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Integrated local energy systems (Energy islands)

RENergetic

Community-empowered Sustainable Multi-Vector Energy Islands

Project Nº 957845

D6.1 – Interim evaluation of actions impact on Pilot site 3

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Executive Summary

The current document reports on the work and interim results as of 1 April 2022 for WP6 tasks and operations, carried out in the first 18 months of the RENergetic Project.

The purpose then of this deliverable is to detail Project vision, concepts, ideas and viable solutions offered into Pilot 3 actions (OSR and Segrate) in order to increase energy efficiency, renewability push and independence or energy autarky.

Two main themes emerge:

1) The WP6 AI and Machine Learning methods for predictive and prescriptive approaches either for MW consumption (demand) and/or supply plans
2) The social, organisational and municipality requirements to fit in with real social environments like Segrate in North of Italy.

Both themes are fully investigated and reported in this first Interim document.

Referring to other Project deliveries, this work has direct connections with the IT platform developments as it is described in Deliverable 3.1. Also, Deliverable 7.1 and Deliverable 2.1 will touch upon Segrate and OSR arguments for regulatory/business models and social evidence respectively.

Overall, this Deliverable 6.1 document is defining a plan forward and trajectory for the RENergetic project. This WP6 activity is in fact supporting the delivery of a strategic “replicability pack” for Energy Island solutions with advancements on:

1. Support services (replicabilities) to implement RENergetic services in any new Pilot.
2. RENergetic Platform, AI methods (tech method)
3. RENergetic social influence methods (social method)
4. RENergetic Business Models, Legal aspects

The Pilot 3 described into this document will try to maximise and align with such prospective above. The finalized Pilot 3 Epics will reflect such strategy accordingly within WP6 overall.

The objective of RENergetic is to demonstrate the viability of so-called ‘urban energy islands’. Energy islands seek to achieve the highest possible degree of self-sustainability with regards to the supply of its energy demand, be it electricity or heat through local renewable resources. At the same time an urban energy island may offer ancillary services to the public grid surrounding it.

These islands place the consumer at the centre of the energy transition, giving them an active part in energy communities capable of producing their own energy, sharing the surplus with the rest of the public grid and optimizing consumption. RENergetic will demonstrate that Urban Energy Islands increase both the number of renewables in these areas and the energy efficiency of local energy systems. RENergetic will demonstrate the viability of this energy islands in three site pilots, each of them of a different nature: New Docks, a residential area in Ghent – Belgium, Warta University Campus in Poznan, Poland and San Raffaele Hospital and its investigation and research campus in Segrate-Milan, Italy. The impact of the Urban Energy Islands is assured as technical, socio-economic and legal / regulatory aspects are considered while safeguarding economic viability.

RENergetic will be carried out over the stretch of 42 months involving 14 European partners: Inetum (Spain, France, and Belgium), Clean Energy Innovative Projects and Gent University (Belgium), Poznan University of Technology, Veolia and Poznan Supercomputing and Networking Center (Poland), Ospedale San Raffaele, Comune di Segrate and University of Pavia (Italy), Energy Kompass GMBH (Austria), the University of Mannheim and the University of Passau (Germany), University of Stuttgart (Germany) and Seeburg Castle University (Austria).

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Table of Acronyms and Definitions

Acronym	Definition
DoW	Document of Work (RENergetic Project)
EV	Electric Vehicle
HVAC	Heating, Ventilation and Air Conditioning
OSR	Ospedale San Raffaele
PV	Photovoltaic
REN-Index	RENergetic-Index
AI	Artificial Intelligence
EI	Energy Island
ML	Machine Learning
MLOps	Machine Learning Operations
MSMs	Moving Series Machines

I. INTRODUCTION

I.1. Purpose and organization of the document

This Deliverable 6.1 reports on the work and interim results as of 1 April 2022 for WP6 tasks and operations carried out in the first 18 months of the RENergetic Project. This document is organized in four main sections:

- Pilot Descriptions
    - OSR and Segrate baselines, local implementations and layout
    - Stakeholders and Roles (Personas)
- Detailed description of the actions
    - Pilot 3 strategy: energy intelligence
    - Energy measures and AI methods (OSR)
    - Social, Legal and Municipality engagements (SEGRATE)
- Pilot 3: Epics, AI algorithms, data
    - Preliminary user stories implementations
    - Data analytics
    - Social events
- Next steps 2022-2023
    - Epics, Users Stories and Social awareness
    - Replicability packages and reproducibility

The above bullet points together reflect the Project activities as foreseen in WP6 description: from task 6.1, to task 6.4 respectively. Numerous WP6 tasks gather input from WP2 (social and psychological models) as well as WP3 (RENergetic software development for advanced AI services). This has facilitated the Pilot 3 alignment with various parallel Project developments and strategies, as well as the other two Pilot deliveries (Poznan and Gent Pilot sites).

The basic needs reflect the key interest between OSR and Segrate to engage in and exploit the RENergetic services both as AI and social facilitation tools over the key stakeholders. The predominant OSR goal (according to the WP6 description in the Project's DoW) is implementation of multi-vector energy efficiency solutions centered on AI solutions with focus on energy managers. Instead, the Segrate counterpart (in the same Pilot 3) will benefit by the exploration and assessment of the social and regulatory means of compliance to new RENergetic services (comprised of AI and social facilitation) for a target audience from common Segrate citizens (less interested in AI) to the political roles supervising entire neighbourhoods.

The purpose then of this document is to detail Project vision, concepts, ideas and viable solutions offered into Pilot 3 actions (OSR and Segrate) in order to increase energy efficiency, renewability push and independence or energy autarky.Referring to other Project deliveries, this work has direct connections with the IT platform developments as it is described in Deliverable 3.1. Also, Deliverable 7.1 and Deliverable 2.1 will touch upon Segrate and OSR arguments for regulatory/business models and social evidence respectively.

Some prospective actions and planning for 2022-2023 are finally provided.

NOTE: Please note that the Epics: EV Smart Charging and Interactive Platform are still under study and development as of 1st April 2022. Such Epics will be part of the next Deliverable 6.2.

I.2. WP6 Strategy

The energy systems involved in this Pilot 3 are:

- OSR energy sources (heat, cool and electric), and
- Segrate energy source (heat system in Milano 2 - 'teleriscaldamento')

For both energy environments, the overall Pilot 3 focused on testable and viable solutions to respond to key RENergetic Project targets: enhanced EI efficiency, renewability and autarky.

Strategic dispositions in OSR are towards advanced technical solutions to deploy AI methods whereas in Segrate the energy strategy is about organisational and social means of compliance to set up favourable political, legal, commercial and stakeholders capacity building to scale up, at a municipality level (Segrate test case), the range of RENergetic socio-technical services and *municipality-oriented* solutions. This is depicted in Figure 1 with emphasis on WP 6 coordination and feeds across other WPs in the total Project.

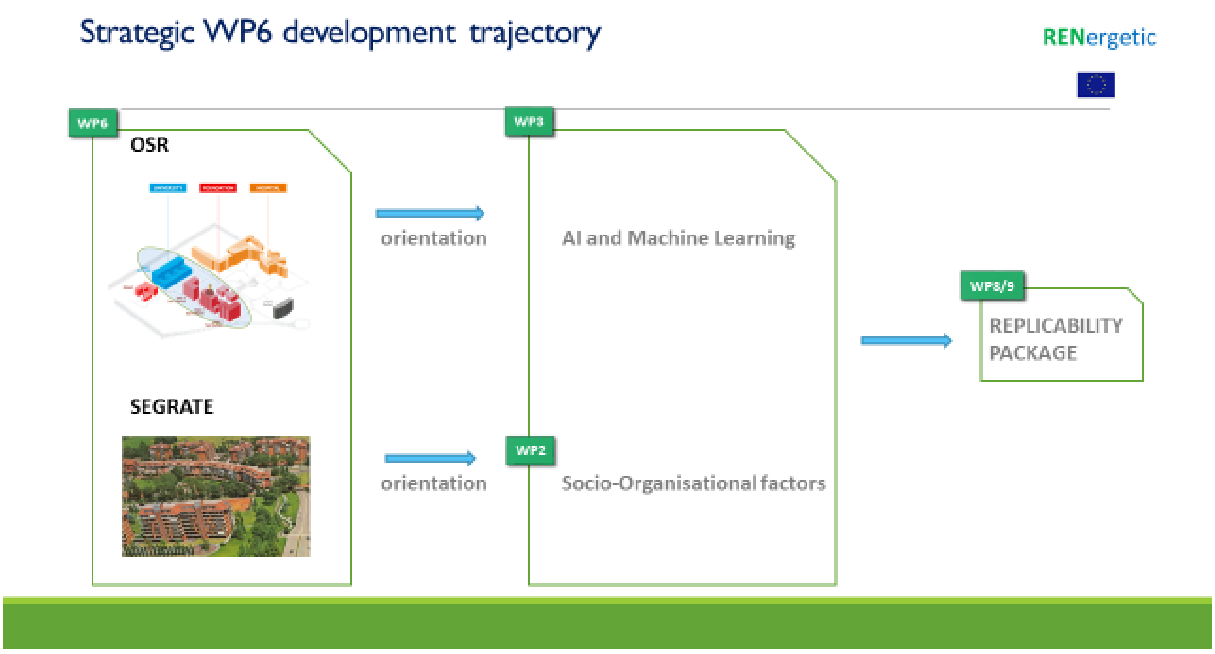


Figure 1 – High-strategic view of WP6 developmental trajectory

In particular, Figure 1 shows how WP6 connects strongly with other activities across WP2, WP3, WP8 and WP9. The AI and Machine Learning technical solutions to enhance multi energy vector optimisation and predictive/prescriptive capacity, are mostly designed and developed in OSR's WP6 actions in conjunction with WP3 activities. Instead, Segrate part deals more with municipality's capacity building solutions to render RENergetic services feasible to multi-level and multivariate stakeholders in real-city contexts. Notably, both OSR and Segrate are part of the same total Pilot 3 in Milano.

WP6 is carried out in close cooperation with WP2 activities on social, psychological and organisational factors and investigations on the projected RENergetic roles of the future. Finally, the overall convergence in WP8 and WP9 will make WP6 bounded into a "replicability package" as full fledge finalized RENergetic solution or service to replicate out of the WP6 endeavour. To summarize, OSR's aim is to generate more AI oriented methods to test first on local scale (within OSR buldings) whereas Segrate shall test and scale them up by gauging all necessary socio organisational means of compliance to render them effective and potentially replicable (see WP8). Notably, WP3 will service WP6 by supplying a beta version of a RENergetic software Platform delivering the required AI and computational means required.

II. PILOT DESCRIPTIONS

Although Pilot 3 is a single one, the description requires to differentiate the needs and the specifications between OSR and Segrate accordingly. This will ease the final discussion where reproducibility and replicability "internal" to the same Pilot 3 is recommended.

II.1. Descriptions of OSR

The Ospedale San Raffaele (OSR) is a world-renowned and highly specialized multi-disciplinary medical centre as show in Figure 2. OSR is located in the west North east side area of Milano and service directly the SEGRATE - MILANO - VIMODRONE area complex (North of Italy). An overview of the site location with respect to Milano is in Figure 3 below.

Research side view

Medical side view

Figure 2 – Ospedale San Raffaele - OSR complex (Research and Medical side views)

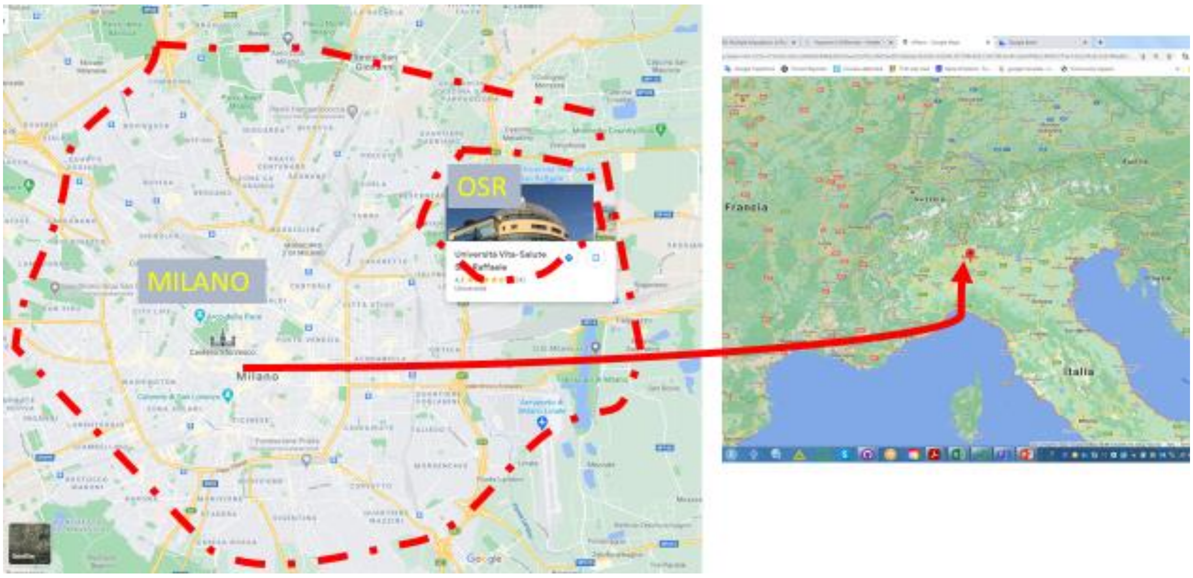


Figure 3 – OSR location in Milano city area

OSR is physically located and proximal to Milano 2, the target neighbourhood part of Segrate municipally, as shown in Figure 4

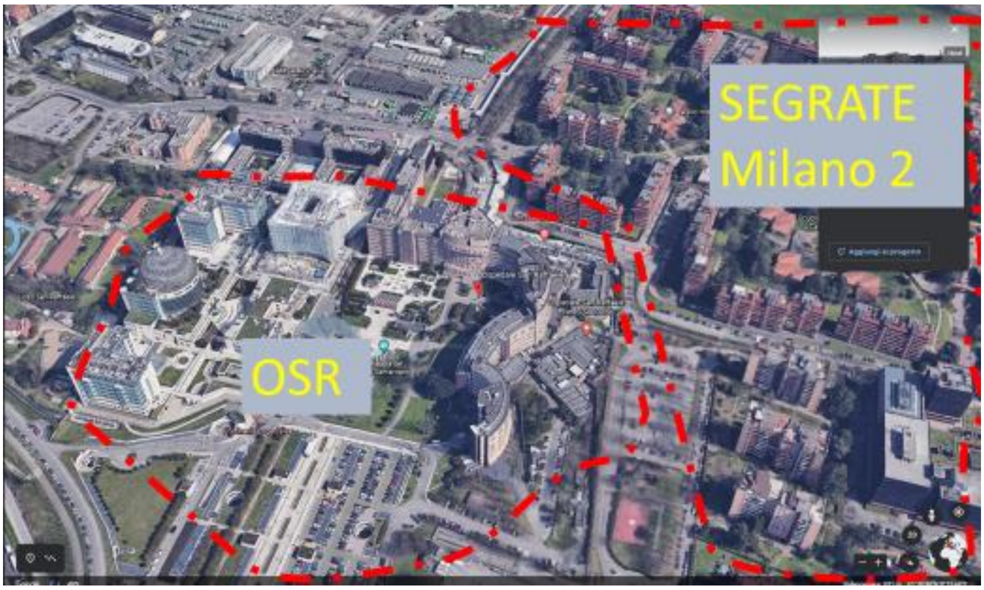


Figure 4 – OSR-Segrate proximity

OSR service target is on treatment, clinical research and teaching activities with more than 50 clinical specialties available and with over 1340 beds, with a yearly 51,000 patient admissions, 72,000 emergency room encounters and delivery over 1.5 million outpatient medical services. Also, the Biomedical research constitutes, together with assistance and teaching, one of the pillars on which the OSR stands. With its over 1500 researchers (translational and clinical base) and more than 150 laboratories spread over an area of 130,000 m2, the complex represents a unique model of interaction where teaching, basic research and clinical research are strictly related to each other

II.1.1. Local Settings and Infrastructure

Overall, the energetic system (supply/demand complex) is paramount for clinical service support and wellbeing. OSR clearly requires dedicated systems for energy supply, energy management, equipment and network installations. The energy supplies acquired from the outside are electricity and methane. Methane is used in the OSR plant of cogeneration (built in 2008) for the production of hot water, superheated water (steam), freezing water and electricity. The cogeneration plant supplies thermal energy to the Milano 2 area in Segrate city, with a total of 11 MW of thermal power. The supply contract is flexible and allows to cover the needs of Milano 2 partially in the winter season and completely in the summer one.

The global electricity consumption and natural gas consumption can be measured directly by the delivery counters / points service providers. The quantities of the four energy carriers leaving the co-generator are measured by dedicated meters, and are distributed to individual buildings through sub-plants. Electricity reaches all buildings whereas water (hot/cold/superheated) does not. Presently, the share of electricity supplied to each single building is not directly monitored, but it is possible to know the thermal and cooling energy supplied to the buildings attested to each substation. Cooling energy is used exclusively for air conditioning, while thermal energy is used partly for air conditioning and partly for the production of hot water as well as technical uses.

Some buildings have refrigeration units powered by electricity, but there is no dedicated meter. It is therefore not possible to divide consumption analytically between the various buildings and services.

As regards of electricity consumption for which there is no partial accounting system of consumption, the breakdown may be implemented by analysing the consumption data, the annual distribution and the breakdown of the several buildings related to the intended uses.

II.1.2. The OSR Cogenerator

The total multi-vector energy source for OSR (heat and electricity) and Segrate (heat for Milano 2) is supplied 100% by the OSR owned Cogenerator plant, located proximal and external to the OSR premises as shown in Figure 5. Figure 6 and 7 provides exemplary pipelining for heat/cooling function and the yearly MW supply of multiple energy sources respectively.

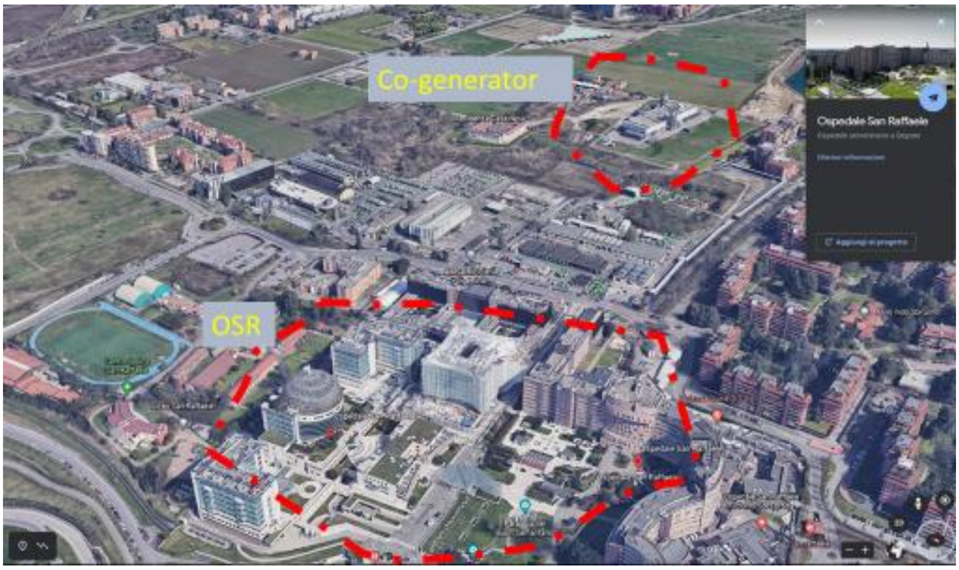


Figure 5 – OSR – Co-generator location

The Co-generator is furnished with n. 4 cogeneration gas engines (Caterpillar gas model (thermal power of 4.425 kW)), n.1 Hot Water Boiler, n.1 Heat pump (capacity of 1.364 MW), n.3 Steam Boilers, n1. Ground Water Heat Pump, and n.6 different Absorption Fridges and n.3 Compression Fridges, as shown in Figure 7.

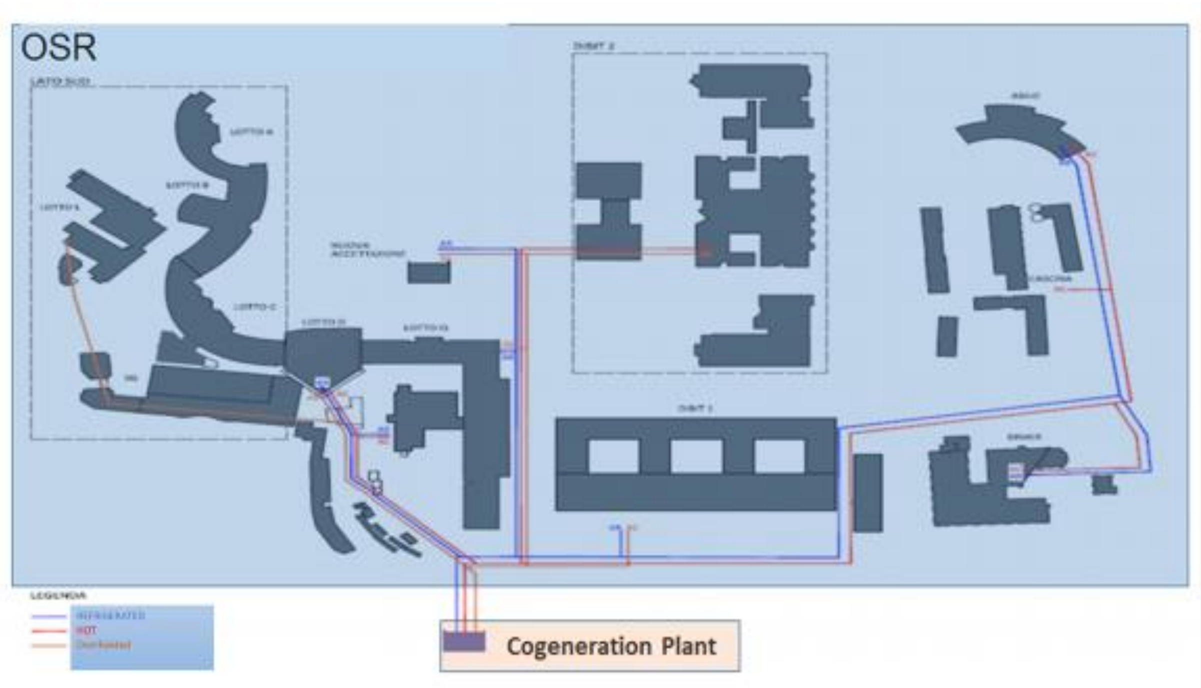


Figure 6 – OSR – Cogenerator with exemplary pipelines for refrigerated/hot/overheated water for (heat/refrig systems) *[see Figure 7 for main power capacities)]*

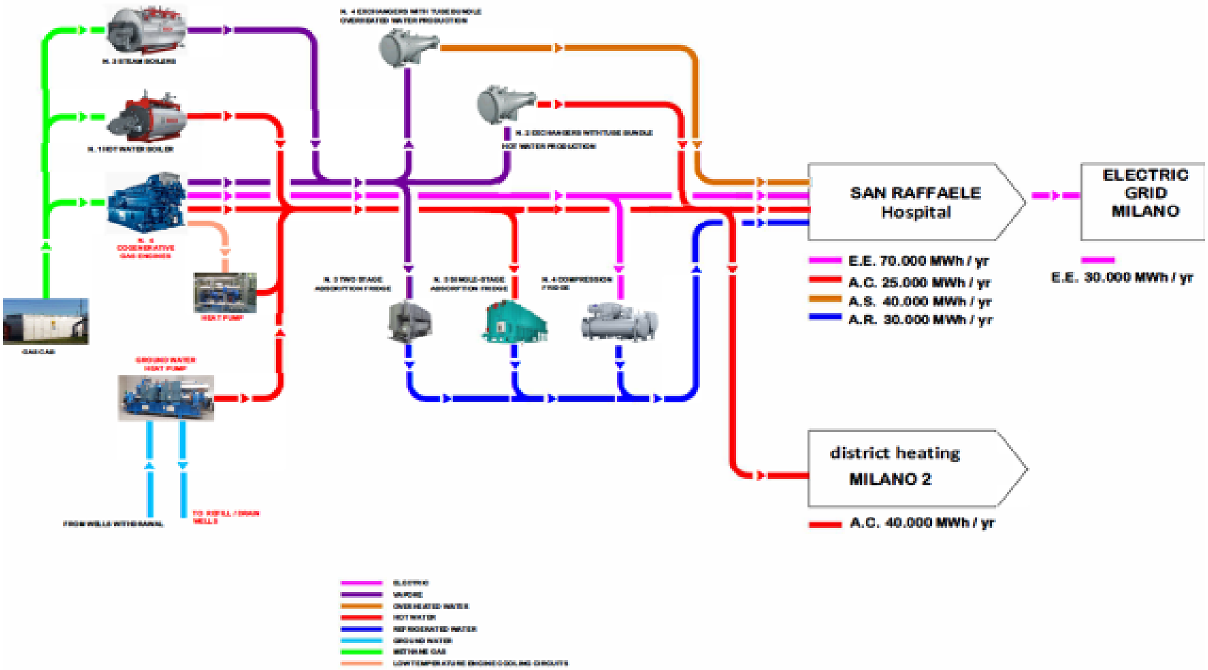


Figure 7 – Co-generator capacity palnt and multi-vector energy sourcing in MWh/yr

II.1.3. Availability of Renewable Energy Sources

As of 1st April 2022, no existing and/or planned PV infrastructure is expected in OSR structures. However, the high potential for renewable energy sources (like PV) could be considered according to the computed Degree Day[1] patterns across the 2021 and 2022 as shown in Figure 8 below. Reference is for both OSR and SEGRATE areas.

Clearly, the very low Degree Days in the spring-summer periods for Pilot 3 in Italy is due to high pressure/high solar expositions. This condition would reveal ideal to consider for PV energy source utilization and dispositions.

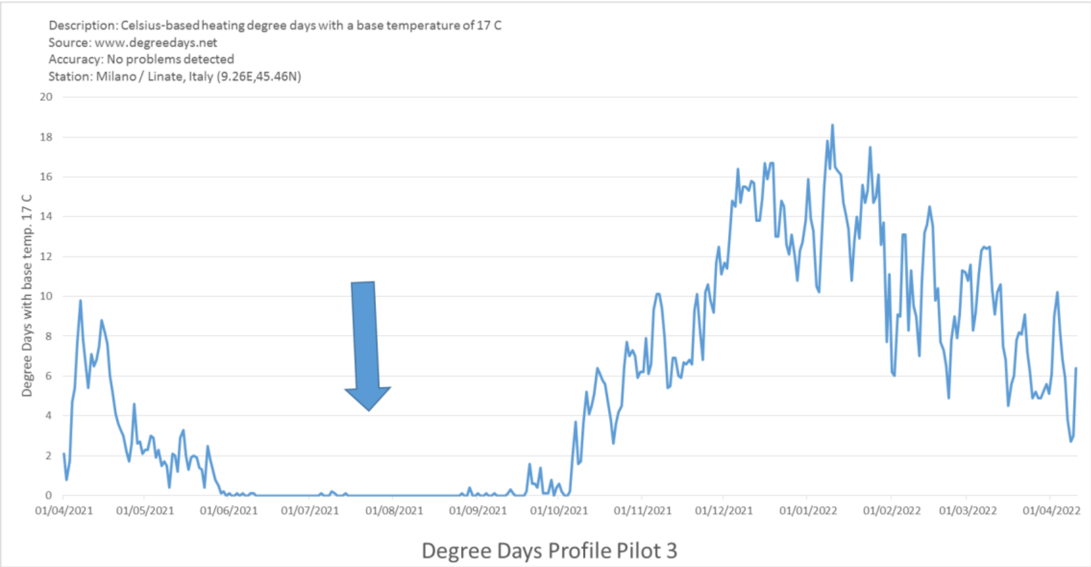


Figure 8 - The degree days profile from 2021 and 2022 for Pilot 3

II.1.4. OSR energy consumption trends

Figure 9 below gives scope and perspective about the expected OSR electric demand in MWh per month. Past trends between 2017 to 2019 period in OSR complex is reported.

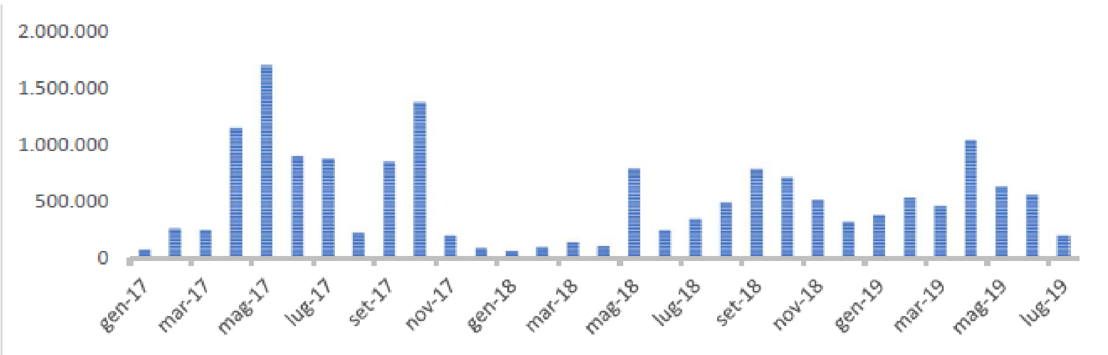


Figure 9 – Estimate of monthly electricity consumption in OSR (2017-2019) in MWh

[1] A Degree Day is unit used to determine the heating requirements of buildings, representing a fall of one degree below a specified average outdoor temperature (usually 18°C or 65°F) for one day

The OSR main source for electricity/heat supply is by the co-generator natural gas consumption. It's natural gas consumption in m^3 is trended across the same three past years (2017-2019) and reported below in Figure 10.

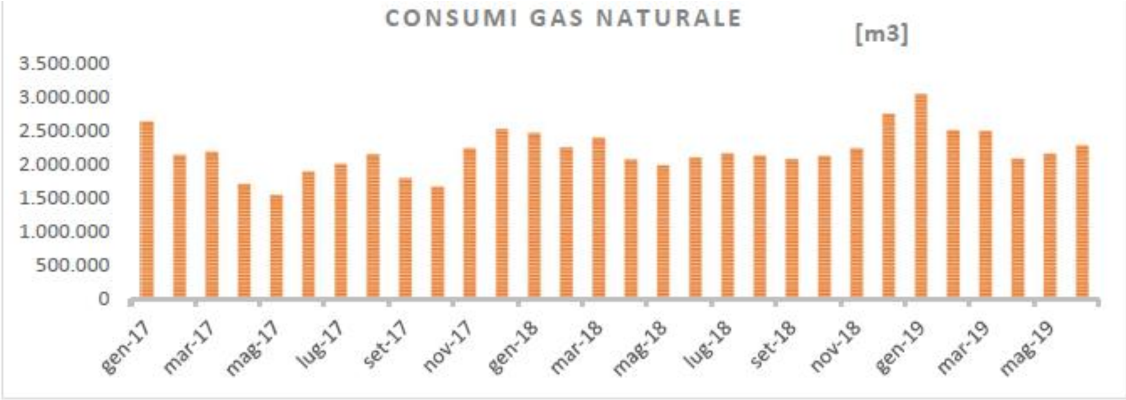


Figure 10 – Monthly gas (m3) consumption in OSR (2017-2019)

II.1.5. OSR Stakeholders

The stakeholders[2] as formally defiend by OSR are split into the following three broad areas with differentiable multi-vector energy needs and processes:

I. **HOSPITAL area** (this is the **less flexible area** to optimize as the patients and operators **cannot afford energy unbalances** for obvious reasons)
   a. Over 1340 beds;
   b. +50 hospital specialties (e.g., Ankle and Foot Surgery, Arrhythmology and Electrophysiology, Bariatric Surgery, Breast Surgery, Cardiac Surgery, Cardiology, Dentistry, Dermatology, Diagnostic Imaging, General Medicine, General Surgery, Gynaecology and Obstetrics, Etc.)

II. **FOUNDATION area** (Professionals and Administrators in Administration, Research offices, Diagnostics and Laboratories, Administration/Secretariat)
   a. Researchers: over 1,500 scientists, working in state-of-the-art facilities covering a surface of 130,000 square meters

III. **UNIVERSITY area** (Personnel, Management, Students, Professors, Assistants)
   a. Complete Medical School (including specialty courses and residencies), Nursing School, a Psychology graduate and post-graduate programs, and Allied health Professions School.

It is very relevant to note that the **FOUNDATION** and **UNIVERSITY areas** are the core focus/areas for RENergetic Project. This is due to the fact that they contain useful level and variation of energy flexibility required to search for AI oriented optimizations and socio-technical solutions for higher EI efficiency, autarky and renewability goals. Figure 11 locates the areas in the OSR panorama.

[2] *this descriptior in this section does reflect real name in OSR and not necessarily reflects the descriptors views in other deliverables of the Project.*

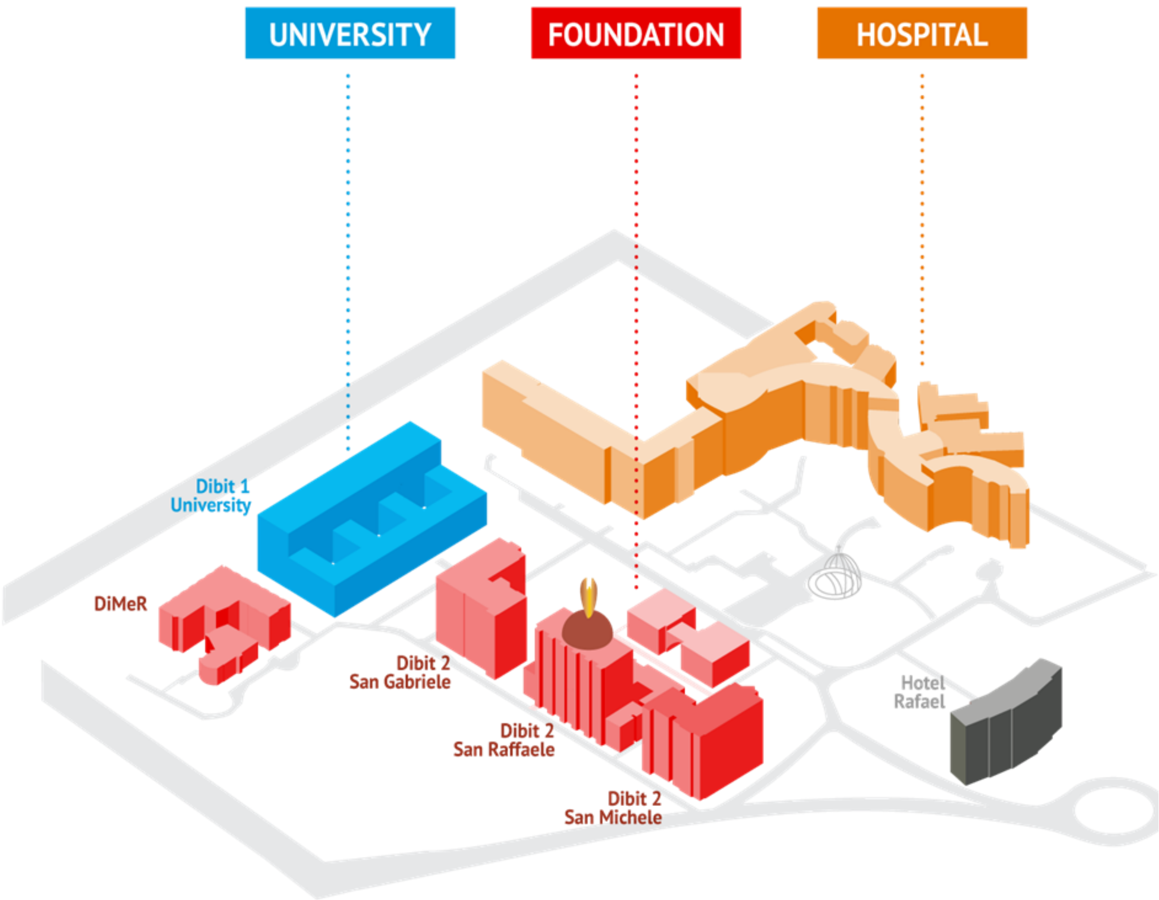


Figure 11 – OSR main Stakeholder areas for RENergetic: FOUNDATION + UNIVERSITY

II.1.6. OSR Roles

As shown in Figure 12, all *stakeholders (Personae)* and *roles* [3] related to Ospedale San Raffaele are divided in:

- Gruppo Sand Donato (GSD = Owner/Holding of OSR)
    - High level management
    - Energy manager
- Ospedale San Raffaele (OSR)
    - High level management
    - Technical department 1 _ Technical experts
    - Technical department 2 _ Operators
    - Hospitals employees _ Clinicians
    - Hospitals employees _ Administrative
    - Commercials
    - Professors / Teachers
    - Students
- Energy Island
    - Energy Manager (production & control of demand/consumption)
    - Plant Energy Manager (Co-generator supply)

[3] *all descriptors in Figure 12,13,14,15,17, 18, 19 and 20 are finer-grained descriptions than standard more generic descriptors of roles and stakholders in Del 7.4*

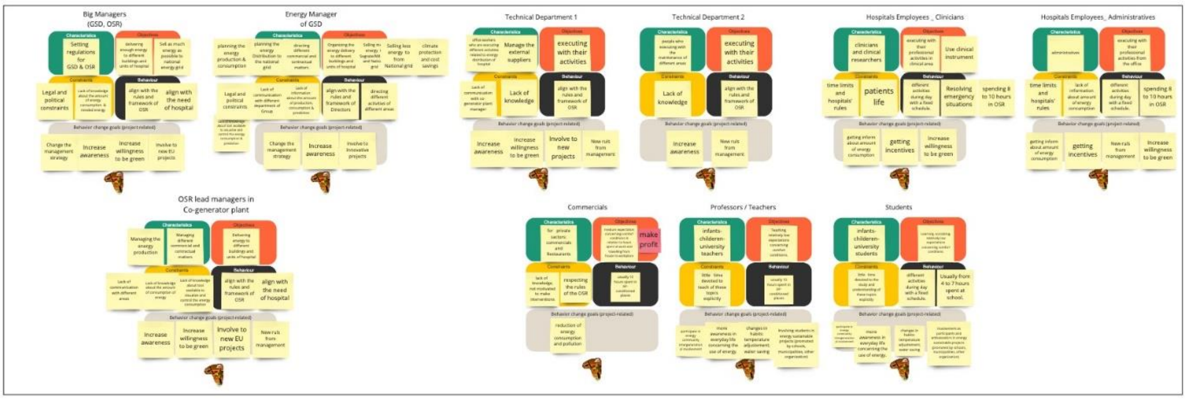


Figure 12 – OSR Stakeholders and full roles

After an in-depth OSR analysis in the first 6 months (2021) of the Project, the following personas/roles were further defined and specified in Figure 13.

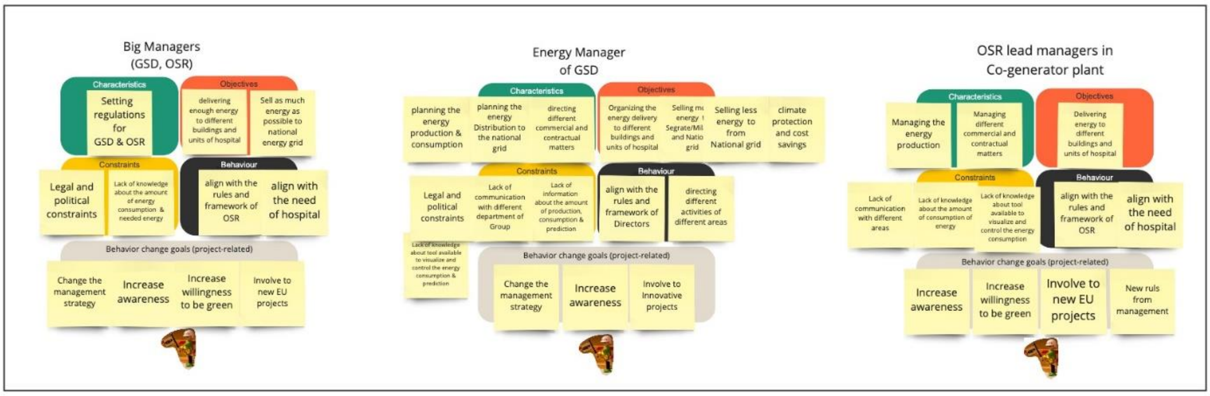


Figure 13 – OSR Energy Management roles refined

High level managers of GSD & OSR: Are the ones who are setting the regulations to be able to deliver enough energy to different buildings and units of hospital. They also decide how much energy from energy island is possible to sell to the national energy grid.

There are some constraints in legal and political level i.e. Lack of knowledge about the amount of energy consumption and forecasting of needed energy for internal use of the hospital. What they need to do is aligning the rules, framework and needs of OSR. This sometimes implies to change the management strategy. increase awareness, willingness to be green and involve to new projects (e.g., EU, innovation, etc.).

Energy Manager of GSD: Is the one who is planning the energy production, planning the energy Distribution to the national grid and directing different commercial and contractual matters.

In his activities he needs to reach some important objectives: organizing the energy delivery to different buildings and units of hospital, selling more energy to Segrate/Milano2 and National grid, buying less energy from National grid and finally climate protection and cost savings.

The constraints that he faces are: Legal and political constraints, lack of communication with different department of Group, lack of information about the amount of production, consumption and prediction, lack of knowledge about tool available to visualize and control the energy consumption and prediction.

There are some changes which can help him improve his work such as: Change the management strategy and increase awareness.

Plant Energy Manager (Co-generator supply): Is the one who is managing energy production, different commercial and contractual matters to be able to deliver the needed energy to different buildings and units of hospital.

There are some constraints such as: Lack of communication between energy island and different areas, lack of knowledge about the amount of energy consumption, lack of knowledge about tools available to visualize and control the energy consumption.

He needs to align with the rules and framework of OSR and align with the need of hospital. But he also needs to increase awareness, willingness to be green, involve to new projects (e.g., EU, innovation,etc) and maybe receive new rules and regulation from management.

The Technical operations and departments are depicted in Figure 14.

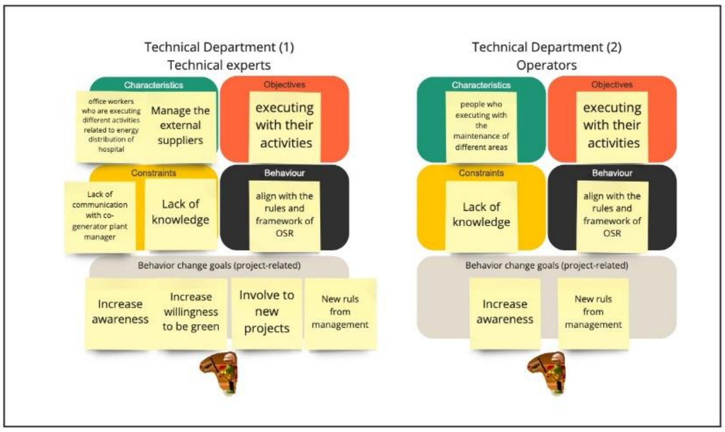


Figure 14 – OSR Technical Departments and roles

Technical department 1 _ Technical experts: Are engineers who are working mostly from the office and are executing different activities related to energy distribution of hospital and managing the external suppliers.

To execute their activities there are some constraints such as lack of communication with co-generator plant manager and lack of knowledge

What they have to do is to be aligned with the rules and framework of OSR and Increase their awareness, willingness to be green, involve to new projects and new rules from management.

Technical department 1 _ Operators: Are people who are executing with the maintenance of different areas.

Usually they are external contractors/suppliers. To execute their activities there have some constraints such as lack of communication with direct responsible and most of the time there are lack of knowledge.

They need to align with the rules and framework of OSR, increase awareness and receive new rules from management.

Figure 15 shows Hospital’s main operators about the medical domain as well as the research and university roles.

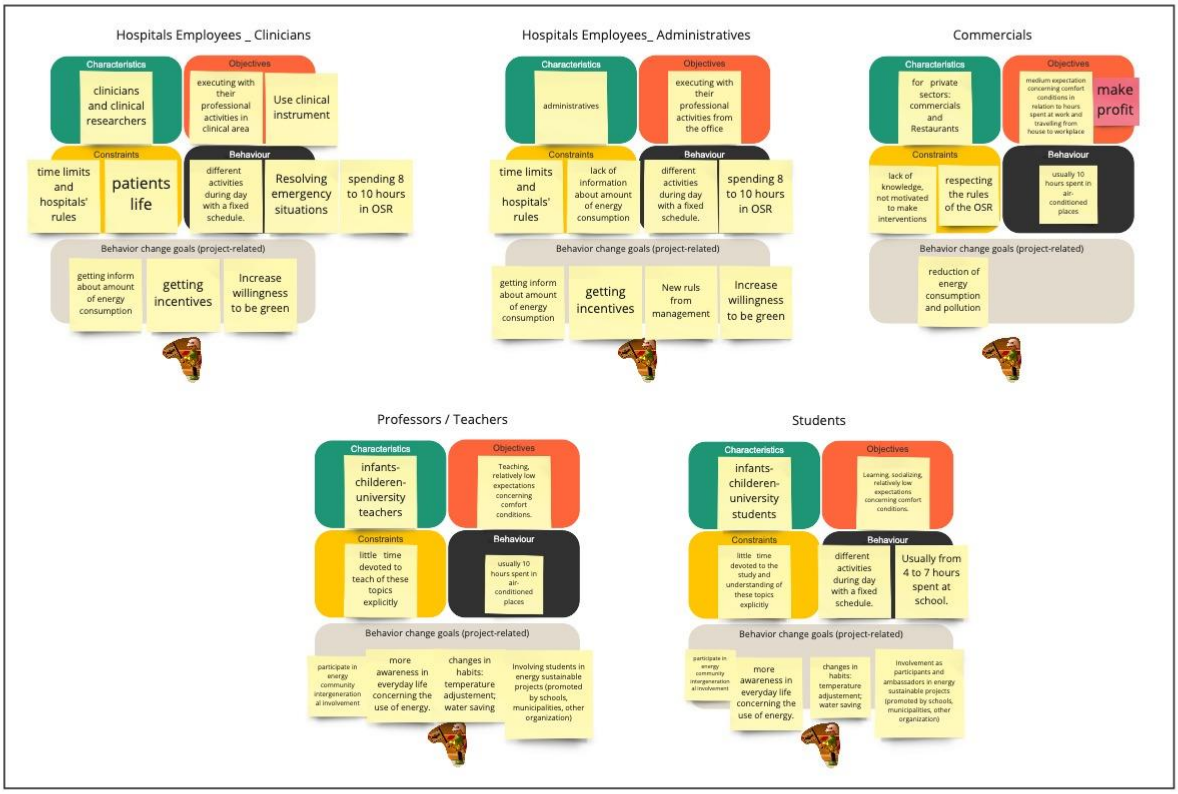


Figure 15 – Hospital's roles in OSR

Hospitals employees _ Clinicians: Are clinicians and clinical researchers who are executing their professional activities in the clinical area by using clinical instruments.

The main constraint for the clinicians is the time limit and patients' life.

There are different activities during the day with a fixed schedule. They are faced with lots of emergency situations which they have to resolve.

Usually, they spend 8 to 10 hours inside of the hospital and their priority is saving people's life and health issues. Therefore, they need to be informed about the amount of their energy consumption, get incentives and increase willingness to be green.

Hospitals Employees/Administrative: Are the ones who are executing their professional activities from the office with time limits of 8 to 10 hours a day by respecting hospitals' rules. They proceed with their activities by doing different activities during the day with a fixed schedule.

Their main constraint is lack of information about the amount of energy consumption. This said, they need to get informed in this regard, get incentives, and new rules and strategies from management and finally they need to Increase their willingness to be green.

Commercials: Are private restaurant, bar, supermarket and other commercial activities inside of the hospital.

Their main objective is making profit and their expectation concerning comfort conditions is related to the hours spent at work.

Their main constraints are lack of knowledge and inability to make interventions respecting the rules of the OSR.

Sometimes they feel the need for energy consumption and pollution reduction.

Professors / Teachers: Are university professors, infants and children's teachers.

They have relatively low expectations concerning comfort conditions.

Their main constraint is that usually they spend 10 hours a day in air-conditioned places and little time devoted to teaching these topics explicitly

- Participate in energy community
- Intergenerational involvement
- More awareness in everyday life concerning the use of energy.
- Changes in habits: temperature adjustment; water saving

Students: Mostly university students, Masters and PhDs with relatively low expectations concerning comfort conditions. Also:

1. Little time devoted to the study and understanding of these topics explicitly
2. Different activities during day with a fixed schedule.
3. Usually from 4 to 7 hours spent at school.
4. Participate in energy community intergenerational involvement
5. More awareness in everyday life concerning the use of energy.
6. Changes in habits: temperature adjustment; water saving
7. Involved to Innovative projects
8. Involvement as participants and ambassadors in energy sustainable projects (promoted by schools, municipalities, other organization)

II.2. Descriptions of SEGRATE

Segrate is a Municipality in Milan metropolitan area, close to Milan on east. It is 17,49 sqkm wide, it has 35.234 inhabitants with a density about 2.000 inhabitants per sqkm. Segrate layout is shown in Figure 16. As it happened in many municipalities in the close ring of Milan, Segrate is a recent settlement that grew from the sixties of the XX century from a rural origin. Segrate never had a strong industrial core and it developed mainly as residential settlement with some tertiary excellences: Mondadori (designed by Niemeyer), Fininvest, IBM, Microsoft (now moved).

The city was designed by separated neighborhoods, some of which with a very high quality of urban fabric and architecture. In Segrate there is a very strong presence of wide scale infrastructures: the Forlanini Airport (Linate), three multimodal logistic centers, high speed train lines, the two main roads that connect the east of Lombardy to Milan (Segrate occupies the "last mile" of the highway BRE.BE.MI). The environmental impact of such big infrastructures is extremely relevant, considering both the occupation of soil and the impact of activities and induced traffic.

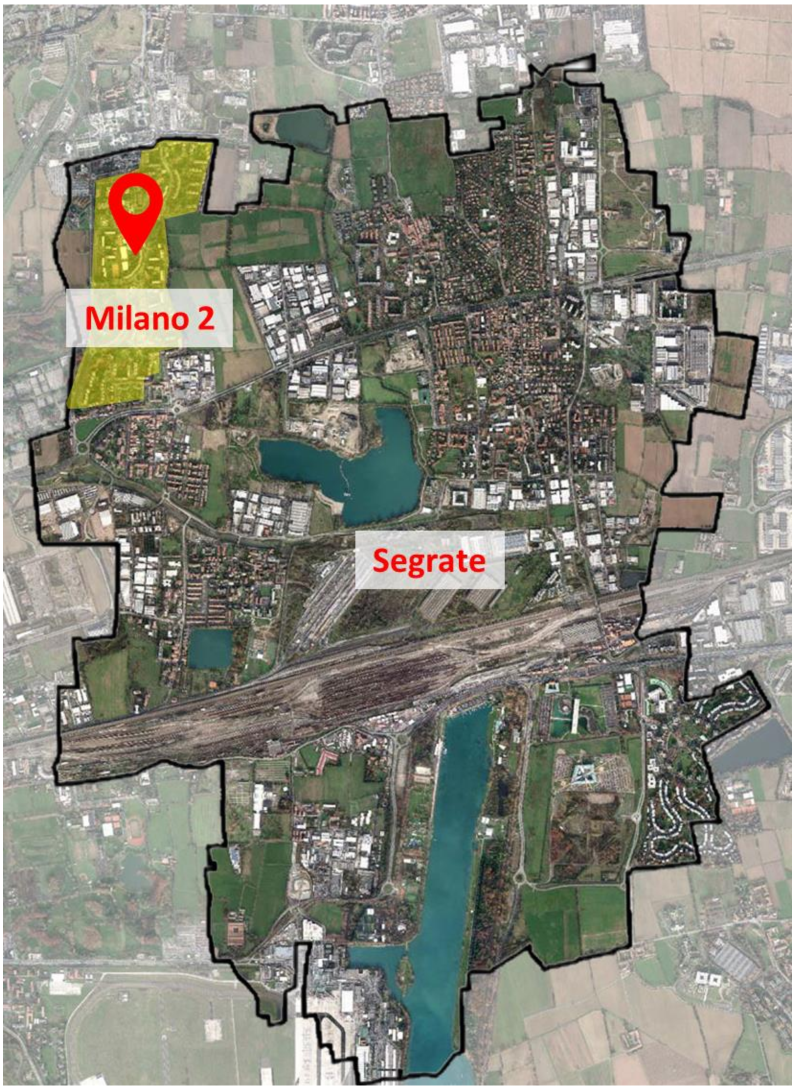


Figure 16 - Segrate municipality and Milano 2 neighbourhood – Pilot Site 3

Segrate is composed by 7 recognizable neighborhoods that were built with an independent system of mobility and energy supply. Milano 2 is one of these neighborhoods that is close to OSR (part of OSR is in Segrate Municipalty, part is in Milan Municipality). The territorial division of the neighborhoods, together with the high level of public services equipment and their isotropic distribution in the different neighborhoods, are robust reasons to deploy the optimization of supply and demand analyzed in OSR into a real city context.

II.2.1. Local Settings and Infrastructure

As already explained, Segrate Municipality represents a peculiar case study: from the legal and contractual point of view, the neighbourhood Milano 2 is a very complex organized system. From a top-down point of view,. it is possible to recognize 5 levels of organization (and each level is supported by specific laws):

1. Municipality level;
2. Neighbourhood level;
3. Superblock level;
4. Building level;
5. Single private apartment/small business owners.

From level 1 to level 4, there are specific roles appointed to represent the group they belong to. In particular:

- Municipality level:
    - Political figures: Segrate Mayor, Assessor for City Planning, Assessor for Milano 2 Neighbourhood; Segrate City Council;

  Management figures: Director of Territory and private building, General Secretary, Energy Manager;
    - Technical figures: Public works group, mobility and viability group, urban planning group, public buildings management group, energy management group, environment group;
- Neighbourhood level: Neighbourhood manager, Neighbourhood council;
- Superblock level: Superblock manager, superblock energy management;
- Building level: building manager, building energy management;
- Single private apartment/small business owners: individuals or families.

Because the neighbourhood represents the real city complex system, the relations among all the citizen and the involved subjects (in the different levels) is rarely linear; it implies that the organizational levels cannot be considered as separated layers. The clearest definition for this urban context is: heterogeneous-organized order, that aims to define a hybridization between the classic top-down scheme (visible in all the monofunctional and directly controlled contexts) and the bottom-up governance (that characterizes the highest level of democratic and liberal administration model).

The implications here is that multiple stakeholders bring different agendas on the RENergetic table. Therefore, the selection of specific energy strategies, Project Epics and User stories necessitate careful balance between multiple interests, not only at Municipality level (political vs technical objectives) but also at Neighbourhood, Superblock, Building as well as single private citizen level.

II.2.2. Local Stakeholders and Roles

After an in-depth analysis in the first 6 months of the Project, the following personas were defined in Figure 17, 18, 19, and 20 separately as all SEGRATE stakeholders (Personae) in Milano2. These are divided in:

- Private:
    - Inhabitants/house holders
    - Small business owners
    - Workers/City users
    - Students
- Municipality:
    - Politicians
    - Municipality technician
    - Municipality energy manager
- Contractual units:
    - Neighbourhood manager
    - Superblock manager
    - Building manager

- Energy provider:
  - Public energy provider (for electricity – national grid)
  - Private energy provider (for heat – OSR)
  - Comunione Calore
  - Guldbransen

II.2.2.a. Private

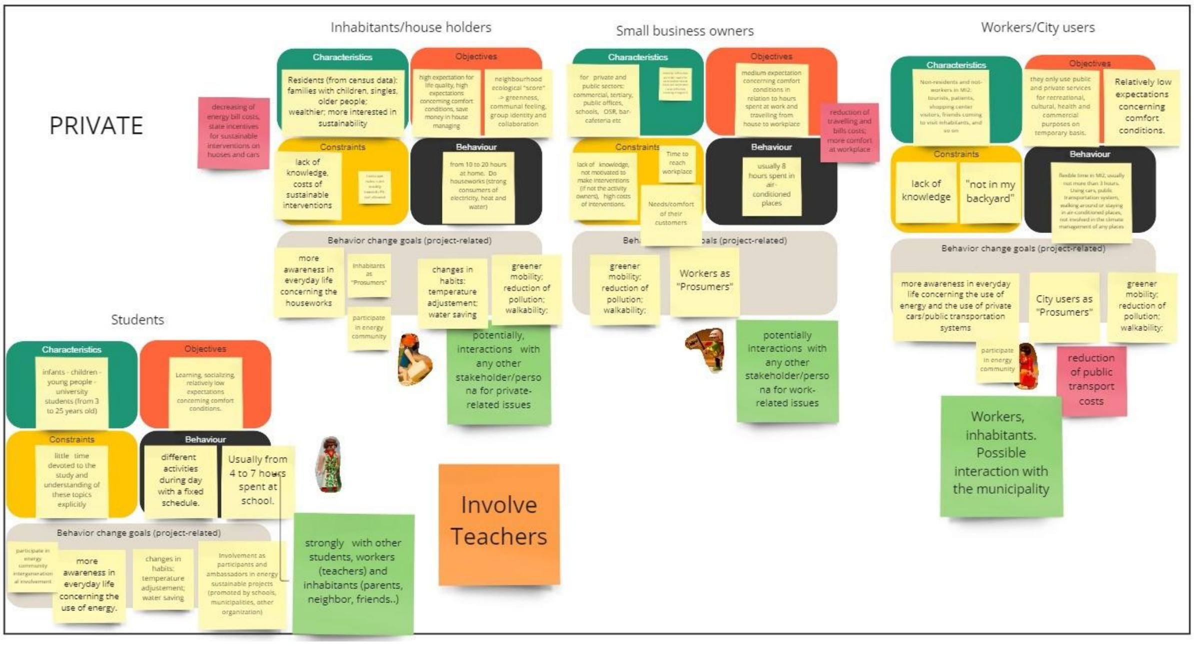


Figure 17 - Personae - Milano 2 Private stakeholders

Inhabitants/house holders: Residents (from census data) - families with children, singles, elder with high expectation for life quality, high expectations concerning comfort conditions, and with an ideal goal of saving money in house managing. They spend from 10 to 20 hours at home and do housework (strong consumers of electricity, heat and water). The most relevant barriers to achieve their scopes are the lack of knowledge about energy related topics and the costs of sustainable interventions (on houses and life-style changes). Possible incentives that can aid participation in REN project are decreasing of energy bill costs, incentives for sustainable interventions on houses and cars from the State. In the general framework of Milano 2, they can have interaction potentially with any other stakeholder/persona for private-related issues.

Workers: Identified as people that work in Milano 2 (for private and public sectors: commercial, tertiary, public offices, schools, OSR, bar-cafeteria etc.). They usually spend 8 hours in air-conditioned places, and have medium expectation concerning comfort conditions in relation to hours spent at work and travelling from house to workplace. The most relevant barriers to achieve their scopes are the lack of knowledge about energy related topics, the lack of motivation to make interventions (if not the activity owners) to improve energy efficiency, high costs of interventions, and time to reach their workplace. Possible incentives that can aid participation in REN project are reduction of travelling and bills costs; more comfort at workplace. In the general framework of Milano 2, they can have interaction potentially with any other stakeholder/persona for private-related issues.

Students: Are infants - children - young people - university students (from 3 to 25 years) that aim at learning, and socializing, with a relatively low expectations concerning the comfort conditions of buildings and public spaces. They perform different activities during day with a fixed schedule; usually they spend from 4 to 7 hours at school. Here, the most relevant barriers are little time devoted to the study and understanding of these topics explicitly. The involvement in RENergetic can create more awareness in everyday life concerning the use of energy. Moreover, they can become participants and ambassadors in energy sustainable projects (promoted by schools, municipalities, other organization). In the general framework of Milano 2, they have strong connections with other students, workers (teachers) and inhabitants (parents, neighbours, friends).

City users: Are defined as non-residents and not-workers in MI2: tourists, patients, shopping center visitors, friends coming to visit inhabitants, and so on. They only use public and private services for recreational, cultural, health and commercial purposes on temporary basis. Relatively low expectations concerning comfort conditions. They have flexible time in MI2, usually spending not more than 3 hours here. They use cars, public transportation system, walk around or stay in air-conditioned places, not involved in the climate management of any places. So, they are not interested in the implementation of any actions related to energy issues in this context. The only incentives possible that can aid the participation in RENergetic project is reduction of public transport costs. The involvement in RENergetic can create more awareness in everyday life concerning the use of energy and the use of private cars/public transportation systems transforming them in "Prosumers". In the general framework of Milano 2, they have connection with workers and inhabitants, maybe also with the municipality.

*II.2.2.b. **Municipality***

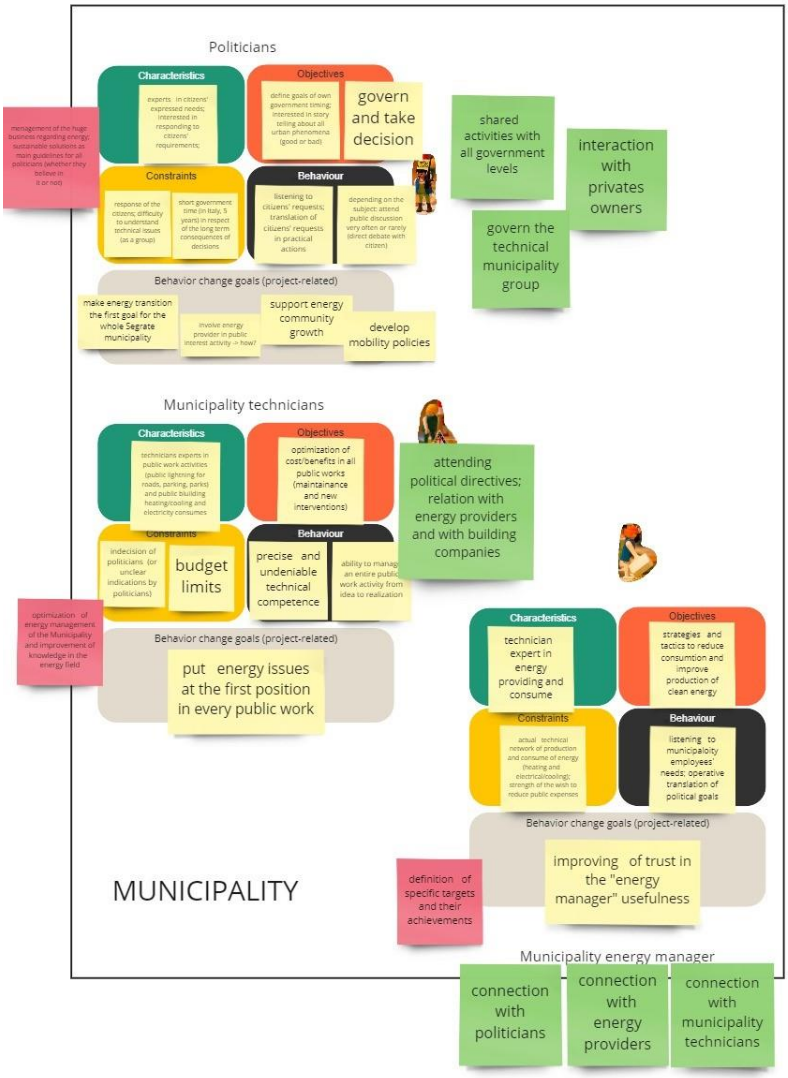


Figure 18 - Personae - Milano2 Municipality stakeholders – source: Miro Board on Segrate Pilot site

Politicians: Are experts in citizens expressed needs and interested in responding to citizens' requirements (they are elected by citizens). They listen to citizens' requests and translate citizens' requests into practical actions; they attend public discussion very often or rarely (direct debate with citizen). They want to define goals of own government timing; they are interested in story telling about all urban phenomena; they govern and take decisions on the all-municipal territory. Some of the most relevant barriers that can constraint participation in REN project are: response of the citizens; difficulty to understand technical issues (as a group); short government time (in Italy, 5 years) in respect of the long-term consequences of planning decisions. Furthermore, possible incentives that can aid participation in REN project are the management of the huge business regarding energy and the definition of sustainable solutions as main guidelines for all politicians. The involvement in RENergetic can make energy transition the first goal for the whole Segrate municipality and can ease the involvement of energy provider in public interest activity. In the general framework of Milano 2, politicians share activities with all government levels, have interactions with private owners, and guide the technical municipality group.

Municipality energy manager: Is a technician expert in energy providing and consume that listens to municipality employees' needs and performs the operative translation of political goals. He defines strategies and tactics to reduce consumption and improve production of clean energy. Some of the most relevant barriers that can constraint participation in REN project are actual technical network of production and consume of energy (heating and electrical/cooling), and the strong desire to reduce public expenses. Furthermore, possible incentives that can aid participation in REN project are the definition of specific targets and their achievements. The involvement in RENergetic can improve the trust in the "energy manager" usefulness. In the general framework of Milano 2, he has connection with energy providers, politicians and municipality technicians.

Municipality technicians: Are technicians and experts in public work activities (public lightning for roads, parking lots, parks) and public building heating/cooling and electricity consumption. They have precise and undeniable technical competence; ability to manage an entire public work activity from idea to realization. They aim at optimizing cost/benefits in all public works (maintenance and new interventions). Some of the most relevant barriers that can constraint participation in REN project are budget limits and unclear indications by politicians. Possible incentives that can aid participation in REN project are the optimization of energy management of the Municipality and the improvement of knowledge in the energy field. The involvement in RENergetic can put energy issues at the first position in every public work. In the general framework of Milano 2, they attend political directive, have relation with energy providers and with building companies.

II.2.2.c. ***Contractual units***

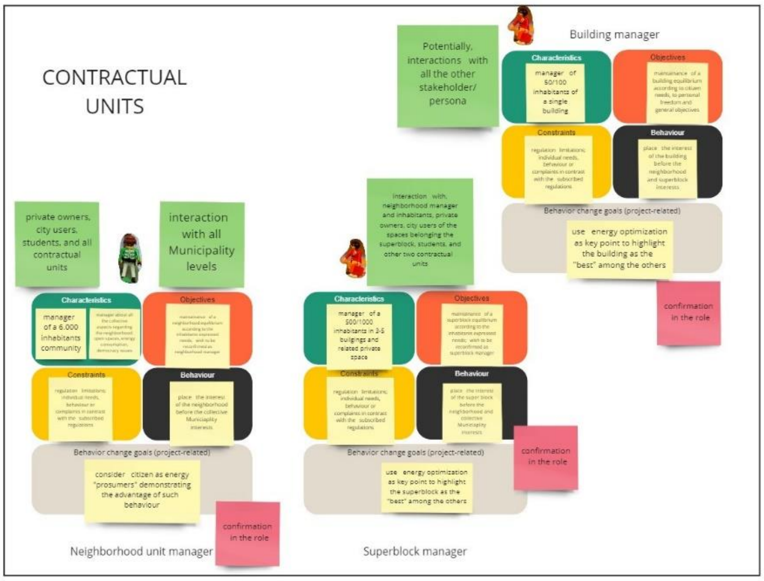


Figure 19 - Personae - Milano2 "Contractual units" stakeholders – source: Miro Board on Segrate Pilot site

Neighbourhood unit manager: Is the manager of a 6.000 inhabitants' community, manager about all the collective aspects regarding the neighbourhood (i.e., open spaces, energy consumption, democracy issues); he places the interest of the neighbourhood before the collective Municipality interests. He maintains a neighbourhood equilibrium according to the inhabitants' expressed needs; he works accordingly to his wish to be reconfirmed as neighbourhood manager. Some of the most relevant barriers that can constraint participation in REN project are regulation limitations; individual needs, behaviour or complaints in contrast with the subscribed regulations. The most appealing incentive that can aid participation in REN project is his confirmation in the role. The involvement in RENergetic could help to consider citizen as energy "prosumers" and demonstrate the advantages of such behaviour. In the general framework of Milano 2, he has interaction with all Municipality levels, private owners, city users, students, and all contractual units.

Superblock manager: Is a manager of a 500/1.000 inhabitants in 3-5 buildings and related private spaces. He places the interest of the superblock before the neighbourhood and collective Municipality interests. His main objective is the maintenance of a superblock equilibrium according to the inhabitants' expressed needs. Moreover, he works accordingly to his wish to be reconfirmed as superblock manager. Some of the most relevant barriers that can constraint participation in REN project are regulation limitations; individual needs, behaviour or complaints in contrast with the subscribed regulations. The most appealing incentive that can aid participation in REN project is his confirmation in the role. The involvement in RENergetic could help using energy optimization as key point to highlight the superblock as the "best" among the others. In the general framework of Milano 2, he interacts with neighbourhood manager and inhabitants, private owners, city users of the spaces belonging to the superblock, students, and other contractual units.

Building manager: Is the manager of 50/100 inhabitants of a single building and places the interest of the building before the neighbourhood and superblock interests. His main objective is the maintenance of a building equilibrium according to citizen needs, to personal freedom and general objectives. Some of the most relevant barriers that can constraint participation in REN project are regulation limitations; individual needs, behaviour or complaints in contrast with the subscribed regulations. The most appealing incentive that can aid participation in REN project is his confirmation in the role. The involvement in RENergetic could help using energy optimization as key point to highlight the building as the "best" among the others. In the general framework of Milano 2, he has interactions with all the other subjects.

II.2.2.d. ***Energy Provider***

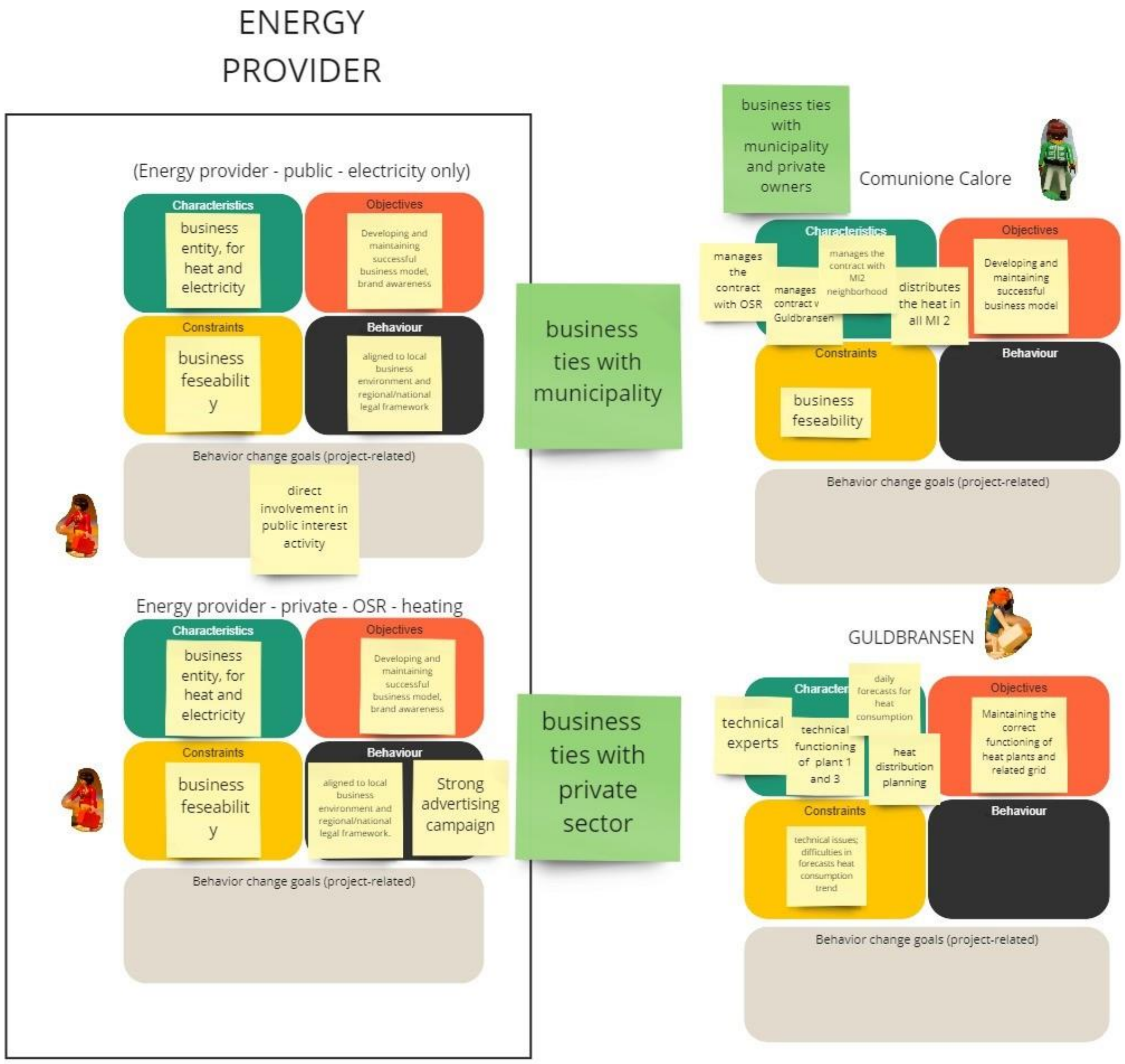


Figure 20 - Personae - Milano2 Energy providers stakeholders – source: Miro Board on Segrate Pilot site

Public sector energy provider: Is a business entity, for heat and electricity (here only for electricity) that aims at developing and maintaining successful business model. It is aligned to local business environment and regional/national legal framework. Here, the most relevant barrier to the development of a new, more efficient and more sustainable kind of energy supply is the business feasibility. The involvement in RENergetic could define strategies and actions to start and enhance energy transition process. In the general framework of Milano 2, it has business ties with municipality.

Private sector energy provider: Is a business entity, for heat and electricity (here the OSR-Vimodrone cogenerator is a heat provider only) that aims at developing and maintaining successful business model. It is aligned to local business environment and regional/national legal framework and makes strong advertising campaign Here, the most relevant barrier to the development of a new, more efficient and more sustainable kind of energy supply is the business feasibility. In the general framework of Milano 2, it has business ties with private sector (mainly) and public sector (because it is the heat provider also for the public buildings in Milano2).

In Milano 2, there are two more entities related to the energy provider sectors: both entities are not formally in the RENergetic consortium, therefore they are less confident in active participation with personell hours in RENergetic for such basic reason they are not in the Project.

Comunione Calore: Is a legal entity that distributes the heat in Milano 2 neighbourhood and manages the contract (for heat supply and internal technological infrastructure) with OSR, Milano 2 neighbourhood and Guldbransen (see next paragraph) and it wants to develop and maintain a successful business model. Here, the most relevant barrier to the development of a new, more efficient and more sustainable kind of energy supply is the business feasibility. In the general framework of Milano 2, it has business ties with municipality (it manages also the heat supply to the public building in Milano 2) and private owners. As a reminder: Milano 2 receives 11MW from OSR-Vimodrone cogenerator and owns 2 internal plants that can be activated if the heat demand exceeds the 11MW threshold (rarely activated per year).

Guldbransen: Is a business entity with technical experts that takes care of the correct technical functioning of the internal heat plants and related technological infrastructure. It also provides daily forecasts for heat consumption and for the heat distribution planning. The most relevant barriers that can constraint participation in REN project are technical issues and difficulties in forecasting heat consumption trend. Moreover, in the general framework of Milano 2, it has direct connections only with Comunione Calore.

II.3. Business Models: OSR-SEGRATE-Cogenerator

The present business model between OSR and SEGRATE is based on the OSR Cogeneration plant supplying OSR and Milano 2 (part of SEGRATE) for thermic energy.

Also, the OSR Cogenerator supplies 100% OSR with Electricity. Notably, the Cogenerator produces and supplies all the electrical energy demanded by OSR but it also plans to regularly sell a surplus additional electricity quantity (planned) to the national grid. The Cogenerator has undoubtedly a business core as energy producer and national re-seller.

However, once the Cogenerator planned electric supply schedule underestimates/overestimates the OSR MW electricity or thermic demand or even in case of a plant block occurrence, then the Cogenerator and OSR are forced to buy electricity from the national grid (at very high costs and discomfort for the users).

The unwanted supply energy imbalances between electricity supplies to OSR versus the Grid servings are events to minimize all the time. Every unplanned energy supply by the Cogenerator returns generally an additional cost in production.

Notably, the OSR energy consumption profiles are divided into two main categories:

1. consumption of hotel type for the well-being of patients and staff:

   Continuous and cover the internal and external lighting, elevators and handling organs, the summer and winter conditioning of the environment, the ventilation of rooms, the preparation of water domestic hot water, laundry and kitchen consumptions

2. consumption more closely related to health functions, or to processing equipment e diagnosis:

   Different duration on a case-by-case basis, relate to equipment diagnostics, the air treatment of operating rooms and sterilization of instruments

The expected model of energy segmentation and commercial oriented demand is projected towards the following energy model tailored for the common Hospital environments in Italy (according to trends of Italian National Level benchmarks in 2019). This is shown in Figure 21 with referenced % enery segmentation respectively:

1) 37% natural gas
2) 52% electricity
3) 8% heat (from fluids)
4) 3% other (EVs and renewables)

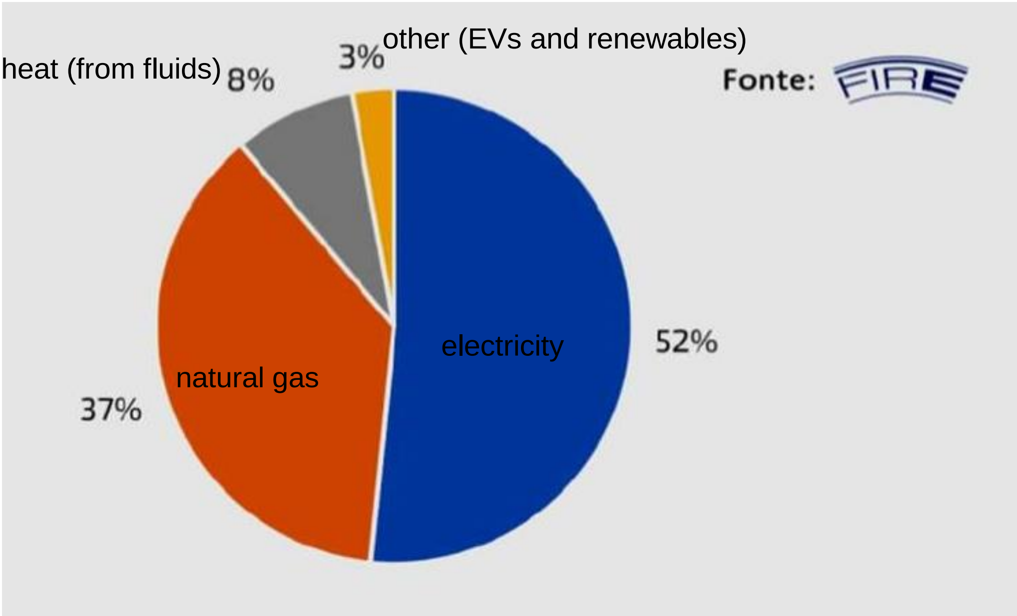


Figure 21 - Model of energy segmentation in Hospitals (FIRE - Italian National Level benchmark, 2019)

III. Detailed description of the actions

III.1. Pilot 3 Strategy

As stated in the *Introduction,* the overall Pilot 3 focused on testable and viable solutions searching for both AI enhanced energy island efficiency, renewability and autarky equipped with replicable social/organisational capacity building fit to real municipality contexts, the Segrate part of the Pilot 3.

Strategic for Pilot 3 is the experimentations on dedicated scenarios of implementation, called Epics (with dedicated User Stories). The main Pilot 3 directions on some selected Epics revolve around the development of AI tools and Machine Learning methods to forecasting intelligence, classification and predictive/prescriptive models to augment *precision energy* or right-fitting the EI energy-demand cycles. Substantially, and according to WP6 tasks, an effort towards designing AI forecasting/predictive methods to scale up to urban city environments.

According to Figure 22, the three RENergetic main Epics covered by this Pilot 3 strategy are Forecasting, Interactive Platform and Charging Stations for Electric Vehicles (EV). It is to note that forecasting is a horizontal asset which is clearly exploitable by all the other Epics developments. **As of 1 April 2022, the Forecasting is the main Epic discussed in this interim Deliverable 6.1.** Other developments and Pilot 3 Epics will follow and be published later on within other Project deliverables.

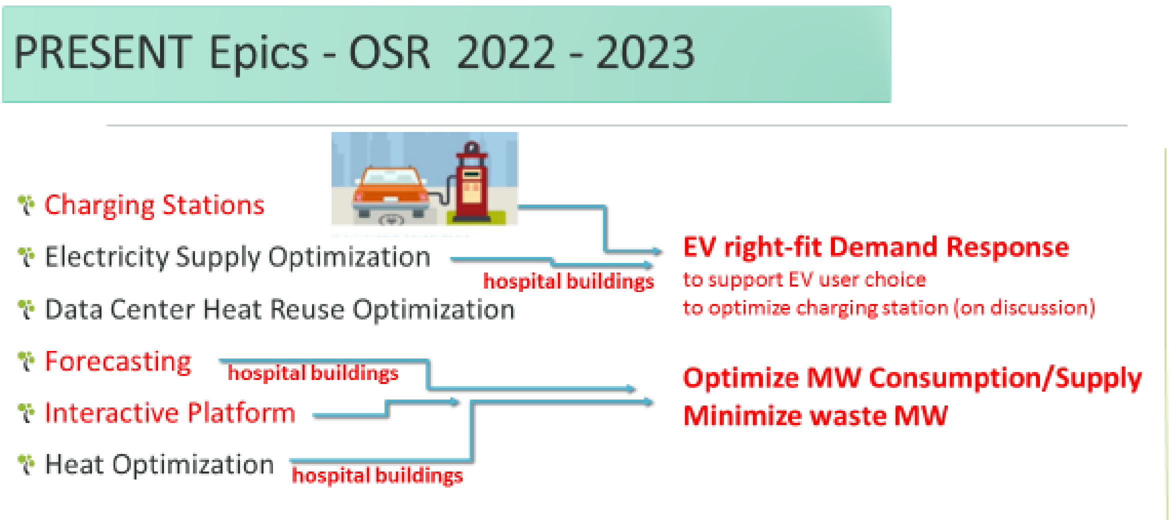


Figure 22 – Present EPICS 2022-2023 for Pilot 3 (focus on AI solution in OSR)

In practical terms, Pilot 3 targets OSR total or building energy intelligence both with supply / demand predictive models, anomaly detection for energy consumption, root cause analysis and simulation, predictive energy efficiency classification, EV charging station optimizations, prescriptive models to minimize energy supply unbalances, predictive models of energy market costs and last, but not least, the Pilot then targets organisational capacity models to reliably implement and deploy such new AI methodologies at scale like the Segrate municipality.

Thus, if OSR part in Pilot 3 deals more with AI methods, the Segrate development team will deal more on how, when who takes such new RENergetic AI services and deploy them into real organisational and social environments: Segrate large-scale municipality.

Overall, with this differentiation, Pilot 3 aims at combining a socio-technical intervention and experimentation altogether.

III.2. Epic: Forecasting

III.2.1. Forecasting approach

The epic Forecasting delivers an energy island capacity to learn patterns in the historical data and provide temporal forward projections in the future about one or more target variables of interest [6] [6]. Such predicted variables being, for instance, energy island consumption or supply of MWh heat or electricity, energy source renewability percentages or specific building efficiency indexes. The application is evidently cross-sectional to the three Pilots available.

The forecasting methods and the algorithms that generate such forecasts will produce new data and information to either inform managers or citizens decision-making process or to directly (automatically) affect and modify the behaviour of an energy actuator directly on a technical system. In the former case, the forecasting acts as a pure decision support system, in the latter case as automatic Artificial Intelligence (AI) controller of the behaviour of a technical energy system.

Notably in both cases, the forecasting capacity is based on data availability and MLOps (Machine Learning Operations) that would deliver, orchestrate and train ML models iteratively on streams of incoming data on a regular basis.

It is evident that this Forecasting epic is fundamentally a horizontal capacity affecting all the other epics due to its all-purpose applicability and serving across multiple functions and cross-epic objectives. Wherever anticipating a response to mitigate risk or optimise solutions is required, so the forecasting and machine learning is.

It is paramount to note that this epic does not limit to pure forecasting function, but several other AI skills are in place. This is depicted in Figure 23 below.

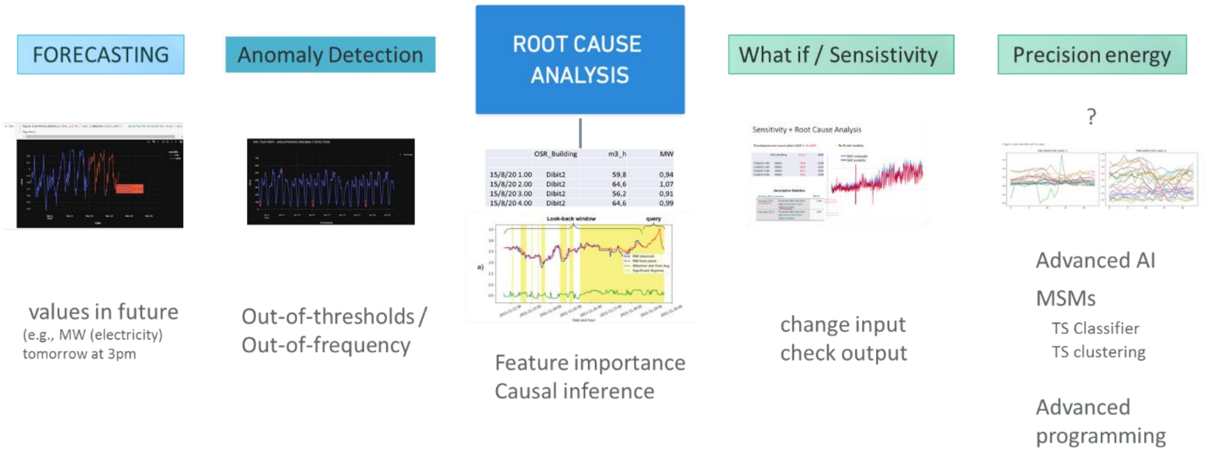


Figure 23 - AI functions within Forecasting epic

In fact, as shown in Figure 23, together with Forecasting, other support functions like Anomaly Detection, Root Cause Analysis, Sensitivity and Precision Energy are accounted for by the Forecasting epic.

In this sense, the pure prediction of values (classic forecasting) is supported and enriched by AI algorithms dedicated to further detect:

- out-of-threshold values (e.g., over-peaking values)
    - The target variable values are being monitored to detect projected too high (or too low) values
    - The detection algorithm is nominal or embedded into the same forecasting algorithm

- feature importance and causal inference (causal factors)
    - In presence of exogenous features supporting the time series prediction, only those features important to the task are retained and identified
    - In some AI algorithms, like Temporal Fusion Transformers, the very shapelet (I.e., profile of the target variable in the time series) can provide evidence on the importance of historical time segments *attentioned* as important to the prediction.
    - Together with detection of important exogenous features or time windows for prediction, some causal inference can be assessed both in model-testing or model building approach interventions. This has relations with sensitivity analysis as well.
- predicted output change due to simulated input change (‘what if analysis’)
    - A trained and tested AI model (algorithm) can be tested by simulation
    - Simulation consists to perturb input randomly (model building hypothesis) or modify input selectively (model testing) to aim at assessing impact on the predicted output.
- meta-predictions or forward oriented precision classifications/predictions based on time-aware energy profile characteristics (precision energy models)
    - A doubly indexed time series classification is operated either from single or multiple data sources. The first time-index is the number instances repeated over time. The second time-index is the lag-order of the time series itself.
    - After a successful time series classification (a dedicated algorithm) with a fixed time series lag-order as by the second index, the classified time series are pooled together backwards and ordered by the first time-index to generate a single composite time series.
    - The composite time series is then forecasted itself by a dedicated algorithm
    - The temporal forward prediction from the preceding step is in turn classified itself by the original pre-trained time series classifier. The result is a classification based on the expected shapelet or *time series profile* of the target variable over time.
    - The result is a precise classification prediction based on future forecasted states or expected future energy profiles.

Such additional four approaches above (bullets 1) to 4)) together with standard forecasting methods are expected to generate a strong leverage on RENergetic AI capacity. An AI business and operational capacity positioned to replicate RENergetic services over any new Pilot involved in the future.

A core vision for forecasting methods in RENergetic is depicted by the following Figure 24.

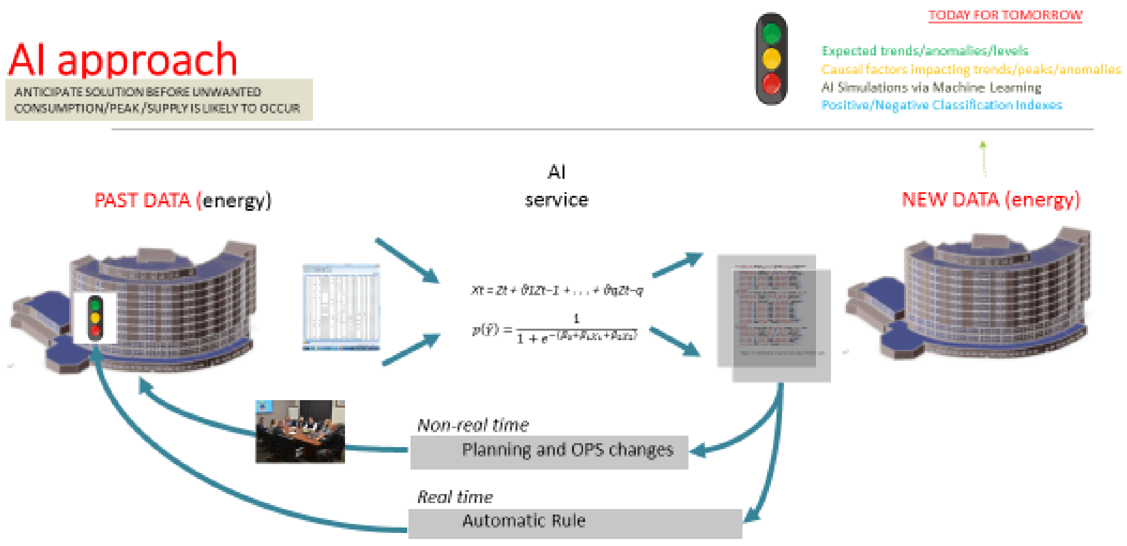


Figure 24 - AI vision and Forecasting concept

According to Figure 24, historical data are streamed and dedicated forecasting, Machine Learning (ML) and Deep Learning (DL) algorithms are trained on such data according to selected Pilot User Stories.

III.2.2. OSR areas covered by Forecasting

As of 1st April 2022, Dibit 1, the OSR large medical university complex of offices and class-rooms), Dibit 2, complex of three large research and administrative buildings as well as the Dimer, a large OSR acceptance building, are the primary OSR locations/areas targeted for the Forecastng Epic applications. All Areas are described in the Figure 25 below.

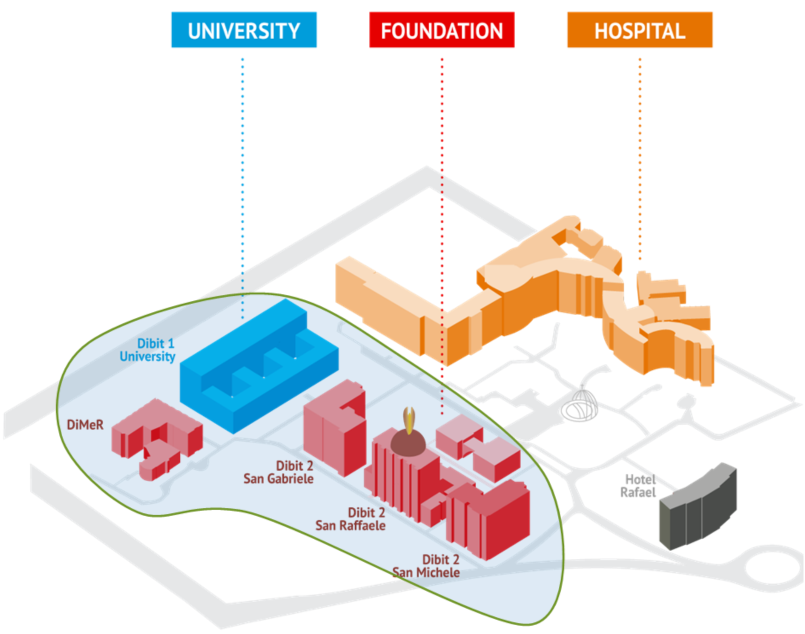


Figure 25 – Dibit 1, Dibit 2 and Dimer for Forecasting Epic

All involved OSR premises cover energy flexible areas involving specifically

Dibit 1		
	(Faculties: medicine/psychology/philosophy)	*n. units*
	University Large Classrooms	(+10)
	University labs + Libraries	(+15)
	University meeting rooms	(+5)
	Univeristy Students, Professors and Administrators	(+2500)
Dibit 2		
	Research offices	(+ 150)
	Research Labs (energy intensive)	(+100)
	Meeting Rooms	(+50)
Dimer		
	Attendance room/Check-in desks (patients/administrators/parents)	(+500/day)

III.2.3. Data models and Locations

III.2.3.a. Data models

Dispositions and predictive data analytics from AI field applications (e.g., Deep Learning, Machine Learning and Statistical modelling) are used to energy demand (or supply) prediction, classification and regression models. In this tyep of applications the following RENergetic DATA MODEL abourt the features involved is considered and presented in Figure 26.

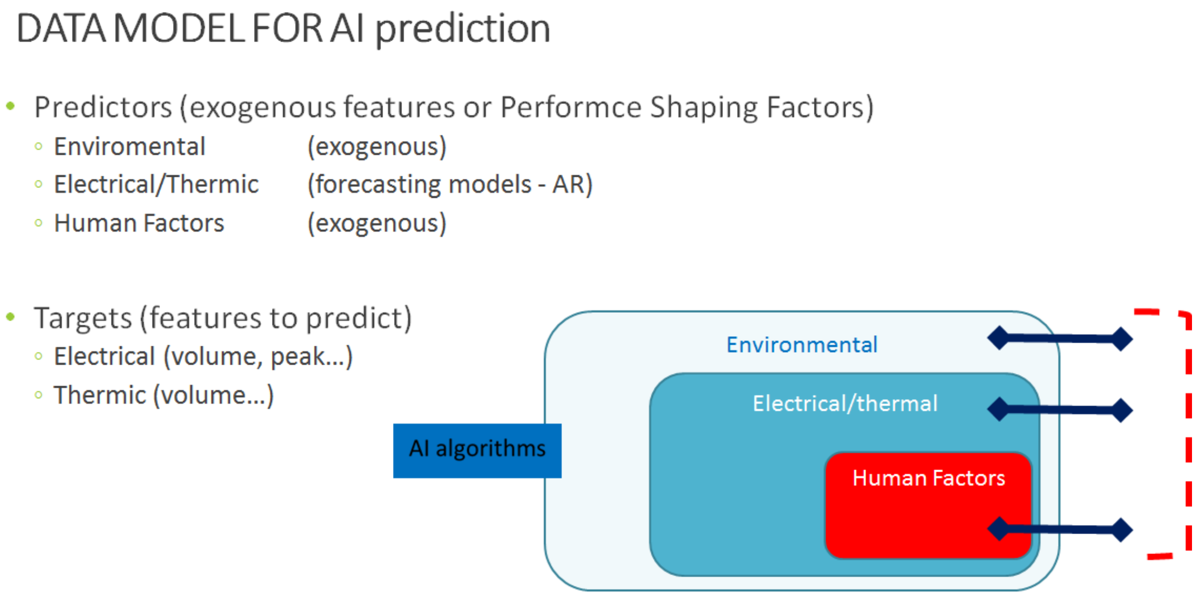


Figure 26 – Data Model for Pilot 3

As shown above in Figure 26, the Targets features (i.e., variables) to forecast (timeseries), predict (regression) or classify (classification) are either electrical or heat vectors (e.g., MWh or KWh, see below) mapped to some Predictor features, being Environmental, Electrical/heat or Human Factors features.

This mapping of Targets to Predictors features is carried out by carefully designed and fine-tuned AI algorithms within the RENergetic software Platform (see WP3 – Forecasting sections). The general mathematical formalization of the objective functions for any AI algorithm is presented in WP3 (Forecasting section).

The AI algorithms learn patterns in the features space available (the data samples available) as part of a much broader set of data requirements to energy forecasting, classification and causal path analysis: the general objective function is to maximise energy autarky, minimise energy waste and optimize multi vector energy impact on global energy targets.

Specifically, the Predictor features to be used are threefold:

1 Environmental: outdoor/indoor Temperature degrees, whether condition categories, outdoor/indoor degree day, time of day, weekday, season, humidity, air pollution levels, etc...

2 Human Factors: occupancy rates (volume of people in buildings), density per building, building activity type, server utilization rates, lab instrumentation, lifts presence and utilization rate, job acvtivity shedulings/workshifts, etc...

3 Electrical Heat vectors: Hot/Refrigerated Water (m3/h), MWh (electricity or heat). Note: in time series models the Predictor and Target feature are the same

Target features (to be predicted): (partial list):

- *MWh* measure (electricity or heat)
  - Demand volume (per hr/day)
  - over-/under-consumption volumes (= actual - planned/programmed)
  - Volume variability (std) (ave per day or week)
  - Used/Planned ratio (planned as benchmark value or norm)*100%
  - Peak severity (e.g., 1=info 2=medim 3=high severity)
  - Peak density (per hr/day/week)
  - Peak frequency (per hr/day/week)
  - Peak distance (per hr/day/week)
  - Unbalance levels (planned – actual sold-to-grid) (per week, day, hrs)
- *REN-Index* measure[4]
  - Index < or > of 0 (breakpoint)
  - Index dimension (ave. day/week)
  - Index Peak density (ave. day/week)
  - Index Peak frequency (ave. day/week)
  - Index Peak distance (ave. day/week)
- *Euro/MWh (known as PUN in Italian Market)*
  - Energy cost prediction (euro) / to sell to or to buy from (grid)

—

Obviously, the forecasting algorithms process the above targets variables/features as feature predictors depending by the autocorrelation or Deep Learning model assumed by the analysis.

III.2.3.b. Locations

Two main forecasting scenarios both for heat and electricity vectors are considered as shown in Figure 27 and Figure 28. That is, scenario A in Figure 27 is a single-building approach forecasting energy consumption and/or supply prediction for single local environments. Target

[4] In RENergetic applications the REN-Index is the ratio of a building daily (24hrs) average MW consumption to the building in-period (current month) consumption with exemplary form:

$$REN - Index = \frac{mean24hMWconsumption}{in - periodMWconsumption}$$

here is to generate MW energy predictions (energy demand or supplies) internally to a single building process. The predictive models deal with local solutions for the energy managers involved to control the energy flows (consumptions vs supplies).

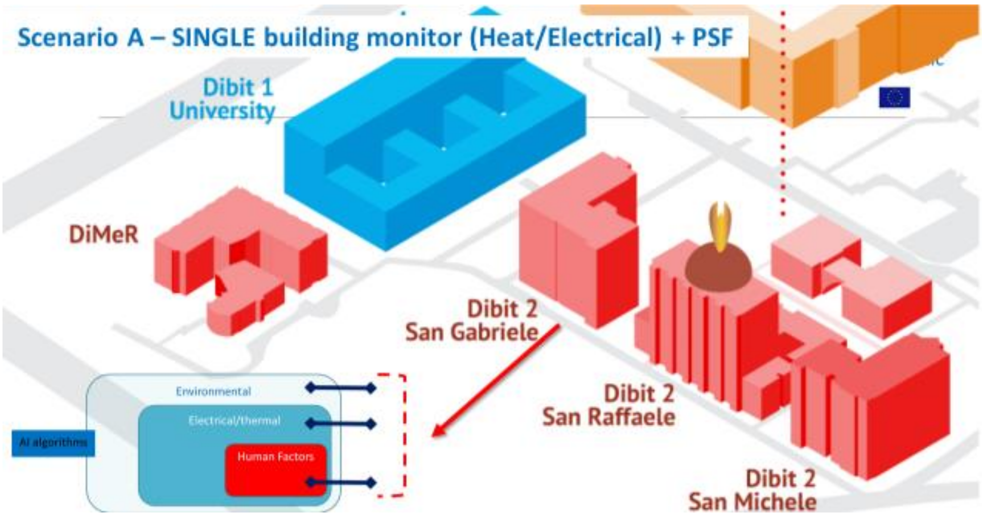


Figure 27 – Scenario A: Forecasting for single−building (local energy response)

Scenario B in Figure 28 below targets a multi−building location. Here the AI algorithms will predict MW energy consumptions or supplies for entire OSR segments and multiple buildings altogether. This has the advantage of not only to apply AI predictive intelligence to global OSRparts (multi−building global predictions) but to identify local parts (single buildings) impacting the most on global energy demands of the composite total measure of prediction. This AI capacity would pave the way to real multi vector and multi building energy optimization solutions to explore in the course of 2022.

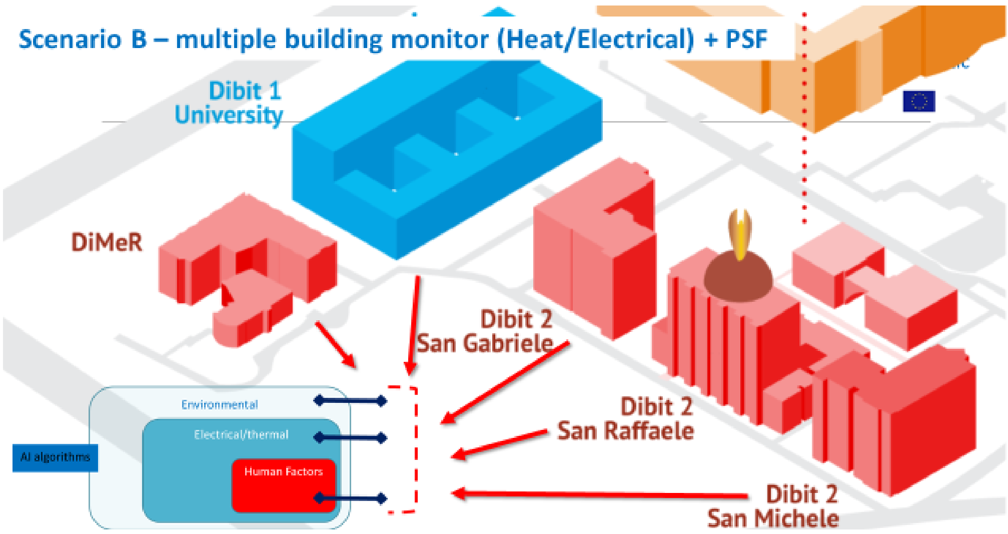


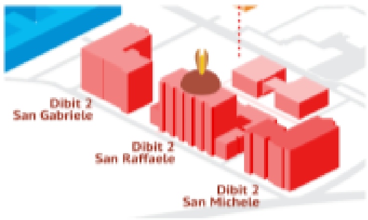
Figure 28 – Scenario B: AI models for multi−building (global energy response)

As of 1st April 2022, the main target feature both for Scenario A and B (for all time−series forecasting descried so far) remains the MW demand or supply at the hour sampling rate. Also, forecasting here is taken on a broad sense and considers that the RENergetic AI model solutions offered would deliver for both Scenario A and B: pure Forecasting, Anomaly Detection, Root Cause Analysis, Sensitivity and/or Precision Energy capacity within the RENergetic platform software as described in Deliverable 3.1 of WP3.

III.2.4. AI algorithms learning energy data

As an example, the Dibit 2 data model configuration is presented in Figure 29.

Dibit 2 Heat/Electricity



excerpt data

Datetime Index	Building	Water Temp in	Water Temp out	Hot Water m3/h	MW	m3	MWh
15/8/20 1.00	Dibit2	87	73,2	59,8	0,94	1025204,69	22606,2
15/8/20 2.00	Dibit2	87,8	73,3	64,6	1,07	1025263,56	22606,2
15/8/20 3.00	Dibit2	87,4	73,2	56,2	0,91	1025314,38	22606,2
15/8/20 4.00	Dibit2	86,7	73,3	64,6	0,99	1025381,56	22606,2

Figure 29 – data sample configuration for Dibit 2 buildings

In this example of Figure 29, single or ensemble AI algorithms will predict the Target feature heat MW values {0.94, 1.07, 0.91, 0.99, …} (in long format matrix) sampled at hourly rate, Datetime Index, for Building Dibit2. This time−series forecasting of the MW can be improved by testing (in the algorithms) the importance of certain Predictor features like Water Temp in, Water Temp out, Hot Water m3/h or m3 of water flow.

The full actual data model as of 1 April 2022 in Pilot 3 is reported later on in section IV. Data.

III.2.4.a. Fundamental AI algorithmic process

The following mathematical specifications in Figure 30, developed by Dr Baranzini Daniele (OSR) are taken from WP 3 (Figure 17). In particular, the general objective functions required to any algorithm in RENergetic forecasting, and even more in this Pilot 3, is driven by a clear bias−variance trade off approach applied to any Machine Learning model were:

any *kth* AI RENergetic algorithm

$k = \{1,\ 2,\ 3,\ \ldots n\}$ expressing an approximation function

$$\widehat{F(\dot{x})}$$

mapping x observed input vectors to y observed output responses, shall assume

$$\widehat{F(\dot{x})} = \arg\max(y_{obs} \cong y_{pred})$$

to maximise asymptotic approximation between observed y_{obs} and predicted y_{pred} response values: a minimal *bias*. This is operated by some dedicated loss function minimization of the form

$$\arg\min\ L(y, F(x))$$

which is intended to reduce and contain cross-generalization error performances across measurements and trials: a minimal *variance*.

Overall, the RENergetic AI methods are expected to maintain high accuracy and high consistency/reliability across applications. That is, an adequate bias-variance trade off.

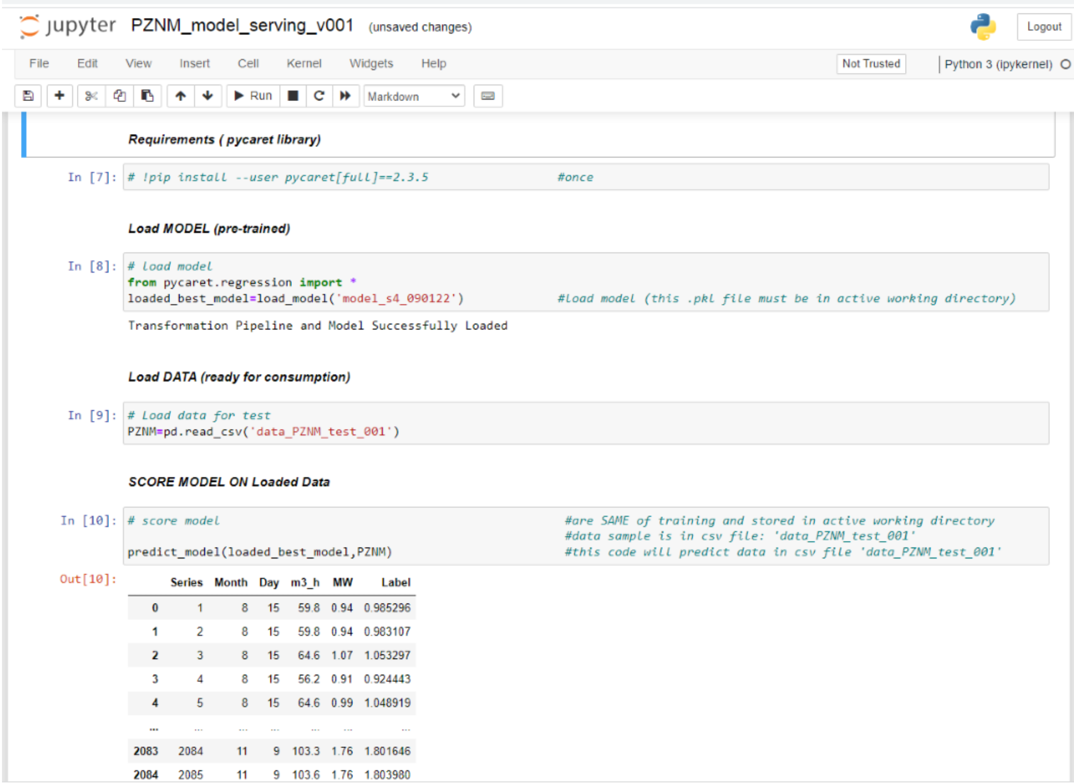
Figure 30 – Fundamental AI algorithmic process (Dr D. Baranzini [2])

This formal specification above is suggested to protect and control for any AI algorithmic model drifts, which must be monitored over time and with regularity. The entire Forecasting reliability and AI service capacity depends on this fundamental mathematical specification.

III.2.4.b. Scoring and performance of AI algorithms

To demonstrate the AI application core elements some Python [5] interpreter code is provided in Figure 31 and Figure 32 below. The Python code represented in the two Figures respectively specify the Python coding imports for:

1) Pythion API pre-trained model and relative API to score it in Kubeflow [3]
2) Python APIs to monitor performance according to MAE, RMSE, MAPE and SMAPE metrics



jupyter PZNM_model_serving_v001 (unsaved changes)

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (ipykernel)

Requirements (pycaret library)

In [7]:
```
# !pip install --user pycaret[full]==2.3.5                    #once
```

Load MODEL (pre-trained)

In [8]:
```
# load model
from pycaret.regression import *
loaded_best_model=load_model('model_s4_090122')              #load model (this .pkl file must be in active working directory)
```
```
Transformation Pipeline and Model Successfully Loaded
```

Load DATA (ready for consumption)

In [9]:
```
# Load data for test
PZNM=pd.read_csv('data_PZNM_test_001')
```

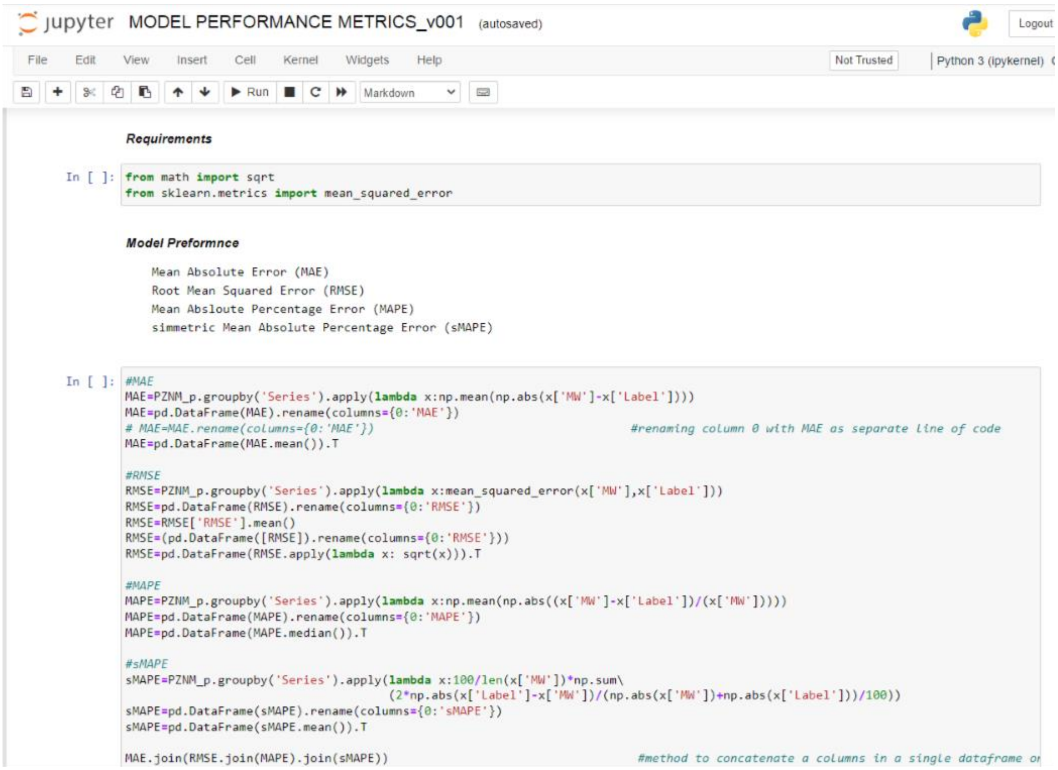
SCORE MODEL ON Loaded Data

In [10]:
```
# score model                                                 #are SAME of training and stored in active working directory
                                                              #data sample is in csv file: 'data_PZNM_test_001'
predict_model(loaded_best_model,PZNM)                         #this code will predict data in csv file 'data_PZNM_test_001'
```

Out[10]:

	Series	Month	Day	m3_h	MW	Label
0	1	8	15	59.8	0.94	0.985296
1	2	8	15	59.8	0.94	0.983107
2	3	8	15	64.6	1.07	1.053297
3	4	8	15	56.2	0.91	0.924443
4	5	8	15	64.6	0.99	1.048919
...	...	...	...	...	...	...
2083	2084	11	9	103.3	1.76	1.801646
2084	2085	11	9	103.6	1.76	1.803980

Figure 31 − Python API to load and score a pre trained model for MW prediction demand



jupyter MODEL PERFORMANCE METRICS_v001 (autosaved)

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (ipykernel)

Requirements

In [ ]:
```
from math import sqrt
from sklearn.metrics import mean_squared_error
```

Model Preformnce

```
Mean Absolute Error (MAE)
Root Mean Squared Error (RMSE)
Mean Absloute Percentage Error (MAPE)
simmetric Mean Absolute Percentage Error (sMAPE)
```

In [ ]:
```
#MAE
MAE=PZNM_p.groupby('Series').apply(lambda x:np.mean(np.abs(x['MW']-x['Label'])))
MAE=pd.DataFrame(MAE).rename(columns={0:'MAE'})
# MAE=MAE.rename(columns={0:'MAE'})                           #renaming column 0 with MAE as separate line of code
MAE=pd.DataFrame(MAE.mean()).T

#RMSE
RMSE=PZNM_p.groupby('Series').apply(lambda x:mean_squared_error(x['MW'],x['Label']))
RMSE=pd.DataFrame(RMSE).rename(columns={0:'RMSE'})
RMSE=RMSE['RMSE'].mean()
RMSE=(pd.DataFrame([RMSE]).rename(columns={0:'RMSE'}))
RMSE=pd.DataFrame(RMSE.apply(lambda x: sqrt(x))).T

#MAPE
MAPE=PZNM_p.groupby('Series').apply(lambda x:np.mean(np.abs((x['MW']-x['Label'])/(x['MW']))))
MAPE=pd.DataFrame(MAPE).rename(columns={0:'MAPE'})
MAPE=pd.DataFrame(MAPE.median()).T

#sMAPE
sMAPE=PZNM_p.groupby('Series').apply(lambda x:100/len(x['MW'])*np.sum\
                                (2*np.abs(x['Label']-x['MW'])/(np.abs(x['MW'])+np.abs(x['Label']))/100))
sMAPE=pd.DataFrame(sMAPE).rename(columns={0:'sMAPE'})
sMAPE=pd.DataFrame(sMAPE.mean()).T

MAE.join(RMSE.join(MAPE).join(sMAPE))                         #method to concatenate a columns in a single dataframe or
```

Figure 32 − Python API to test model cross−generalisation performance

All Python API codes above are designed generated by Dr Baranzini Daniele in OSR as of 1st April 2022.

III.2.5. User Stories

The Forecasting Epic is then translated operationally into a set of User Stories. This process instantiates a strategic view, the Epic, into an operational model, a set of real energy operations, the User Stories.

Examples of User Stories for OSR in the Forecasting Epic are simplified and summarised in Table 1 below. At minimum, each User Story reports on active and passive roles (ROLES), a development status (STATUS STORY), a short simple description (STORY DESCRIPTION) and the type of AI predictive models and functions. The complete information of User Stories as developed as of 1st April 2022 is given in the original Table (see Annex 1 − User Story Chart).

Table 1 – Pilot 3 User Stories examples

ID	ROLES	STATUS *	STORY DESCRIPTION	Model **
G03	Heat energy consumption in buildings			
OSR User STORY 1				
G-3 OSR – 1	Lead energy manager in OSR (GSD)	READY	I, as an energy manager of GSD (allocated in OSR) want to forecast the expected MW heat energy demanded by total OSR (Dibit 2 + Dibit 1 + Dimer + Others) in order to spot undesirable trends in MW volumes with risks of being forced to buy energy from national grid or check if surplus MW energy (predicted not to be consumed) could be rendered available to re-distribute or to re-sell.	M1, M2, M3, M4
OSR User STORY 2				
G-3 OSR –2	Lead energy manager in OSR (GSD)	READY	I, as an energy manager of GSD (allocated in OSR) want to forecast the heat building inefficiency in OSR with REN-EI Index. This index will anticipate of 1 to 5 days the risk (and associated energy trend pattern) of a building (or more buildings aggregated) to deviate too much from the in-period norm of expected energy heat consumption. The objective is to intercept any signal of expected inefficiency before it occurs in order to enact a proactive response.	M2, M5

* STATUS STORY: READY, IDLE, NOPE.

** *Models:* M1: Forecasting, M2. Root-cause analysis, M3. Anomaly Detection, M4. Sensitivity Analysis, M5 PRECISION ENERGY (MSMs + Linear Programming)

As of 1st April 2022, the full list of user stories (planned or already on implementation) is in Annex 1 User Story Chart. All User Stories are dynamic and can be changed depending of feasibility and availability criteria about data, processes and functions implied in the Pilot implementations.

III.2.6. Drivers and Barriers

III.2.6.a. OSR view

In OSR, the global electricity consumption and natural gas consumption can be measured directly by the delivery counters / points service providers. The quantities of the four energy carriers (engines) leaving the co−generator are measured by dedicated meters, and are distributed to individual buildings through sub−plants. However, the following conditions and constraints exist:

- The share of electricity supplied to each single OSR building is not directly monitored
- It is possible to know the thermic/heat and cooling energy supplied to the buildings attested to each station, not all floors or single buildings or even offices/rooms
- Water (hot/cold/overheated) does not reach all buildings completely
- Cooling energy is used exclusively for air conditioning, while thermic energy is used partly for air conditioning and partly for the production of hot water and technical uses

III.2.6.a.1. Barriers

As of 1st April 2022, various OSR buildings like Dibit 1 or 2 have refrigeration units powered by electricity or heat ventilation systems servicing at room level across multiple floors and multiple buildings but:

- There is no equal distribution of dedicated meters at the same fine−grained level
- It is possible to measure heat and electricity at multiple building or building level as this is a centralised global measurement point. But that could limit interventions to dissect the share of energy vector consumptions at finer−grained level
- It is therefore not possible to divide consumption analytically between the various buildings and services.

Overall, the above preliminary descriptions show that parts/locations of OSR buildings (1) become a black box at a certain measurement detail level, (2) struggle to implement energy waste recovery measures and methods (e.g., sensors to augmented energy data integration and monitoring), and (3) lag behind in renewable and innovative energy approaches to energy consumption for future energy reshaping plans.

All such barriers shall be accounted for while refining and fine-tuning the Forecasting Epic and User Stories.

III.2.6.a.2. Drivers

Following on from the previous sections above, some drivers to the Forecasting Epic can be summarised as follows:

- The use of Forecasting would facilitate a process to optimize better energy supply right fitted to real or expected real energy demands. In fact, a superior demand forecasting (prediction of consumption) would favour and inform energy manager decision making for pre−emptive actioning to minimize energy waste resulting in less electricity/heat overproduction or underproduction.

- Also, Proficient and reliable forecasting will limit "unplanned" overproductions that could force the EI to resell to the national grid at unprofitable prices (at most). An underproduction could result in uncomfortable building conditions or even black outs.
- The Energy Manager in OSR are keen to explore and maximise the AI algorithmic potential not only for anticipatory response actions but also for simulation ("what if analysis") and causal modelling (root casue analysis) to spot key predictors maximising energy fit for the systems.
- The anticipation of days of what buildings across many on OSR are subject to energy inecfficiency (e.g., via REN−Index and MSMs algorithms) would increase decsion making effectiness of the entire EI. This should be visible by impact on dedicated energy KPIs.
- As anticipated in previous section "1.2. WP6 strategy", OSR forecasting methods and ideas above are expected to be generalized into Segrate enviroments. As of 1st April 2022 this expectation shall be fully reassessed from mid 2002 to 2023 for feasibility and implementability.

III.2.6.b. Segrate view

Segrate is composed by 7 recognizable neighbourhoods that were built with an independent system of mobility and energy supply. Milano 2 is one of these neighbourhoods that is close to OSR (part of OSR is in Segrate Municipality, part is in Milan Municipality). The territorial division of the neighbourhoods, together with the high level of public services equipment and their isotropic distribution in the different neighbourhoods, are robust reasons to deploy the Forecasting Epic methods (AI for energy prediction and simulation), and all optimization of supply and demand analysed in OSR into a real city context.

III.2.6.b.1. Barriers

As of 1st April 2022, some constraints follow:

- Milano 2 (in Segrate) is not part of Project consortium. This was a key reason of the difficult relations to establish Epic−related Milano 2 and RENergetic shared actions.
- Scaling up the Forecasting Epic requires Segrate municipality and various localised political agenda alignments yet
- The business models driving Segrate energy plans in 2022 and 2023 are not presently lined up yet for sustaining a concerted action

III.2.6.b.2. Drivers

As of 1st April 2022, the following drivers are foreseeable:

- A high Segrate social engagement initiative has initiated via the PBM meeting in Milano in late March 2022. See section III.13.. This is a clear orientation to foster strategically over all 2022 and 2023 in Segrate.
- The fact of the Ukraine−Russia war is still on, an urgent new energy request in Italy towards renewability and major focus on energy savings and efficiency is requested at national level. This condition must be understood as an opportunity towards RENregetic oriented solutions fopr Pilot 3 applications and strategies for 2023.

The university engagements with renewability and sustainability projects (between Segrate, OSR and Pavia) and towards scholar exercises to design RENergetic oriented solutions in architectonical proposals has been presented in PBM in Segrate (see III.14.). This must be continued and aligned with the Forecasting and other future Epics in Pilot3.

III.3. Social Engagement

Independently by the specific Epic implementation and associated User Stories, the following social engagement initiatives were committed by Segrate as a large−scale community. Such social oriented events have become strategic to explore the large−scale replicability capacityand transfer (see WP8) from OSR to a real municipality environment like the Segrate one. Segrate was targeted before OSR as it reflects more the social constructs required by an EI overall.

It is to note that Segrate involvement and its social analysis has the role to:

1. Explore the organizational awareness about the concepts in RENergetic
2. Assess all means of compliance at muinicipality level to implement RENergetic
3. Expand the way the municipality engages in and with RENErgetic future services

All three points above are strategic to develop a SEGRATE plan towards an effective/reliable RENergetic capacity building process. In fact, no RENergetic technical solution is considered valid and feasible without support, full awareness and involvement of its core stakeholders and roles.

What follows are the example of social engagement and local activites for Pilot 3 as of 1st April 2022.

III.3.1. Co−Lab and Energy activities with Citizens

In conjunction with the Segrate PMB meeting (29−31 March, 2022), in the Centro Civico (in Segrate city center) on Monday 28th March afternoon, we organized some activities to presentthe RENergetic project to the citizens:

- Presentation of physical installation design proposal for REN project (see Figure 34 and 35) made by students from University of Pavia of the first and third year of Master Degree course in Building Engineering and Architecture. In particular the courses involved are “Architectural Design Theory and Techniques “ (first year) by professor Tiziano Cattaneo and “Urban Planning I “ (third year) by professors Roberto De Lotto and Elisabetta Venco;
- Discussion with university students about the meaning of Energy Communities in urban contexts;
- RENergetic game for children;
- Energy Transition Vision in Segrate prepared by WP2 personnel

The afternoon activities began with the university students’ presentation of the physical installation design proposal, as shown in Figure 33.

Figure 33 - Presentation of physical installation design proposal (students of the first and third year of Master Degree course in Building Engineering and Architecture, University of Pavia).

Starting from these projects the Municipality will define the specific guidelines and the design suggestions for the real creation of the installations that will be placed in the square near the Centro Civico, in the city center of Segrate and in the Centro Parco, a big green area near the city center as well and widely used by the citizens.

In the Figure 34 and 35 below are some of the design proposals and the mock-ups of the physical installations respectively.

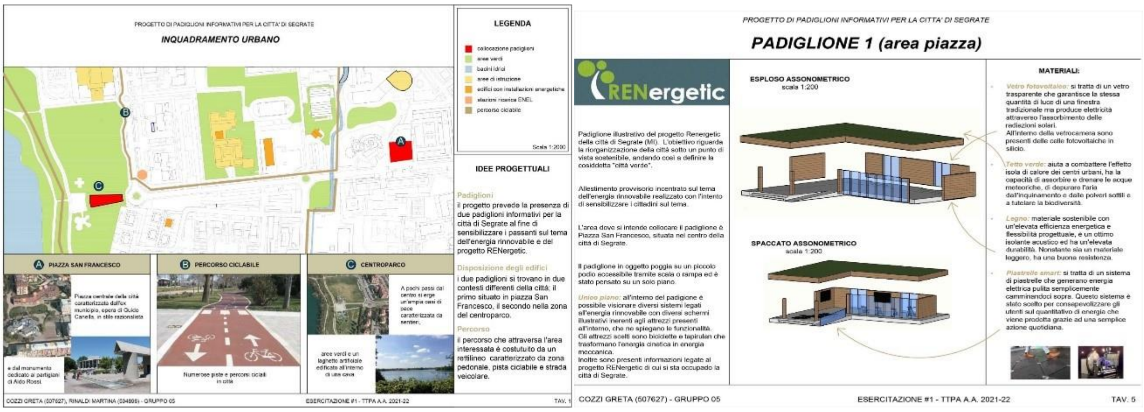


Fig cont.

Figure 34 - Some design proposals created by the students of the first year during the course of Architectural Design Theory and Techniques of Master Degree course in Building Engineering and Architecture (University of Pavia)

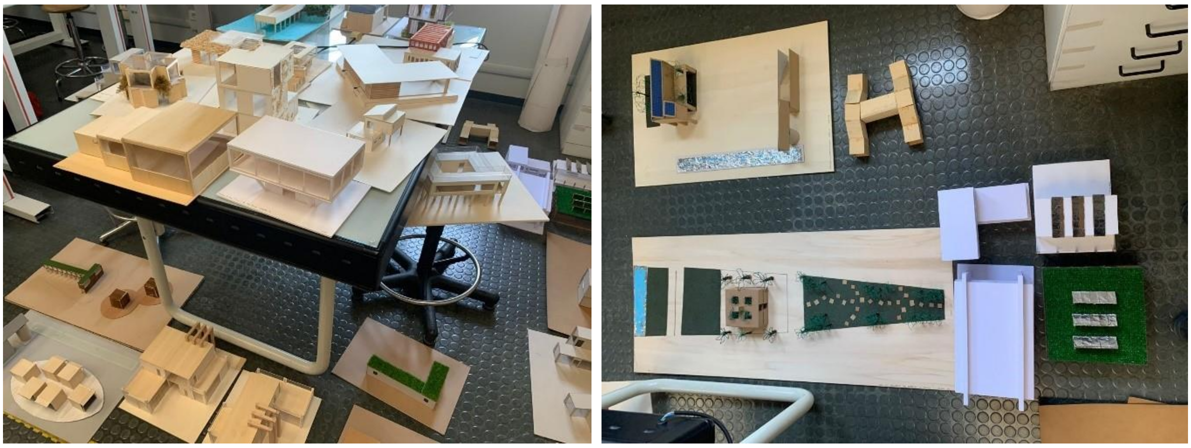


Figure 35 - Some mock-ups of the physical installations created by the students of the first year during the course of Architectural Design Theory and Techniques of Master Degree course in Building Engineering and Architecture (University of Pavia)

Some other activities specifically dedicated to children included a quiz (like a challenge among 4 children) on some curiosity related to energy and renewable sources and the design of the ideal city including renewable energy sources. In Figure 36 below is the quiz board and some of the children's drawings.

Figure 36 - Some of the drawings prepared by children during RENergetic game

Other actions targeted the so called “Energy Transition Vision”: to understand how non−expert people imagine and describe possible scenarios for the energy transition process and for their direct involvement.

During this activity, the RENergetic project was presented and widely described to all the people that stopped by the panels: the background of European and Italian energy situation, the meaning of consumer−producer−prosumer, the role of renewable energy sources to reduce pollution, inequalities, costs and to increase sustainable life−style choices, the idea of energy community and energy island in urban context, and the main aim of the project were presented.

A proposal of 4 main questions (see Figure 37 and 38), suggesting possible answers, was given to allow interested citizens passing−by to write their own ideas on such specific topics:

1. With whom?

- Your neighbours
- Your local government
- Clubs-organizations
- Local energy fans

- Your religious community

2. How would you participate?

- Initiator
- Producer/Prosumer
- Investor
- Contributor
- Customer/Consumer

3. Why? What motivates you?

- New technologies
- Save money
- Energy autarchy
- Fight climate change
- Social community
- Regional value
- Learn new things

4. What? Which actions would you support?

- Adapt consumption to the energy available (i.e.,smart EV charging)
- Solar on public roofs
- Building renovation
- Heat pump
- Solar in open spaces
- Pellet heating
- Solar on private roofs
- Wind energy
- Biomass

Figure 37 - The panels with the “Energy Transition Vision”

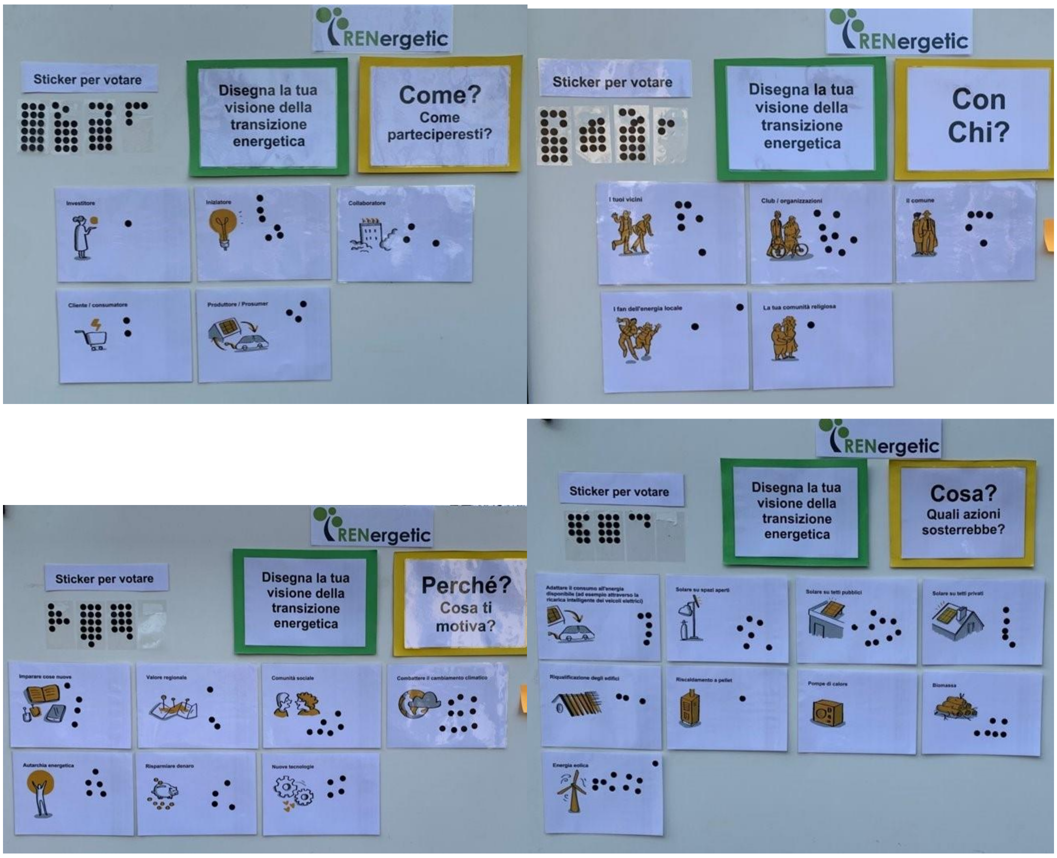


Figure 38 - The results of the “Energy Transition Vision”

Below, Figure 39 some pictures of the RENergetic activities at Centro Civico in Segrate.

Figure 39 - Citizens participation to RENergetic activities

Finally, the university students of Urban Planning (third year of the Master Degree course in Building Engineering and Architecture, University of Pavia) answered some questions related to RENergetic project and the general concepts of Energy Community and Energy Island:

1) **WHAT IS RENERGETIC ABOUT FROM YOUR POINT OF VIEW?**
2) **HOW DOES AN ENERGY COMMUNITY LOOK LIKE?**
3) **CONSIDERING THE DIFFERENT BUILDING TYPES, HOW DOES AN ENERGY COMMUNITY CHANGE AND DEVELOP?**

Their valuable and diverse perspectives, ideas and suggestions could be relevant for dissemination strategies and actions in Segrate Pilot 3, for future social engagement events, as well as for replicability processes in late 2022 or 2023.

Below in Figure 40, 41 and 42 are examples of questions and answers as gathered during the event. The complete file “Quotes from Students on RENergetic.pdf” is available under request in the SharePoint [4] folders of the Project .

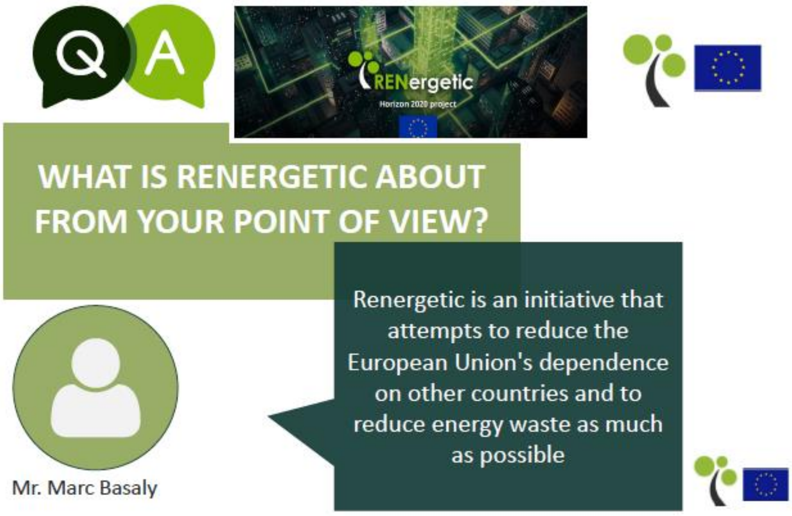


Figure 40 - Mr Marc Basaly answers to "What is RENergetic about from your point of view?"

Figure 41 - Miss Lucrezia Conti answers to "How does an energy community look like?"

Figure 42 - Mr Federico Giubilei answers to "Considering the different building types, how does an energy community change and develop?"

IV. QUANTITATIVE DATA

[NOTE: as of 1st April, the following section is about the first Forecasting Epic. The next final Deliverable 6.2 will provide further extensions on the data used across all final Epics in the Pilot 3]

The data to serve the Epic Forecasting AI algorithms are considered in the light of energy sources (primarily heat, electric, renewable sources). Data for machine learning processes consists in a two−way matrix form with data in long format structure as shown in Table 2 below.

Table 2 − Example of long format data for AI algorithm consumption

Date time Index	Building	Water Temp in	Water Temp out	Hot Water m3/h	MW	m3	MWh
15/8/20 1.00	Dibit2	87	73,2	59,8	0,94	1.025.204,69	22.606,2
15/8/20 2.00	Dibit2	87,8	73,3	64,6	1,07	1.025.263,56	22.606,2
15/8/20 3.00	Dibit2	87,4	73,2	56,2	0,91	1.025.314,38	22.606,2

15/8/20 4.00	Dibit2	86,7	73,3	64,6	0,99	1.025.381,56	22.606,2

In particular, each column denotes a variable of interest either being the target of prediction (e.g., MW values) or a variable supporting the prediction of the target (e.g., Hot Water m3/h). Each row instead denotes the time index for each feature in the columns.

IV.1. Data acquisition systems

As of 1st April 2022, the data variables and time indexes are reported here in Annex 2 –Data Availability Pilot 3.

IV.2. Preliminary data analysis

The following sections reports on the main application of AI methods on Dibit 2 Buildings in OSR.

IV.2.1. AI Algorithms on OSR Buildings

Forecasting and Machine Learning models' results are tested and validated mainly on Dibit 2 buildings in OSR. The following sections present partial results as of 1st April 2022.

IV.2.1.a. Forecasting MW consumption

A visual output of the trained Machine Learning model to predict MW consumption ahead of time in Dibit 2 buildings is in Figure 43 below. The forecast horizon of MW at 1 hour sampling rates can be extended from 1 to 3 days. Predictions beyond 3 days forward are not recommended and re−fit of the model is preferable to keep model error predictions under control.

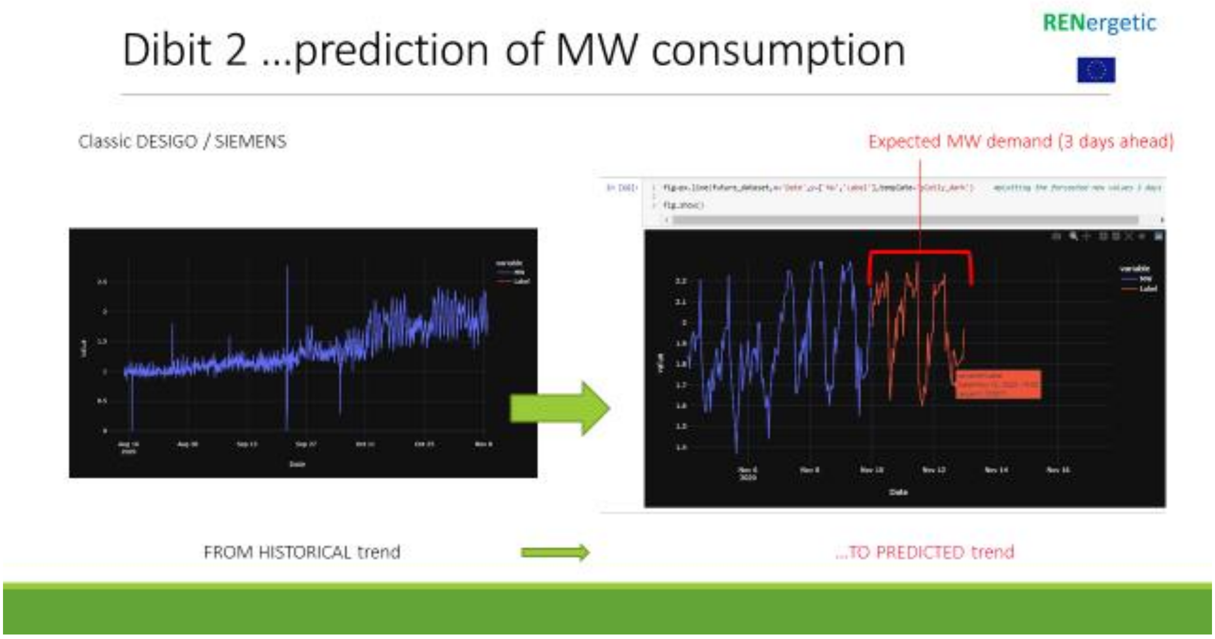


Figure 43 – MW consumption prediction for Dibit 2 buildings (OSR)

Figure 43 shows on the left the historical trend in blue (classic trend visualization by common BMS systems by Siemens like Desigo) and to the right side the RENergetic model prediction trend is plotted on the far−right side in red, extending the blue coloured historical trend. The advantage to get the insights of "expected" MW volume, peaks or frequencies ahead of time is clearly informing any energy manager decision making process.

Specifically, the selected Machine Learning model trained to predict Dibit 2 MW consumptions at hourly rate is presented in MLOps Schema 1 below. The schema shows the Python coding to compute final model results and description of objectives (sec A), the finalized Predictors and Target Features (sec. B), the initialized set of machine learning models undergoing cross−comparisons (sec C) and the final selection of the Least Angel Regression algorithm (sec D). The Machine Learning model selected is reliable and the model can be now deployed for practical operational use in the RENergetic software platform (see WP3, Deliverable 3.1).

MLOps Schema 1 – Least Angle Regression algorithm to predict Dibit 2 MW consumption

A) Model Results

Time series 'model_s4' (GitHub version)

Algorithm: Least Angle Regression

(Machine Learning model)

total time period copvered by model: 15-Aug-2020 -> 09 Nov 2020 window

test set performce (07-Nov-2020 -> 09 Nov 2020 window)

> Test RMSE: 0.109
> Test MAPE: 0.043
> Correlation: 0.872
> R-squared: 0.761

target feature: MW (thermic)

exogenous features: m3/h, Series, Month, 'Day

B) Data input

```
In [7]: data.drop(['Date','MW_MA12'],axis=1,inplace=True)          #drop Date and MW_MA12
        data=data[['Series','Month','Day','Hour','m3_h','MW']]     #reorder columns with [['1','2','3']] code
        data
```

Out[7]:

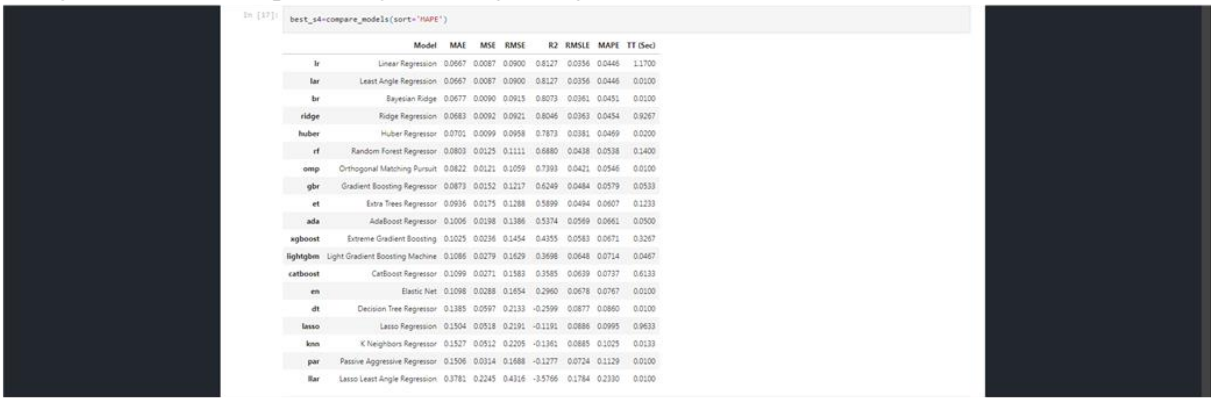
	Series	Month	Day	Hour	m3_h	MW
0	1	8	15	1	59.8	0.94
1	2	8	15	2	59.8	0.94
2	3	8	15	2	64.6	1.07
3	4	8	15	4	56.2	0.91
4	5	8	15	5	64.6	0.99
...	...	...	...	...	...	...
2083	2084	11	9	20	103.3	1.76
2084	2085	11	9	20	103.6	1.76
2085	2086	11	9	22	104.8	1.91
2086	2087	11	9	23	104.8	2.01
2087	2088	11	9	23	114.7	2.17

2088 rows × 6 columns

train-test split

```
In [8]: # train=data[data['Series']> ]

        train=data.loc[:2015]
        test=data.loc[2016:]
        train.shape, test.shape

Out[8]: ((2016, 6), (72, 6))
```

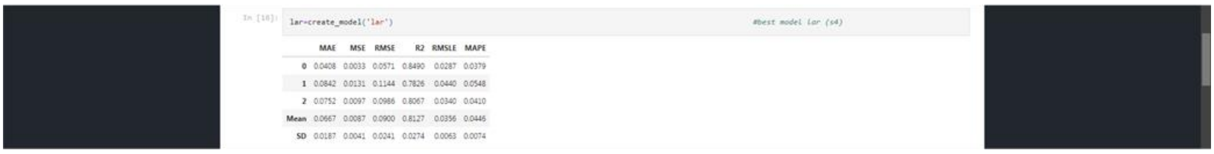
C) Machine Learning Models (cross-comparison)



```
In [17]: best_s4=compare_models(sort='MAPE')
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
lr	Linear Regression	0.0667	0.0087	0.0900	0.8127	0.0356	0.0446	1.1700
lar	Least Angle Regression	0.0667	0.0087	0.0900	0.8127	0.0356	0.0446	0.0100
br	Bayesian Ridge	0.0677	0.0090	0.0915	0.8073	0.0361	0.0451	0.0100
ridge	Ridge Regression	0.0683	0.0092	0.0921	0.8046	0.0363	0.0454	0.9267
huber	Huber Regressor	0.0701	0.0099	0.0958	0.7873	0.0381	0.0469	0.0200
rf	Random Forest Regressor	0.0803	0.0125	0.1111	0.6880	0.0438	0.0538	0.1400
omp	Orthogonal Matching Pursuit	0.0822	0.0121	0.1059	0.7393	0.0421	0.0546	0.0100
gbr	Gradient Boosting Regressor	0.0873	0.0152	0.1217	0.6249	0.0484	0.0579	0.0533
et	Extra Trees Regressor	0.0936	0.0175	0.1288	0.5899	0.0494	0.0607	0.1233
ada	AdaBoost Regressor	0.1006	0.0198	0.1386	0.5374	0.0569	0.0661	0.0500
xgboost	Extreme Gradient Boosting	0.1025	0.0236	0.1454	0.4355	0.0583	0.0671	0.3267
lightgbm	Light Gradient Boosting Machine	0.1086	0.0279	0.1629	0.3698	0.0648	0.0714	0.0467
catboost	CatBoost Regressor	0.1099	0.0271	0.1583	0.3585	0.0639	0.0737	0.6133
en	Elastic Net	0.1098	0.0288	0.1654	0.2960	0.0678	0.0767	0.0100
dt	Decision Tree Regressor	0.1385	0.0597	0.2133	-0.2599	0.0877	0.0860	0.0100
lasso	Lasso Regression	0.1504	0.0518	0.2191	-0.1191	0.0886	0.0995	0.9633
knn	K Neighbors Regressor	0.1527	0.0512	0.2205	-0.1361	0.0885	0.1025	0.0133
par	Passive Aggressive Regressor	0.1506	0.0314	0.1688	-0.1277	0.0724	0.1129	0.0100
llar	Lasso Least Angle Regression	0.3781	0.2245	0.4316	-3.5766	0.1784	0.2330	0.0100

D) Final Machine Learning model: Least Angle Regression (“model S4”)



```
In [18]: lar=create_model('lar')          #best model lar (s4)
```

	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	0.0408	0.0033	0.0571	0.8490	0.0287	0.0379
1	0.0842	0.0131	0.1144	0.7826	0.0440	0.0548
2	0.0752	0.0097	0.0986	0.8067	0.0340	0.0410
Mean	0.0667	0.0087	0.0900	0.8127	0.0356	0.0446
SD	0.0187	0.0041	0.0241	0.0274	0.0063	0.0074

Finally, the AI model performance is also monitored by the AI Operator (e.g., role dedicated to control the AI services of the RENergetic Platform) or directly by the Energy Manager controlling the overall measurement gap between predicted and observed trends values in the time-series test tests.

This error gap shall be kept by the AI algorithms generally below a 5% MAPE (Mean Absolute Percentage Error) or other acceptable performance criteria. An example of visualization of the error gap in the test set time-series for Dibit 2 is in Figure 44 below where the gap (difference) between the predicted (red series) and observed (blue series) values is displayed.

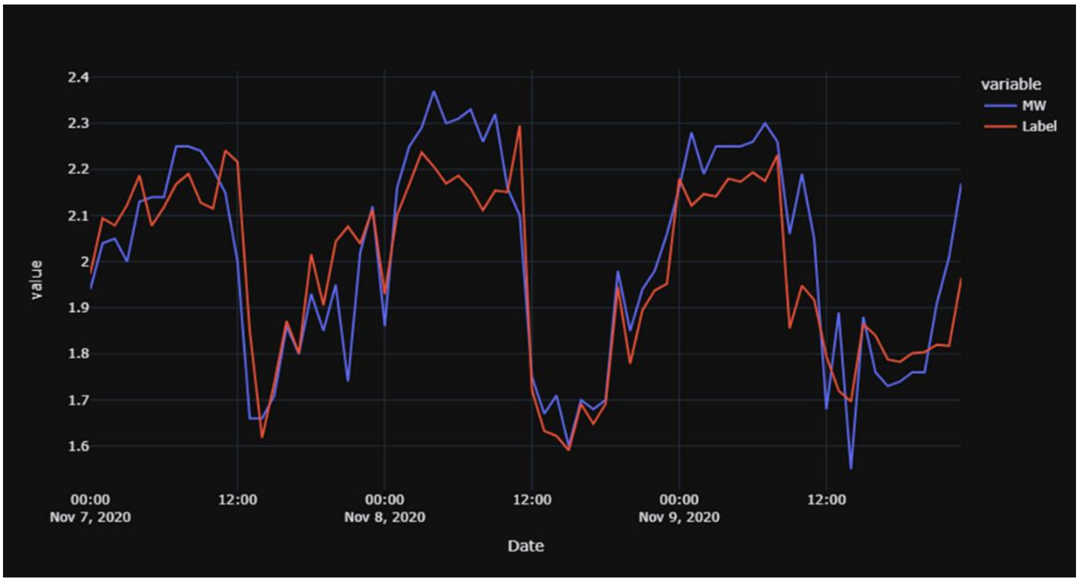


Figure 44 - Error of prediction as gap between predicted vs observed values in Dibit 2 MW consumption folrecast

IV.2.1.b. Machine Learning simulations (MW savings)

Out of MW prediction forecasts in Dibit 2 as by previous section the finalized Machine Learning model was then tested for simulation purposes: simulate perturbation in the Predictor Feature m3/h (the exogenous feature used in the MW forecast) to test safely if a reduction of m3/h hot water inflows in Dibit 2 buildings could positively reduce the forecast MW consumption accordingly. The model simulation is reported in Figure 45 and it was "simulated" targeting some hours intervals only (between 6pm and 4am) with a reduction of 5 m3/h units.

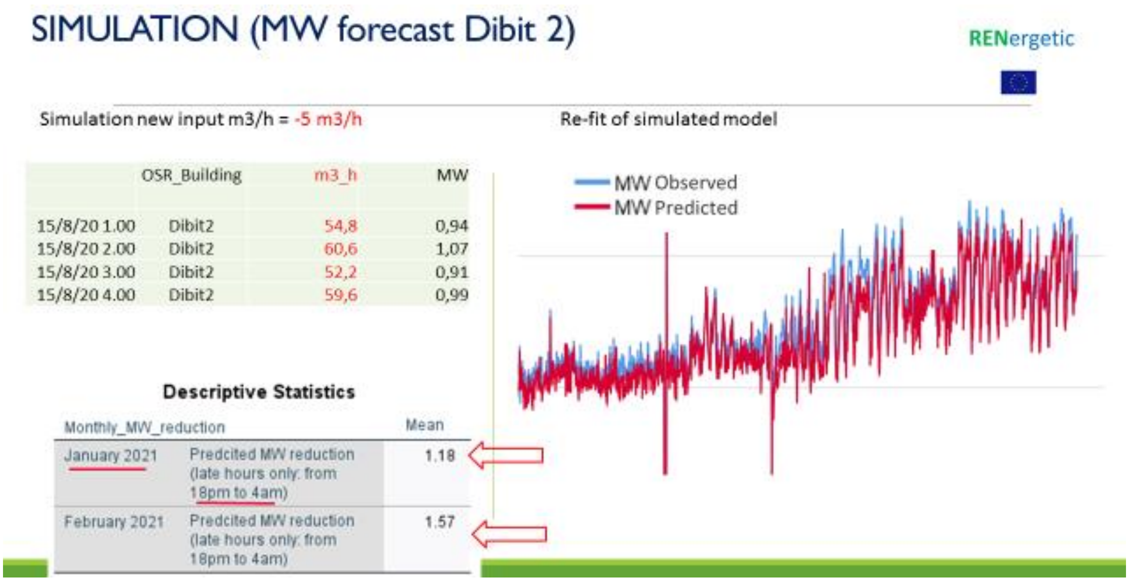


Figure 45 − Sensitivity analysis and simulation of input features

The simulation proved that such change in m3/h could save more than one MW per month. A very important finding worth exploring further for the economical and operational implications to reduce energy waste more concretely.

Overall, the AI model (Machine Learning model in previous section) and data for simple forecasting operations were thus fully exploited to support sensitivity and root cause analysis as well to inform and enrich OSR Energy Managers decision making processes.

IV.2.1.c. Precision Energy with REN−Index and MSMs

REN-Index

The prediction ahead of time (2-3 days) of what is the expected OSR building efficiency in MW consumption is computed by a new indicator, the RENergetic Index or simply the REN-Index.

The REN-index represents the spread of observed versus expected energy consumption rates over time by one or multiple buildings. It signals both a *point-in-time* energy spread and the rate of change of such variation *over-time*.

The REN-Index,

$$\frac{point - in - time\ (MW)}{in - period\ value\ reference\ (MW)}$$

is the ratio of the averaged *point-in-time* local MW consumption to the *in-period value reference* (average) demand.

Moving Series Machines (MSMs)

This index is predicted via a new innovative AI method called Moving Series Machines (MSMs) by Dr D. Baranzini [1]. MSMs are useful Machine Learning methods to promote and introduce the concept of precision energy. MSMs is a meta-predictor estimator that combines time-series forecast to time-series classification. This provides a more precise, sensitive and accurate building efficiency measure than any individual ML model time-series or classification estimators. MSMs fuse classic ML forecasting and classic classification tasks by enriching and encoding instance-based classification with time-series shapelets information.

In the MSMs process, the first Machine Learning operation is to learn to classify the REN-Index with a *source time-series classificator* by learning shaplets profiles of 24hrs time-windows. This is followed by a *backward ensembling (I.e.,* backward composition) of such original multiple shaplets of 24hrs time-windows data as composite input for a new time-series estimator, called *moving series model*. The *moving series model* is then run to forecast temporal forward multi-step predictions of the same length of the original 24hrs time-windows. Such forecasted shaplets are finally classified by the originally trained *source time-series classificator*. This final time-series classification returns the REN-Index value as a meta-learning operation.

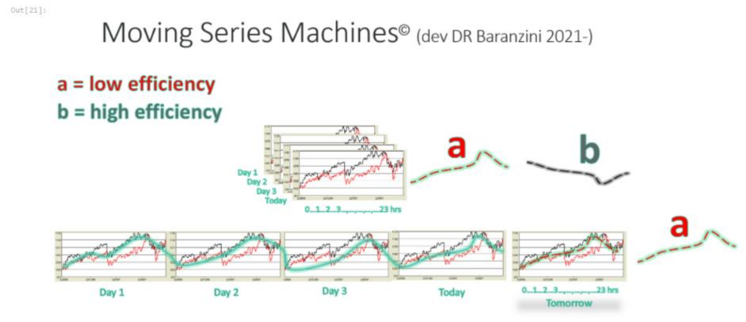
Specifically, the selected MSMs trained to predict the REN-Index of Dibit 2 is presented in *MLOps Schema 2.* The schema shows the Python coding and results to train the *source time-series classificator* for learning shaplets of 24hrs time-windows.

In particular the schema depicts the MSMs objectives (sec A), specifications of the *source time-series classificator* (a support vector classifier by tslearn API) (sec B), the finalized input data with REN-Index as target (as shapelets of 24 hours) (sec C), fit of the model as an instnace of a TimeSeriesSVC machine (the tslearn API) (sec D) and the final classification of Dibit 2 buildings profiles (shapelets) as ‘0 class’=high REN-Index efficiency or ‘1 class’=low REN-Index efficiency (sec E).

MLOps Schema 2 – MSMs and REN-Index

A) MSMs objectives

Out[21]:



B) Specs for the *Source Time-Series Classificator* (TimeSeriesSVC, tslearn API)

TIME SERIES CLASSIFIER (RENergetic)

ALGORITHM TYPE: time series classifier from tslearn API

> NAME Algorithm: TimeSeriesSVC
>
> OBJECTIVE: classification of heat energy time series for heat consumption (MWh) in Dibit 2 building in OSR
>
> `classify into RENergetic Index binary values:: 1=inefficient consumtion  0=efficient consumption`

Samplig Rate: 24 hr PREDICTION: profile

MW consumption Dibit2 from 8-Nov-2020 07:00:00 to 9-Nov-2020 22:00:00

NOTE @10-11-21 model is draft demo purpose only (no cross-validation and manual hypermparmenter optimization is provided at the moment)

C) Finalized input data with REN-Index target

Compute RENenergetic Index

In [12]:
```
piv['REN_Index_cat']=piv['REN_Index'].apply(lambda x: '0' if x < 1 else '1')      #REN Index for Classifcation
piv.tail()
```

Out[12]:

in_period	hr / day	0	1	2	3	4	5	6	7	8	9	...	18	19	20	21	22	23	MW_d	MW_p	REN_Index	REN_Index_cat
	5	1.88	1.74	1.81	1.72	1.92	1.87	1.97	1.98	1.97	2.23	...	1.83	1.90	1.67	1.76	1.79	1.82	1.780000	1.91875	0.927687	0
	6	1.92	1.79	1.71	1.80	1.88	1.85	1.88	1.76	2.00	2.00	...	1.72	1.81	1.76	1.88	1.86	1.84	1.776667	1.91875	0.925950	0
11	7	1.94	2.04	2.05	2.00	2.13	2.14	2.14	2.25	2.25	2.24	...	1.93	1.85	1.95	1.74	2.02	2.12	1.992917	1.91875	1.038654	1
	8	1.86	2.16	2.25	2.29	2.37	2.30	2.31	2.33	2.26	2.32	...	1.70	1.98	1.85	1.94	1.98	2.06	2.013750	1.91875	1.049511	1
	9	2.16	2.28	2.19	2.25	2.25	2.25	2.26	2.30	2.26	2.06	...	1.74	1.76	1.76	1.91	2.01	2.17	2.014167	1.91875	1.049729	1

5 rows × 28 columns

D) Fit of the Model (TimeSeriesSVC)

FIT MODEL

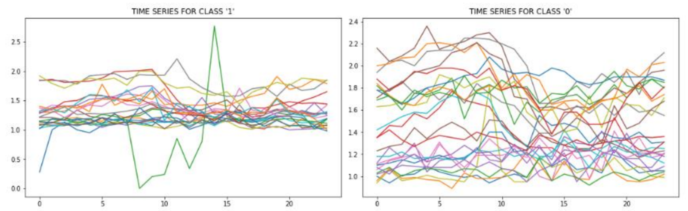
In [15]:
```
test_size=0.10                                                          #train test split
seed=34784
X_train,X_test,y_train,y_test=model_selection.train_test_split(X,y,test_size=test_size,random_state=seed)
# print(X_train.shape,X_test.shape, y_train.shape, y_test.shape)

clf = TimeSeriesSVC(C=5, kernel="poly", gamma=.1, probability=True)     #TIME SERIES SVC
y_pred=clf.fit(X_train, y_train).predict(X_test)
```

E) Final Dibit 2 classification of shaplets (Class ‘1’ vs ‘2’ building efficiency profiles)

TARGET: building efficiency (RENenergy Index)

In [19]:
```
import numpy
import matplotlib.pyplot as plt

n_classes = len(set(y_train))
plt.figure()
support_vectors = clf.support_vectors_
f = plt.figure()
f.set_figwidth(15)
f.set_figheight(9)

for i, cl in enumerate(set(y_train)):
    plt.subplot(n_classes, 2, i + 1)
    plt.title("\nTIME SERIES FOR CLASS %a" % cl)
    for ts in support_vectors[i]:

        plt.plot(ts.ravel())

plt.tight_layout()
plt.show()
```

<Figure size 432x288 with 0 Axes>



The MSMs on the REN-Index can be now deployed for practical operational use in the future RENergetic software platform (see WP3, Deliverable 3.1).

V. QUALITATIVE DATA

[NOTE: as of 1st April, the following section is about the social engagements for all Pilot 3 initiatives and independent by any specific Epic. The next final Deliverable 6.2 could provide further extensions of qualitative data used across all final Epics in the Pilot 3]

V.1. Stakeholders' Interviews

Given the specific situation of Milano 2 neighbourhood, the stakeholders' interviews were performed only with Municipality staff. From their answers, it is possible to highlight the general framework in Milano 2 and to define the most significant elements for implementation projects (on public buildings and space and also on private areas) in Segrate municipality territory (considering that other neighbourhoods have the compatible components and structures to start the process towards new energy islands definition).

These interviews (fully reported below) represent qualitative data that analyse motivators and barriers that can aid or constraint the participation to RENergetic project and the achievement of energy-related sustainable goals. They also represent an important element to be included into user stories definition.

After general questions on professional/cultural background, role and commitments to Segrate, more specific questions are developed: explanation of demand/response issues, of heat DR and of intelligent EV charging and EV DR.

The interviews were developed online (using Zoom platform) on 26th July, 2021.

Name of the interviewees:

- Cristiana Paolucci – Municipality technician (C.P.);
- Antonella Riggio – Municipality technician (A.R.);
- Francesco Di Chio – Politician (F.D.C.)

Q.0. I ask you to introduce herself, tell us about your professional background and commitments to the context [Segrate, MI, Italy]

C.P. - I am an engineer by training. In general, I deal with public works and mobility. I worked as a freelance professional, in the land registry, and then I made competitions in large and small municipalities, always dealing with public works (e.g., maintenance, design). Lately, office work has been focused on finding ways to promote smart transportation and mobility.

A.R. – I am an architect. I became freelance and then entered the municipality of Segrate. In the municipality, for 30 years, I have been involved in the sector private construction sector. In this context, we started participating in energy-saving courses applied to condominiums and single-family homes. Between 2008-2009, I was involved to prepare the first energy-saving regulation with the scope of rewarding citizens to take advantageous measures for the environment (e.g., installation of solar thermal, solar panels). This regulation, apart from some new features, is still used. The case is unique because the municipalities generally do not carry out performance and feasibility analyses (of the law 10/91). Four years ago, I was moved to the public works and maintenance office, and I was also able to pursue energy-saving issues here (e.g., schools) working also on public buildings.

F.D.C - I have been in Segrate for 28 years. Trained in architecture, I work together on the themes of the energy transition.

V.1.1. Heat DR

Q.1. Do you know what "demand/response" is?

C.P. - It is the set of actions for the study of the need for a demand that is needed with respect to the availability of energy. The economic factor, cost study, the peak determines the final cost of energy to the end-user.

A.R. - I know it, it deals with the change in energy consumption, towards the green. As for automation, good information is needed considering the public use of the various buildings. In our projects we used basic software and equipment for electrical and energy-saving, trying to set homogeneous temperatures in the buildings and, more recently, I am part of this working group on energy islands.

F.D.C - In summary, it is how to adjust the demand for energy and supply to optimize the use of energy. It was in use mainly in industrial settings and more recently in the residential, the main concern is on the network.

Q.2. From your point of view, what benefits would you expect from such an automatic heat regulation in your work environment?

C.P. - For administrators, the advantage is the precise monitoring of what we produce and what we consume, including remote control of anomalies. The software will tell me something more than a bill that I look at and pay. Young people are more used to this kind of thing, in my opinion, this will affect the future. Young people tend to see the benefit more than the problem. The software would now be clearer than bills full of data and in paper form.

A.R. **–** From my experience, seeing both schools and apartments in management, I notice that there are certain age groups (e.g., the elderly) that adapt with greater difficulty to temperatures. As in nurseries, keeping 19 degrees is difficult (babies are cold when they are changed). Considering these two groups, a series of complaints would arise (e.g., "the temperature is inadequate"). For the rest, I think it's not a problem. For example, middle and high schools or civic centres that have a smaller length of stay in the buildings. For houses, on the other hand, it is difficult. The request is different, even in considering rehabilitation centres: some people who are physically impaired remain still for many hours. People with little mobility, always ask for a temperature above average and an extension of the heating foreseen for the winter season (typically by a week). It is right that the energy islands have a differentiation according to the type of municipal building that falls within that area.

F.D.C - If analysis and management allow me to make better use of energy even outside the single home, I prefer it to go to that community. Of course, the management and interaction must also be worth it. Energy flows are made more elastic and the network more stable.

Q.3. What would prompt you to accept such a demand/response technology for heat?

C.P. - As a user, I would understand the advantages, but the economic costs are still a concern. To date, these technologies have significant costs. Probably one part of the users would be interested, another part might not be so inclined to change (change is a social issue). The administration should carry out a clarification campaign and be simple to make itself understood to make it clear that it does not disadvantage the user (e.g., additional problems, costs, disturbances). Explain that it is a passage that takes place over time by sharing opportunities at the community level. The challenge is to explain and publicize the thing externally.

A.R. - As a citizen, I would have some doubts about leaving the entire management to the software, I would ask if these have already been used and have worked, in terms of true returns. Verifying the appropriateness of the green aspect is important, but I would look at the economic aspect: the lower cost over time in terms of expenditure. As an administrator, I consider that if I create a network to which the energy island is connected, being able to have savings (consumption but also infrastructure and type of energy produced) is important. Obviously, by changing, I would have higher initial costs which I would then amortize. The “right of first refusal” would also apply: we build the network and we have the incentive to redistribute energy to the condominiums.

F.D.C - I trust and I am happy that it is an automated process. My perplexity is about the knowledge of the theme and how the network is built to make the physical instrument more dynamic and evolutionary. The tool must be simple and flexible to be understood, just like the infrastructures must go hand in hand with the development of the territory. The municipality must have a strong role.

Q.4. From your point of view, what would be the main concern in such heat question-and-answer management?

C.P. - The biggest concern is regulation and organization. The problem also lies in the question of the responsibility of the actors. As a citizen, the fact that there is supervision I would take it as an advantage. For the administration, the major disadvantages are the many changes to the rules, regulations, the effort to communicate the methods of regulating the system, even from a legal point of view. In Segrate, the same regulation cannot be applied to all cases: each "energy island" is separate, it cannot be standardized due to the components of the area (e.g., settlements characteristics, urban planning). The administration should immerse itself in specificity every time. The user would enjoy superior governance that acts as a guarantor. The problem of privacy is tangential, I do not think it would be a question of taking sensitive consumer elements (eg consumer health). Then, if I don't want to share my consumption with others, I'm not part of the energy community! But if I decide to be part of this community, and I understand the rule, then I do.

A.R. - Everything that is "historical", for the average, consolidated user, is not questioned (e.g., whether it is efficient or not). For the new, we ask ourselves a thousand questions, also because it is a change. In 2010, the province of Milan had set up a team to give explanations on energy consumption and savings, a desk with people trained on the subject and I saw an influx quite interested in the subject, they raised doubts, support of this kind is needed.

F.D.C - The social aspect worries me more. The idea of imagining a community that meets physically and economically puzzles me. Ensuring serenity in management and overcoming social obstacles is difficult. In addition to the approach, it must be understood that the energy source is also important for the citizen. If the citizen were not harassed by advertising (e.g., spam calls from call centres) I would be the first to be genuinely interested in the transition.

Q.5. If your demand/response technology includes a feedback interface/dashboard (within your workplace): What kind of feedback would you like to receive?

C.P. - A very interesting thing would be to be able to make a comparison between the energy islands. The comparison would serve to understand the issues of "advantage" and "complexity" of the use of energy in contexts, it would allow us to understand if in the end we went in favour or reached the goal set at the beginning in that isolated data. The relationship between the commitment and the result.

V.1.2. EV Smart Charging

Q.1. Do you know what "intelligent EV charging" is?

C.P. - I know what it is but we have never dealt with it. We in Segrate have electric recharge from different companies. Some EV charging stations have already been around for about ten years. We have noticed that use is increasing, the workstations are often busy. We have received requests to install new columns and integrate them where we could, but they are still old-fashioned infrastructures.

A.R. - When dealing with buildings, I came across this topic again.

F.D.C - The issue is important, not tangential to the transition. I would like to understand the difference between recharging at certain kilowatts in specific EV charging station versus others. Which approaches? What effects, for example on batteries?

Q.2. From your point of view, what benefits would you expect from planning your charging based on renewable energy signals as described? What added value could it offer you personally?

C.P. - Unfortunately, the transition brings very high costs to long-term benefits. Psychologically, other investments are prioritized. Spending 30,000 euros on an electric car, what for? Comparing the full tank of electricity to the full tank of petrol, we are not so sure. Also, for urban transport: how much must the ticket cost to replace electric buses? The transition will never happen in my opinion.

A.R. - The technology convinces me, at a family level we made evaluations for changing the car and we considered what it means to have a box, the ability to recharge etc. Even without state incentives, I would believe it, but costs remain an important variable for a family, being more people.

F.D.C - We are in a phase in which we are not informed about the criticalities of the system. In some countries, we have problems with energy overload, and it can seem almost counterintuitive. In some places, the costs are more affordable, to what extent does it make sense to encourage 24-hour electric charging cycles? I believe there is a need to better understand the state of affairs, technology is still the only thing that can help us. I think that the private must do it on its own. The public has to give space, be a facilitator, make infrastructure available and let people ride the times. We have already put out obsolete columns. The public must create certain conditions and intervene in the structures of competence. We still act conventionally, therefore and also for reasons of competence, it is better to leave it to the private sector. We need more ready and prepared figures in common to cope with all this.

Q.3. What would prompt you to book your recharge in advance, based on renewable energy signals?

C.P. - I would be willing to pay something more in emergencies, but in the daily routine, I would always consider the possibility of spending less.

A.R. - I would like to understand the cost of choosing one EV charging station instead of another. The cost makes the difference, to me, it is not known that that specific place also gives you other advantages.

Q.4. From your point of view, what are you worried about using this charging system?

C.P. - The origin of the energy is a problem, when everything is electrified, we will need 5 to 10 times more energy, the demand will increase exponentially.

A.R. - In municipal areas, it does not worry me, because the autonomy of a car allows you to use it every day (home/work) around 150 km of autonomy. What leaves me a little perplexed are the refills along the ring roads and highways. For a business or leisure trip, it is more complex.

F.D.C - We have very limited interests, we look at photovoltaics, wind power but maybe in 30 years the problem will arise of how to dispose of them and how to continue to find the raw materials that constitute them. I remember that there was the possibility of focusing on kinetic energy, but we do not consider it. Just as in the past, there was talk of the methane gas revolution as a solution, but it already seems obsolete to us. Perhaps only nuclear power can change things, but it is an issue that continues to scare us. There is also hydrogen, but the electrical component is still needed. At the network level, the problem remains. The hope is that something new will come that we don't know about.

Q.5. If you were to try an app with this type of charging system: What features would you want?

C.P. - The remaining kilometres, nearest EV charging station and top-up costs (also considering the range). Knowing if a restaurant has a charging station is also important.

A.R. - Considering the screens of our phones, on the first page you have the data that interest you and that you use the most or information on the nearest column. On another page, information for daily consultation (e.g., average consumption).

Q.6. From your point of view, what benefits would you expect from allowing flexible smart charging? What added value could it offer you personally?

C.P. - I would prefer an equipped station, but it's difficult. The direction is that those who buy an electric car will want to recharge them at home. Stations are important at strategic points.

Q.7. What would make you decide on the option where you change your car flexibly based on available energy instead of "as soon as possible"?

C.P. - The organizational aspect is not too big a problem. Everyone would organize their day the freelancer would be better off than the employee.

F.D.C - It depends on the work needs. Anyone would work on a charging process for a long time with greater savings.

Q.8. From your point of view, what would you worry about deciding on flexible smart charging?

F.D.C – The question to ask is whether the sustainable theme or the economic one is worth more? As an administrator, I have to say the topic of sustainability (it costs more but has a direction). In the lower-middle range of the population, which is recently approaching the issue, however, would opt for the economic issue, also because electricity continues to cost more than fossil fuel.

Q.9. If that smart EV charging would also have a dashboard with feedback on your charging process and status: What kind of feedback would you like to receive?

No answers.

VI. Planned Activity

The planned activity from mid 2022 to 2023 in Pilot 3 has two main paths:

1. Exploring viable additional User Stories across activate Epics (Forecasting, EV Smart Charging, and Interactive Platform)
2. Alignment of social engagement processes, business models in SEGRATE Municipality and AI technical solutions

For 1) above the following planned actions are considered for the next 6 months in 2022 and the start of 2023.

For 2) above the planned activities shall focus on a more stringent cooperation between WP6 (AI solutions), WP2 (social elements) and WP8 (replicability pack). As of 1st April 2022, the first milestone is to meet at the next PMB meeting in Poznam (Poland) on next June 2022 and project a dedicated cross-WPs collaboration plan and timeline.

VII. Summary and Conclusion

As stated in the *Introduction,* the overall Pilot 3 focused on testable and viable solutions, searching for both AI enhanced energy island efficiency, renewability and autarky as well as for social engagement, propensity and organisational capacity to implement an EI. Such techno-social range of solutions shall prove to be *replicable* and fit to real municipality contexts, the Segrate part of the Pilot 3.

The various range of solutions for AI predictive and prescriptive approaches, shall necessitate organisational requirements to fit in real social environments. In this sense, the following conclusions are implied for this interim Deliverable 6.1.

Between 2022 and initial 2023 the complete product "RENergetic software" is to be delivered as:

1. Solution provider of AI and advanced energy optimization solver
2. Solution provider of social methods to intercept roles and stakeholders
3. A Multi user interface to manage such content solutions
4. An Automated AI software (backend + frontend) to manage the RENergetic solution
5. Available services/supports

Finally, at the start of 2024 the RENergetic project shall deliver a “replicability pack” for Energy Island solutions with:

1. Tree based solution selection to implement RENergetic services
2. RENergetic Platform, AI methods (tech method)
3. RENergetic social influence methods (social method)
4. RENergetic Business Models, Legal aspects

The Pilot 3 will try to maximise and align with such prospective above. The finalized Pilot 3 Epics will reflect such strategy accordingly.

VIII. References and Internet Links

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IX. Annexes

IX.1.1. Annex 1 - User Story Chart

Forecasting user Stories-SEGRATE	This epic is about the different forecast user stories either in heating or electricity domains. It is about applying three different models/application: Forecasting, Root-cause analysis and anomaly detection		
Responsible	Daniele Baranzini (OSR)		
		Rating (1 = low, 5 = high)	
Stakeholder	Story	Urgency	Impact
A	**Waste heat generation from industry/ Factory**		
1 to EXPand	*CATEGORY #1: OSR Strategic Forecast of heat energy demand*		
Lead energy manager in OSR (GSD)	I, as an energy manager of GSD (allocated in OSR) want to forecast the expected MW heat energy demanded by OSR in order to spot undesirable trends (MW volumes, efficiency, peaks) with risks of being forced to buy energy from national grid or check if surplus MW energy (predicted not to be consumed) could be rendered available to re-distribute or to re-sell.	4	5
1 EXPanded-a	*CATEGORY #1a: OSR Strategic Forecast of heat energy demand as MW volume*		
Lead energy manager in OSR (GSD)	I, as an energy manager of GSD (allocated in OSR) want to forecast the expected MW heat energy demanded by OSR in order to spot undesirable trends in MW volumes with risks of being forced to buy energy from national grid or check if surplus MW energy (predicted not to be consumed) could be rendered available to re-distribute or to re-sell.	4	5
1 EXPanded-b	*CATEGORY #1b: OSR Strategic Forecast of heat energy demand as MW effcieincy (REN-EI index)*		

Lead energy manager in OSR (GSD)	I, as an energy manager of GSD (allocated in OSR) want to forecast the expected MW heat energy demanded by OSR in order to spot undesirable trends in MW efficiency (with REN-EI Index) with risks of being forced to buy energy from national grid or check if surplus MW energy (predicted not to be consumed) could be rendered available to re-distribute or to re-sell.	4	5
1 EXPanded	*CATEGORY #1c: OSR Strategic Forecast of heat energy demand as MW peaks*		
Lead energy manager in OSR (GSD)	I, as an energy manager of GSD (allocated in OSR) want to forecast the expected MW heat energy demanded by OSR in order to spot undesirable trends in MW peaks with risks of being forced to buy energy from national grid or check if surplus MW energy (predicted not to be consumed) could be rendered available to re-distribute or to re-sell.	4	5
2 to EXPand	*CATEGORY #2: OSR Strategic Forecast of heat energy demand (Co-generator view)*		
OSR's lead manager in Co-generator plant	I, as OSR's lead manager in Co-generator plant want to forecast the expected MW heat energy demanded by OSR in order to visualize expected trends, to spot risks of overconusmption leading to buying from the national grid, to verify if surplus MW energy (predicted not to be consumed) could be rendered available to re-distribute or to re-sell to external clients, as well as to simulate the Co-generator programme set up for the next week shedule according to the expected (forecased demand) and to finally assess the expected profitability of selling more or less energy to the national grid due to the projected heat energy consumption.	4	5
3 to EXPand	*CATEGORY #3: Milano2 Strategic Forecast of heat energy demand*		
OSR's lead manager in Co-generator plant	I, as OSR's lead manager in Co-generator plant want to have the Milano2's MW heat energy demand prediction in order to 1) respond to the real Milano2 heat energy needs up to 11 MW by contract, 2) to monitor trends and potentially re-fit (if necessary) the Co-generator energy production plan according to predictions, 3) to anticipate if surplus MW energy (predicted not to be consumed in Milano2) could be rendered available to re-distribute in OSR to internal units or to re-sell (electrical power) to external clients like national grid or charging stations company in OSR, 4) to o simulate the Co-generator programme set up for the next week according to the expected (forecased demand in Milano2), and finally 5) to assess the expected profitability of selling more or less energy to the national grid due to the projected heat energy consumption in Milano2.	3	5

4 to EXPand	*CATEGORY #4: OSR Operational Forecast of heat energy demand*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast: 1) OSR building consumption volumes, 2) OSR building efficiency levels (REN-EI index) and/or 3) OSR building energy peaks (MW heat) in order to respond to real risks of unwanted/unplanned OSR heat energy volumes, low efficiency Indexes or forcasted energy peaks that must be avoided whenever possible.	5	5
4 EXPanded	*CATEGORY #4a: OSR Operational Forecast of heat energy demand*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast OSR building consumption volumes in order to respond to real risks of unwanted/unplanned OSR heat energy volumes	5	5
4 EXPanded	*CATEGORY #4b: OSR Operational Forecast of heat energy demand*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast OSR building efficiency levels (REN-EI index) in order to respond to real risks of unwanted/unplanned OSR heat energy low efficiency Indexes that must be avoided whenever possible.	5	5
4 EXPanded	*CATEGORY #4c: OSR Operational Forecast of heat energy demand*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast OSR building energy peaks (MW heat) in order to respond to real risks of unwanted/unplanned OSR forcasted heat energy peaks that must be avoided whenever possible.	5	5
B	**Energy consumption in a factory**		

5 to EXPand	*CATEGORY #5: OSR Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building 1) heat consumption volumes, 2) heat efficiency levels (REN-EI index) and/or 3) heat energy peaks (MW heat). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building heat consumption volumes, efficiency or peaks control.	5	5
5 EXPanded	*CATEGORY #5a: OSR Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building heat consumption volumes. B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building heat consumption volumes.	5	5
5 EXPanded	*CATEGORY #5b: OSR Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building heat efficiency levels (REN-EI index). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building heat consumption efficiency (REN.EI index).	5	5

5 EXPanded	*CATEGORY #5c: OSR Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building heat energy peaks (MW heat). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building peaks control.	5	5
6 to EXPand	*CATEGORY #6: Milano2 Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on Milano2 building 1) heat consumption volumes, 2) heat efficiency levels (REN-EI index) and/or 3) heat energy peaks (MW heat). B) easily test AI simulations on such learned ML models in (A) and evaluate how changes on the predictor variables would modify the target response with a sensitivity analysis on Milano2 building heat consumption volumes, heat efficiency or heat peaks control.	5	5
6 EXPanded	*CATEGORY #6a: Milano2 Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on Milano2 building heat consumption volumes. B) easily test AI simulations on such learned ML models in (A) and evaluate how changes on the predictor variables would modify the target response with a sensitivity analysis on Milano2 building heat consumption volumes.	5	5

6 EXPanded	*CATEGORY #6b: Milano2 Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on Milano2 building heat efficiency levels (REN-EI index). B) easily test AI simulations on such learned ML models in (A) and evaluate how changes on the predictor variables would modify the target response with a sensitivity analysis on Milano2 building heat efficiency.	5	5
6 EXPanded	*CATEGORY #6c: Milano2 Machine Learning predictions (root-cause-analysis) (Heat)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on Milano2 building heat energy peaks (MW heat). B) easily test AI simulations on such learned ML models in (A) and evaluate how changes on the predictor variables would modify the target response with a sensitivity analysis on Milano2 building heat peaks control.	5	5
7 to EXPand	*CATEGORY #7: OSR AI simultations impacting Milano2 heat energy*		
OSR's lead manager in Co-generator plant	Role specs: I, as an OSR's lead manager in Co-generator plant, will need to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on OSR buildings in temrs of thermic energy savings (based on 1) heat consumption volumes, 2) heat efficiency levels (REN-EI index) and/or 3) heat energy peaks (MW heat)). B) easily test AI simulations on such learned OSR ML models in A) in order to evaluate how changes on OSR predictor variables could provide Milano2 opprotunities to avail of potential more heat energy rendered now available.	5	5
7 EXPanded	*CATEGORY #7a: OSR AI simultations impacting Milano2 heat energy*		

OSR's lead manager in Co-generator plant	Role specs: I, as an OSR's lead manager in Co-generator plant, will need to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on OSR buildings in temrs of thermic energy savings (based on heat consumption volumes). B) easily test AI simulations on such learned OSR ML models in A) in order to evaluate how changes on OSR predictor variables could provide Milano2 opprotunities to avail of potential more heat energy rendered now available.	5	5
7 EXPanded	*CATEGORY #7b: OSR AI simultations impacting Milano2 heat energy*		
OSR's lead manager in Co-generator plant	Role specs: I, as an OSR's lead manager in Co-generator plant, will need to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on OSR buildings in temrs of thermic energy savings (based on heat efficiency levels (REN-EI index)). B) easily test AI simulations on such learned OSR ML models in A) in order to evaluate how changes on OSR predictor variables could provide Milano2 opprotunities to avail of potential more heat energy rendered now available.	5	5
7 EXPanded	*CATEGORY #7c: OSR AI simultations impacting Milano2 heat energy*		
OSR's lead manager in Co-generator plant	Role specs: I, as an OSR's lead manager in Co-generator plant, will need to: A) easily use (train and test) ML models to identify patterns of variables/factors with the highest impact on OSR buildings in temrs of thermic energy savings (based on heat energy peaks (MW heat)). B) easily test AI simulations on such learned OSR ML models in A) in order to evaluate how changes on OSR predictor variables could provide Milano2 opprotunities to avail of potential more heat energy rendered now available.	5	5

8 to EXPand	*CATEGORY #8: OSR Machine Learning predictions (root-cause-analysis) (electricity)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building 1) electricity consumption volumes, 2) electricity efficiency levels (REN-EI index) and/or 3) electricity energy peaks (MW heat). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building electricity consumption volumes, efficiency or peaks control.	5	5
8 EXPanded	*CATEGORY #8a: OSR Machine Learning predictions (root-cause-analysis) (electricity)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building electricity consumption volumes. B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building electricity consumption volumes.	5	5
8 EXPanded	*CATEGORY #8b: OSR Machine Learning predictions (root-cause-analysis) (electricity)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building electricity efficiency levels (REN-EI index). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building electricity efficiency.	5	5
8 EXPanded	*CATEGORY #8c: OSR Machine Learning predictions (root-cause-analysis) (electricity)*		

OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on OSR building electricity energy peaks (MW heat). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of OSR building electricity peaks control.	5	5
9 to EXPand	*CATEGORY #9-GLOBAL: OSR Operational Forecast of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast: 1) GLOBAL OSR building consumption volumes (MWel+MWth), 2) GLOBAL OSR building efficiency levels (REN-EI index combining MWel+MWth) and/or 3) GLOBAL OSR building energy peaks (combined MWel+MWth) in order to respond to real risks of GLOBAL unwanted/unplanned energy volumes, low efficiency Indexes or forcasted energy peaks that must be avoided whenever possible.	5	5
9 EXPanded	*CATEGORY #9a-GLOBAL: OSR Operational Forecast of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast: GLOBAL OSR building consumption volumes (MWel+MWth) in order to respond to real risks of GLOBAL unwanted/unplanned energy volumes that must be avoided whenever possible.	5	5
9 EXPanded	*CATEGORY #9b-GLOBAL: OSR Operational Forecast of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast: GLOBAL OSR building efficiency levels (REN-EI index combining MWel+MWth) in order to respond to real risks of GLOBAL unwanted/unplanned low efficiency Indexes that must be avoided whenever possible.	5	5

9 EXPanded	*CATEGORY #9c-GLOBAL: OSR Operational Forecast of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	I, as an OSR's technical department manager, want to forecast: GLOBAL OSR building energy peaks (combined MWel+MWth) in order to respond to real risks of GLOBAL unwanted/unplanned forcasted energy peaks that must be avoided whenever possible.	5	5
10 to EXPand	*CATEGORY #10-GLOBAL: OSR Machine Learning predictions (root-cause-analysis) of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on GLOBAL OSR 1) energy consumption volumes (MWel+MWth) , 2) GLOBAL efficiency levels (REN-EI index combinining MWel+MWth) and/or 3) GLOBAL energy peaks (MWel+MWth). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of GLOBAL OSR energy consumption volumes, efficiency or peaks control (combined MWel+MWth).	5	5
10 EXPanded	*CATEGORY #10a-GLOBAL: OSR Machine Learning predictions (root-cause-analysis) of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on GLOBAL OSR energy consumption volumes (MWel+MWth). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of GLOBAL OSR energy consumption volumes (combined MWel+MWth).	5	5

10 EXPanded	*CATEGORY #10b-GLOBAL: OSR Machine Learning predictions (root-cause-analysis) of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on GLOBAL OSR GLOBAL efficiency levels (REN-EI index) combinining MWel+MWth). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of GLOBAL OSR energy efficiency (combined MWel+MWth).	5	5
10 EXPanded	*CATEGORY #10c-GLOBAL: OSR Machine Learning predictions (root-cause-analysis) of GLOBAL energy demand (multi-vector electicity/thermic MW)*		
OSR's technical department manager	Role specs: I, as an OSR's technical department manager, want to: A) easily use (train and test) ML models in order to identify patterns of variables/factors with the highest impact on GLOBAL OSR GLOBAL energy peaks (MWel+MWth). B) easily test AI simulations on such learned ML models in (A) in order to evaluate how changes on the predictor variables would modify the target response in terms of GLOBAL OSR energy peaks control (combined MWel+MWth).	5	5
C	**Heat energy consumption in buildings**		
11 singles	*CATEGORY #11: OSR AI forecast of building occupancy/heat demand mismatch*		
OSR's technical department manager	I, as OSR's technical department manager, want to use the AI forecasts about building occupancy measures (options: people volume, frequency, timing or behaviours) to estimate a fit of heat energy demand based on occupancy levels and inform the OSR's lead manager in the Co-generator plant to fine tune the heat energy supply accordingly.	4	4
D	**Electric energy consumption in buildings**		

12 singles	*CATEGORY #12: OSR AI forecast of building occupancy/elecricity demand mismatch*		
OSR's technical department manager	I, as OSR's technical department manager, want to use the AI forecasts about building occupancy measures (options: people volume, frequency, timing or behaviours) to estimate a fit of electricity energy demand based on occupancy levels and inform the OSR's lead manager in the Co-generator plant to fine tune the electricity energy supply accordingly.	4	4

IX.1.2. Annex 2 – Data Availability Pilot 3

Energy Reference	Building reference	Property / Quantity	Unit of Measurement	Sampling rate	Data size	show (example layout)
1) HOT WATER 2) SUPER-HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	Instant Power	MW(Mega Watt)	1h (can reduce to 15 mins)	from 15/08/2020 to Febrary 2020	0,95
1)HOT WATER 2) SUPER-HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	Heat Instant Energy	MWh	1h (can reduce to 15 mins)	from 15/08/2020 to 15/02/2021	1025381,56
1) HOT WATER 2) SUPER-HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	Circuits flow	[m3/h]	1h (can reduce to 15 mins)	from 15/08/2020 to 15/02/2021	59,8
1) HOT WATER 2) SUPER-HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	Volume	[m3]	1h (can reduce to 15 mins)	from 15/08/2020 to 15/02/2021	994852,06
1) HOT WATER 2) SUPER HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	IN_flow temperature degrees	[°C]	1h (can reduce to 15 mins)	from 15/08/2020 to 15/02/2021	87,8

1) HOT WATER 2) SUPER-HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	OUT_flow temperature degrees	[°C]	1h (can reduce to 15 mins)	from 15/08/2020 to 15/02/2021	65,2
1) HOT WATER 2) SUPER-HEATED WATER 3) COLD WATER	1-[Dibit 1, Dibit 2, Dimer, Emodinamica, D, Asilo, Cascina Melghera] 2-[Dibit 1, Dibit 2, Emodinamica, D, Q, R] 3-[Aritmologia, Asilo, Cascina Melghera, Dibit 1, Dimer, D, Q, R]	outdoor temp	[°C]	1h (can reduce to 15 mins)	15/08/2020 - now	19,5