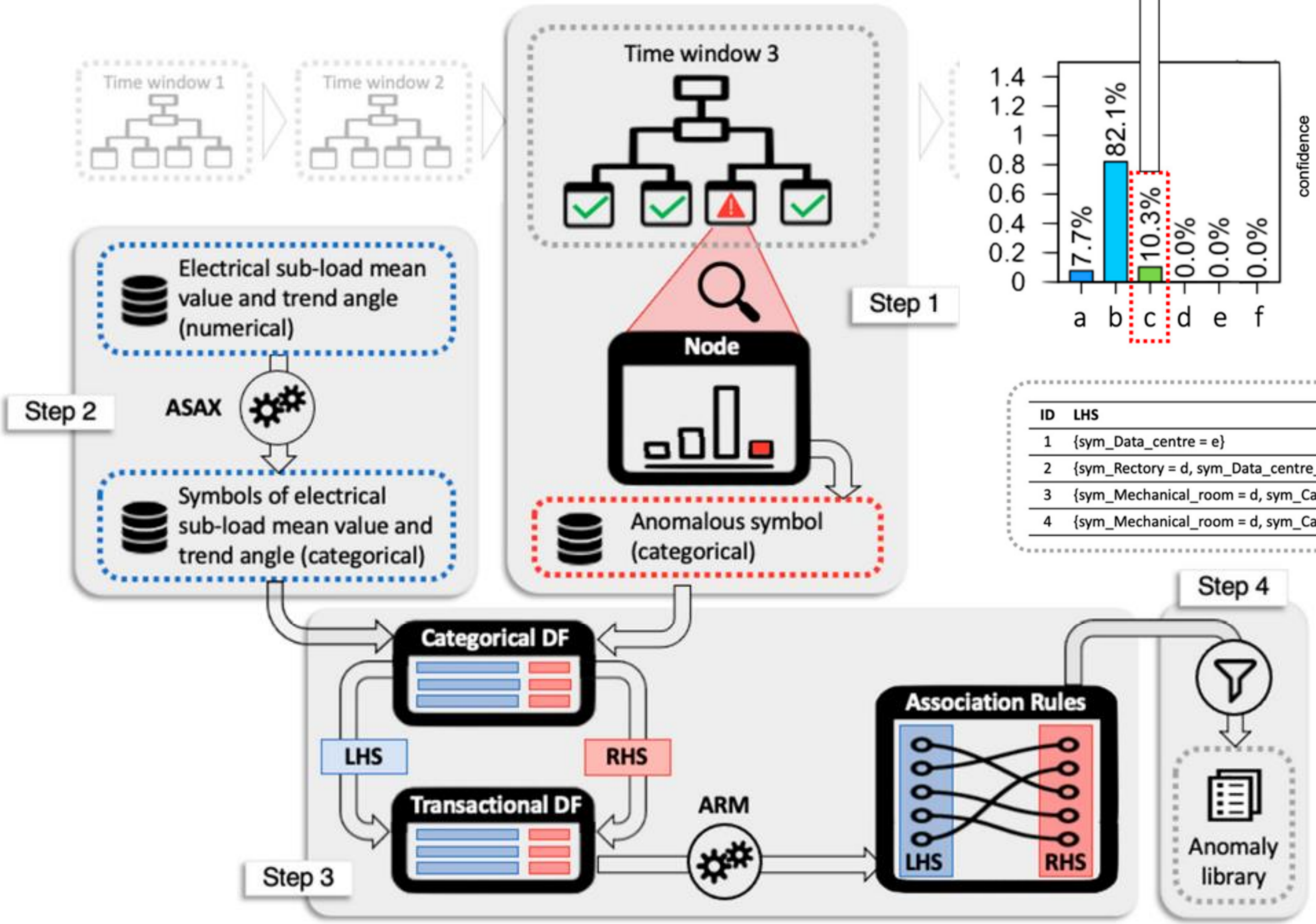
Sub loads feature extraction and categorization through ASAX encoding

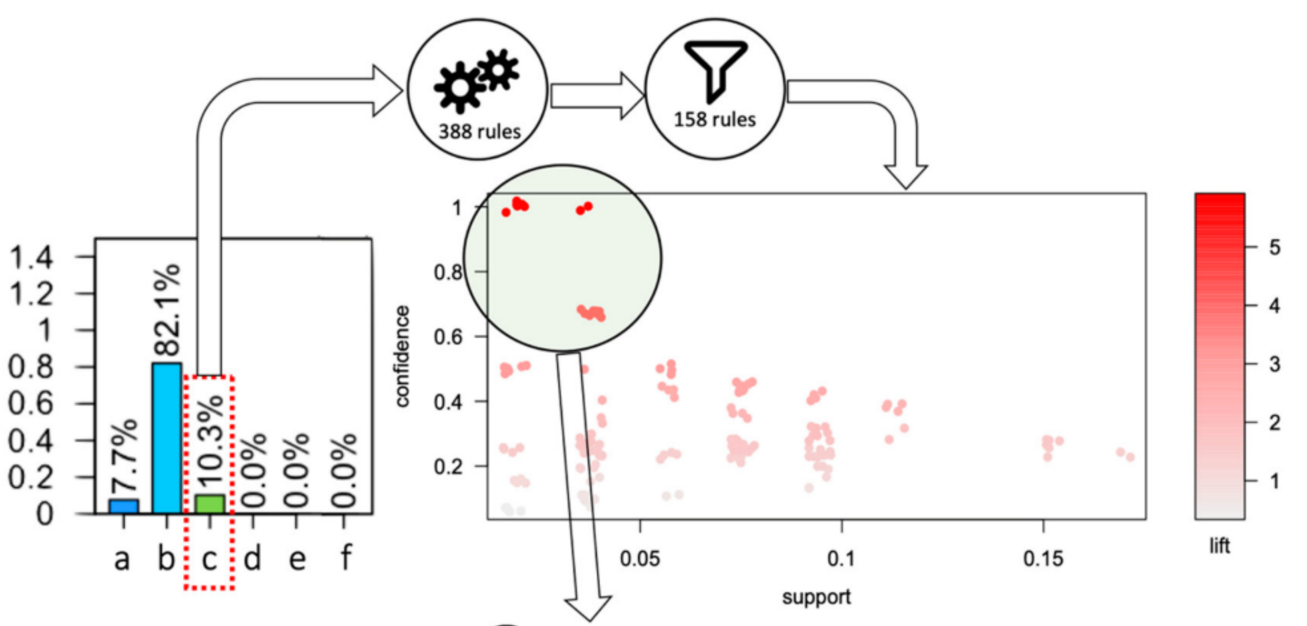
- Electrical Load
- Trend angle





Diagnosis of anomalies through ARM





Anomaly library (19 rules)

ID	LHS	RHS	Support	Confidence	Lift
1	{sym_Data_centre = e}	{sym_Total_Power = c}	0.01886792	1.00000000	5.300001
2	{sym_Rectory = d, sym_Data_centre_trend = DOWN}	{sym_Total_Power = c}	0.01886792	1.00000000	5.300001
3	{sym_Mechanical_room = d, sym_Canteen_trend = DOWN}	{sym_Total_Power = c}	0.01886792	1.00000000	5.300001
4	{sym_Mechanical_room = d, sym_Canteen = c}	{sym_Total_Power = c}	0.01886792	1.00000000	5.300001

An anomaly library is build using ARM

It is possible to infer the sub-loads that are responsible for the meter-level anomalous behaviour

Chiosa, R.; Piscitelli, M.S.; Capozzoli, A. A Data Analytics-Based Energy Information System (EIS) Tool to Perform Meter-Level Anomaly Detection and Diagnosis in Buildings. Energies 2021, 14, 237. https://doi.org/10.3390/en14010237

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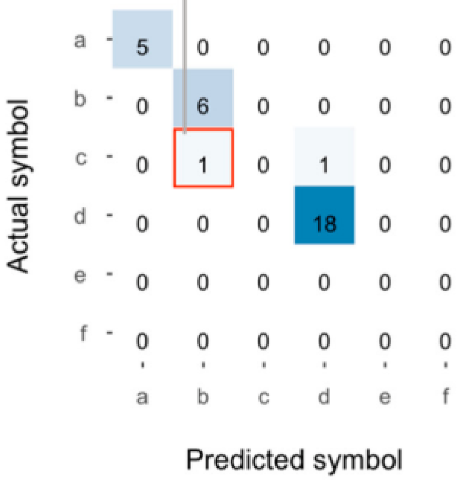
Friday 2019-01-04
Node 5

Predicted "b"
Actual "c"

Higher Electrical Load



Confusion Matrix

Algorithm : evtree
Time window 2 (06:30 - 08:59)
Tested on: January 2019

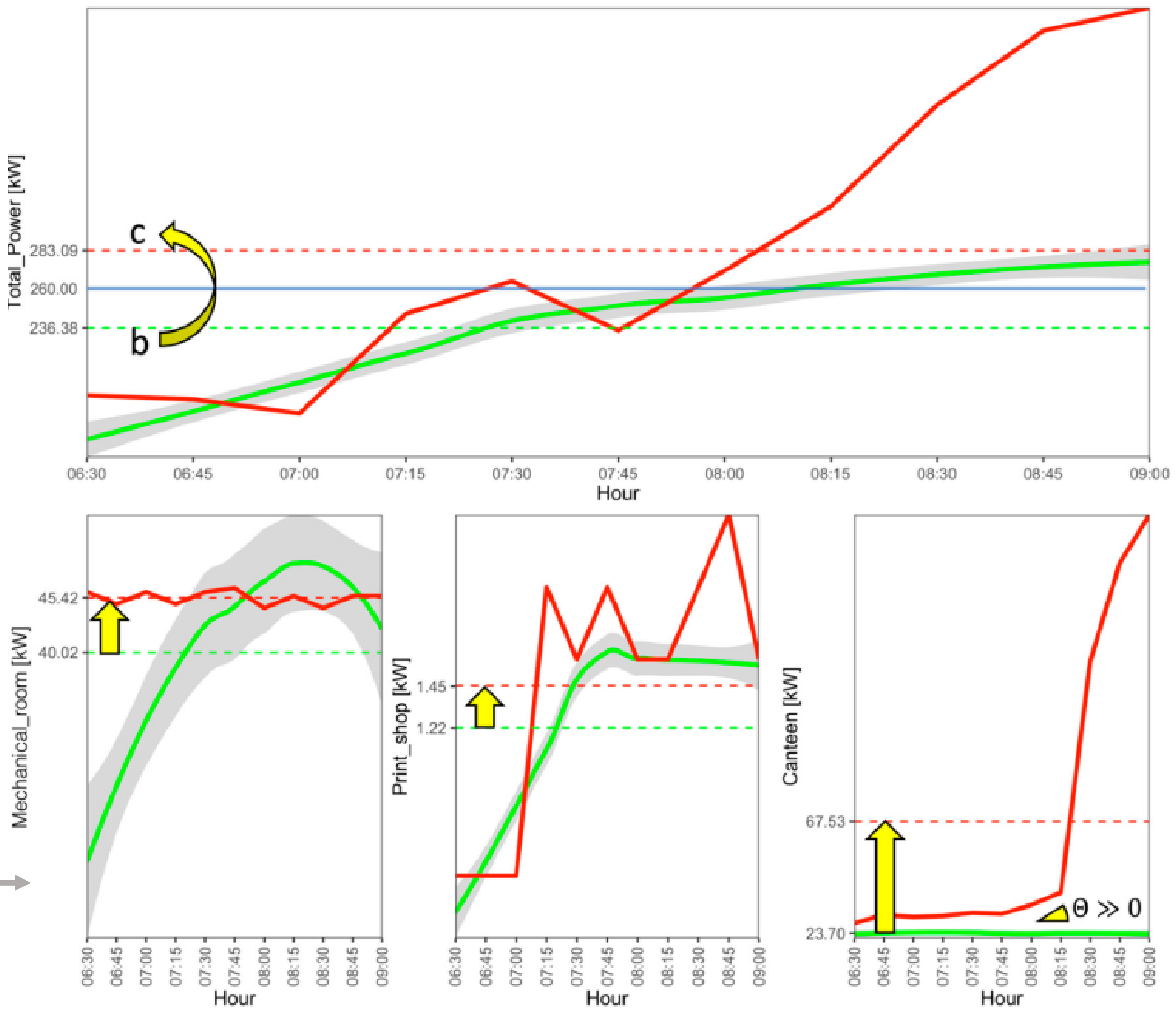
Performance	Value [%]
Accuracy	93.55
Precision	100.00
Recall	100.00

Sub-loads **electrical load and trend angle** in the observed time window

Comparison between observed sub-loads condition and **anomaly library**

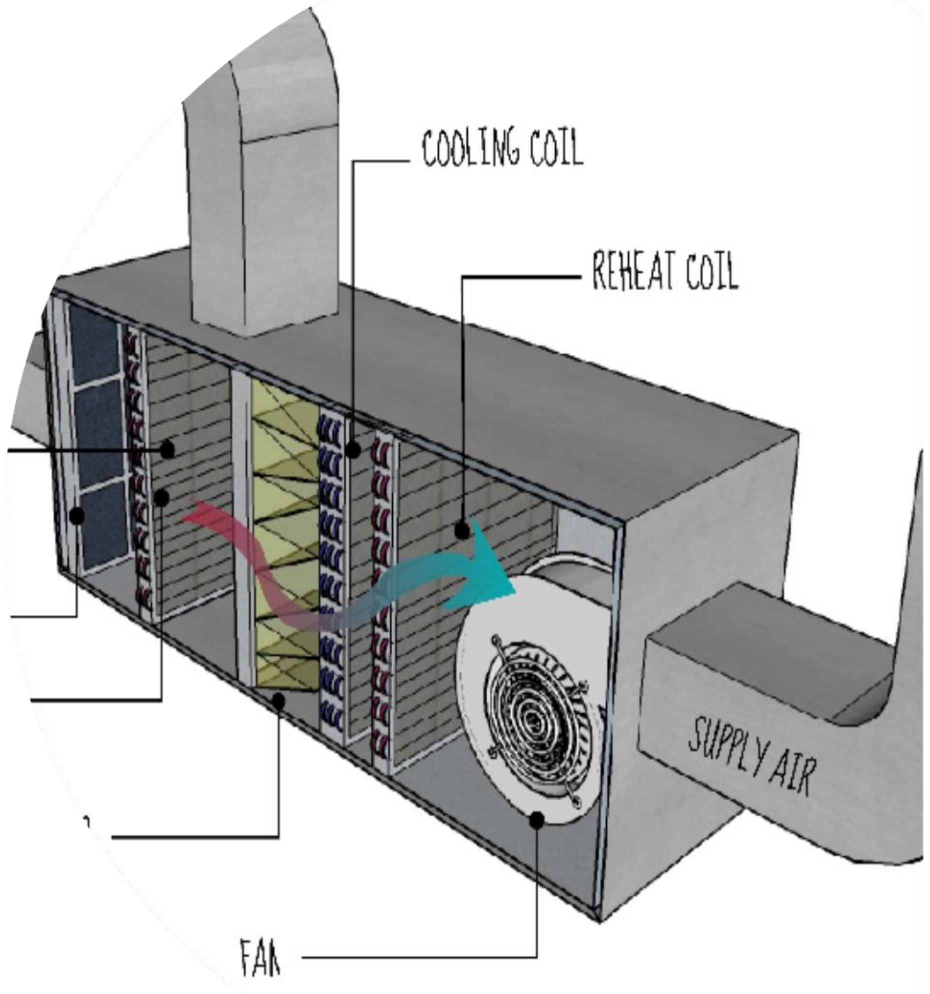
Best match

Total load symbol	Sub-load symbol	Sub load trend angle	Sub load
C	C	UP	Printshop
C	C	STABLE	Mechanical room
C	C	UP	Canteen
...	...	...	...



Fault
Detection
Diagnosis

Application at component level



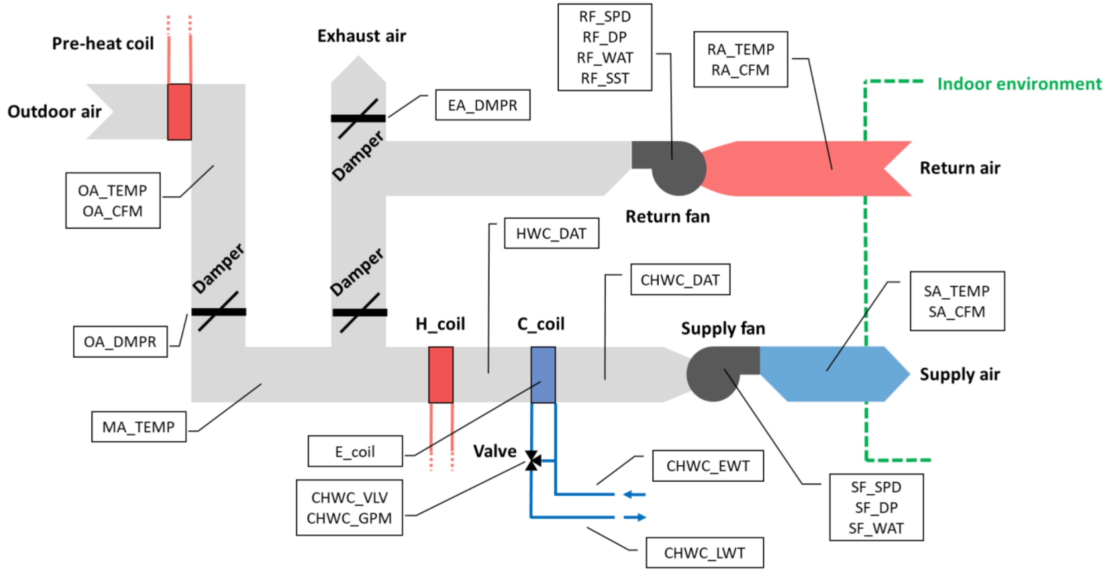
Fault Detection and Diagnosis in AHU systems

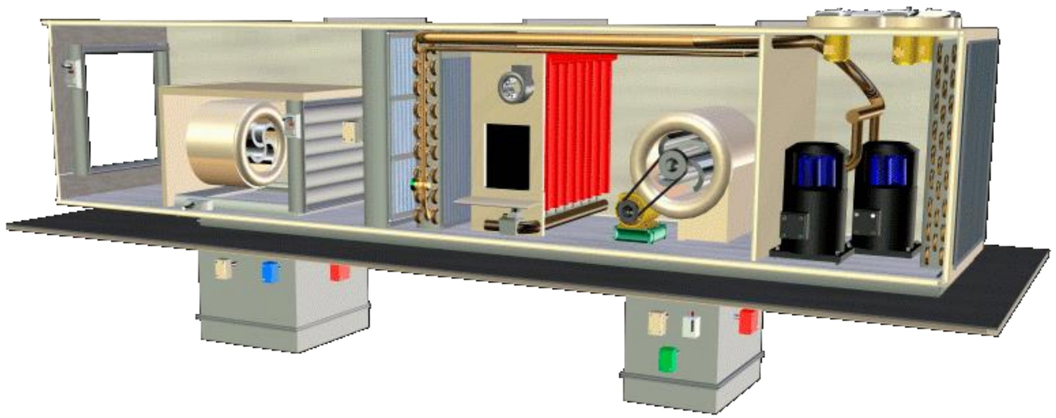
- One of the most sources of component and control faults in HVAC is related to Air Handling Units management. A study conducted on more than 55.000 Air Handling Units of HVAC systems, showed that 90% of them runs with one or multiple faults

- the developed FDD tool is capable to automatically detect and diagnose up to 11 typical faults in AHU with an accuracy of 90%

FDD tool for the identification and diagnosis of faults in AUHs: Case study

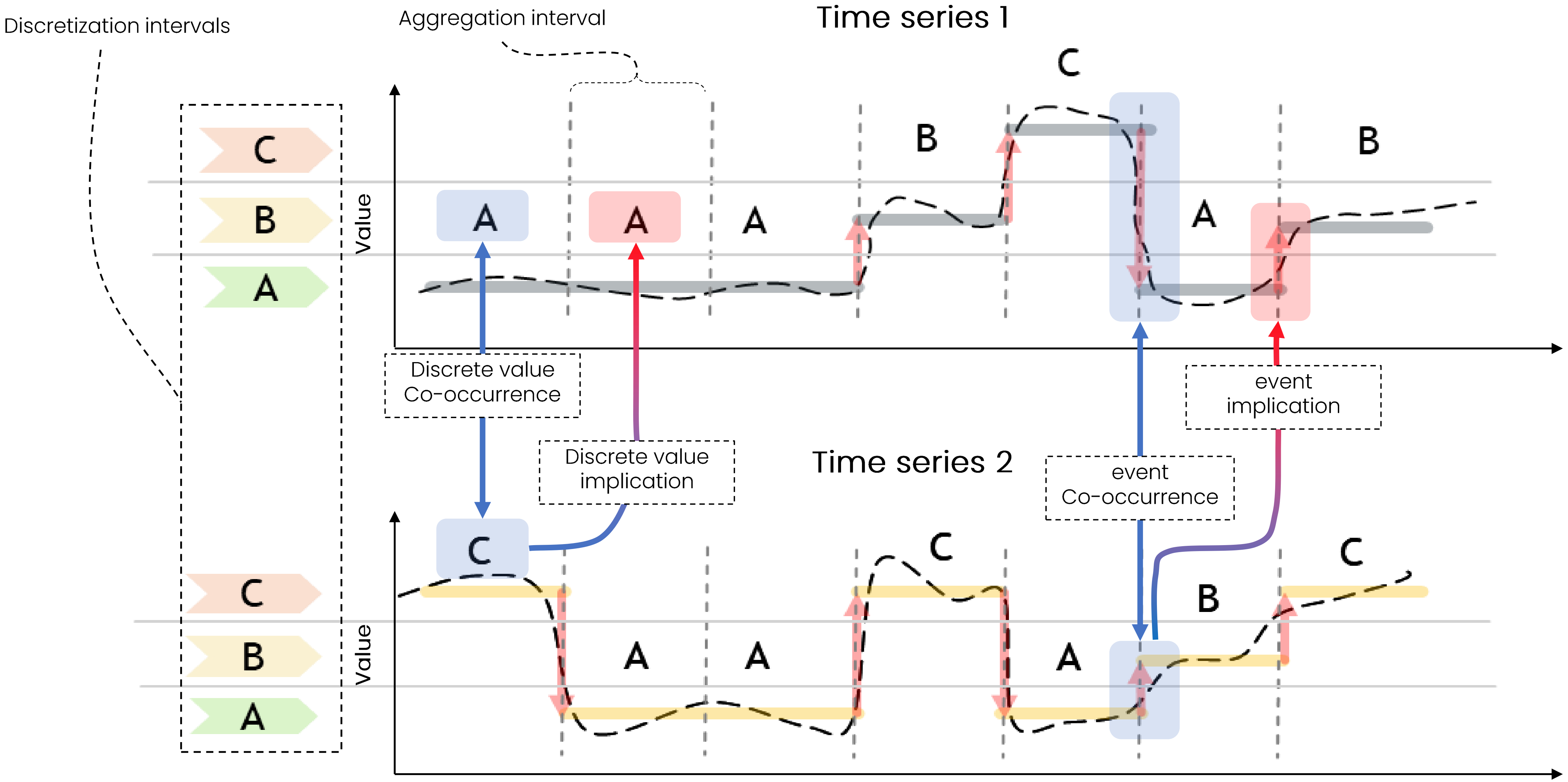
Piscitelli M.S., Mazzarelli D.M., Capozzoli A. Enhancing operational performance of AHUs through an advanced fault detection and diagnosis process based on temporal association and decision rules. Energy and Buildings.





Objective	Fault detection and diagnosis in HVAC systems	
Spatial scale/final use	Components of an AHU system (ASHRAE RP-1312)	
Sampling frequency	1 minute	
Type of data	Climatic data	External temperature
	System data	< 20 operational variables (fan, valves, dampers, setpoints)
	Building physical parameters	-
Recording period length	33 days cooling condition	

Identification and diagnosis of faults in AUHs : Methodological framework

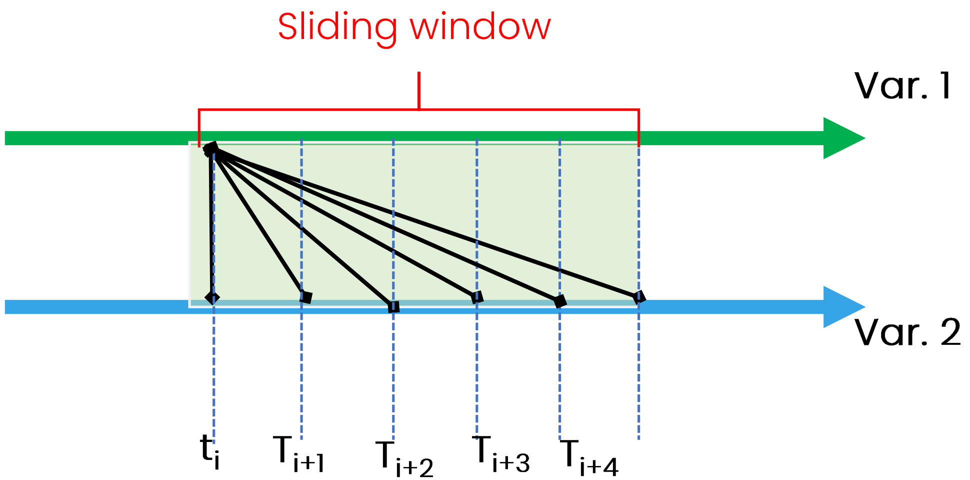


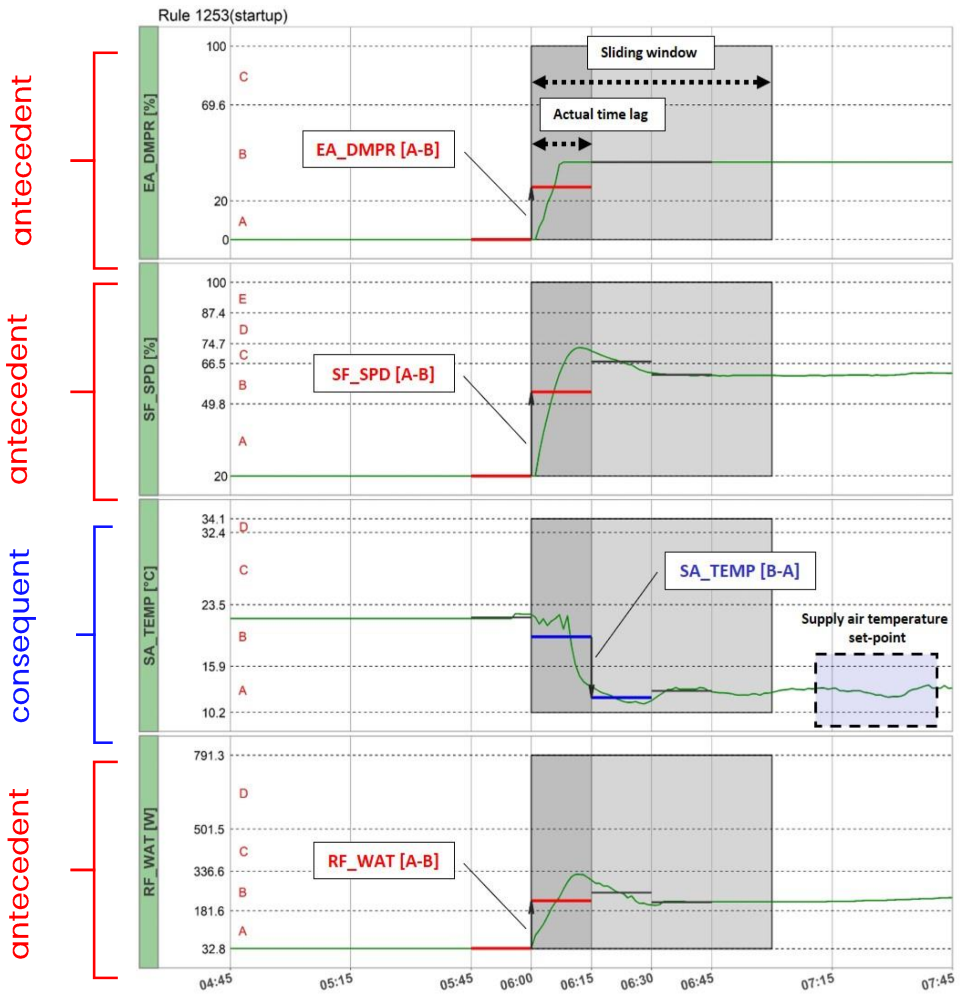
Identification and diagnosis of faults in AUHs : event co-occurrence and implication during transient period

Piscitelli M.S., Mazzarelli D.M., Capozzoli A. Enhancing operational performance of AHUs through an advanced fault detection and diagnosis process based on temporal association and decision rules. Energy and Buildings.

Rule extraction through association rule mining

$$X \xrightarrow{t} Y$$



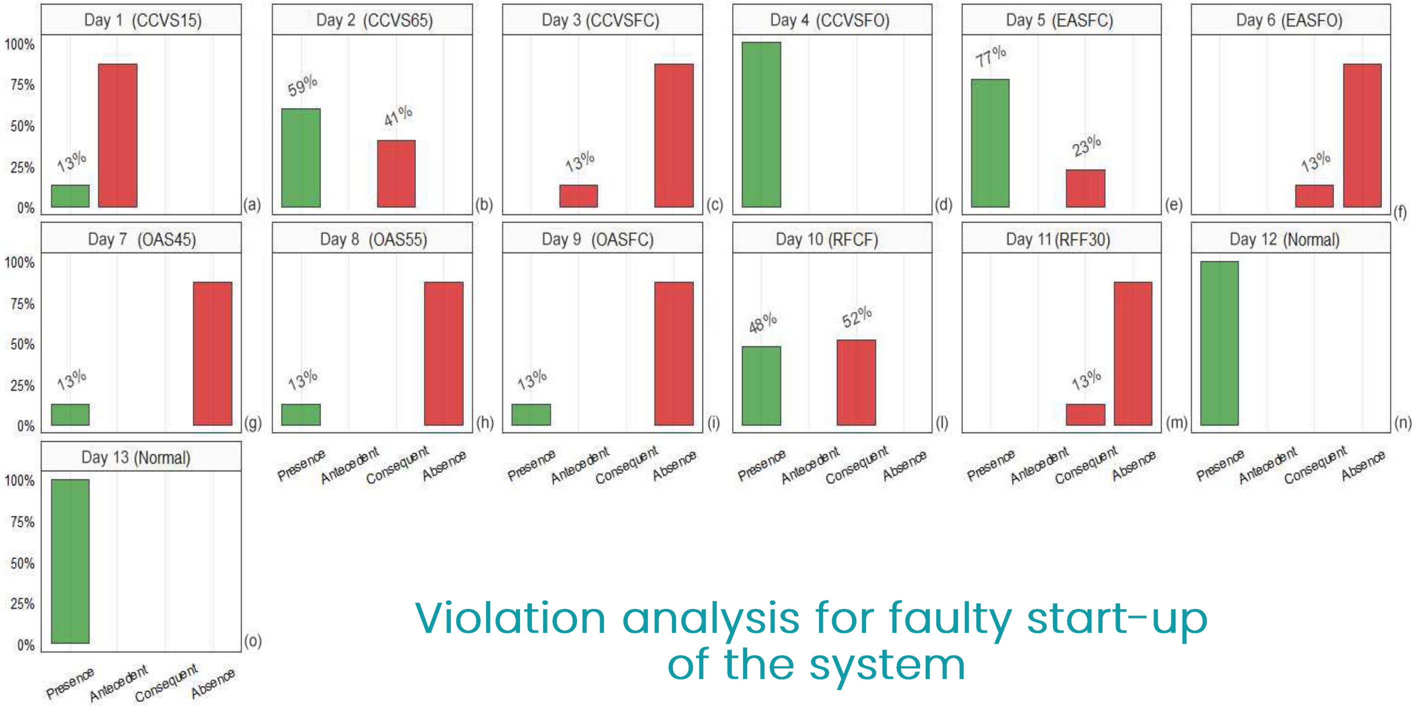


association rules can be used for mining implications between events in the time domain that are frequently associated together. The output is a set of IF-THEN interpretable rules that are used to represent patterns.

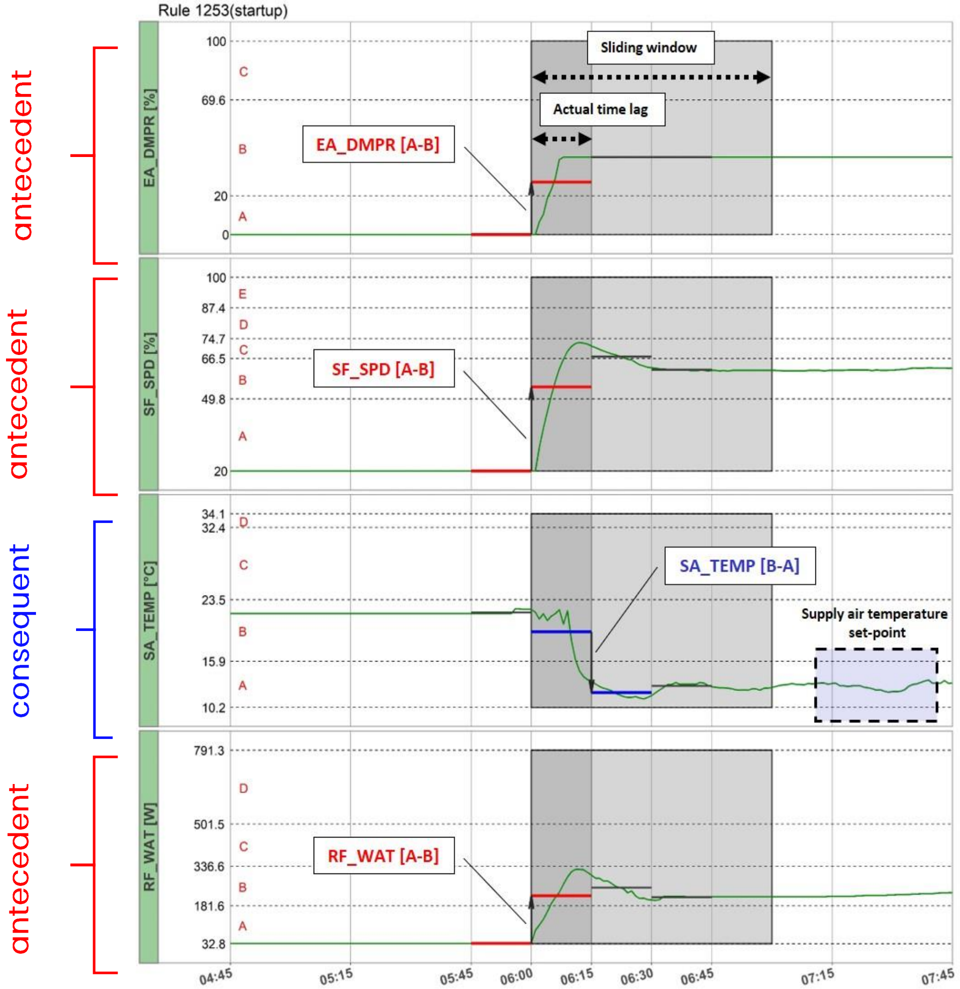
SF_SPD [A-B] & EA_DMPR [A-B] & RF_WAT [A-B] → SA_TEMP [B-A]

Identification and diagnosis of faults in AUHs : event co-occurrence and implication during transient period

Piscitelli M.S., Mazzarelli D.M., Capozzoli A. Enhancing operational performance of AHUs through an advanced fault detection and diagnosis process based on temporal association and decision rules. Energy and Buildings.



Violation analysis for faulty start-up of the system



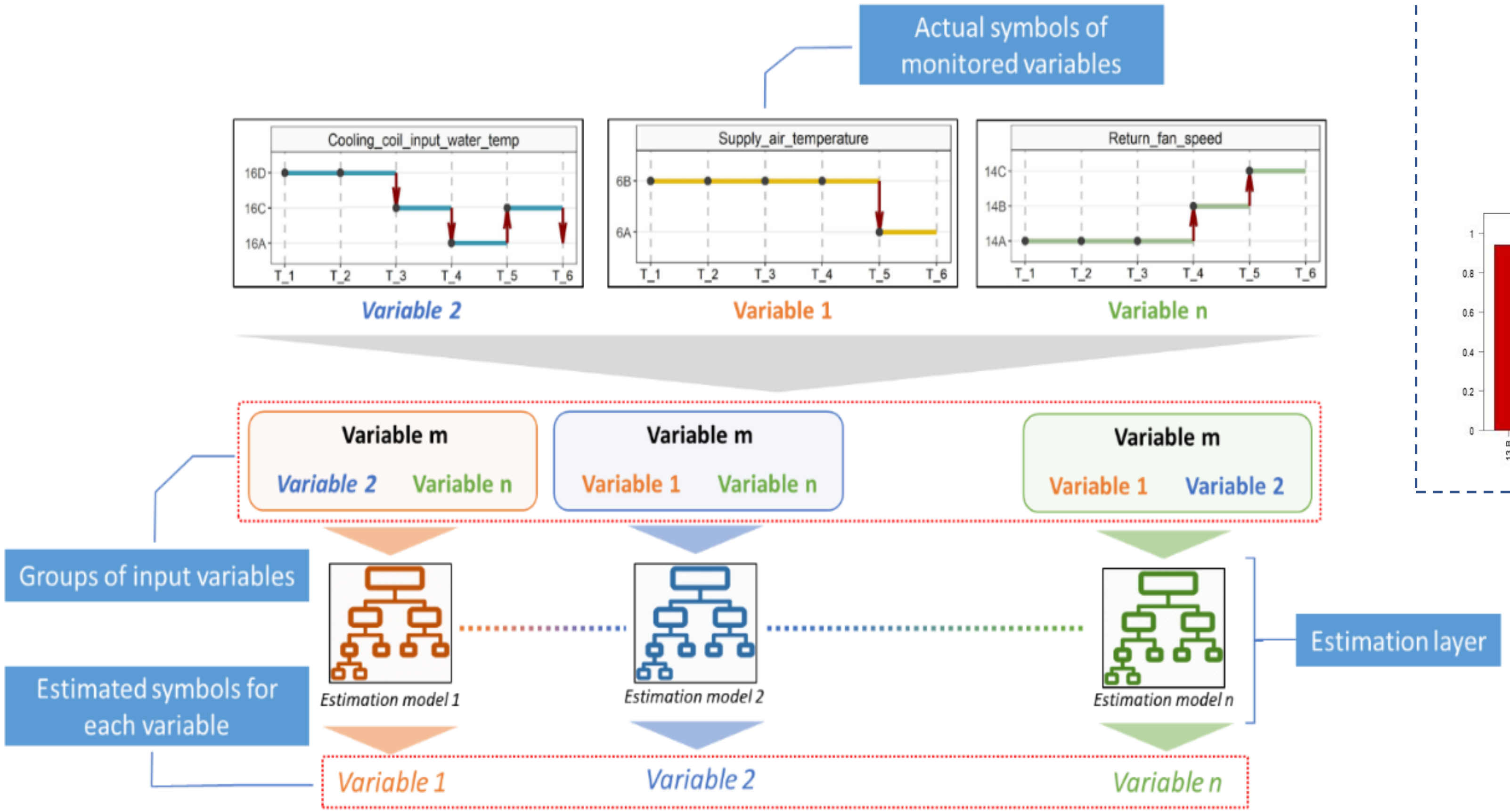
<u>association rules</u> can be used for mining implications between events in the time domain that are frequently associated together. The output is a set of IF-THEN interpretable rules that are used to represent patterns.

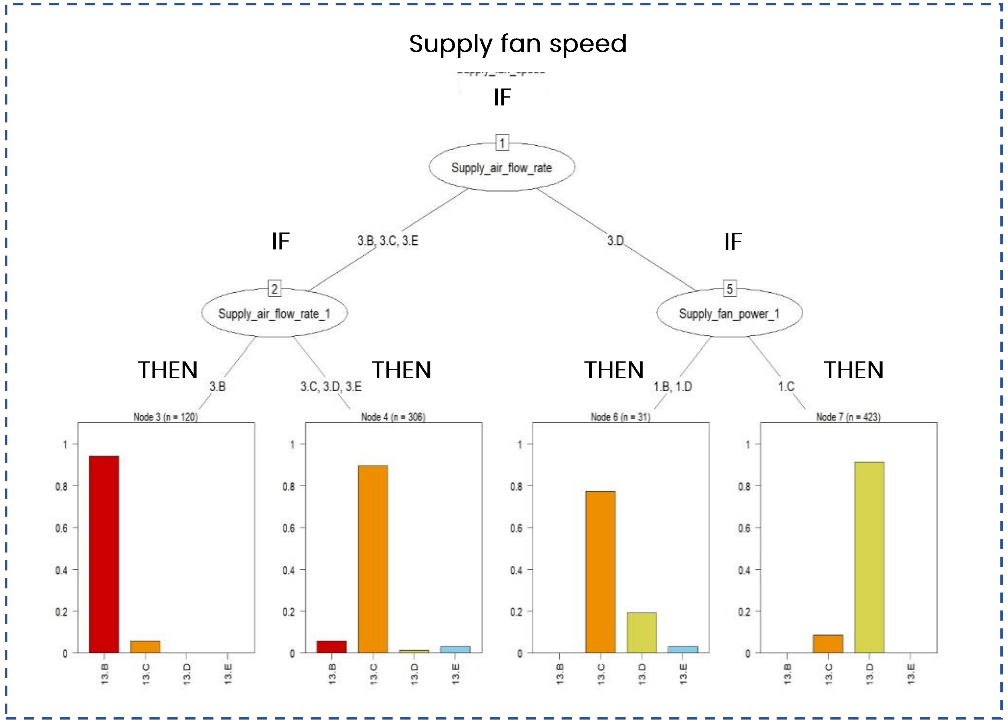
SF_SPD [A-B] & EA_DMPR [A-B] & RF_WAT [A-B] → SA_TEMP [B-A]

Identification and diagnosis of faults in AUHs : discrete value co-occurrences and implications during non transient period

Piscitelli M.S., Mazzarelli D.M., Capozzoli A. Enhancing operational performance of AHUs through an advanced fault detection and diagnosis process based on temporal association and decision rules. Energy and Buildings.

Estimation layer of the system "Normal" operation





For the development of the classification trees, all the variables are selected once at a time as target attribute while the remaining ones are used as input attributes.

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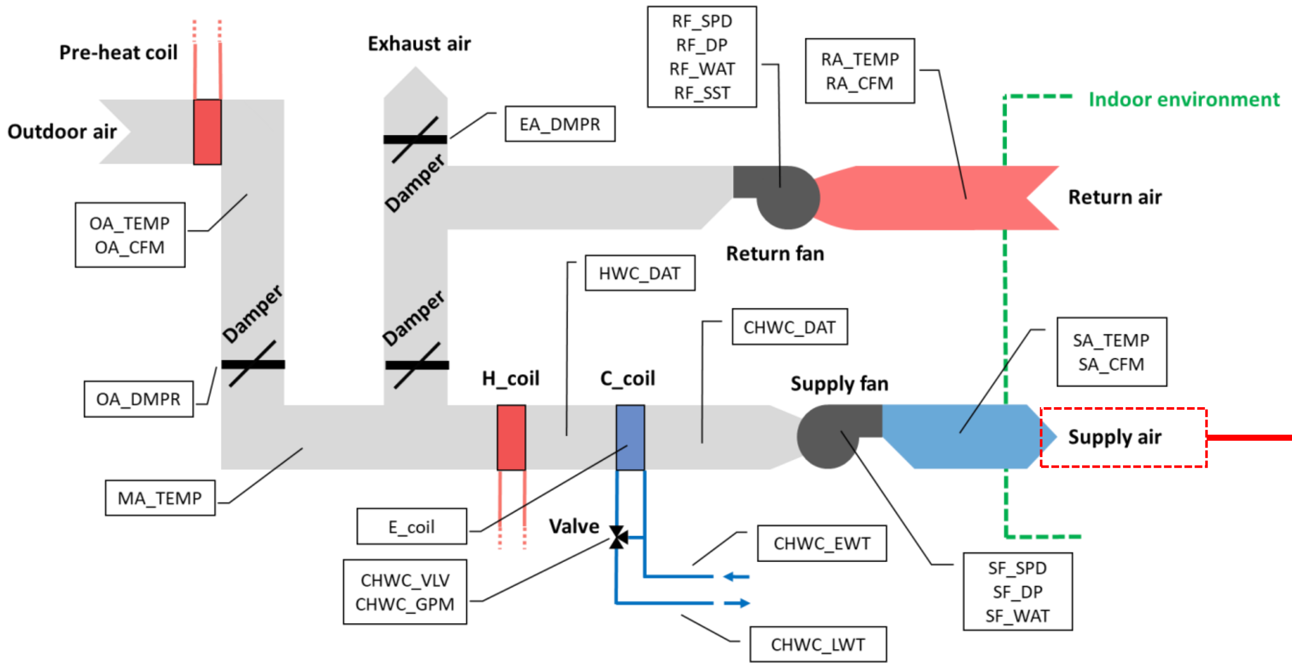
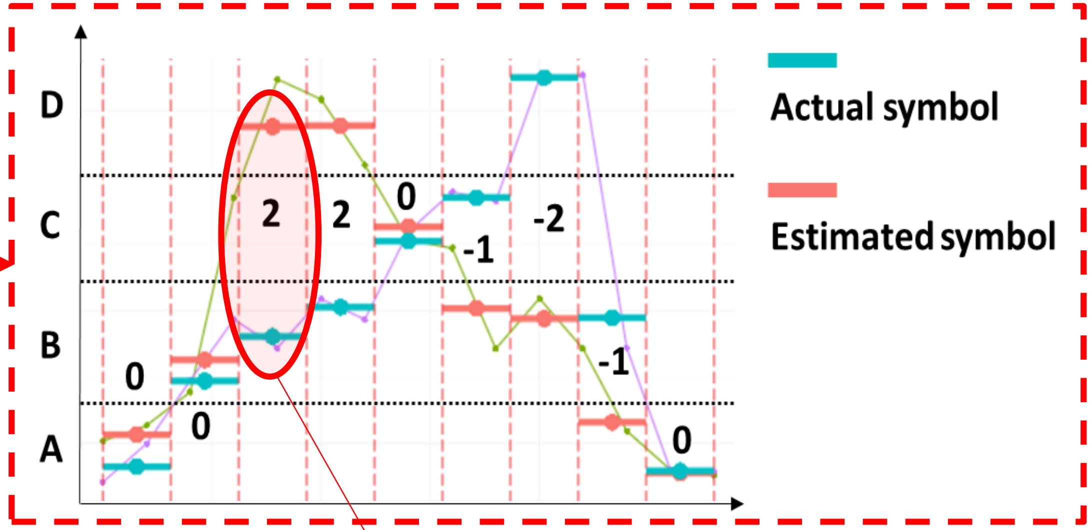
Identification and diagnosis of faults in AUHs : discrete value co-occurrences and implications during non transient period



The most probable discrete state can be estimated and compared to the one evaluated from the actual data. Deviations from the estimations can suggest the presence of fault.



Predicted – actual

Evaluation of residuals in symbolic discrete-state TS

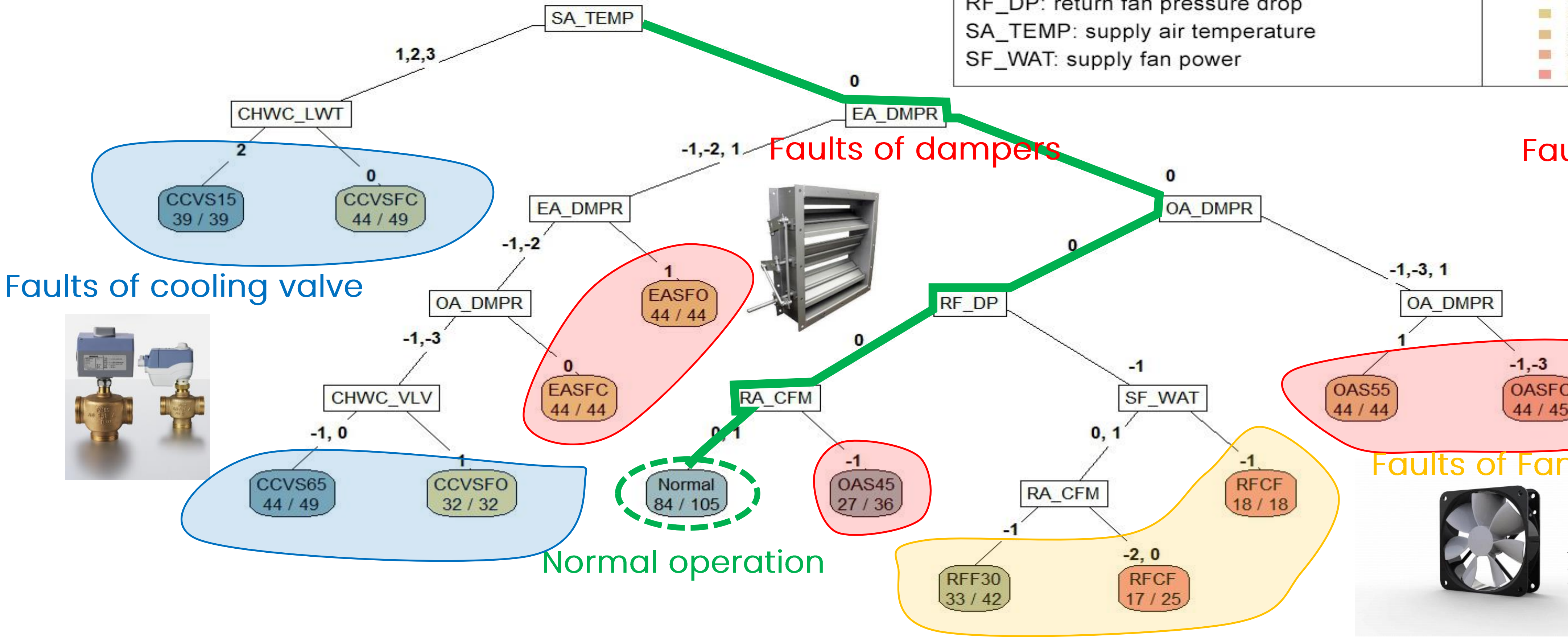
The difference between two equal symbols is assumed to be 0, while the residual differs from zero if the symbols are at least one alphabet apart.

Piscitelli M.S., Mazzarelli D.M., Capozzoli A. Enhancing operational performance of AHUs through an advanced fault detection and diagnosis process based on temporal association and decision rules. Energy and Buildings.

Identification and diagnosis of faults in AUHs : Fault diagnosis through residual analysis

Up to 11 typical faults in AHUs identified with the 90% of accuracy

Nomenclature of the input variables	Predicted fault tag
CHWC_LWT: cooling coil outlet water temperature	CCVS15
CHWC_VLV: cooling coil valve position	CCVS65
EA_DMPR: exhaust air damper position	Normal
OA_DMPR: outdoor air damper position	OAS45
RA_CFM: return air flow rate	RFF30
RF_DP: return fan pressure drop	CCVSFC
SA_TEMP: supply air temperature	CCVSFO
SF_WAT: supply fan power	EASFC
	EASFO
	OAS55
	OASFC
	RFCF



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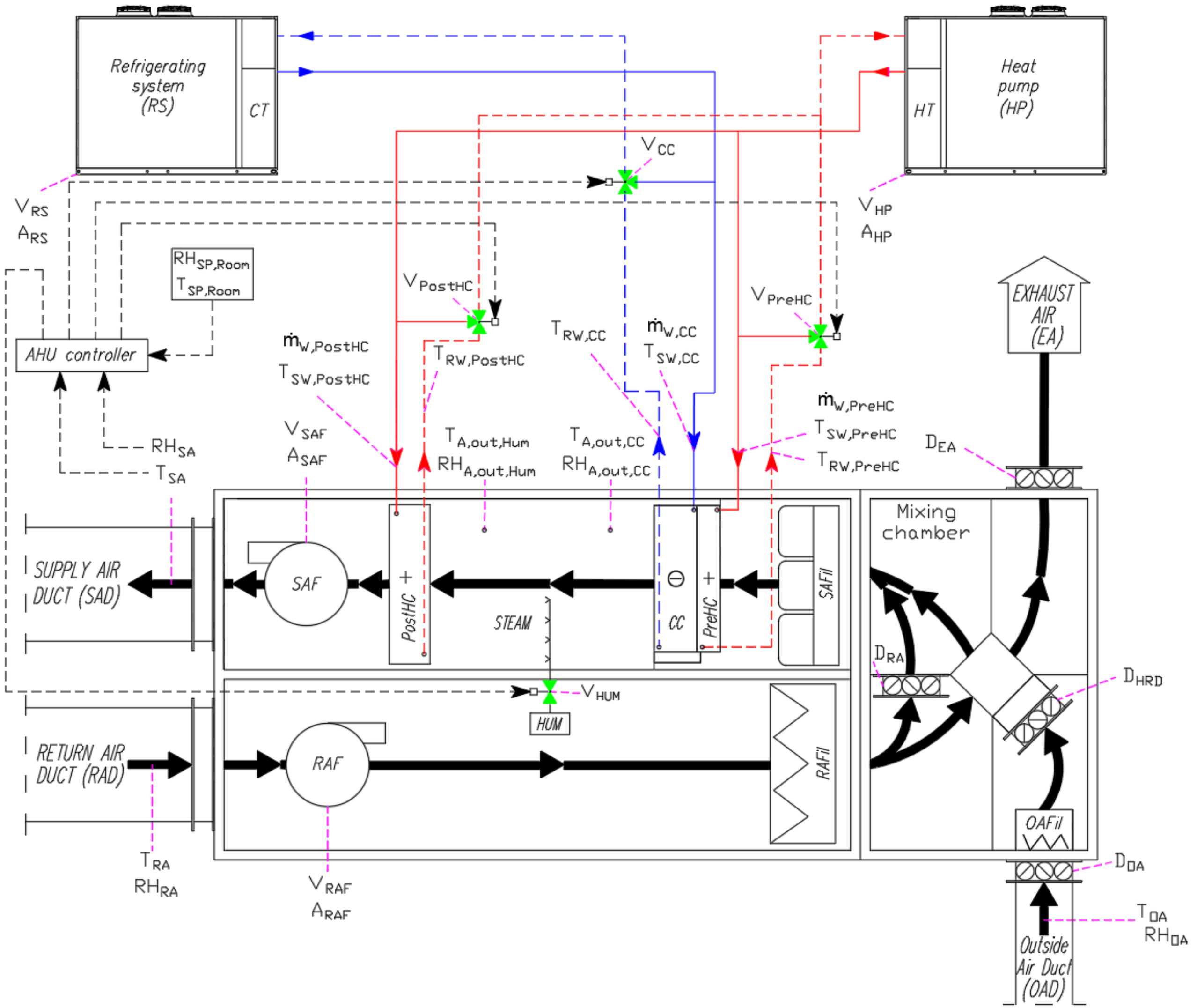
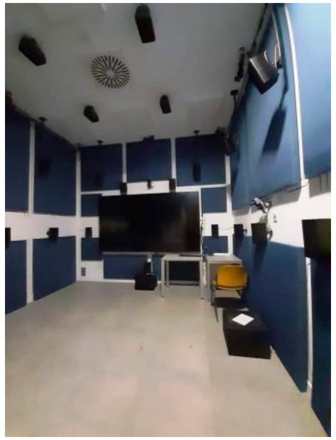
Experimental campaign on FDD for AHU in collaboration with SENS i-Lab

The experimental campaign has the following objectives:

1. Design and setup of monitoring infrastructure
2. Experimental campaign and simulation of artificial faults during operation
3. Test of FDD strategies on the case study
4. Production of publicly available dataset



Monitoring infrastructure installed in the SENS i-Lab facility



Monitored Parameters	Symbol	Measuring Range	Accuracy
Return air temperature	T_{RA}	0÷50 °C	±0.8 °C
Return air relative humidity	RH_{RA}	0÷100%	±3%
Supply air temperature	T_{SA}	0÷50 °C	±0.8 °C
Supply air relative humidity	RH_{SA}	0÷100%	±3%
Outside air temperature	T_{OA}	-50÷50 °C	±0.75 °C
Air temperature at outlet of cooling coil	$T_{A,out,CC}$	-50÷50 °C	±0.75 °C
Opening percentage of 3-way valve supplying the PostHC	OP_{V_PreHC}	0÷100%	-
Opening percentage of 3-way valve supplying the PreHC	OP_{V_PostHC}	0÷100%	-
Opening percentage of 3-way valve supplying the CC	OP_{V_CC}	0÷100%	-
Opening percentage of valve of the Hum	OP_{V_Hum}	0÷100%	-

Monitored Parameters	Symbol	Measuring Range	Accuracy
Outside air relative humidity	RH_{OA}	0÷100%	±2%
Air relative humidity at outlet of cooling coil	$RH_{A,out,CC}$	0÷100%	±3%
Air temperature at outlet of humidifier	$T_{A,out,Hum}$	-50÷50 °C	±0.8 °C
Air relative humidity at outlet of humidifier	$RH_{A,out,Hum}$	0÷100%	±3%
Air temperature at outlet of post-heating coil	$T_{A,out,PostHC}$	-50÷50 °C	±0.8 °C
Air relative humidity at outlet of post-heating coil	$RH_{A,out,PostHC}$	0÷100%	±3%
Water temperature at inlet of pre-heating coil	$T_{SW,PreHC}$	-10÷60 °C	±0.3 °C
Water temperature at outlet of pre-heating coil	$T_{RW,PreHC}$	-10÷60 °C	±0.3 °C
Water mass flowrate entering the pre-heating coil	$\dot{m}_{W,PreHC}$	0÷0.65 l/s	±2%
Water temperature at inlet of cooling coil	$T_{SW,CC}$	-10÷60 °C	±0.3 °C
Water temperature at outlet of cooling coil	$T_{RW,CC}$	-10÷60 °C	±0.3 °C
Water mass flowrate entering the cooling coil	$\dot{m}_{W,CC}$	0÷0.65 l/s	±2%
Water temperature at inlet of post-heating coil	$T_{SW,PostHC}$	-10÷60 °C	±0.3 °C
Water temperature at outlet of post-heating coil	$T_{RW,PostHC}$	-10÷60 °C	±0.3 °C
Water mass flowrate entering the post-heating coil	$\dot{m}_{W,PostHC}$	0÷0.65 l/s	±2%
Current of heat pump	A_{HP}	0÷30 A	±0.5% FS
Voltage of heat pump	V_{HP}	0÷280 V	±0.5% FS
Current of refrigerating system	A_{RS}	0÷30 A	±0.5% FS
Voltage of refrigerating system	V_{RS}	0÷280 V	±0.5% FS
Current of supply air fan	A_{SAF}	0÷15 A	±0.5% FS
Voltage of supply air fan	V_{SAF}	0÷280 V	±0.5% FS
Current of return air fan	A_{RAF}	0÷5 A	±0.5% FS
Voltage of return air fan	V_{RAF}	0÷280 V	±0.5% FS

Artificially implementable faults in the SENS i-Lab facility

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Faults of valves

- post-heating coil valve stuck (fully open)
- post-heating coil valve stuck stuck (fully close)
- post-heating coil valve stuck stuck (partially open - 0÷100%)
- cooling coil valve stuck (fully open)
- cooling coil valve stuck stuck (fully close)
- cooling coil valve stuck stuck (partially open - 0÷100%)
- pre-heating coil valve stuck (fully open)
- pre-heating coil valve stuck stuck (fully close)
- pre-heating coil valve stuck stuck (partially open - 0÷100%)

Faults of humidifier

- humidifier valve stuck (fully open)
- humidifier valve stuck stuck (fully close)
- humidifier valve stuck stuck (partially open/close)

Faults of fans

- supply air fan at fixed speed (0÷100%)
- return air fan at fixed speed (0÷100%)

sensor faults

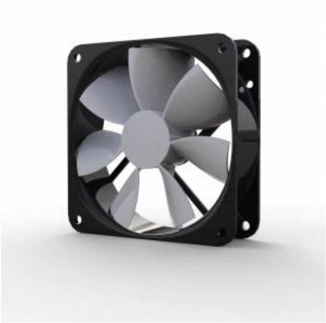
- return air temperature positive/negative offset
- return air relative humidity positive/negative offset

Faults of filters

- outside air filter block fault
- supply air filter block fault

Faults of damper s

- outside air damper stuck (fully open)
- outside air damper stuck (fully close)
- outside air damper stuck (partially open/close)
- return air damper stuck (fully open)
- return air damper stuck (fully close)
- return air damper stuck (partially open/close)
- exhaust air damper stuck (fully open)
- exhaust air damper stuck (fully close)
- exhaust air damper stuck (partially open/close)
- heat recovery system air damper stuck (fully open)
- heat recovery system air damper stuck (fully close)



Lesson Learned and future perspectives

- Despite off-line tests are essential for assessing the reliability of data analytics processes, aspects related to data volume, computational cost, updating of models, decline in accuracy are often neglected.

- **Through the experimental facility and the experimental campaign, it will be possible to deploy FDD algorithms in a controlled environment and assess their effectiveness in real conditions.**

- **The data-driven ADD/FDD tools need a proper amount of data for their deployment.** In this context a Knowledge driven-based approach can introduce domain knowledge and user experience into the analytical process, especially in the case initial information is not enough for deploying a data analytics-based FDD/ADD tool. A perfect integration of both approaches can significantly improve robustness, accuracy, and generalizability of FDD tools.

BAEDA Lab experience in FDD and ADD in energy&buildings

Questions?

Speaker

Prof. Alfonso Capozzoli

17 June 2021