Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

Final report 19.11.2021

Positive Gap

Low-cost optimization measures for more energy-efficient buildings

---

Source: Energo database

Scuola universitaria professionale della Svizzera italiana
Dipartimento ambiente costruzioni e design
Istituto sostenibilità applicata all'ambiente costruito

SUPSI

energo®
Efficienza energetica
per edifici

Date: 19.11.2021

Location: Bern

Publisher:
Swiss Federal Office of Energy SFOE
Energy Research and Cleantech
CH-3003 Bern
www.bfe.admin.ch

Subsidy recipients:
ISAAC – Istituto di Sostenibilità Applicata all'Ambiente Costruito
Campus Trevano CH-6952 Canobbio
https://www.supsi.ch/isaac

Association Energo, Filiale Suisse Romande
Av. de Sévelin, CH-1004 Lausanne
http://www.energo.ch/

Authors:
Domenico Altieri, SUPSI - ISAAC, domenico.altieri@supsi.ch
Giovanni Branca, SUPSI - ISAAC, giovanni.branca@supsi.ch
Carlo Gambato, SUPSI – ISAAC, carlo.gambato@supsi.ch\

Energo tutors:
Joel Lazarus, Association Energo, Filiale Suisse romande, joel.lazarus@energo.ch
Michael Rickli, Association Energo, Filiale Suisse romande, michael.rickli@energo.ch

SFOE project coordinators:
Nadège Vetterli, nadege.vetterli@anex.ch

SFOE contract number: SI/501937-01

The authors bear the entire responsibility for the content of this report and for the conclusions drawn therefrom.

Zusammenfassung

Invasive energetische Sanierungsansätze an Wohngebäuden sind oft anspruchsvoll in Bezug auf Anfangsinvestitionen und Umsetzungszeit, während schnelle und wirtschaftliche Energieoptimierungsmaßnahmen meist eine attraktivere und machbarere Strategie darstellen. Daher ist eine quantitative Studie erforderlich, um die Maßnahmen zu identifizieren, die unter Berücksichtigung variabler Wetterbedingungen zu den höchsten Energieeinsparungen führen. In dieser Arbeit wird ein künstliches neuronales Netzwerk über einen vom Energo-Verband zur Verfügung gestellten Datensatz trainiert und die komplexe Beziehung "Optimierungsmaßnahmen-Energieeinsparung" als Blackbox modelliert. Sensitivitätsindizes werden durch das trainierte Netzwerk berechnet, um den Einfluss jeder Maßnahme auf die Variabilität des Energieverbrauchs zu analysieren und zu quantifizieren, wobei gegenseitige Wechselwirkungen berücksichtigt werden.

Das trainierte Surrogatmodell liefert hochgenaue Vorhersagen der Energieeinsparungen ausgehend von den Wetterbedingungen und dem Vektor der angewandten Optimierungsmaßnahmen innerhalb des analysierten Zeitfensters. Darüber hinaus wird eine quantitative Analyse vorgeschlagen, um die Effektivitätsbereiche der einzelnen Optimierungsmaßnahmen zu ermitteln, wobei sowohl Modell- als auch meteorologische Unsicherheiten berücksichtigt werden.

Zusammenfassend beschreibt die Studie eine Methodik, die auf der Anwendung von Surrogatmodellen basiert, mit dem Ziel, die effektivsten Energieoptimierungsmaßnahmen zu identifizieren, die die Definition von effizienteren und wirtschaftlicheren Wartungsplänen ermöglichen.

Résumé

Les approches de rénovation énergétique invasive sur les bâtiments résidentiels sont souvent exigeantes en termes d'investissement initial et de temps de mise en œuvre, tandis que les mesures d'optimisation énergétique rapides et économiques représentent la plupart du temps une stratégie plus efficace et réalisable. Il est pourtant très intéréssant d’analyser ce type de mesures sur le plan quantitatif afin d’identifier l'ensemble des actions conduisant aux économies d'énergie les plus importantes compte tenu de certains conditions. Dans cette étude de recherche, un réseau de neurons artificiel est développé sur un ensemble de données fournies par l'association Energo, et la relation complexe "Mesures d'optimisation - Économies d'énergie" est modélisée sous forme de « black boxe ». Des indices de sensibilité sont calculés par le réseau formé pour analyser et quantifier l'influence de chaque mesure sur la variabilité de la consommation d'énergie, en tenant compte des interactions mutuelles.

Le meta-modèle d’apprentissage fournit des prévisions très précises des économies d'énergie à partir des conditions météorologiques et du vecteur des mesures d'optimisation appliquées dans la fenêtre temporelle analysée. En outre, une analyse quantitative est proposée pour identifier les plages d'efficacité de chaque mesure d'optimisation, en tenant compte à la fois des incertitudes du modèle et des incertitudes météorologiques.

En conclusion, l'étude décrit une méthodologie basée sur l'adoption de meta-modèle dans le but d'identifier les mesures d'optimisation énergétique les plus efficaces permettant l'élaboration de plans de maintenance plus performantes et plus économiques.

Summary

Invasive energy retrofitting approaches on residential buildings are often demanding in terms of initial investment and implementation time, while fast and economic energy optimization measures represent most of the time a more attractive and feasible strategy. A quantitative study is therefore needed to identify the set of actions leading to the highest energy savings accounting for variable weather conditions. In this work, an Artificial Neural Network is trained over a dataset provided by the Energo association, and the complex relation "Optimization measures-Energy Saving" is modeled as black-box. Sensitivity indexes are computed through the trained network to analyze and quantify the influence of each measure on the variability of the energy consumption, accounting for mutual interactions.

The trained surrogate model provides highly accurate predictions of the energy savings starting from the weather conditions and the vector of applied optimization measures within the analyzed time-window. In addition, a quantitative analysis is proposed in order to identify intervals of effectiveness of each optimization measure, taking into account both uncertainties due to the model and meteorological factors.

In conclusion, the study describes a methodology based on the adoption of surrogate models with the aim of identifying the most effective energy optimization measures allowing the definition of more efficient and economic maintenance plans.

Main findings

The proposed approach has been shown to be effective in identifying energy optimization actions with the greatest potential, given the uncertainty involved. Focusing on the two best low-cost optimization measures, a potential total monthly saving greater than $2*10^4$ kWh can be reached by each one with a reduced variance, value to be considered on the whole analyzed building stock. In terms of best macro-categories of intervention, the highest median savings are reported for the *Furnace setpoint temperature* ($\approx 1.83*10^4$ kWh) and the *Heating schedule time* ($\approx 1.65*10^4$ kWh) activities, with the lowest efficacy values reached by the *Ventilation* category ($\approx -0.5*10^4$ kWh) and activities related to hydraulic adjustments and hot water schedule time, $0.5*10^3$ kWh and $0.35*10^4$ kWh respectively. Finally, focusing on the hot water production process, temperature regulations ($\approx 0.91*10^4$ kWh) are more energy efficient if compared with the hydraulic interventions on the circulation system ($\approx 0.05*10^4$ kWh). In percentage terms, the best single optimization measures analyzed manage to achieve a median potential monthly savings of just under 2%, which is about four times higher than the median value of all recorded underconsumption events. Quantifying potential energy savings in terms of confidence intervals, and thus not just taking a qualitative approach, is a major achievement. This was made possible by a robust data-driven model calibrated on real historical data collected systematically for more than 5 years by Energo.

Contents

Abbreviations

LICOM - Low-investment cost optimization measures

CECE - Cantonal energy performance certificate for buildings

EPG - Energy performance gap

ANN – Artificial neural network

ES – Energy saving

GSA – Global sensitivity analysis

PMF – Probability mass function

EASI - Effective algorithm sensitivity indices

Figures

Tables

1 Introduction

1.1 Background information and current situation

The Positive Gap Project is part of a wider series of studies and research projects developed by SUPSI in collaboration with other organizations operating on the national territory. In particular, it is worth mentioning that many activities, carried out by SUPSI and the Energo Association, aim at the development of new methodologies for monitoring and for reaching a more effective energy optimization. The GAPxPLORE[1] project developed between 2017 and 2019 in collaboration with the University of Geneva and the Minergie, CECE and Energo Associations, represents one clear example of this specified line of research

Thanks to the GAPxPLORE project it has been possible to analyze the energy performance gap (EPG) between measured and calculated energy consumption in the Swiss residential sector. This project confirmed the existence of a significant EPG depending on the thermal quality of the building. It was also possible to quantify the EPG by defining median, maximum and minimum values according to the type of building.

The quoted study also highlighted limitations such as the nature of the energy values that are compared (the type of energy consumption, weighting factors adopted, etc.). Besides, it was particularly difficult to evaluate energy consumption based on different approaches and databases.

Starting from the results obtained from previous research activities, the characterization of the EPG must be able to be detailed on the basis of energy consumption monitored continuously and systematically. The focus in this perspective shifts to the operational phase of the building, during which consumption can be optimized. This approach employs real consumption data, structured and connected to changes in climatic conditions, allowing increasingly accurate modelling of building consumption and reducing the gap between design and operation.

1.1.1 Energo

Energo is a swiss association of public and private institutions. It helps to significantly reduce the energy consumption and energy costs of buildings. Since its foundation in 2001 within the framework of the SwissEnergy program, energo has become a leading competence center for energy efficiency throughout Switzerland. Energo's mission is to provide independent, tailor-made analyses and advice on the optimization and modernization of building services.

1.2 Purpose of the project

The building stock represents one of the main contributions to the final Swiss national energy demand. Indeed, in Switzerland more than 40% of energy consumption and about one third of climate-damaging CO_2 emissions are caused by the buildings sector. The widespread adoption

[1] Cozza S., Chambers J., Geissler A.,Wesselmann K., Gambato C., Branca G., Cadonau G., Arnold L., Martin K. Patel M.K. (2019). GAPxPLORE: Energy Performance Gap in existing, new, and renovated buildings, Swiss Federal Office of Energy SFOE

of low efficient heating supply systems, coupled with a optimized maintenance strategy, leads to a large potential for energy consumption reduction.

An invasive retrofitting approach aimed at increasing the energy efficiency, such as the building envelope renovation or replacement of an energy production unit, is often demanding in terms of initial investment and implementation time. In this case, the payback time of the energy-saving investment is often longer than the lifetime of the element, hence why most of the times, low-investment cost optimization measures (LICOM) represent a more attractive and feasible strategy to reduce energy consumption in buildings while ensuring a profitable return on investment.

The LICOM effectiveness can be quantified through the concept of *performance gap* [1] that refers to the difference in terms of energy consumptions between the measured and the predicted value, this last quantified through a regression model calibrated on measured energy performance over a sufficiently long period of time (in general 3 years) and corrected for the variation in outdoor temperature. Performance gap is calculated and provided directly by ENERGO.

A quantitative study is therefore required to identify the LICOMs leading to the highest energy savings independantly of the effects of different meteorological conditions. Indeed, particular climatic conditions can affect the building stock's energy consumption regardless of the selected set of LICOMs and this effect should be separated.

1.3 Objectives and methods

The identification of a robust ranking associated with the analyzed LICOMs represents a challenging computational task under several points of view.

To increase the robustness of the results the applied methodology should be based on a sufficiently large dataset of consistent energy consumption records, adopted LICOMs and weather indicators, referring to well-tracked building stock. Moreover, the employed data must cover the longest possible time-window in order to account for multiple boundary conditions that can affect the final figures.

The data collection task has been completed thanks to our collaboration with the Energo association, whose energy consumption monitoring activity since many years allows the acquisition of relevant data on different building types with a detailed tracking of performed LICOMs.

Once the required dataset is defined, a preliminary analysis must be carried out to identify adequate time-windows in which we can compute the total energy savings knowing the corresponding set of applied LICOMs. Another difficulty is that multiple LICOMs are often adopted within the same time-window, hence an advanced computational approach is needed to quantify the contribution of each of them to the final output of interest.

In the presented work, an artificial neural network (ANN) [2] is employed to model and analyze the complex relation "LICOMs vs Energy saving". Indeed, correlation coefficients cannot be derived directly from the initial dataset since the energy consumption in a fixed time-window is simultaneously affected by multiple LICOMs. Basic assumptions cannot be chosen at first due to the lack of studies in the technical literature on the topic. What we found is that the validated ANN can separately model each input-output relation, hence it can be efficiently employed to perform advanced sensitivity analyses by creating synthetic data.

Sensitivity indexes [3] are computed to quantify the influence of each input on the variability of the analyzed output, while, a more quantitative analysis is then performed to identify the most probable variability range of the energy saved by each LICOM accounting for different uncertainty sources.

2 Data

2.1 Dataset features

The analyzed building stock is characterized by a consistent dataset of consumption and optimization data for a time window longer than four years.

Positive and negative energy savings are structured in a specific database in which the following information is listed:

- *Start Date of the event*
- *End Date of the event*
- *Performance gap found*
- *Economic gap calculated*
- *ID of the building case*

The optimization measures undertaken on the followed building stock are reported in a different database, with the following main data fields:

- *Date*
- *Description of the measures (the "LICOMs")*
- *Category of intervention*
- *ID building*

The selected building stock provides well-populated and coherent data within a sufficiently long global time window. More specifically, a total of maximum 5000 energy consumption events can be obtained from the chosen dataset, however, the total events employed will be reduced depending on the analysis contraints. The observations have to be furtherly grouped in a reduced time window to increase the computational efficiency, keeping the meaningfullness of both causes and effects. Additional details on the adopted methodology will be provided in the next sections.

Furthermore, to account for the influence of the weather conditions on the energy savings, an additional database is employed. This includes:

- *Ambient temperature*
- *Wind Speed*
- *Solar irradiation*
- *Humidity*
- *Rainfall*

The daily average of each parameter is exported from the archive of the MeteoSwiss ground-level monitoring networks, through the IDAWEB[2] web platform.

[2] https://gate.meteoswiss.ch/idaweb

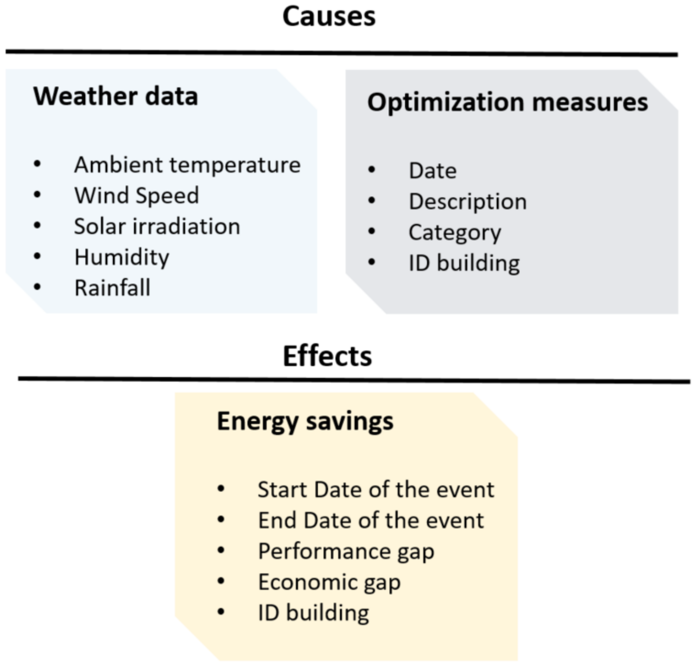

Figure 1 Dataset and features

2.2 Optimization measures classes

The activity of data structuring, cleaning and filtering is based on the master thesis [4] and the energy savings this project is focused on are due to ensure heating and hot water, mainly because these represent the most reliable data.

The heterogeneity of the possible optimization measures (LICOMs) requires their grouping in predefined classes which will simplify the whole numerical analysis. In this regard, a total of 63 classes are adopted, partially following the work [4]. They are listed in Table 1 and can be further grouped into 13 main categories. A brief description of each LICOM category is provided in Table 2.

In the 5 years of monitoring taken as a reference, the data collected by ENERGO were not equally consistent with the various details of the optimization measure. In particular, it was possible to characterize the type of intervention, identifying specific classes, while additional details (e.g. on the setpoints regulation or the heating curve change) were fragmentary and not standardized. For this reason, the adopted approach does not account for detailed adjustments, but rather focuses on quantifying the effectiveness of each intervention class, with the assumption that all operations are guaranteed internal comfort and thus, in the numerical model each intervention is associated with a binary input in a specific time-window of analysis (applied - not applied).

2.3 Preliminary analysis of the events

The consumption events, recorded over a 5 years period, can be analyzed in terms of total duration (days) and gap with respect the energy signature (kWh).

Figure 2 shows the global distribution in terms of duration of all the recorded consumption events, whether they are over- or under-consumption. The median value appears to be around 40 days, while a duration that overcomes 100-120 days seems quite rare.

In addition, it is also interesting to analyse the evolution of the consumption events duration as the period of the year changes. From Figure 2B, that shows the event duration distribution per each month, it can be observed how the median value increases in the summer while the variance of the distributions seems to increase in december.

Table 1 List of analyzed LICOMs

LICOM	DESCRIPTION	LICOM	DESCRIPTION	LICOM	DESCRIPTION
'BOILER_CHANGE'	Boiler change	'HEAT_HYDRO_BALANCE'	Hydraulic balance	'REGUL_T_DAY'	Day setpoint temperature
'BURNER_OPT'	Burner power adjustment	'HW_CIRC_CHANGE'	Hot water circulator change	'REGUL_T_DAY_ECO'	Day ECO setpoint temperature
'FURNACE_1_OFF'	Interruption of one furnace during summer	'HW_CIRC_POWER'	Hot water circulator power	'REGUL_T_MAIN'	Main setpoint temperature
'FURNACE_CHANGE'	Furnace change	'HW_HYST'	Hot water hysteresis change/interlocking differential	'REGUL_T'	Setpoint temperature
'FURNACE_OPT'	Furnace cascade optimization	'HW_PUMP_AUTO'	Hot water circulator pump on AUTO mode	'REGUL_T_NIGHT'	Night setpoint temperature
'HEATING_CIRC_TIME'	Heating circular schedule	'HW_TIME'	Hot water circulation schedule	'REGUL_T_NIGHT_ECO'	Night ECO setpoint temperature
'HEAT_TIME_CONST'	Heating time constant	'HW_TIME_LOAD'	Hot water load schedule	'REGUL_T_NIGHT_OFF'	Night heating interruption setpoint temperature
'REGUL_TIME'	Heating time	'HW_LIFTING'	Hot water-lifting temperature change	'REGUL_T_NIGHT_ON'	Night heating start setpoint temperature
'HEATING_CURVE'	Heating curve slope change	'HW_T_GUIDE'	Hot water guide temperature	'REGUL_T_OFF'	Heating interruption setpoint temperature
'HEATING_CURVE_HIGH'	Upper heating curve change	'HW_T_GUIDE_DAY'	Hot water day guide temperature	'REGUL_T_ON'	Heating start setpoint temperature
'HEATING_CURVE_LOW'	Lower heating curve modification	'HW_T_GUIDE_NIGHT'	Hot water night guide temperature	REGUL_WINTER_MODE'	Winter Mode modification
'HEATING_CURVE_PARALLEL'	Parallel heating curve modification	'HW_T_METER_CHANGE'	Hot water sensor position change	'VENTIL_GV'	High-speed ventilation schedule
'HEATING_HYST'	Heating hysteresis modification	'HW_T_OFF'	Hot water heating temperature stop	'VENTIL_HC'	Ventilation heating curve
'HEATING_LIFTING'	Heating lifting temperature change	'HW_T_ON'	Hot water heating temperature start	'VENTIL_HEAT_ROOM'	Ventilation opening in the heating curve
'HEATING_NIGHT_LOWERING'	Heating night lowering	'REGUL_AUTO'	Regulation system on AUTO mode	'VENTIL_PV'	Low-speed ventilation schedule
'HEATING_T_OFF'	Heating interruption temperature	'REGUL_CHANGE'	Regulation system change	'OTHER'	Special and/or specific optimization measures of particular systems, or which do not enter into one of the previous categories
REGUL_T_FURNACE'	Setpoint furnace temperature	'REGUL_MANU'	Regulation system on MANUAL mode		
'REGUL_T_MAX_AERO'	Maximum aerotherm temperature	'HEAT_MAINT'	Maintenance work of heating system		
REGUL_T_MAX_BOILER'	Maximum boiler setpoint temperature	'HEAT_RAD_INSUL'	Radiator pipes insulation		
'REGUL_T_MIN_BOILER'	Minimum boiler setpoint temperature	'REGUL_THERM_VALVE_ CHANGE'	Thermostatic valves change		
'HEAT_CIRC_CHANGE'	Hot water circulator change	MAINT_SOLAR'	Thermal solar installation maintenance		
'HEAT_CIRC_POWER'	Hot water circulator power	'HW_MAINT'	Hot water system maintenance		

Category

- Heat production and storage optimization
- Hot water temperature regulation
- Heating day-night setpoint temperature
- Heating schedule time
- Furnace setpoint temperature
- Heating curve optimization
- Hot water schedule time
- Maintenance
- Regulation system method
- Hydraulic heating regulation
- Ventilation regulation
- Hot water idraulic regulation
- Other

Table 2 Description of each LICOM category

Category	Description
Heat production and storage optimization	Optimization measures on the furnace and boiler, such as adjusting the burner output or stopping the boiler during warmer weather in a cascade furnace system. Minor replacement work is also included.
Hot water temperature regulation	Temperature level regulation for hot water production. For health reasons this temperature must reach appropriate temperature levels to avoid problems with bacteria formation. However, there is a significant savings potential depending on the type of system (Combined or separate heating system)
Heating day-night setpoint temperature	The setpoint temperature often refers to a single room or related to an external sensor not controlled by an internal thermostat. In many cases the most relevant measures is the day-night setpoint temperature regulation.
Heating schedule time	It groups the main adjustments of the operating time of the system. The start and end of the heating period, the hours of operation of the heating system during the winter period and in milder seasons are the most common interventions.
Furnace setpoint temperature	Groups all adjustments of the boiler operating time at certain temperature levels. The heating system hysteresis adjustment and the maximum and minimum bolier setpoint temperature are examples.
Heating curve optimization	Adjustment measures of the heating curve by means of slope adjustment or translation up or down of the curve.
Hot water schedule time	Relates to the time of the charging period of the domestic hot water bolier and the circulation period in the system.
Maintenance	This category includes low-investment maintenance of the system (e.g. burner cleaning, circulation pump checks and small replacements).
Regulation system method	This defines the type of regulation on the heat generator (automatic mode using a preset programme or manual mode which can be modified according to individual requirements).
Hydraulic heating regulation	This category groups together all the interventions on the hydraulics of the system, in particular on the flow rate and speed of the water flow in the heating circuit by regulating the circulation pumps.
Ventilation regulation	Groups together all the adjustments relating to the ventilation system (air flow rates, heating and cooling temperatures, etc.).
Hot water idraulic regulation	This category groups together all the interventions on the hydraulics of the system, in particular on the flow rate and speed of the hot water flow in the heating circuit by regulating the circulation pumps.

While the second aspect is less significative in statistical terms, probably in part linked to the specific wheater conditions, the first aspect can be explained in more operational terms. Analysing Figure 3, it can be seen that the optimization measures undertaken in the summer months have an increasing and therefore more lasting optimization potential as the colder months approach. In contrast, LICOMs applied just before summer, generally generate shorter average consumption events.

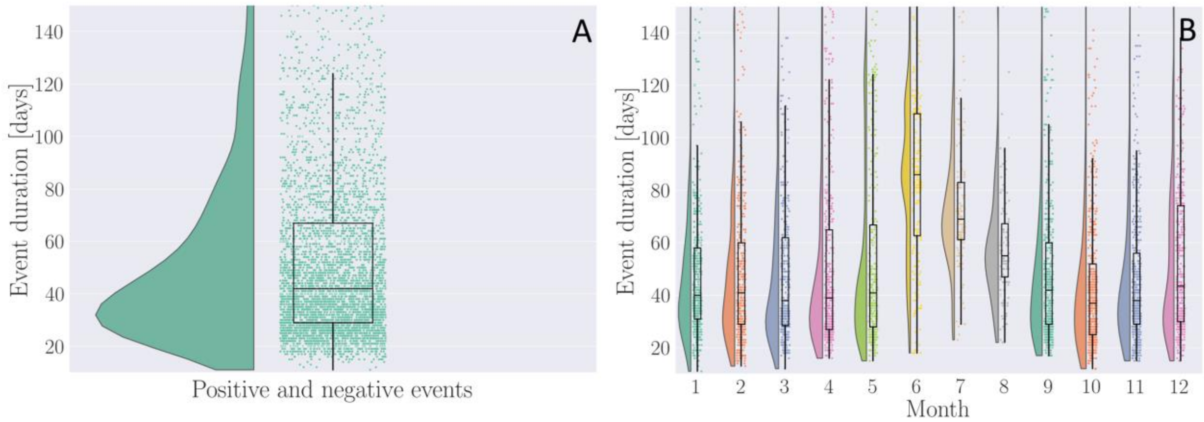

Figure 2 Raincloud plots (Distribution and boxplot) of the recorded consumtpion events duration, (a) global and (b) per month

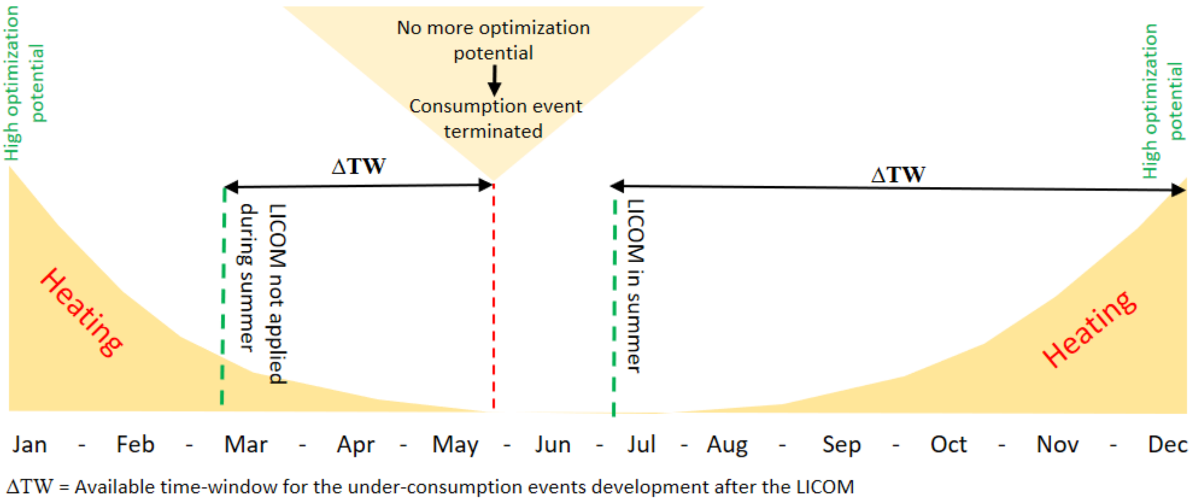

Figure 3 Evolution of the optimization potential due to the heating use variability

The preliminary analysis of the events dataset can be further detailed by separating the distributions per type of event, namely an over or underconsumption. Figure 4A reports the difference in terms of duration, underlying how the overconsumption events result to be shorter, with a median value lower than 40 days. This is due to the intervention of the operator who, following constant monitoring, acts when an overconsumption event occurs. One of Energo's objectives is precisely to intervene as soon as possible in order to minimise the duration of any over-consumption, although there is an operating limit of around two weeks due to the monitoring frequency and the timing of reception and intervention.

On the other hand, in terms of energy efficieny (Figure 4B), the overconsumption events show a median value around 5’000 kWh (per event) while in case of underconsumption this value increases until 7’000 kWh.

In terms of under-consumption, the value of 7’000 kWh corresponds to a saving of about 2*l* of oil equivalent per m^2 for the entire building stock analysed (92 buildings with an average surface area of about 6’200 m^2). This value corresponds to the potential average saving statistically recorded by the energo database of approx. 8% of the initial consumption.

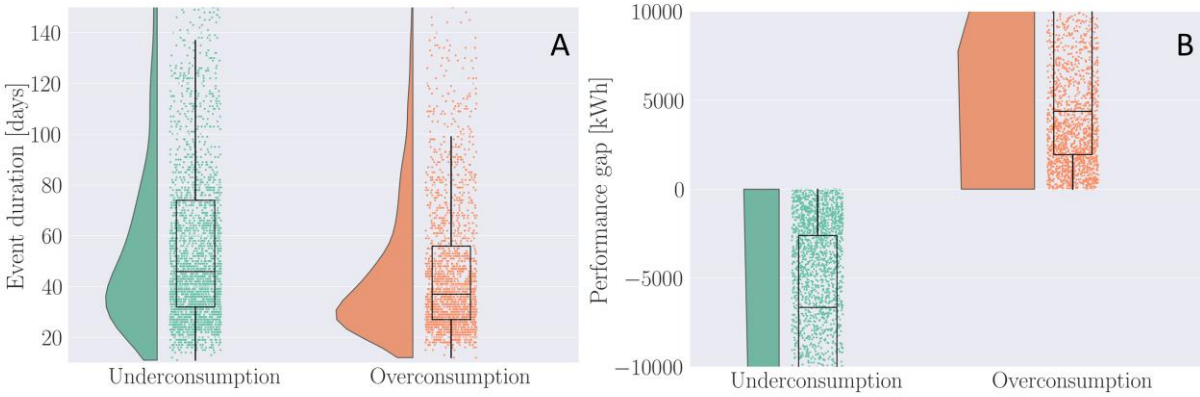

Figure 4 Raincloud plots (distribution and boxplot) of the (a) duration and (b) energy saving of the recorded consumtpion events, per type

Finally, Figure 5 shows both the total number and the total energy consumption of the recorded events, distinguished per month and type. It is clear how the number of events decreases in the summer months and then reaches pick values in the winter (around 300 underconsumption events per month). A similar pattern can be identified in Figure 5B, showing the higher global energy underconsumptions in November, December and January, with an average of about -7*10^6 kWh per month (computed as the sum of the underconsumption events).

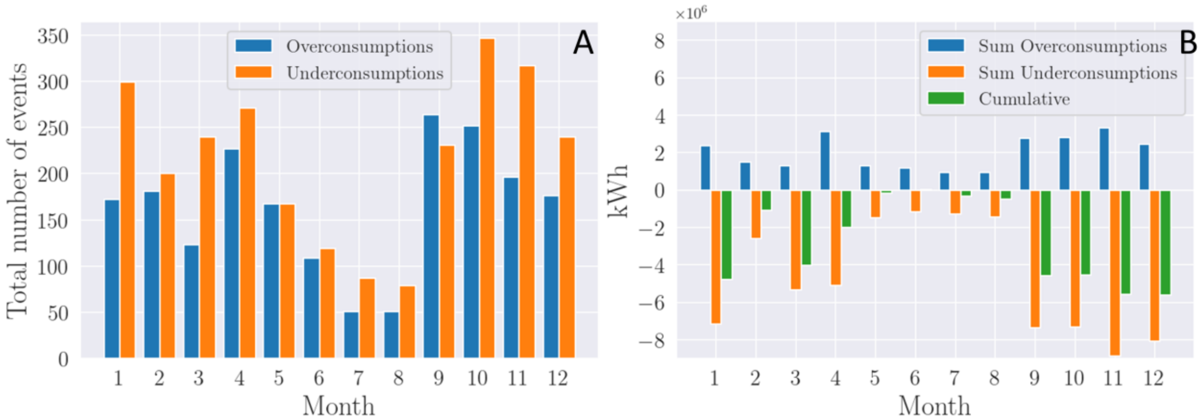

Figure 5 (a) Total number of events and (b) total over/underconsumptions [kWh] per month

It should be noted that ENERGO does not use a tracking system related to indoor space usage. Therefore, it was not possible to make explicit and analyze the influence of occupant behavior on the effectiveness levels of various optimization measures. Nevertheless, the monitoring activity over a long period (5 years) has allowed collecting data on energy consumption that in practice corresponds to a multitude of different scenarios of occupation and space usage. This aspect makes the results obtained more robust because they are implicitly associated with different boundary conditions, but without offering the possibility to quantify how and to what extent user behavior has greater effects on energy performance.

2.4 Building stock

The initial dataset employed for the numerical analysis is based on a residential building stock of 92 units located in the canton Geneva.

In total, 175 properties are covered by the energy efficiency activity, where "property" means a single flat or, as is more often the case, an aggregate of flats. Table 3 reports some statistics on the consumption events characterizing the analyzed properties over a period of 5 years.

In terms of total energy performance gap, 165 (94%) properties show a global underconsumption (5 years), with a maximum and minimum value of 715'613 kWh and 1'815 kWh, respectivley. On the other side, 10 properties (6%) show a global overconsumption, that reach the maximum value of 480'392 kWh in one case, however this last property has to be considered as an outlier since the second wrost case show an overconsumption of "only" 57'911 kWh. The table reports details even on the amount of events per single property with the associated median duration (median value refers to the set of over- and under-consumption events recorded for the specific property). On this regards more general statistics have been explored in the previous paragraph.

Referring to the entire building stock during the analyzed 5-years period, a global energy underconsumption of 14'264'497 kWh is reached (26'602'138 kWh underconsumed and 12'337'641 kWh overconsumed), with a total of 1'698 underconsumption events and 1'270 overconsumption events.

Table 3 Energy consumption events per propriety

Property	Total saving [kWh]	Total Underconsumptions events [kWh]	Total Overconsumptions events [kWh]	Total number of underconsumtpion events	Total number of overconsumtpion events	Median energy gap for a single underconsumption event [kWh]	Median energy gap for a single overerconsumption event [kWh]	Median duration a single underconsumption event [days]	Median duration a single overconsumption event [days]
1	-715613	-895969	180356	12	8	-46656.5	25066	80.5	35.5
2	-711004	-836926	125922	8	4	-43285.5	25328.5	57	26
3	-497430	-962403	464973	14	9	-37659.5	30652	34	27
4	-393720	-475830	82110	9	4	-19770	19188.5	40	37.5
5	-378000	-808513	430513	4	3	-170955	119682	141	111
6	-356303	-482548	126245	12	7	-25729	15780	61	45
7	-332248	-354958	22710	10	1	-17186.5	22710	49.5	47
8	-310576	-480725	170149	16	12	-17128	7893.5	43.5	35.5
9	-308494	-563334	254840	16	10	-27293	10193.5	38.5	31
10	-272852	-371043	98191	9	6	-6157	9328.5	36	36
11	-258903	-312053	53150	8	5	-6161	9636	37.5	42
12	-201493	-248829	47336	11	7	-16786	4469	88	47
13	-199406	-280458	81052	9	6	-8674	6727	27	34
14	-197284	-217090	19806	12	6	-9452.5	3596	54	32.5

15	-188187	-304593	116406	12	10	-18541	8176.5	42	36.5
16	-172469	-214068	41599	12	8	-8060	3704.5	58.5	36
17	-168274	-438819	270545	10	13	-12796.5	16393	41	38
18	-159635	-283377	123742	6	5	-19339.5	26484	68	81
19	-157707	-225345	67638	13	6	-15097	8542	34	38.5
20	-157322	-249223	91901	12	11	-7216.5	7790	56	31
21	-157009	-256647	99638	15	5	-8757	3920	64	35
22	-156773	-236604	79831	14	5	-6989.5	11726	44.5	50
23	-150247	-332543	182296	11	15	-10252	6778	78	40
24	-145936	-186689	40753	20	12	-7256.5	3287.5	41	32
25	-141650	-222257	80607	7	6	-14447	13469.5	65	68
26	-135602	-226396	90794	10	6	-4270	17526	32.5	86
27	-134733	-251985	117252	7	10	-24361	5271.5	122	45.5
28	-129803	-160909	31106	9	7	-6184	2912	63	27
29	-129510	-424384	294874	18	14	-15444	15904.5	44.5	36.5
30	-129463	-173905	44442	15	9	-4566	4830	46	31
31	-127930	-221648	93718	14	8	-9725.5	6906	62	63
32	-127686	-156369	28683	8	5	-13543.5	4596	118.5	49
33	-126522	-420898	294376	10	10	-28188.5	21449.5	50.5	54
34	-125868	-169424	43556	7	5	-19495	6744	96	51
35	-125226	-193075	67849	12	6	-12778	4613	62	38.5
36	-124199	-169966	45767	9	7	-14342	5442	83	39
37	-122471	-149522	27051	4	4	-21545.5	6188	98	67
38	-121063	-162193	41130	14	7	-9636	6458	52.5	45
39	-119337	-188281	68944	11	8	-9455	6131	37	52
40	-108643	-121839	13196	9	3	-8382	3892	75	64
41	-108566	-184331	75765	8	8	-15714.5	5255.5	98.5	57.5
42	-107615	-137348	29733	10	1	-10295.5	29733	39	71
43	-107463	-149522	42059	11	6	-6164	4750.5	51	54.5
44	-104806	-181466	76660	9	9	-8971	5339	55	38
45	-104050	-118654	14604	8	5	-10943.5	2379	62.5	32
46	-98255	-137587	39332	7	6	-12456	6867.5	123	87
47	-97694	-115341	17647	13	5	-1960	3463	43	48
48	-97600	-161387	63787	13	5	-9167	16622	51	73
49	-97374	-174450	77076	14	10	-9074.5	5516.5	52.5	41.5
50	-95600	-161969	66369	15	8	-8087	6787	47	38
51	-94099	-102089	7990	8	1	-6969	7990	34	45
52	-93834	-102673	8839	8	3	-9925.5	2778	43	23
53	-90299	-150652	60353	12	9	-7408.5	6061	57	34
54	-89680	-153701	64021	16	13	-7010	3348	44.5	33
55	-86447	-144839	58392	9	9	-4600	6371	42	33

56	-85149	-120639	35490	8	6	-13253	6839	103	50
57	-84783	-150353	65570	9	7	-15637	8068	44	35
58	-83823	-104192	20369	4	3	-4138	6974	61	60
59	-82462	-96295	13833	5	4	-17049	3475	77	37.5
60	-80745	-95422	14677	5	3	-3629	4723	29	24
61	-79385	-103622	24237	12	7	-7252	3226	45.5	32
62	-78087	-92007	13920	4	2	-23540	6960	125	91
63	-78068	-117826	39758	8	10	-10885	3232	59	37.5
64	-78039	-91619	13580	9	2	-7584	6790	35	34.5
65	-77842	-131990	54148	17	8	-6575	5279	42	42.5
66	-77362	-140354	62992	10	10	-6696	4132	45	33.5
67	-77011	-90608	13597	7	3	-14170	2374	41	29
68	-75782	-121870	46088	11	10	-6698	3470.5	77	28
69	-75586	-87709	12123	6	4	-12025.5	2703	43.5	24
70	-74883	-106328	31445	11	4	-8345	8251	52	38
71	-73399	-129568	56169	11	4	-9750	10599.5	51	57
72	-73113	-113750	40637	7	3	-13313	6987	48	35
73	-72707	-81481	8774	4	5	-2033.5	1733	49	57
74	-71707	-122237	50530	3	6	-38557	2535	101	34
75	-71469	-103607	32138	4	5	-17052.5	6204	87	27
76	-70611	-121514	50903	8	5	-8626.5	11212	36	32
77	-66098	-101144	35046	8	7	-6311	3963	74.5	51
78	-65885	-116621	50736	9	3	-7129	18429	73	98
79	-62495	-62809	314	6	1	-4118	314	57	19
80	-60975	-91532	30557	13	9	-4364	1554	56	37
81	-60767	-133967	73200	13	7	-7053	4354	46	35
82	-59701	-73429	13728	9	6	-8413	1518.5	66	29
83	-58433	-110930	52497	4	6	-11808	3240.5	43.5	24.5
84	-56874	-84871	27997	9	6	-6651	3809.5	73	33.5
85	-56739	-84208	27469	16	8	-4019	2258.5	49	43.5
86	-56213	-263610	207397	9	13	-16203	15195	34	29
87	-54425	-100720	46295	13	12	-4385	1873	39	36.5
88	-52990	-152247	99257	11	8	-15397	8330.5	59	45
89	-52938	-116175	63237	3	3	-5410	5633	54	66
90	-52814	-100503	47689	5	5	-11851	8781	89	35
91	-51664	-92317	40653	10	9	-7598.5	3559	42.5	37
92	-50750	-96028	45278	11	11	-3806	2776	50	47
93	-50606	-59582	8976	12	4	-2816	1685	38	35
94	-50174	-132172	81998	15	11	-6265	4414	56	61
95	-49552	-55747	6195	6	1	-10889	6195	70	99
96	-49412	-83955	34543	11	7	-4452	2737	65	44

97	-47354	-380469	333115	7	8	-50446	11134	62	32.5
98	-47091	-148896	101805	11	7	-5605	9801	33	46
99	-46707	-63359	16652	7	3	-3190	5672	64	54
100	-45953	-67943	21990	9	7	-7345	3169	47	35
101	-45891	-128284	82393	9	10	-6069	4132.5	66	35.5
102	-45135	-90849	45714	10	11	-3829	1306	96.5	36
103	-45064	-179772	134708	13	12	-7840	6335.5	43	34.5
104	-43632	-61941	18309	11	6	-4421	2717	64	39
105	-43299	-74776	31477	11	7	-6084	2525	42	45
106	-42094	-81080	38986	12	9	-3985	2996	57.5	47
107	-41121	-109289	68168	11	12	-7945	4011	42	37
108	-41053	-172004	130951	14	9	-6531	9489	38.5	51
109	-37987	-40067	2080	2	4	-20033.5	472.5	131	24.5
110	-37877	-58792	20915	11	6	-5497	2949	49	40
111	-37713	-58211	20498	9	2	-3701	10249	32	37
112	-37345	-47623	10278	3	3	-14190	4383	68	32
113	-37201	-46524	9323	2	5	-23262	2073	93	30
114	-36719	-70152	33433	10	8	-2626	2442	46	43.5
115	-36383	-63728	27345	12	6	-2055	2502	39	39
116	-36061	-80084	44023	9	4	-11013	9902	54	58
117	-35925	-102172	66247	14	12	-5283	3231	45	41
118	-35853	-75359	39506	9	11	-6311	4154	74	45
119	-35705	-96664	60959	10	13	-3386.5	3548	47.5	32
120	-35288	-124582	89294	19	16	-6875	3707	38	32.5
121	-35065	-122347	87282	12	13	-5183.5	4880	44.5	35
122	-34234	-66665	32431	18	11	-2546.5	1422	34.5	29
123	-34234	-37718	3484	16	4	-1747.5	1038.5	36.5	36.5
124	-33935	-51706	17771	3	2	-3325	8885.5	46	47
125	-33802	-49246	15444	8	11	-2162.5	1026	52.5	36
126	-32155	-49870	17715	8	6	-5125.5	2224	51.5	31
127	-31591	-48647	17056	13	8	-3362	1871	42	38.5
128	-30735	-50758	20023	7	9	-4767	2580	60	30
129	-30419	-147878	117459	17	15	-7223	2906	41	33
130	-29244	-35508	6264	6	4	-3203.5	1039.5	44	34
131	-28148	-45253	17105	4	4	-10610.5	4081	50.5	31
132	-28066	-50598	22532	8	6	-1708.5	3585.5	38.5	41.5
133	-27274	-45642	18368	5	5	-7993	3092	60	47
134	-27137	-51713	24576	8	7	-6327	2227	61	40
135	-24670	-70983	46313	10	7	-5218.5	5790	32.5	42
136	-24517	-133557	109040	9	10	-10736	7661.5	49	50.5
137	-24130	-444462	420332	17	13	-20008	25492	42	35

138	-24001	-66673	42672	13	9	-1733	2985	36	34
139	-23698	-32227	8529	6	3	-4353	1200	61.5	35
140	-23382	-159647	136265	15	11	-8997	9130	50	48
141	-22324	-113002	90678	7	5	-8502	6379	64	60
142	-21954	-38704	16750	10	5	-3277	1491	47.5	28
143	-21904	-34109	12205	8	3	-3115.5	3078	40	47
144	-21829	-60168	38339	18	11	-1380.5	3042	31.5	46
145	-21740	-178443	156703	8	10	-8568.5	6626	67.5	57
146	-21628	-65652	44024	10	8	-5816.5	4122	46	32.5
147	-21397	-31067	9670	9	6	-4072	284	72	25
148	-20723	-47421	26698	9	12	-4346	1775.5	79	32.5
149	-20711	-154454	133743	11	15	-7619	5820	44	48
150	-19345	-76283	56938	8	5	-3722	5098	61	57
151	-19212	-59038	39826	6	1	-7630	39826	36.5	85
152	-18958	-23291	4333	4	3	-5283.5	955	50.5	33
153	-18934	-36893	17959	16	9	-1883	1776	45	31
154	-17707	-27451	9744	13	7	-791	838	36	27
155	-14411	-54678	40267	7	6	-8657	2861	78	38
156	-14063	-188659	174596	12	12	-7701.5	11490	36.5	46.5
157	-13984	-73619	59635	6	5	-8835.5	7947	30.5	45
158	-8929	-20679	11750	5	4	-2707	3289	34	34.5
159	-7819	-32162	24343	10	6	-2127.5	3073	41.5	54.5
160	-7317	-60039	52722	5	6	-9760	6349	39	37
161	-5898	-13334	7436	6	4	-1789	1740	39	42
162	-5816	-81556	75740	6	6	-12798.5	7560.5	52.5	40.5
163	-5388	-22368	16980	11	6	-1721	2783	33	38
164	-2850	-75835	72985	10	12	-2621.5	3579.5	41	59.5
165	-1815	-24694	22879	9	6	-2129	3207.5	33	34
166	2463	-60170	62633	11	16	-2113	2210	39	29.5
167	4397	-26642	31039	5	6	-3179	3934	34	29.5
168	5459	-49491	54950	8	13	-5302	2549	37.5	32
169	5725	-41418	47143	8	11	-5106	3813	34	30
170	10529	-23707	34236	4	9	-4769.5	3232	37	27
171	11475	-64758	76233	7	9	-6287	4889	47	52
172	27209	-26083	53292	6	6	-3697.5	5029.5	38.5	45
173	52978	-101833	154811	7	11	-17123	10889	51	34
174	57911	-46781	104692	4	6	-11857.5	13791.5	47	73.5
175	480392	-340733	821125	20	22	-5034.5	4118	39.5	30
	Σ -14264497	**Σ -26602138**	**Σ 12337641**	**Σ 1698**	**Σ 1270**	**Global Median -7257**	**Global Median 4596**	**Global Median 48**	**Global Median 38**

3 Procedures and methodology

The adopted approach is based on an ANN by wich sensitivity indexes are computed to quantify the relevance of each optimization measure on the energy consumption of the whole building stock. The data-driven methodology needs of a preliminary stage for the filtering and cleaning of the collected data, required for the construction of a suitable training dataset used during the calibration of the selected surrogate model. The quantification of the sensitivity indexes is followed by the identification of performance ranges for the analysed LICOMs, in order to provide a meaningful result for understanding the levels of energy efficiency that can be achieved with low-cost optimisation measures. Pre and post-processing stages are therefore required (Figure 6) both to calibrate the inputs for the proposed computational approach and to extract the main quantitative findings from the final numerical results.

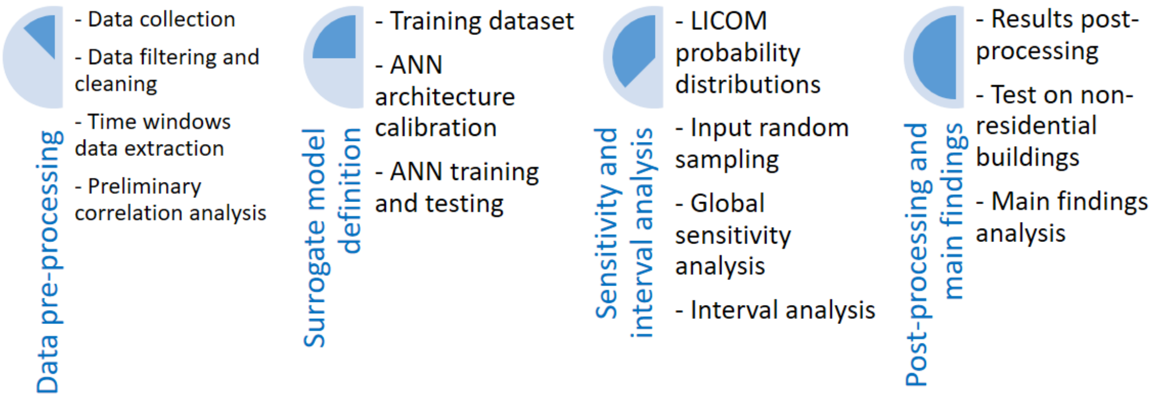

Figure 6 Main project stages

3.1 Correlation analysis

A preliminary study is carried out by computing the correlation between a quantitative measure of the consumption energy savings (ES) and the employed classes of optimization measures (OM). The numerical analysis is performed by identifying only one time-window ΔT_s, by which the global period of analysis ΔT is divided. Therefore, a total of $\Delta T/\Delta T_s$ observations are obtained and for each one both the causes and effects are identified in ΔT_s. The computed

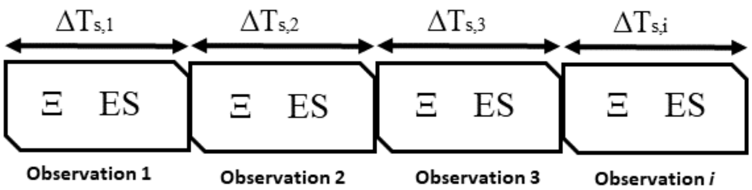

Figure 7 Global time-window structure for the correlation analysis

correlation is affected by the selected ΔT_s, since different intermediate time-windows correspond to different OM frequency vectors Ξ and ESs. Hence a correlation vector is computed for each identified optimization measure by varying the corresponding ΔT_s. The median value of computed vector is extrapolated, together with the associated variance, in order to provide a more robust assessment of the most important measures. As previously specified, this numerical approach is not able to account for the overlapping phenomenon, and more advanced methodologies would be required to account for complex interactions. Moreover, the accuracy of the obtained correlation vector is reduced due to the missed differentiation in terms of time-windows between input (Ξ) and output (ES).

3.2 Surrogate model

A more advanced numerical methodology is required to model complex interactions between all inputs. Metamodel based approaches [5,6] can capture more insights from black-box physical models and are therefore suitable for analyzing hidden non-linear interdependencies.

3.2.1 ANN

Over the past years, ANNs have experienced a relevant growth in popularity thanks to their easy implementation and flexibility linked with the capability of learning complex and non-linear relations within the analyzed problem. In general, the structure of an ANN tries to simulate the human brain network of neurons. More specifically, we can identify three different typologies of nodes, namely, input – hidden – output node, as shown in Figure 8. In addition to an input and output layer, we can have one or more hidden layers that increase the network capability of modeling high non-linear input-output patterns.

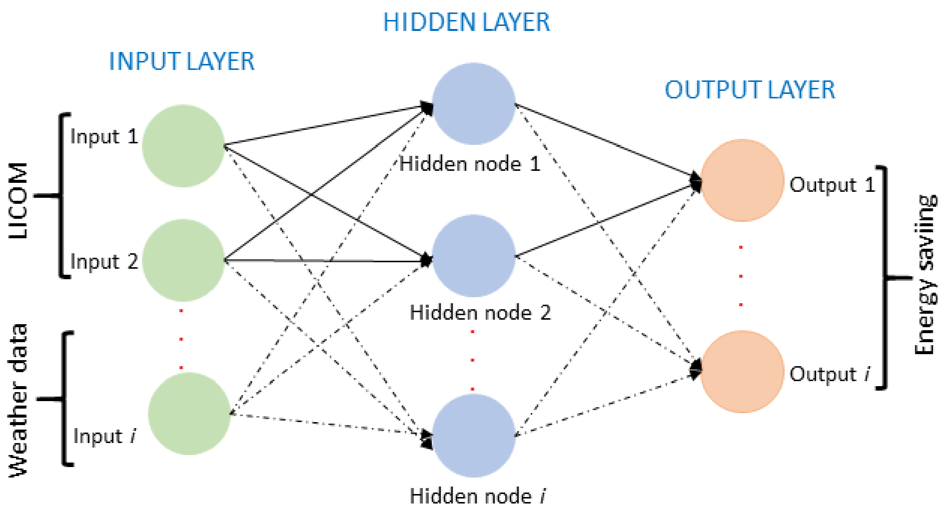

Figure 8 ANN structure

Thus, the ANN is characterized by a set of nodes (or neurons) that can be distributed on a single hidden layer or more (deep learning problems). Each neuron z_h, in the hidden layer h, receives one or more inputs x that are multiplied by proper weights w (connections in Figure 8) and simply summed before feeding the neuron. Below its mathematical formulation:

$$z_h = \sum_{p=1}^{n_i} w_{hp} \cdot x_p + b_h \qquad 1$$

where n_i represents the number of inputs, while b_h is the bias term. The non-linearity of the input-output relation is taken into account by the so-called activation function. Different activation functions can be adopted, the one used for this study is the hyperbolic tangent sigmoid, that is continuous, differentiable and bounded between 1 and -1. In case of one single hidden layer, the input data go through the first hidden activation function for each hidden neuron and then they are processed by another activation function to produce the final prediction y_t.

In case of a supervised problem, the learning process aims at tuning the weights parameters in order to minimize the square of the residuals between the predicted values $\hat{y}_t$ and the training data y_t:

$$L = \frac{1}{n} \cdot \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \qquad 2$$

with n equal to the cardinality of the training dataset. In this regard, the back-propagation algorithm represents a key element of the training stage since it allows computing the partial derivative of the loss function L for every weight and bias of the network and thus the adoption of a gradient-based optimization algorithm. For further details on the learning process refer to [2].

3.2.2 Time-window based approach

The adopted numerical approach requires the definition of four different time windows to extract data from each dataset, namely:

- **ΔT_0** - Time-window to shift each observation
- **ΔT_1** - Time-window for the screening of optimization measures
- **ΔT_2** - Time-window for the screening of the energy savings and weather data
- **ΔT** – Global time-window of analysis

The use of a different time-window for each specific optimization measure does not lead to a feasible numerical approach. Hence, the proposed methodology is based on a three-dimensional time-window vector, $\Gamma=[\Delta T_0, \Delta T_1, \Delta T_2]$, that is employed to compute the frequency vectors of the applied LICOMs Ξ; the data weather vector Θ; and the corresponding *ES*, respectively. More specifically, as shown in Figure 9, each i-th observation of the training dataset is defined by computing Ξ over the time-window ΔT_1; while Θ and the corresponding energy savings over ΔT_2. Figure 10 reports for example the normalized vectors Θ and *ES* for a specific Γ.

Moreover, each observation is temporally shifted of ΔT_0, this allows increasing the dimension of the training dataset without including duplications. The total time-window of analysis can be computed as follow:

$$\Delta T = n \cdot \Delta T_0 + \Delta T_1 + \Delta T_2 \tag{3}$$

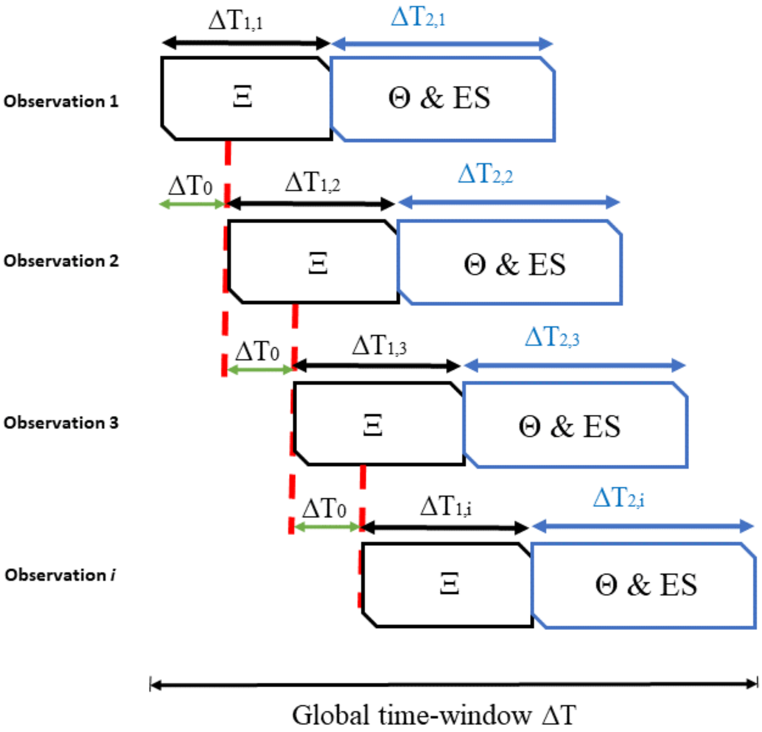

Figure 9 Time-windows scheme

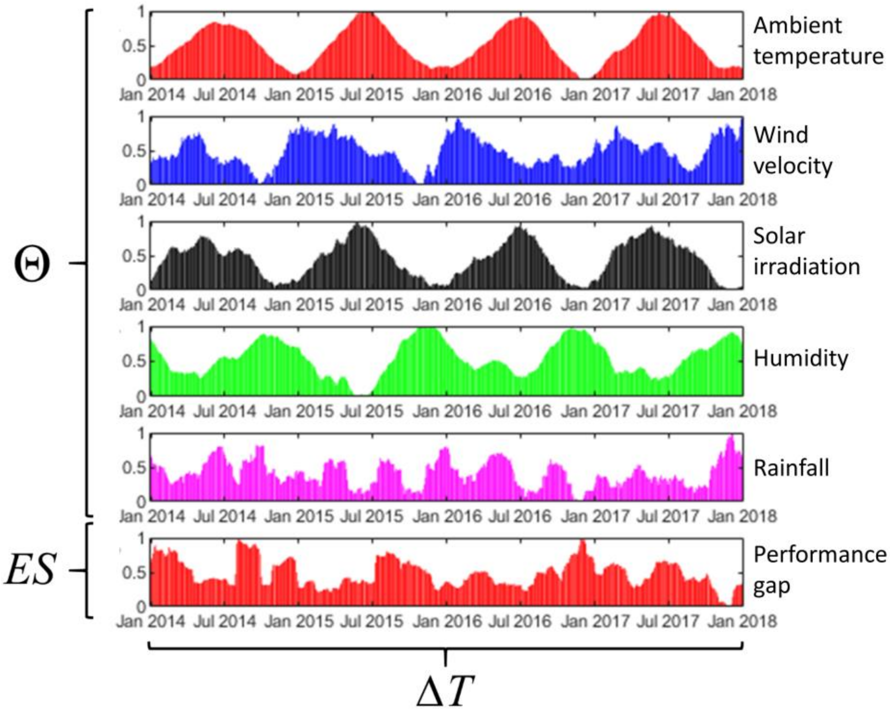

Figure 10 Θ and ES vectors for a selected global time-window

In particular, since ΔT_1 and ΔT_2 (a few days) are negligible with respect to the total ΔT (years) the ratio $\frac{\Delta T}{\Delta T_0} \approx n$ is almost equal to the total number of observations.

3.3 Sensitivity analysis

In this section, a brief introduction to global sensitivity analysis (GSA) [3] is carried out. GSA is employed to rank the analysed OMs by using artificial samples generated from a set of trained ANNs.
The GSA is based on a decomposition of the variance of each output parameter resulting from variations of the input parameters x_i, i=1,2,..N in the range of interest.
Let Y be the output of a deterministic model $f(X)$. Assuming mutually independent inputs, the variance of Y can be expressed as [7]:

$$Var(Y) = \sum_{i=1}^{d} D_i(Y) + \sum_{i<j}^{d} D_{ij}(Y) + \cdots + D_{12\ldots d}(Y) \qquad 4$$

where $D(Y) = Var[E(Y \mid X_i)]$ and $D_{ij} = Var[E(Y \mid X_i, X_j)] - D_i(Y) - D_j(Y)$. The first order Sobol' indexes express the contribution of each input i on the output variance and can be calculated as:

$$S_i = \frac{D_i(Y)}{Var(Y)} \qquad 5$$

In addition, when the problem dimensionality d increases, the so-called total indexes [3] can be introduced to account also for interactions effects:

$$S_{T_i} = S_i + \sum_{i<j} S_{ij} + \sum_{j \neq i, k \neq i, j<k} S_{ijk} + \cdots = \sum_{l \in \phi} S_l \qquad 6$$

where ϕ represents all the possible input combinations and $S_{ij} = D_{ij}(Y)/Var(Y)$.

The training dataset is employed to define a set of discrete probability mass functions (PMFs) based on which the artificial dataset for sensitivity analyses is generated. For example, Figure 11 shows the PMFs associated with nine analyzed optimization measures. The probability of occurrence of each LICOM within the selected time window ΔT_1 is reported, thus by modifying ΔT_1 the discrete probability will change accordingly.

Unfortunately, the use of a single optimal ANN for computing sensitivity indexes leads to reduced robustness in the results. This is due to the uncertainty that affects the surrogate model calibration coming from both architecture definition and weights initialization. To account for this drawback a set of multiple ANNs is adopted to compute a distribution of sensitivity indexes associated with each LICOM. It is worth specifying that the training and calibration stage of surrogate models always lead to epistemic uncertainty due, for instance, to the selection of the optimal hyperparameters.

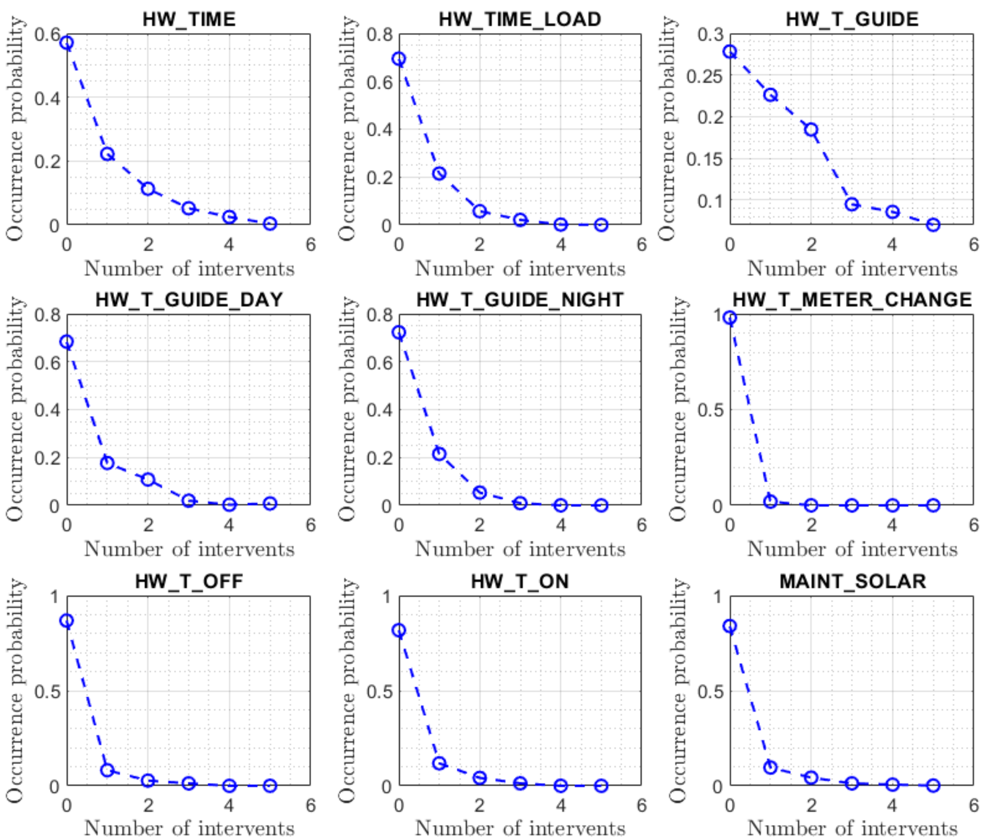

Figure 11 PMFs associate with nine LICOMs showing the probability of occurrence

4 Calibration stage

4.1 Time-windows calibration

The definition of a training dataset, starting from a row database of LICOMs and energy consumptions, requires the adoption of a specific vector Γ. In this regard, ΔT_0, ΔT_1 and ΔT_2 should be selected trying to capture as many as possible LICOMs in ΔT_1 and coherent corresponding effects in ΔT_2, increasing at the same time ΔT_0. A grid search approach is employed to tune the vector Γ by maximizing the accuracy of the network. Figure 12 shows the evolution of the coefficient of determination R^2 obtained by exploring multiple combinations of ΔT_0, ΔT_1 and ΔT_2, more specifically, each of the three graphs corresponds to a different value of ΔT_0. Finally, the vector Γ has been selected considering these results combined with expert elicitation (Table 4)

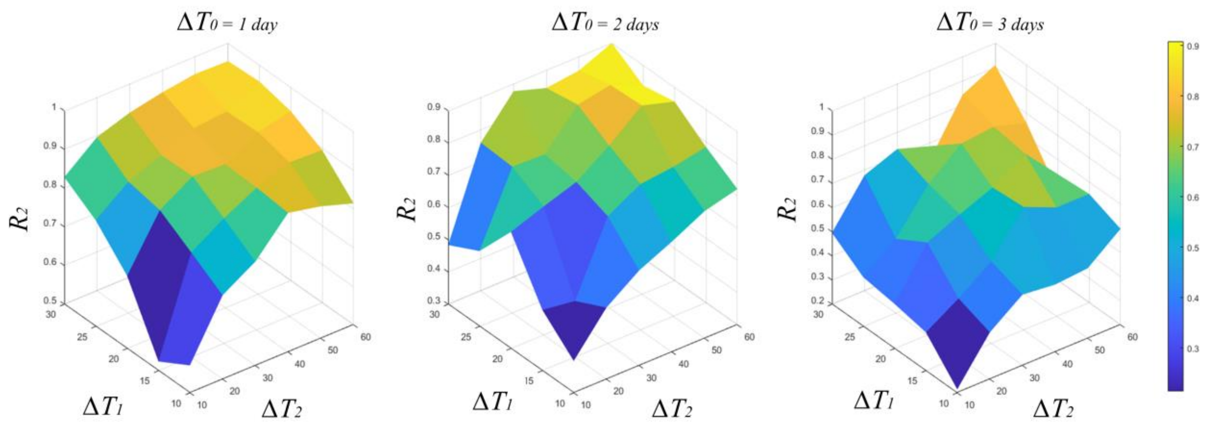

Figure 12 Grid search approach for the vector Γ calibration

ΔT_0	ΔT_1	ΔT_2
2 days	15 days	30 days

Table 4 Vector Γ adopted for the analysis

The global time window ΔT (Equation 3) for the training dataset definition goes from the beginning of 2013 to the end of 2018, for a total of 2'191 days and around 1'100 observations.

Table 5 provides statistical details on the occurrences of each LICOM considering five different time-windows. It is clear how the majority of the measures shows a relatively low frequency (less than one occurrence per ΔT), even increasing the associated time-window. Moreover, the high standard deviations indicate that the LICOMs are highly sparse, increasing the difficulty in analyzing their relative effectiveness. Finally, the mean and standard deviations of the energy-saving reported in Table 5 are computed in a time-window translated of ΔT with respect to each LICOM.

Time window [days]	20		40		60		80		100	
LICOM	Occurrences									
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
'BOILER_CHANGE'	0.039	0.253	0.079	0.359	0.080	0.400	0.158	0.501	0.214	0.516
'BURNER_OPT'	0.390	0.672	0.763	1.025	1.160	1.491	1.526	1.611	2.143	1.792
'FURNACE_1_OFF'	0.104	0.307	0.211	0.474	0.320	0.557	0.421	0.769	0.571	0.640
'FURNACE_CHANGE'	0.065	0.248	0.132	0.343	0.200	0.408	0.263	0.562	0.357	0.488
'FURNACE_OPT'	0.299	0.630	0.605	1.001	0.920	1.382	1.211	1.584	1.643	1.727
'HEATING_CIRC_TIME'	0.052	0.276	0.105	0.388	0.120	0.440	0.211	0.535	0.286	0.561
'HEATING_CURVE'	6.026	7.090	11.947	11.779	17.800	17.325	23.895	21.008	33.143	25.376
'HEATING_CURVE_HIGH'	0.818	1.604	1.632	2.665	2.400	3.629	3.263	4.544	4.500	5.682
'HEATING_CURVE_LOW'	0.766	1.413	1.447	2.226	2.200	3.000	2.895	4.081	4.214	4.865
'HEATING_CURVE_PARALLEL'	0.584	1.239	1.184	1.768	1.720	2.283	2.368	2.499	3.214	2.722
'HEATING_HYST'	0.026	0.160	0.053	0.226	0.080	0.400	0.105	0.459	0.143	0.352
'HEATING_LIFTING'	0.208	0.468	0.368	0.675	0.560	0.870	0.737	0.933	1.143	1.280
'HEATING_NIGHT_LOWERING'	0.026	0.160	0.053	0.324	0.080	0.400	0.105	0.459	0.143	0.352
'HEATING_OFF'	0.312	1.195	0.632	1.746	0.960	2.111	1.263	2.353	1.714	2.384
'HEATING_ON'	0.273	1.284	0.553	1.796	0.840	2.173	1.105	2.447	1.500	2.694
'HEATING_T_OFF'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HEAT_CIRC_CHANGE'	0.039	0.195	0.079	0.273	0.120	0.332	0.158	0.375	0.214	0.414
'HEAT_CIRC_POWER'	0.429	1.409	0.868	2.673	1.320	3.262	1.737	3.739	2.357	3.364
'HEAT_HYDRO_BALANCE'	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
'HEAT_MAINT'	0.247	0.517	0.500	0.726	0.760	0.970	1.000	1.054	1.357	1.710
'HEAT_RAD_INSUL'	0.013	0.114	0.026	0.162	0.040	0.200	0.053	0.229	0.071	0.258
'HEAT_TIME_CONST'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HW_CIRC_CHANGE'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HW_CIRC_POWER'	0.130	0.817	0.263	1.155	0.400	1.443	0.526	1.645	0.714	1.839
'HW_HYST'	0.390	0.876	0.789	1.492	1.200	1.414	1.579	1.953	2.143	1.558
'HW_LIFTING'	0.312	0.782	0.605	1.220	0.920	1.412	1.211	1.751	1.714	2.031
'HW_MAINT'	0.078	0.315	0.158	0.437	0.160	0.374	0.316	0.582	0.429	0.458
'HW_PUMP_AUTO'	0.052	0.276	0.105	0.388	0.160	0.473	0.211	0.535	0.286	0.594
'HW_TIME'	1.156	1.702	2.289	3.153	3.400	2.872	4.579	4.312	6.357	4.271
'HW_TIME_LOAD'	0.714	1.394	1.395	2.553	2.080	2.100	2.789	3.425	3.929	3.091
'HW_T_GUIDE'	2.844	3.142	5.684	4.743	8.640	6.885	11.368	7.697	15.643	9.855
'HW_T_GUIDE_DAY'	0.662	0.982	1.342	1.599	2.040	2.226	2.684	2.730	3.643	3.203
'HW_T_GUIDE_NIGHT'	0.468	0.736	0.947	1.161	1.440	1.502	1.895	2.025	2.571	1.993
'HW_T_METER_CHANGE'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'HW_T_OFF'	0.299	0.762	0.526	1.246	0.800	1.190	1.053	1.747	1.643	1.877
'HW_T_ON'	0.416	0.937	0.816	1.608	1.240	1.763	1.632	2.060	2.286	2.314
'MAINT_SOLAR'	0.338	0.788	0.684	1.141	1.040	1.695	1.368	2.060	1.857	2.434
'OTHER'	1.000	1.298	1.947	2.053	2.880	2.862	3.895	3.230	5.500	4.586
'REGUL_AUTO'	0.117	0.396	0.237	0.590	0.320	0.627	0.474	0.772	0.643	0.990

'REGUL_CHANGE'	0.208	0.408	0.421	0.642	0.600	0.816	0.842	1.068	1.143	1.069
'REGUL_DAY'	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
'REGUL_MANU'	0.078	0.270	0.158	0.437	0.240	0.523	0.316	0.671	0.429	0.910
'REGUL_T'	13.948	14.758	27.158	22.957	40.720	31.490	54.316	36.748	76.714	51.657
'REGUL_THERM_VALVE_CHANGE'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'REGUL_TIME'	2.208	4.053	4.211	6.593	6.320	6.638	8.421	9.430	12.143	10.350
'REGUL_T_BOILER'	0.506	1.253	1.026	1.896	1.560	2.830	2.053	2.877	2.786	2.874
'REGUL_T_DAY'	4.247	4.843	8.342	7.778	12.320	10.703	16.684	13.941	23.357	16.822
'REGUL_T_DAY_ECO'	1.013	1.936	1.974	2.964	3.000	3.742	3.947	4.339	5.571	6.012
'REGUL_T_MAIN'	0.481	1.008	0.947	1.314	1.440	1.685	1.895	1.912	2.643	2.444
'REGUL_T_MAX_AERO'	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
'REGUL_T_MAX_BOILER'	0.377	0.946	0.763	1.731	1.160	1.491	1.526	2.294	2.071	1.792
'REGUL_T_MIN_BOILER'	0.130	0.469	0.263	0.644	0.400	0.866	0.526	0.964	0.714	1.543
'REGUL_T_NIGHT'	5.221	6.688	10.132	10.655	15.280	14.002	20.263	16.556	28.714	24.101
'REGUL_T_NIGHT_ECO'	1.273	2.275	2.579	3.422	3.920	4.453	5.158	4.729	7.000	6.947
'REGUL_T_NIGHT_OFF'	0.104	0.502	0.184	0.692	0.280	0.843	0.368	0.955	0.571	1.060
'REGUL_T_NIGHT_ON'	0.065	0.375	0.105	0.509	0.160	0.624	0.211	0.713	0.357	0.799
'REGUL_T_OFF'	0.312	0.977	0.579	1.388	0.880	1.787	1.158	1.979	1.714	2.748
'REGUL_T_ON'	0.104	0.528	0.158	0.679	0.240	0.831	0.316	0.946	0.571	1.056
'REGUL_WINTER-MODE'	0.104	0.416	0.211	0.577	0.320	0.748	0.421	0.838	0.571	0.990
'VENTIL_GV'	0.065	0.296	0.132	0.414	0.200	0.577	0.263	0.653	0.357	0.724
'VENTIL_HC'	0.026	0.160	0.053	0.226	0.080	0.277	0.105	0.315	0.143	0.352
'VENTIL_HEAT_ROOM'	0.078	0.270	0.158	0.370	0.240	0.523	0.316	0.582	0.429	0.828
'VENTIL_PV'	0.156	0.400	0.289	0.515	0.400	0.707	0.579	0.902	0.857	1.113
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Energy saving [kWh]	195771	394576	326774	462162	461009	699454	587312	673102	724443	955076

Table 5 Statistical details on the LICOMs occurrence

4.2 Surrogate model calibration

The optimization of the ANN architecture follows a *Trial and error* approach. In particular, the number of hidden layers is fixed at one. As to explain this choice, many research works have shown how a single hidden layer is sufficient for a wide range of computational problems [e.g. 8,9], while the number of neurons is considered variable. The final configuration we have chosen is therefore characterized by one layer, sixty-eight input neurons and fifty hidden neurons.

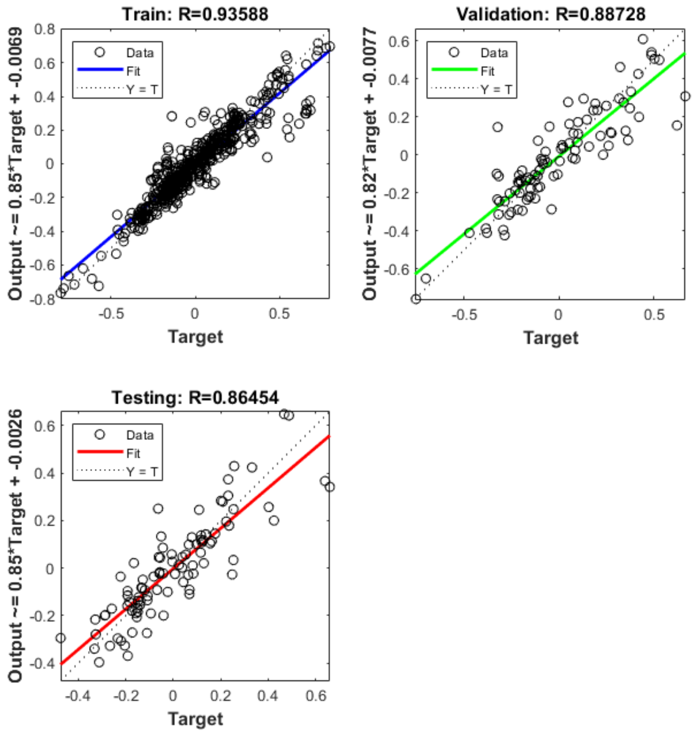

Figure 13 ANN performances in the training, test and validation stage

The training dataset is divided into three parts: 75% training, 12.5% validation and 12.5% test. Figure 13 reports the correlation coefficient R for each stage of the calibration process while Figure 14 shows a comparison between the test observations and the outputs predicted by the final ANN. Both graphs demonstrate the goodness of the adopted surrogate model for approximating the whole phenomenon.

In particular, any observation of over- or under-consumption events should always refer to the time windows adopted in the network calibration phase. In this case, and in the following of the report, every energy gap refers to the consumption events recorded in the 30 days following the application of a set of optimization measures.

Indeed, following a rule of thumb, two variables (in this case predicted values and targets values) can be defined as strongly correlated if R is between 0.7 and 0.89 [10]. In particular, it results:

- $0.00 < R < 0.10$ → Negligible correlation
- $0.10 < R < 0.39$ → Weak correlation
- $0.40 < R < 0.69$ → Moderate correlation
- $0.70 < R < 0.89$ → Strong correlation
- $0.90 < R < 1.00$ → Very strong correlation

The output energy saving (Figure 14) is reported in a normalized form between -0.8 and 0.8 to standardize the different input units. The normalisation process was carried out using the *mapminmax()* function in Matlab which calculates the normalised input (y) from the real value (x) once the range of variation (y_{max} and y_{min}) is imposed. The formula is given below:

$$y = (y_{max} - y_{min}) * \frac{x - x_{min}}{(x_{max} - x_{min})} + y_{min} \quad 7$$

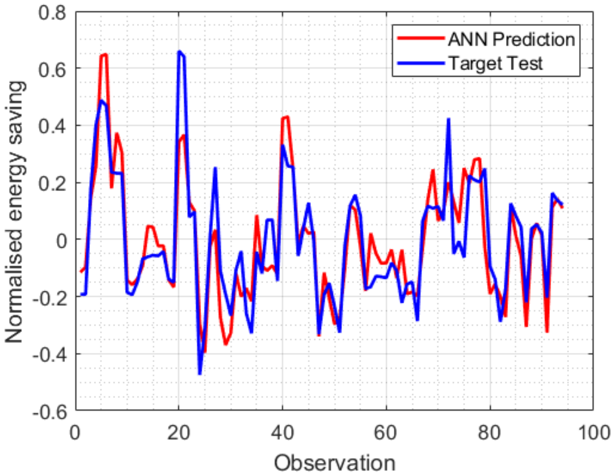

Figure 14 Comparison between ANN predictions and test observations

5 Evaluation of results to date

5.1 First sensitivity indexes distribution

The robustness of the sensitivity analysis is affected by the uncertainty of the model architecture and the apporximation of the calibration process. More specifically, the weights in Equation 1 are randomly initialized before the optimization starts, leading to different accuracy for different seeds even keeping the same ANN architecture.
In this regard, as discussed and proposed in [11], a set of optimal ANNs is defined and multiple sensitivity analyses are performed to identify a distribution of indexes for each LICOM. Figure 16 reports the mean and median values of the indexes with the probability boxes defined by the 25th and the 75th percentiles.
A total of 150 ANNs are pre-selected and for each of them, a minimum of 10’000 scenarios is generated (each scenario is characterized by a set of applied LICOMs) for a total of model evaluations equal to $N = n * (M + 1)$. Considering 63 inputs (M) and 10’000 samples (n) the analysis requires 9,6*10^6 model runs. Latin Hypercube Sampling method [12] is employed for the samples’ generation.

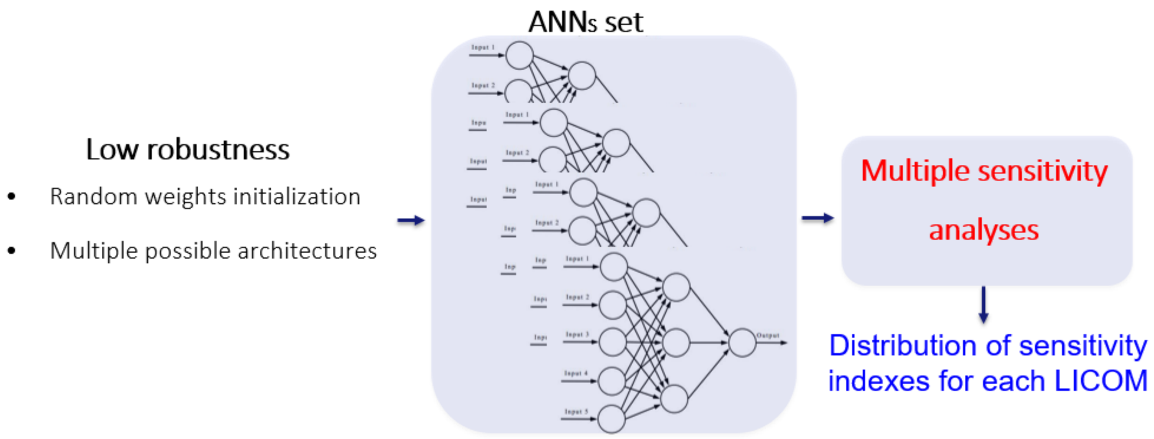

Figure 15 Process of evaluating the distribution of sensitivity indexes by accounting for the uncertainty in the model definition

The results in terms of correlation coefficients [14], defined in section 3.1, have shown low robustness and accuracy when compared with the results provided by the sensitivity analysis based on uncoupled LICOM’ effects. From Figure 16 we can identify the top five median indexes:

1. REGUL_TIME
Time in [h/day] when the heating is turned ON. This includes modifications of the day/night or week/weekend heating schedule. Example: 6h00-22h00 each day => 16 h/day.

2. *HW_T_OFF*
Hot water heating temperature stop, in [°C]. Depending on the possibilities available to set the hot water temperature, it is possible to activate heating e.g. at 45°C (HW_T_ON) and

switch off at 55°C (HW_T_OFF). By doing that the boiler use is improved, the on/off are reduced, and the efficiency of the making of hot water is improved.

3. *HEATING_CURVE*

Heating curve slope change, which is a classical LICOM. When heating a building, a heating curve is identified, meaning one chooses at which temperature of the heating fluid (in radiators, or floor heating, etc.) should be heated according to the outside temperature. E.g. with a slope of 1.5, for 10°C outside temperature, circuit water will be heated at 38°C, for -10°C outdoor temperature, circuit water will be heated at 60°C. Thus, changes to heat curves allow playing with much delicacy with the mid-cold and cold weather conditions. Changes in heating curves could concern the slope, angle, or parallel shift.

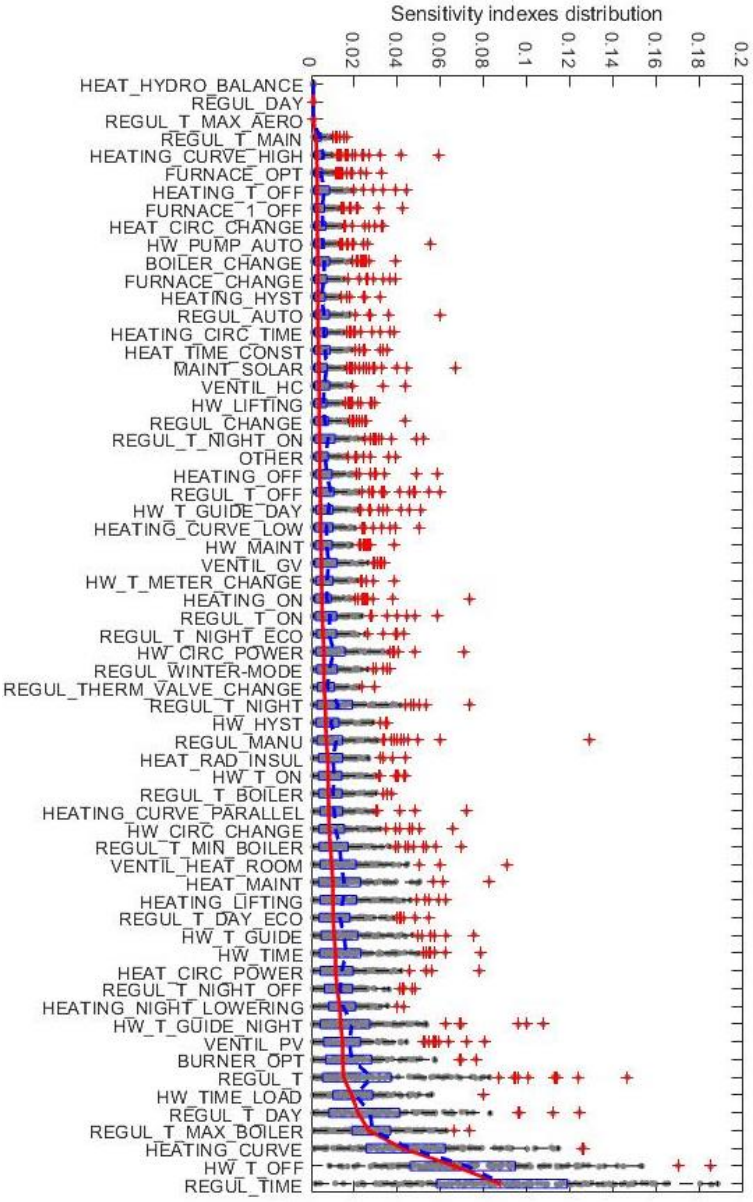

Figure 16 Box-plot of the first-order sensitivity indexes for each LICOM

4. *REGUL_T_MAX_BOILER*
   Maximum boiler setpoint temperature, in [°C]. It means changing the maximum setpoint temperature of the boiler for DHW. Therefore, it limits the furnace (e.g. at 75°C) instead of letting the furnace going up to 100°C e.g. The furnace burns at a more efficient and constant level.

5. *REGUL_T_DAY*
   Heating day setpoint temperature, in [°C]. This parameter is essential during a daily schedule when heating is switched on and during winter months. This represents the most frequent LICOM applied, certainly because it has some visible effect and it is easily doable and often it is not set properly in the default settings of an installation.

It is important to specify that the identified five LICOMs are not the most effective in absolute terms, **the highest indexes do not mean the highest energy savings**. In the following stage of the project, a more quantitative analysis is required to identify trustable intervals of the most probable savings reachable by each LICOM.
Sensitivity analysis does not differentiate between positive and negative contributions to the final energy performances. Indeed, the computed indexes should be read as a **quantitative measure describing the effects of each input (LICOM) on the output variability (energy savings), both in the case of under or overconsumption**.

5.2 Interval analysis

5.2.1 Energy-saving and event duration

The use of a surrogate model acting as a black-box allows us to analyse the most likely variability intervals of the outputs of interest in relation to the specific optimization measures implemented, namely the performance delta versus energy signature and, secondly, duration of the consumption event.
The uncertainty propagated through the neural network mainly takes into account two aspects, namely meteorological variability and uncertainty in the initialisation of the network itself. The considered sources of uncertainty are therefore linked to both physical and modelling aspects.
An artificial dataset of more than 1’000 observations is generated for each specific LICOM, in which only the analyzed optimization measure is applied with variable wheater conditions and model parameters (network weights). Hence, for each LICOM a total of 1’000 predicted performance gaps is collected and three percentiles are computed (25^{th},50^{th},75^{th}). In this analysis, only LICOMs with an adequate occurrence rate are considered.
Figure 17 reports the percentiles associated with each measure, identifying the most probable interval of energy saved, referring to the consumption events associated with the single LICOM. In the same graph, the predicted intervals are reported together with the median value of all the underconsumption events recorded in the original Energo dataset.

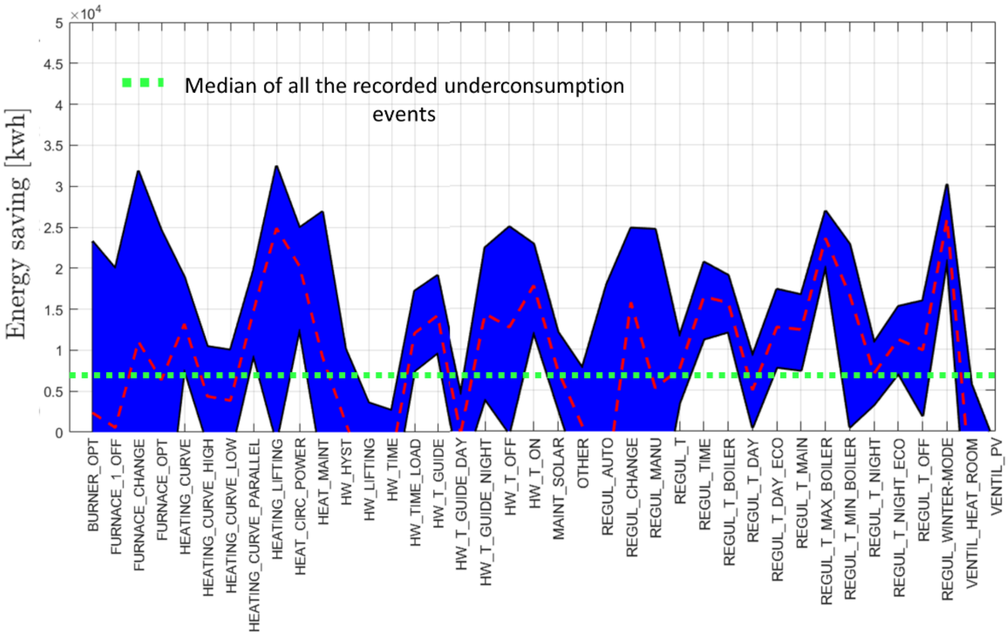

Figure 17 Most probable energy saving interval (25th – 50th – 75th percentiles) for different LICOM

The two LICOMs that show the highest median value with a lower variance are the *Regul_Winter-mode* (median energy saving ≈ $2.5*10^4$ kWh and standard deviation ≈ $0.5*10^4$ kWh) and *Regul_T_Max_boiler* (median energy saving ≈ $2.3*10^4$ kWh and standard deviation ≈ $0.3*10^4$ kWh). In particular, *Regul_T_max_boiler* shows a relatively higher sensitivity index as well, enhancing its primary role in efficiently improving the energy performances.

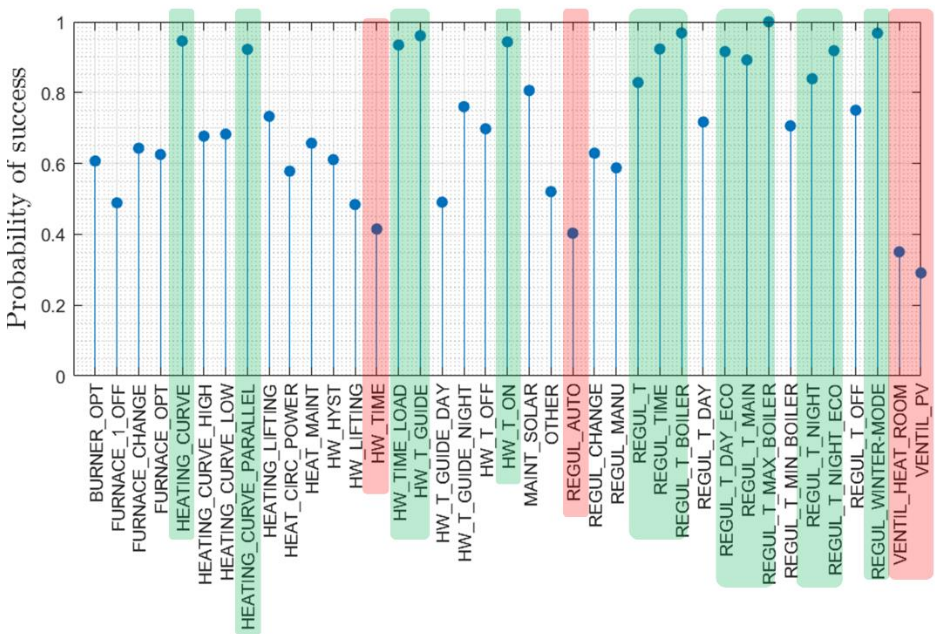

Figure 18 Probability of success

The *Regul_Winter-mode* LICOM sets the summer/winter heating limit by defining the outside temperature at which the heating switches from *on* to *off*. The frequency of this LICOM is consistent with the type of intervention, knowing that not all installations allow this regulation. This measure has a great effect because the number of days during the year when the outside temperature is between 10 and 20°C (mid-season) is large compared to the number of cold days and the number of hot days. Therefore, delaying the switching on of the heating and anticipating its switching off, while always guaranteeing the correct level of indoor comfort, is essential in terms of savings compared to other low-cost actions.

The *Regul_T_Max_boiler* LICOM sets the maximum boiler temperature by adjusting the reference temperature level at which the burner ends its heating cycle. By limiting the maximum boiler temperature on systems with high hot water load set points, the primary temperatures will be limited, resulting in significant savings. In older buildings, reducing this temperature has a greater influence because it reduces heat loss through transmission (uninsulated ducts). It is also important to relate this regulation to the heat emission system (radiators or floor) and the type of production (e.g. oil boiler with or without condensation), preserving the functionality of the system and the quality of the hot water production (in case of combined storage).

Assuming the uncertainty in the magnitude of the LICOM effectiveness, Figure 18 reports the probability of success (meaning the probability of achieving energy savings) for each measures, highlighting those with a probability greater than 0.8 or lower than 0.5. Finally, replicating the procedure employed to obtain the intervals in Figure 17, it is possible to analyze the variability of the consumption events duration (under or overconsumption), here reported in Figure 19. Considering the duration intervals of the consumption events, it can be seen that peak values (> 100 days) are reached by two LICOMs, namely *Hw_T_Guide_day* and *Regul_Winter-mode*, while the lowest values (<20 days) are associated with the *HW_lifting* and the *Regul_T_off.*
To better analyzing the showed results, Table 6 reports the values of the average sensitivity index, average success probability, median energy saving and median event duration, associated to each category defined in Table 1. Each value in Table 6 is computed considering all the LICOMs associated to the different categories, reported as well in Figure 17, computing the final mean or median.

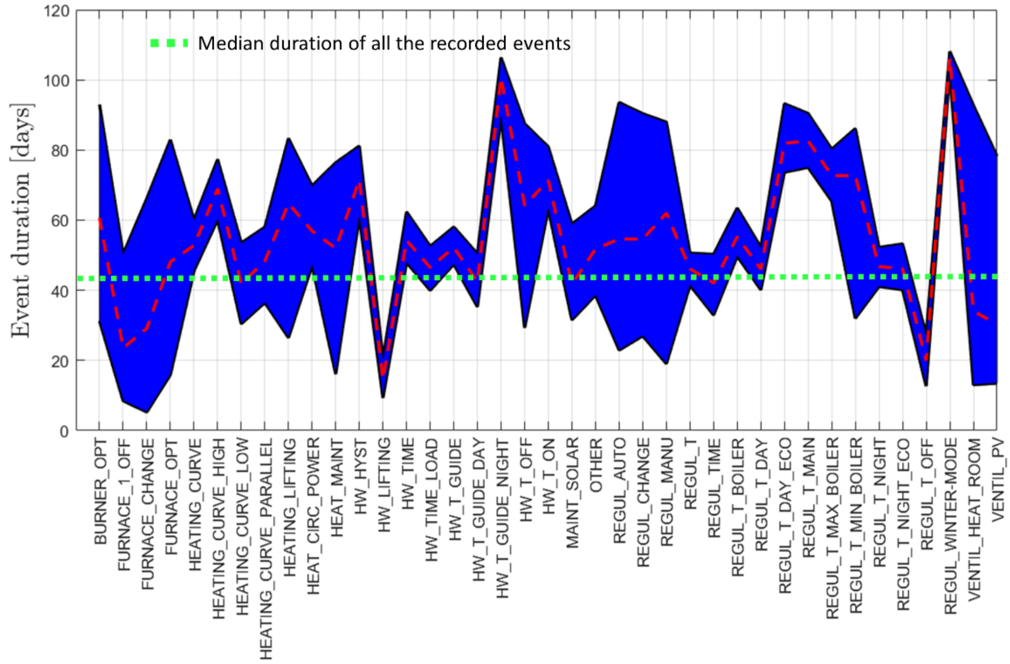

Figure 19 Most probable consumption event duration (25th – 50th – 75th percentiles) due to different LICOM

There are five categories of intervention that show significant values both in terms of sensitivity, success probability and median expected energy savings, namely:

- *Hot water temperature regulation*
- *Heating day-night setpoint temperature*
- *Heating schedule time*
- *Furnace setpoint temperature*
- *Heating curve optimization*

Table 6 Results by optimization measure category

LICOM Category	Heat production and storage optimization	Hot Water hydraulic regulation	Hot Water temperature regulation	Hot water schedule time	Heating day-night setpoint temperature	Heating schedule time	Furnace setpoint temperature	Heating curve optimization	Maintanance	Regulation systems method	Ventilation optimization	Other
Median Sensitivity Index	0.0077	0.0069	0.0198	0.0171	0.0105	0.0880	0.0154	0.0154	0.0078	0.0069	0.0142	0.0061
Success probability	0.60	0.55	0.73	0.67	0.86	0.91	0.86	0.81	0.73	0.54	0.33	0.53
Median saving/10^4 [kWh]	0.78	0.05	0.91	0.35	1.21	1.65	1.83	0.91	0.75	0.57	-0.50	0.00
Event duration [days]	40	44	58	52	61	43	65	52	47	59	33	52

Considering the remaining intervention categories, the lowest efficacy values are found for ventilation (median saving ≈ $-0.5*10^4$ kWh) and activities related to hydraulic adjustments and hot water schedule time, $0.5*10^3$ kWh and $0.35*10^4$ kWh respectively. Moreover, regarding the hot water production process, the effect in terms of energy savings are more relevant in case

of temperature regulations (median saving ≈ $0.91*10^4$ kWh) rather than hydraulic interventions on the circulation system (median saving ≈ $0.05*10^4$ kWh).
It is interesting to note that the interventions linked to the *Heat production and storage optimization* category have a lower average effectiveness if compared to the five categories reported above. This indicates, for example, that a structured furnace replacement schedule for a large building stock leads to improvements in the energy consumption levels that are not comparable to those offered by regular and systematic low-cost optimization measures.
Therefore, since the furnace replacement occurs mainly due to breakage or degradation, it must be considered that such replacement is not a guarantee of obvious energy savings per se but must always be accompanied by an appropriate commissioning and optimization of the system.
In this regard, Table 7 reports the single more effective optimization measure, in terms of median saving, for each analyzed category. It can be seen how an optimal regulation on the furnace setpoint temperature can potentially lead to energy savings of up to more than twice as much as replacing the furnace.
The furnace replacement, even though it is not exactly a low-cost intervention, has however been kept inside the analysis database in order to be able to make comparative analyses with at least one type of important invasive intervention.

Table 7 Most effective optimization measures per category, in terms of median saving [kWh]

Top LICOM per category

	Furnace_change	Hw_hyst	HW_T_guide	HW_time_load	Regul_winter_mode	Regul_Time	Regul_T_max_boiler	Heating_curve	Heat_mant	Regul_change	Ventil_heat_room
LICOM Category	Heat production and storage optimization	Hot Water hydraulic regulation	Hot Water temperature regulation	Hot water schedule time	Heating day-night setpoint temperature	Heating schedule time	Furnace setpoint temperature	Heating curve optimization	Maintanance	Regulation systems method	Ventilation optimization
Success probability	0.63	0.62	0.96	0.93	0.98	0.91	0.99	0.95	0.66	0.63	0.35
Median saving/10^4 [kWh]	0.90	0.60	1.40	1.20	2.55	1.65	2.40	1.40	0.80	1.60	-0.50
Number of occurrences per 100 days	0.36	2.14	15.64	3.93	0.57	12.14	2.07	33.14	1.36	1.14	0.43

It is interesting to note how the act of adjusting the supply, heat production, and space heating temperature, shows a higher probability of success than adjusting system timers. Moreover, optimization actions based on temperature adjustments do not require detailed technical knowledge and can therefore be implemented directly by the building services department in a systematic and fast way.

Table 8 shows the potential monthly percentage savings associated with the various LICOMs. This is calculated with respect the median value of actual recorded energy consumption, equal to about $1.34 *10^6$ kWh every 30 days, referred to the entire optimized building stock. The table reports the 22 LICOMs that reach a monthly potential savings higher than the median value of all under-consumption events. It can be seen that the maximum percentage value is just under 2%. Moreover, applying an energy optimization program based on the first six LICOMs would result in a reduction in the energy consumption of approximately 8-9%. This order of magnitude corresponds to the figure provided in the preliminary event analysis (Par. 2.3).
Finally, it is correct to point out that the internal comfort parameter is not directly tracked by Energo and so each measure considered should be understood as having guaranteed internal

comfort. Moreover, the monthly saving percentage in Table 8 refers to the energy consumption recorded during the optimization period and this can lead to slightly overestimate the potential effectiveness of about 0.2 - 0.4 percentage points.

Table 8 Median monthly saving in %

	LICOM	LICOM Category	Median monthly saving\10^4 [kWh]	Median monthly saving %
1	*Regul_winter_mode*	Heating day-night setpoint temperature	2.55	**1.91%**
2	*Regul_T_max_boiler*	Furnace setpoint temperature	2.4	**1.79%**
3	*hw_T_on*	Hot water temperature regulation	1.8	**1.34%**
4	*Regul_T_min_boiler*	Furnace setpoint temperature	1.7	**1.27%**
5	*Regul_time*	Heating schedule	1.65	**1.23%**
6	*heating_lifiting*	Furnace setpoint temperature	1.6	**1.20%**
7	*Regul_change*	Regulation system method	1.6	**1.20%**
8	*Regul_t_boiler*	Furnace setpoint temperature	1.6	**1.20%**
9	*heating_curve*	Heating curve optimization	1.4	**1.05%**
10	*heating_curve_parallel*	Heating curve optimization	1.4	**1.05%**
11	*hw_T_guide*	Hot water temperature regulation	1.4	**1.05%**
12	*hw_T_guide_night*	Hot water temperature regulation	1.4	**1.05%**
13	*hw_t_off*	Hot water temperature regulation	1.35	**1.01%**
14	*Regul_T_day_eco*	Heating day-night setpoint temperature	1.3	**0.97%**
15	*Regul_T_main*	Heating day-night setpoint temperature	1.3	**0.97%**
16	*Furnace_change*	Heat production and storage optimization	1.2	**0.90%**
17	*hw_time_load*	Hot water schedule time	1.2	**0.90%**
18	*Regul_T_night_eco*	Heating day-night setpoint temperature	1.2	**0.90%**
19	*burner_opt*	Heat production and storage optimization	1.00	**0.75%**
20	*Regul_t_off*	Heating day-night setpoint temperature	1	**0.75%**
21	*furnace_opt*	Heat production and storage optimization	0.9	**0.67%**
22	*heat_mant*	Maintanance	0.8	**0.60%**

6 Applicability for non-residential buildings

The use of a black-box for analyzing the effectiveness of low-cost energy optimization measures can be replicated regardless of the category of use of the building under investigation. To demonstrate this, it was decided to test the accuracy of a neural network for the prediction of over- and under-consumption events, this time for a non-residential building stock.
In detail, a total of 126 buildings, hosting various private and public companies (e.g. Poste CH, Swisscom), were considered, located in eight Swiss cities (Bern, Fribourg, Geneva, Lausanne, Neuchatel, Sion, Delemont).

The Energo dataset available this time covers a 6-year period, from 2014 to 2019, with 2034 optimization measures. Unlike the previous analyses, this time the preprocessing stage for the training database definition is more complex. In fact, although the same configuration of the three time-windows is used, the no longer unique location forces us to operate on a total of 32 data fields dedicated to the weather conditions, having 4 environmental variables (temperature, wind speed, humidity and rain level) in eight different cities.

With regard to the set of optimization measures, no detailed classification (see Table 1) was available this time. It was therefore decided to directly use six macro categories of intervention already defined in the Energo's data acquisition and classification system, namely:

- *Special installations*
- *Electrical installations*
- *Interconnected Systems*
- *Ventilation*
- *Refrigeration installations*
- *Heating*

As a preliminary step, the consumption events associated with the new building stock were analyzed and then compared with the residential stock.

Figure 20 and Figure 21 highlight the differences in terms of event duration and occurrence rate respectively. It is noticeable that in the administrative stock consumption events have a longer average duration, a difference that is accentuated if we focus only on overconsumptions, a category for which the delta reaches about 20 days (53 VS 33). In fact, it can be seen that in administrative buildings the two distribution of durations (overconsumption and underconsumption) are comparable, unlike in residential buildings where overconsumptions last clearly less. As reported by Energo, this is mainly due to the greater difficulty in administrative buildings to intervene promptly if monitoring shows cases of overconsumption.

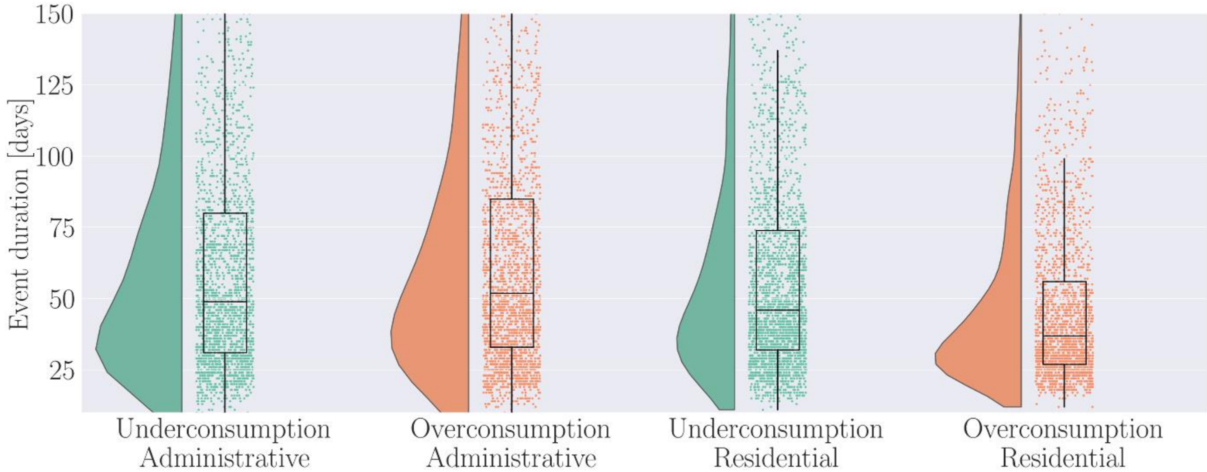

Figure 20 Distribution and boxplot of the duration of the recorded consumtpion events per type and building stock

In terms of occurrence rate, computed as the ratio between the total number of under (or over) consumption events and the total number of event in one specific month, Figure 21 shows how in the residential sector there is in general a higher occurrence of under-consumption events. In addition, the annual evolution of the occurrence rate shows three time intervals in which under-consumptions far exceed over-consumption events in percentage terms. In particular, these time windows seem to coincide with the mid seasons, which by their nature offer less potential for energy optimization.

In addition, around May and September, in residential buildings the heating system is often switched off, thus reducing the optimization potential. In the administrative sector, there is no net shutdown of the system, but rather targeted action is taken with air conditioning and heating according to indoor comfort.

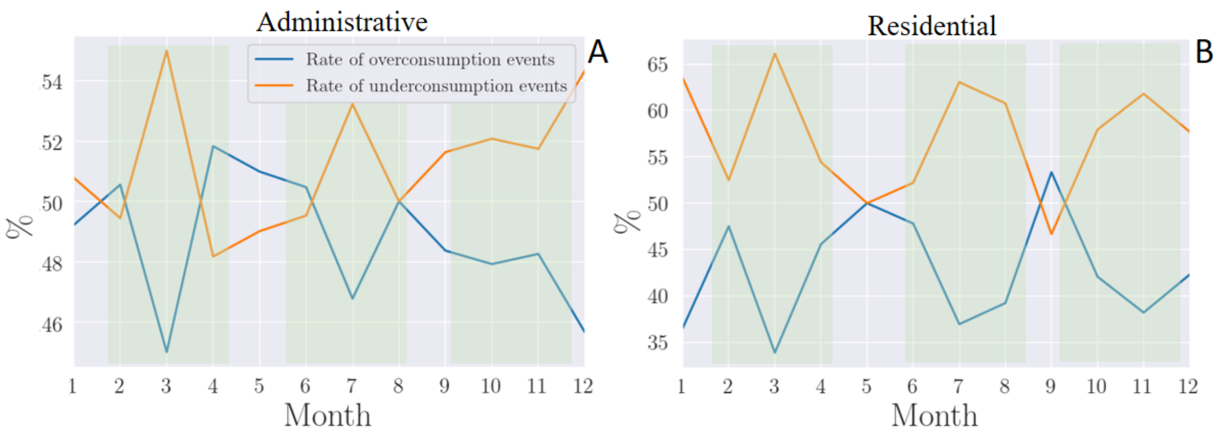

Figure 21 Occurrence rate of the under and overconsumption events per month and building type

Comparing the average amount of energy that characterizes individual events, it can be seen in Figure 22 that both over-consumption and under-consumption events are generally higher in administrative buildings. In particular, the savings events show a difference of about 3’800 kWh in favour of administrative buildings (-10'412 kWh VS -6'652 kWh), while for the over-consumptions this gap rises to about 5'500 kWh (9'905 kWh VS 4'396 kWh). The higher median values of the energy gaps in the administrative buildings, both positive and negative, depend not only on the larger surface of the single property but also on a greater potential for optimization. Indeed, in the administrative properties it is possible acting on the heating system both at night and on weekends.

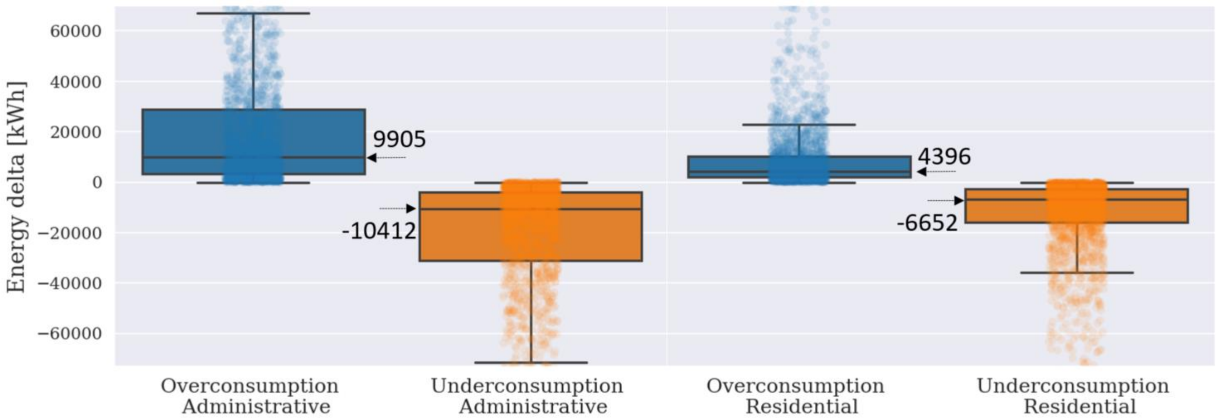

Figure 22 Box-plot of the energy gap associated with each consumption event per type and building stock

In this preliminary analysis, in order to make a consistent comparison between the events in the two building stocks, only consumption events due to heating were considered. However, given the use in the administrative buildings of categories relating to electrical installations as well, and the need to increase the number of events in the training database, in the following part both heating and electrical consumption events were considered to test the possible adoption of a black-box based on an ANN.

The goal is to verify the ANN accuracy level on the new building category, in order to be able to replicate the same approach used for residential buildings.

The final training dataset includes a total of 4’483 consumption events that have been spread on a sequence of time windows as showed in Figure 9. A one-hidden layer ANN is used with an architecture similar to the residential case.

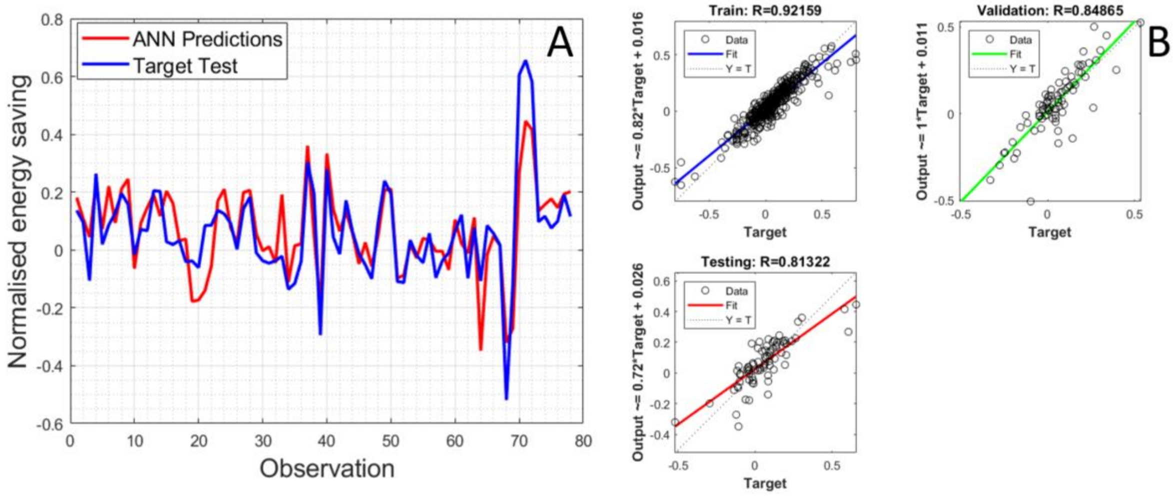

Figure 23 Comparison between the predictions and the target values (a) and R value in the training, testing and validation stage (b)

The model performances, shown in the Figure 23, demonstrates the ability of the proposed approach to also simulate the energy efficiency response of a non-residential building stock subject to low-cost optimization measures. In particular, the correlation coefficient R results to be 0.92 for the training dataset (0.94 for the residential stock) and 0.81 for the testing dataset (0.86 for the residential stock).

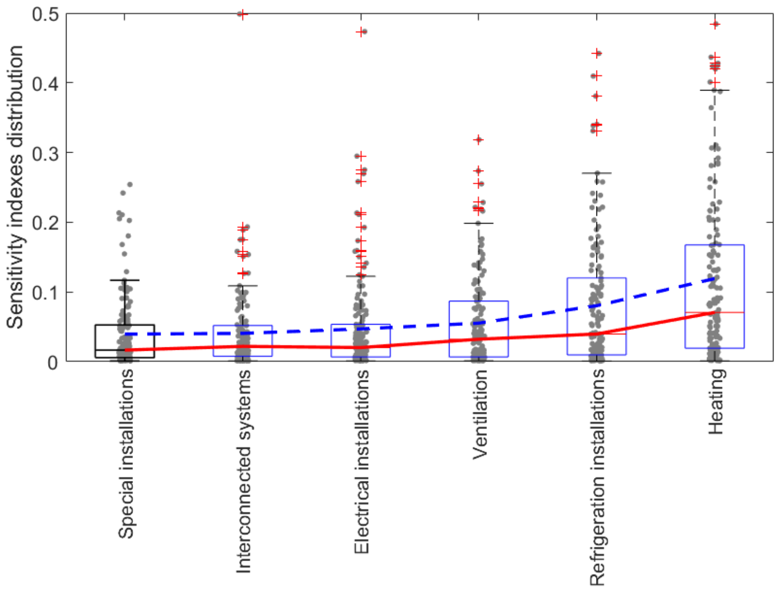

Figure 24 Box-plot of the first order sensitivity index for each category of measure analyzed

Once verified the ability of the model to simulate the response of non-residential buildings, a sensitivity analysis is launched, again incorporating the uncertainty associated with the optimal network architecture as well as the initialization of the weights.

Analyzing results in Figure 24, it can be seen that the optimization measures showing a higher average sensitivity index are those belonging to the following three-macro categories: *Heating*, *Refrigeration installations* and *Ventilation*.

Administrative buildings are generally characterized by the presence of ventilation and cooling systems that are traditionally not present in residential buildings. The optimization of these two systems, according to Figure 24, seems to lead to a higher influence on the energy consumption levels than the optimization of electrical installations (circulation pumps, appliances and lighting), but still less than the optimization of the heating system.

With the spread of ventilation systems and the possibility of installing reversible heat pumps at the same price as non-reversible heat pumps, it can be expected an increasing presence of ventilation and cooling systems in contemporary residential buildings as well. It is therefore possible to assume that the optimization of such systems may prove effective in the next future even in residential buildings.

Finally, the residential case study is characterized by a much more detailed database, especially regarding the applied measures. At the present status, it is not possible to perform a detailed comparison between the results from the residential and administrative buildings, because the latter only present details on macro optimization measures. The test done on the administrative building stock is mainly focused on demonstrate the accuracy of the network in predicting the most probable energy savings with buildings of different use, more details on the measures are required to perform a direct comparison with the residential case study.

7 Future developments

The proposed computational approach and the obtained results lay the basis for an additional development step aimed at structuring a predictive analysis to identify an optimal low-cost maintenance plan.

A balck-box capable of adequately simulating the "LICOM-performance gap" relationship can be used to introduce new control variables to build a robust forecasting probabilistic framework. For example, just by adding the variable "building" to the model it becomes possible to link the success probability of a sequence of measures (with respect a target energy efficiency level) with the building characteristics. Figure 25 shows the steps related to this project and the additional activities with a view to further developments.

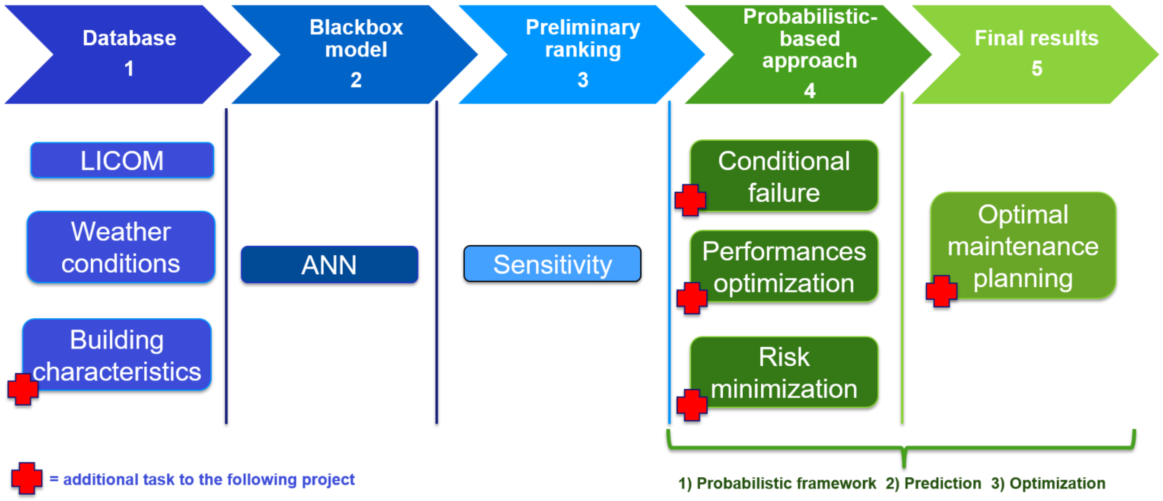

Figure 25 Stages of further development of the present project

A similar approach would represent the first real attempt to define a set of optimal guidelines considering only low invasive and costs effective energy optimization measures adopted during the life-cycle. More specifically, the adopted database is able to cover a wide range of archetypes giving to the next computational step and adeguate level of applicability. Indeed, the existing approaches are mainly calibrated on a single case study (real or simulated) making extremaly difficult a generalization of the obtained results.

Additionally, analyzing potential real impacts of a low-cost optimal intervention scheduling system on new testing buildings requires reaching a higher generalization level. The possibility of being able to decline the probability of success of an intervention as a function of more detailed characteristics of the individual building, would allow to draw up a more effective ranking of priority measures. Such aspect would guarantee the definition of a program-ming of intervention monitored in a sufficiently long time window to verify the expected improvements and in the case to recalibrate in part the preliminary model.

Finally, the possibility of identifying a probabilistic framework allows us to analyse the risk associated with a specific low-cost intervention planning. In particular, the adoption of a low-risk based approach is of paramount importance for a competitive and reliable implementation within the activity of an Energy Service Company (ESCO) (Figure 26). Indeed, it is clear that a probabilistic-based estimation makes it more viable to practically implement a profitable EPC, since the risks taken by the ESCO will be reduced significantly and on the other hand, the measure does not impose additional burdens on tenants.

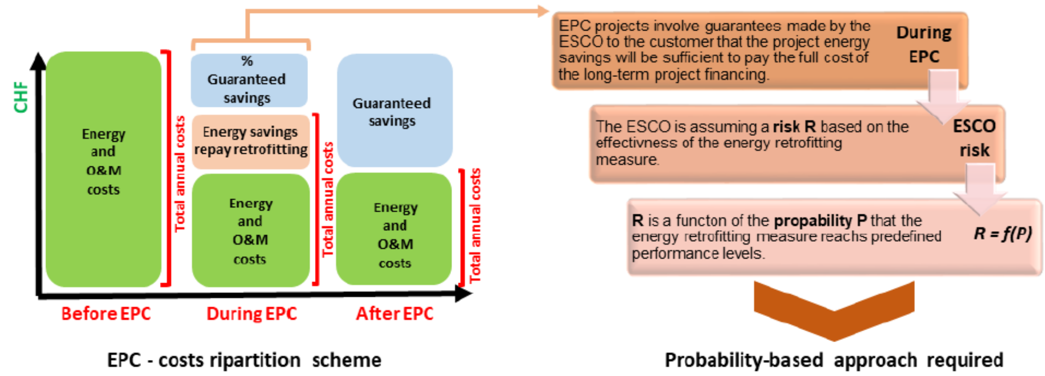

Figure 26 EPC risks reduction by a probability-based approach

8 National and international cooperation

The scientific and technological results focus on the identification and definition of optimization measures (LICOMs) with the greatest impact on energy savings. The transfer of the results to the market is aimed at "*Accelerating the process of energy renovation of buildings through the large-scale implementation of optimization measures with the greatest return on investment*". This is possible with the implementation of support activities carried out during the project.

Support group
The coaching group must be able to assist the research team in transferring the results of the project to the market.
The Positive Gap project support group is composed of:

- Engineer RCVS (Ing. Roland Connus) for the French-part of Switzerland;
- Engineer RCVS (Ing. Jonathan Sancisi) for Ticino;
- Responsible for Energo French-part and Ticino (Joel Lazarus).

Several specific meetings were held during the project. The focus was on data quality and reliability, identification and selection of LICOMs related to energy reduction events.
The contribution of RVCS engineers and technicians was used to better specify the nature of the measurements. It was therefore possible to verify the quality of the work on the optimisation measures and the related positive gap. The knowledge and practical experience of the support team made it possible to detail the significance of the individual optimisation measures, particularly those that brought the greatest benefits.

Dissemination
Regarding the dissemination of the results, the first training course was held on 4.12.2019 for the technicians responsible for the operation of the public housing stock facilities in the municipality of Chiasso. There was a great interest shown for the energo database and the approach to the project's problems, as well as a strong need to identify the most effective low-cost measures, our LICOMs, leading towards a global energy consumption reduction. On 29 January 2021 a half-day of further training has been provided in the CAS Building Management course at SUPSI, during which the first results of the study and the innovative approach adopted will be shown.

Conferences/presentations
On the 3rd and 4th of September 2020, SUPSI in collaboration with Energo was selected to present the Positive Gap project at the Status Seminar organized by Brennet in Arau. During this conference, interesting comparisons and relations with other projects were made. On the 21st of October 2021, the final results were presented to the Swiss Federal Energy Office through an online meeting.

9 Conclusions

The presented project aims at identifying the most effective low-cost measures in residential buildings leading towards a global energy consumption reduction, by accounting for complex interdependencies and environmental factors by means of an artifical neural network.

In the first stage of the project a preprocessing stage of the Energo database was required to identify the optimization measures of interest and a building stock with a robust tracking activity. Secondly, the dataset was integrated with the time evolution of five weather indicators, and organized following the time windows of interest.

A dedicated numerical model, based on an artifical neural network, was calibrated and adopted as black-box in order to simulate separately the effect of each LICOM on the energy performances of the analyzed building stock.

Following the computation of robust sensitivity indexes, a quantitative analysis of the energy savings is required in order to associate with each LICOM the most probable interval of energy saved (kwh) that accounts for the uncertainty associated with the model itself and the weather conditions. Moreover, the proposed numerical model was tested with a different dataset representative of non-residential buildings (offices) that have other plant and energy needs. In this case, the employed dataset is characterized by different optimization measures leading to the definition of only few macro-categories of intervention.

In terms of performance intervals and refering to an energy saving related to the analyzed building stock, the two LICOMs that show the highest median value with a lower variance are the *Regul_winter-mode* (median energy saving $\approx 2.5*10^4$ kWh) and *Regul_T_max_boiler* (median energy saving $\approx 2.3*10^4$ kWh). While, considering macro-categories of intervention, the highest median savings are reported for the *Furnace setpoint temperature* ($\approx 1.83*10^4$ kWh) and the *Heating schedule time* ($\approx 1.65*10^4$ kWh) activities, with the lowest efficacy values reached by the *Ventilation* category ($\approx -0.5*10^4$ kWh) and activities related to hydraulic adjustments and hot water schedule time, $0.5*10^3$ kWh and $0.35*10^4$ kWh respectively. Finally, focusing on the hot water production process, temperature regulations ($\approx 0.91*10^4$ kWh) are more energy efficient if compared with the hydraulic interventions on the circulation system (≈ 0.05*104 kWh). In percentage terms, the best LICOMs manage to achieve a median potential monthly savings of just under 2%, which is about four times higher than the median value of all recorded underconsumption events.

Analyzing the event duration, the range of variation, considering only the consumption events most likely to be associated with LICOMs, varies from a minimum of about 20 days to a maximum of just over 100 days. The analysis of the duration can be important if one wants to optimize and structure a long-term action plan of energy efficiency measures, in order to identify the optimal overlapping between different actions.

In conclusion, the proposed approach is well suited to additional probabilistic analyses that can be performed to identify conditional energy savings, for instance depending on a specific weather condition and/or performance targets, building a probabilistic framework towards a risk-based optimal LICOM schedule.

10 References

1. Khoury, Jad, Pierre Hollmuller, and Bernard Marie Lachal. "Energy performance gap in building retrofit: characterization and effect on the energy saving potential." *19. Status-Seminar «Forschen für den Bau im Kontext von Energie und Umwelt»*. 2016.
2. Bishop, Christopher M. *Neural networks for pattern recognition*. Oxford university press, 1995.
3. Saltelli, Andrea, et al. *Global sensitivity analysis: the primer*. John Wiley & Sons, 2008.
4. Understanding the Energy Performance Gap in the existing building stock. A case study in Swiss collective dwellings. Master Thesis, Michael Rickli, 2019, ETH.
5. Cozad, Alison, Nikolaos V. Sahinidis, and David C. Miller. "Learning surrogate models for simulation-based optimization." *AIChE Journal* 60.6 (2014): 2211-2227.
6. Qian, Zhiguang, et al. "Building surrogate models based on detailed and approximate simulations." (2006): 668-677.
7. Homma, Toshimitsu, and Andrea Saltelli. "Importance measures in global sensitivity analysis of nonlinear models." *Reliability Engineering & System Safety* 52.1 (1996): 1-17.
8. Guliyev, Namig J., and Vugar E. Ismailov. "On the approximation by single hidden layer feedforward neural networks with fixed weights." *Neural Networks* 98 (2018): 296-304.
9. Altieri, Domenico, et al. "Machine Learning Approaches for Performance Assessment of Nuclear Fuel Assemblies Subject to Seismic-Induced Impacts." *ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg* 6.4 (2020).
10. Schober, Patrick, Christa Boer, and Lothar A. Schwarte. "Correlation coefficients: appropriate use and interpretation." *Anesthesia & Analgesia* 126.5 (2018): 1763-1768.
11. Cao, Maosen, et al. "Advanced methods in neural networks-based sensitivity analysis with their applications in civil engineering." *Artificial neural networks: models and applications, Rijeka, Croatia, IntechOpen* (2016): 335-353.
12. Helton, Jon C., and Freddie Joe Davis. "Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems." *Reliability Engineering & System Safety* 81.1 (2003): 23-69.
13. Plischke, Elmar. "An effective algorithm for computing global sensitivity indices (EASI)." *Reliability Engineering & System Safety* 95.4 (2010): 354-360.
14. Benesty, Jacob, et al. "Pearson correlation coefficient." *Noise reduction in speech processing*. Springer, Berlin, Heidelberg, 2009. 1-4.