Climate and cultural based design and market valuable technology solutions for Plus Energy Houses

Report on strategy for building flexibility

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Executive summary

This document presents a comprehensive exploration of energy flexibility and control strategies in building sector across different levels, from system to component, focusing on two specific geo-clusters: Sub-Artic and Mediterranean. The report starts with an introduction to the significance of energy flexibility in modern energy systems. It highlights the need for innovative control mechanisms to balance energy supply and demand effectively. Section 2 delves into energy flexibility, starting with an overview of different levels: energy system, district, building, and component. The concept of geo-clusters is introduced, analyzing their potential and limitations in offering energy flexibility. The district and building levels are examined, emphasizing the role of flexibility in Plus Energy Building (PEB) frameworks. Component-level analysis provides insights into micro-level control possibilities. The subsequent section (3) focuses on flexibility control logics and performance metrics. It discusses various metrics to assess the efficiency and effectiveness of control strategies. The document then proceeds to detailed case studies in two distinct geo-clusters: the Sub-arctic geo-cluster in Norway and the Mediterranean cluster in Italy.

Section 4 presents the Norwegian energy system, climate factors and user behavior. It is remarked that the energy system is characterized, by hydropower generation, electric resistance heating and the highest penetration of EV pro-capita. From transmission system level, the hydropower is the main component that provides flexibility by performing ancillary services such as frequency regulation and seasonal storage. At small scale level (e.g. building or cluster of buildings), it is fundamental to adapt the customer's condition to the system requirements given by the high penetration of EVs. Within this context, the building can provide a significant contribution in terms of flexibility, mainly through the user behaviour related to energy-consuming systems, such as domestic hot water (DHW), comfort preferences and EV-charging habits. In this regard, the present report analysed the potential of the Norwegian demo case (i.e., a multi-family house[1]) considered in the Cultural-E project by focusing on its level of flexibility. Given as target function the minimization of the energy imported from the grid, three flexibility factors are considered before separately and then tighter. They are indoor temperature, DHW tanks control and battery system. Simulation results showed that the combination of these three factors can lead to a reduction of 8% in electricity imported from the grid and 6% of cost reduction.

For the Mediterranean cluster, we focus on the Italian context (section 5). The focus has been in the building domains and examines various load components and appliances. Detailed exploration of the thermal and electrical domains, including battery storage control and electric vehicle charging, is undertaken. The flexibility factors in this case

[1] https://www.cultural-e.eu/norwegian-demo/.

have been limited to the electrical domain, in particular on the PV/battery system and a predictive control based on the minimization of the cost of the energy exchanged with the grid. A comparison analysis based on simulations take into account different prediction horizon and battery rule-based control applied to the low-rise reference building modelled into the Cultural-e project and corresponding to the Italian demo. The results showed that the energy import during so called high-price hours can be reduced of values between 10%-13% depending on the control strategies used.

The succeeding section (6) presents experimental tests and validation of energy building flexibility control strategies in the Mediterranean climate performed at Eurac laboratory. Simulation campaigns, laboratory setups, and implemented control strategies are then discussed showing potential and limit of the real-field implementation. The outcomes of experimental tests are examined, offering insights into future perspectives and possible applications.

The document concludes with Section 7, summarizing the findings, implications, and potentiality of the study.

Nomenclature

Table 1: Acronyms table

Acronym	Complete name
PV	Photovoltaic
EV	Electric vehicle
BESS	Battery energy storage
BMS	Building management system
MPC	Model Predictive Control
RES	Renewable Energy Source
DH	District heating
DHW	Domestic Hot Water
TSO	Transmission System Operator
DSO	Distribution System Operator
DSM	Demand-Side Management
DR	Demand-Response
PEB	Plus Energy Building
ESWH	Electrical Storage Water Heaters
REC	Renewable Energy Community
HVAC	Heating, Ventilation and Air Conditioning

1 Introduction

Energy use in buildings constitutes approximately 40% of the final energy use (a large portion of which goes toward heating, cooling, ventilation and air-conditioning) and 36% of greenhouse gas emissions in Europe [1]. Therefore, a comprehensive phase-in of renewable energy sources must be undertaken to enable the decarbonization of the energy system and reach the two-degree goal [2]. Since the potential of stable sources such as geothermal and hydropower is limited, a large share must come from wind and solar power. The inherent intermittency of these sources leads to new challenges in how energy and power systems are operated. Traditional central load-matching is becoming insufficient as the penetration of these sources increases. A key concept in this context is energy flexibility on the demand side (i.e. in residential or commercial buildings), enabling the grid/system operator to control the demand through penalty signals associated with, e.g. price, CO_2 emissions and grid congestion [3]. The question is then: What is building (energy) flexibility? We cite IEA EBC Annex 67: "*The energy flexibility of a building is the ability to manage its demand and generation according to local climate conditions, user needs and grid requirements. Energy flexibility of buildings will thus allow for demand side management/load control and thereby demand response based on the requirements of the surrounding grids* [4]".

In this report, the focus is on flexibility for residential buildings. The report is structured as follows. Section 2 introduces the flexibility at different energy system levels, i.e., the whole national system, the district/cluster of buildings, the building as it is and the components. Then, section 3 presents a general overview of the classification of control strategies and models that can be used to implement building flexibility and the metrics selected for the current work. After these two general paragraphs, the report becomes more detailed, focusing on the energy-building potential and demonstration in the Sub-Artic geo-cluster represented by Norway (in section 4) and the Mediterranean area represented by Italy (in section 5). In the final version, Section 6 reports the description and the results of the experiments performed in the EURAC laboratory facility, implementing a sub-set of the strategies proposed in section 5. Finally, section 7 draws the main task conclusions.

2 Energy flexibility

Traditional power grids had a central architecture where the few power generation units had located far from the consumers, with a predominance of passive loads and limited storage units. In the last years, we have assisted in a considerable change of this paradigm mainly due to the proliferation of distributed energy resources (e.g., photovoltaic generators, electric storage, …) and non-linear and dynamic loads (e.g. heat pumps, electric vehicles) placed close to the consumption points. The centralized system guarantees the stability and operativity of the power system, properly managing the demand and supply by using the reserve to mitigate the difference and mismatch responsible for the fault, blackouts, and possible disconnection. The monitoring and control actions were centralized and in charge of the transmission system operators (TSOs) or distribution system operators (DSOs). Modifying grid structure by integrating renewable energy sources (RES), usually of variable nature (e.g. solar and wind), required a dynamic load balance on both the supply and demand side. In this context, the building can bring a high potential in terms of demand/energy flexibility representing in the most developed countries about 30% of the total primary energy [5]. Based on the classification strategies reported in [6], it is possible to identify five building demand-side management strategies corresponding to the capability to reduce, shed, shift, modulate or generate DERs onsite.

Even though flexibility is becoming a hot topic, its definition varies on the application context and system levels. As suggested in [7], it is a cross-level concept which ranges from components to the whole energy system and where each layer directly impacts the flexibility potential of the higher one.

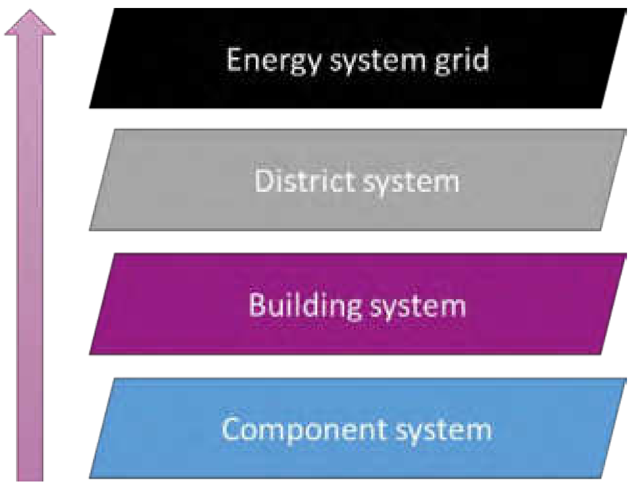


Figure 1 Flexibility domains

2.1 Energy system level

This initial system-wide view allows us to identify the first boundary conditions potentially impacting the energy flexibility issue.

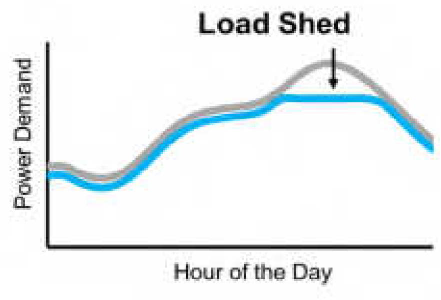
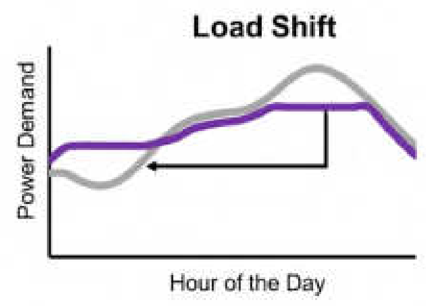
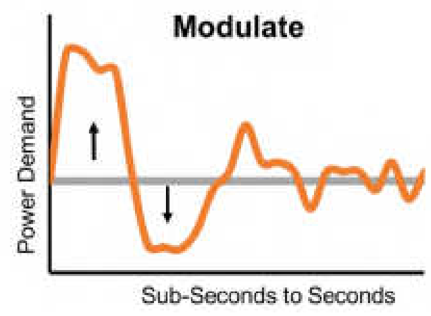
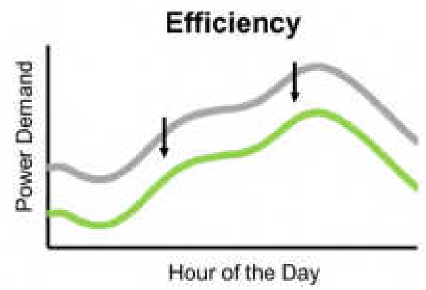
- **Geographical factors**. This entry includes several contributions, mostly from Climatic/Weather conditions, but also from Social and Demographic factors in the consumption behaviours [8], [9], comfort definition and acceptance, readiness, and sharing of changes potentially introduced by the implementation of flexibility;
- Structure of the **Energy Systems** at a Regional/National level;
- Composition and characteristics of the **building stock** at the National/Regional level (here, the focus is mainly on Residential Buildings) and infrastructures.
- Energy Markets and Regulation Frameworks

Carbon emission reduction is one of the main driving forces of energy flexibility [4]. Additional technical and economic *motivations* were declined to search for this ultimate environmental goal. Among this:

- Reduce the mismatch between the production and consumption of renewable energy sources (**RES**) and improve their **introduction and adoption** in the energy system.
- Bottleneck and limitation mitigation in the energy infrastructure (e.g. line congestion)
- Grid infrastructure investment cost reduction

These motivational objectives introduce exploring additional domains as technical and overall economical. Cost reduction may be researched and expected on the grid infrastructure (therefore for TSO) and for each end-user due to possibly lower shared energies purchased from the system. These same objectives may bring to the following possible system-level actions. Demand-side management (DSM) plays a key role in this evaluation. From a utility perspective, DSM means influencing customer uses of electricity to induce desired changes in the utility's load shape [10]. DSM has two main components [4]: energy efficiency (EE) and demand response (DR). Both elements should help to reduce the overall energy consumption and allow the introduction of a flexibility component. At the grid level, the primary mechanism that brings flexibility are load shifting, load shaving and valley filling. Generally, five DSM strategies can be identified according to [11]; their effect on the load profile is shown in Table 2.

Table 2 Summary of the demand-side management strategies for the U.S. DOE GEB [11]

Definition and characteristics	*Load profile example*
Generation: on-site use or dispatch to the grid during peak demand hours	
Load shed: reduction of peak power demand during a short period	
Load shift: changing energy use to reduce the power demand during peak hours or exploiting the RES generation	
Modulate: Adaptation of building demand based on the grid operator signals to support specific service	
Efficiency: power load reduction	

The contribution of each actor that composes the system impacts the final goal just defined at the system level. Moreover, differences at this wider level may affect the effectiveness of the control strategies sketched in the following sections of this document. Suppose the controls are designed to pursue the above economic and environmental objectives. The considered external control signals can present huge variations precisely because of the differences recognized at this scale. Different climatic conditions (see the connection between Climatic conditions and heating/cooling or energy generation through RES) or other market structures or energy mixes (that impact costs and equivalent energy carbon emissions) can dramatically scale the external signals and parameters that enter both control definitions and the final evaluation of the control performances and the actual flexibility impact on its driving objectives.

2.1.1 Geo-clusters: potential and limitations in energy flexibility

The current section introduces four geo-clusters to investigate further the constraint and factor sketched in this section. These Clusters include regions that share similar Climatic conditions and cover the European countries' variability. These clusters are also assumed to hold for the remaining boundary constraints identified in the previous section. This approximation reduces the considered case studies to a finite set of entries, still sufficiently representative of the European context.

We consider each climate-cultural geo-cluster to be represented by the country where the CULTURAL-E demonstrators are located. While this is an oversimplification (consider e.g. the difference in the prevalence of district heating in Sweden and Norway for the Sub-Arctic region, see [12] and [13]), it is necessary to make the classification tractable.

Table 3 The table reports the four selected geo-cluster representing EU countries. In addition, the reference Countries are also provided. They refer to the location chosen to represent each geo-cluster in the developed work. Moreover, a list of cities is provided as a precise reference location for the historical data adopted in the simulation phase (e.g. weather data).

Geo-cluster	Country
OCEANIC	France
CONTINENTAL	Germany
MEDITERRANEAN	Italy
SUB-ARTIC	Norway

For each geo-cluster, the thermal characteristics of the building envelope and the temperature setpoints are different, as shown in the following tables:

Table 4. Envelope thermal characteristics

Geo-cluster	Reference Country	U-VALUE External Wall [W/m²K]	U-VALUE Roof [W/m²K]	U-VALUE Ground floor [W/m²K]	U-VALUE windows [W/m²K]
Mediterranean	Italy	0.18	0.12	0.12	2.89
Continental	Germany	0.13	0.09	0.11	1.12
Oceanic	France	0.25	0.12	0.25	1.3
Sub Artic	Norway	0.10	0.08	0.09	0.76

Table 5. Heating and Cooling temperature set-points

Set Point	Mediterranean	Continental	Oceanic	Sub-Artic
Heating System [°C]	20	21	20	22
Cooling System [°C]	26	26	24	27

The performed simulations use, as boundary conditions, the weather data of a typical year of the considered locations. For the Mediterranean climate, the weather data of Bologna were considered, Stuttgart is the reference location for the Continental climate, Brussel for the Oceanic climate and Oslo for the Sub-Artic climate.

The internal gains consider the presence of people, the lighting and other appliances; their profile has been stochastically determined and takes into account the cultural differences of the four geo-clusters.

Additional information on climate and cultural-dependent energy use can be found in Cultural-E deliverable D2.1, and details on local policies and boundary conditions for the geo-clusters can be found in Cultural-E deliverable D2.3.

Regional-specific characteristics relevant to flexibility are discussed in the separate sections for the sub-artic (i.e. Norway) and Mediterranean (i.e. Italy) geo-clusters.

Electricity load profiles

The electricity load profiles at the national level for each country representing the geo-clusters are compared.

Figure 2 compares the weekly energy loads relative to the peak demand in 2019. It illustrates the seasonal variation in the electricity demand for each country. France and Norway have an evident seasonality with much higher loads in winter than in summer. This behaviour is because a large portion of the building stock utilizes electricity for heating. For Italy and Germany, this effect is less pronounced. Compared to the other countries, Italy has its peak demand during summer, showing the importance of cooling.

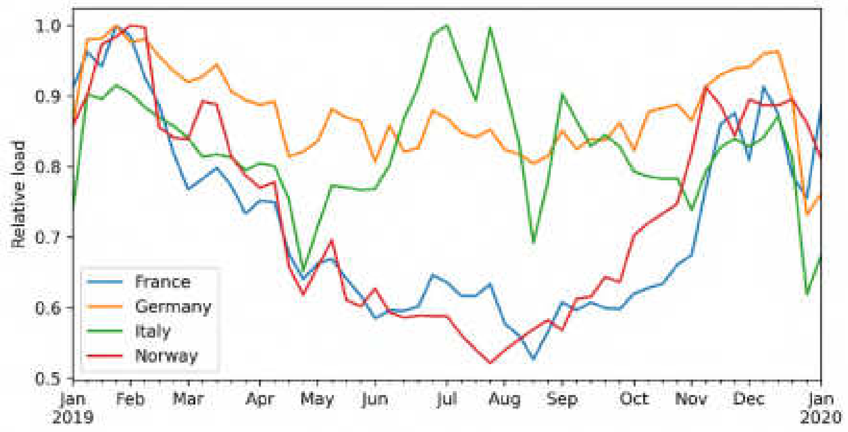


Figure 2: Relative weekly electricity load compared to peak for 2019 for the geo-clusters[2]

Figure 3 shows similar profiles but with hourly resolution for a selected winter (left) and summer (right) week. The y-axis is relative to each country's selected week's peak. Italy (Mediterranean geo-cluster) has the highest daily fluctuations in summer and winter. Norway has the smallest daily fluctuations, possibly due to a high share of energy-intensive industries utilizing electricity evenly throughout the day and night. From a grid utilization perspective, having as flat a profile as possible is desirable. The flexibility sources and control strategies described in this document can contribute to flattening such profiles.

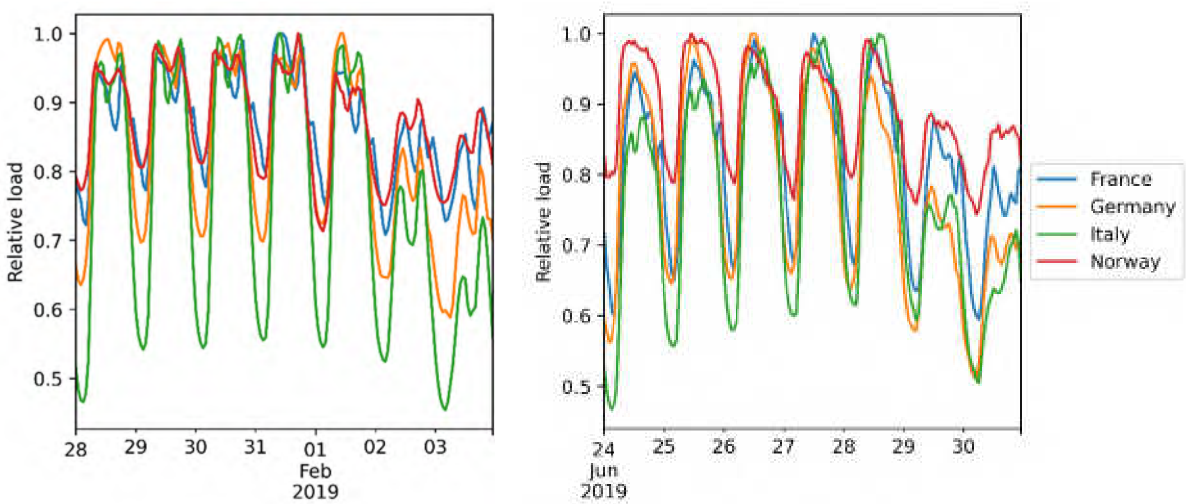


Figure 3: Relative hourly load profiles for selected winter (left) and summer (right) week[3]

[2] Data downloaded from https://doi.org/10.25832/time_series/2020-10-06.
[3] Data downloaded from https://doi.org/10.25832/time_series/2020-10-06.

EV Penetration

EV charging is an electricity profile that can be mentioned as a flexibility source. The potential on a large scale is dependent on the stock of EVs. Figure 4 shows the share of sold cars that are EVs (left) and the share of total stock that are EVs (right) from 2010 to 2020. Currently, only Norway has a significant stock of EVs. However, this is also rapidly changing for other countries in the future, so the EV charging flexibility can affect the local level.

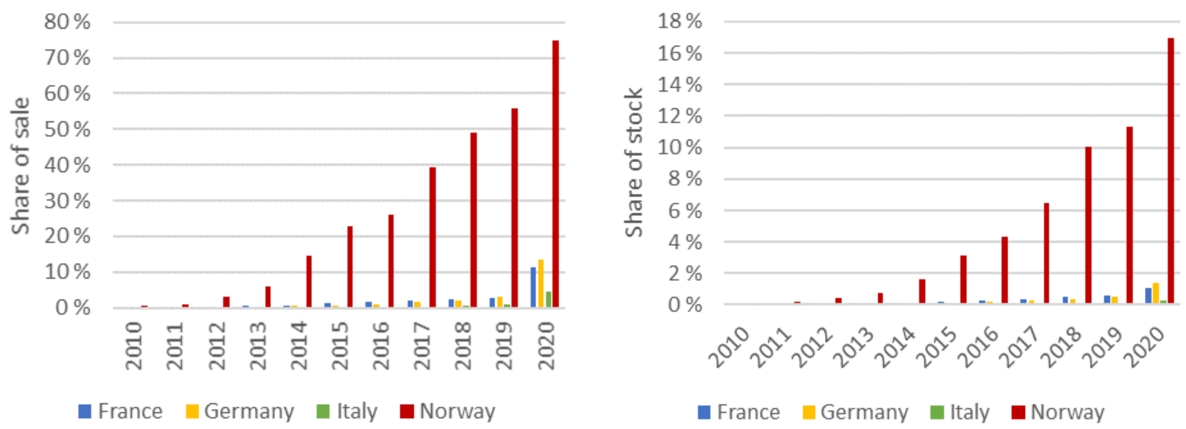


Figure 4: EVs as share of all car sales (left) and EVs share of stock in the geo-clusters (right)[4]

2.2 District level

District or cluster of building level refers to a community where buildings are physically located in the same neighbourhood or composition of buildings where the loads can be coordinated while they are not physically close to each other. In this case, the district/cluster of buildings can be a flexibility provider to a utility operator or an aggregator, according to the case, to modify the demand. As analysed in the recent publication of Annex 82 [14] there are three main control architectures (i.e., centralized, decentralized and distributed) according to the decision-making role and the information shared between the stakeholders. Centralized control may lead to optimal energy system supervision, but it is sometimes difficult to scale. Decentralized control consists of a local strategy, such as broadcasting a signal price that can be gathered to all the buildings to react, shaping and shifting their loads. This approach can have local benefits. A third method is the distributed method which can be hierarchical and non-hierarchical. From an energy model point of view, the district/cluster of buildings can also map and overlap the renewable energy community (REC) concept (Figure 5). A REC is a community of users able to share their renewable production to cover the

[4] IEA (2023), Global EV Data Explorer, IEA, Paris https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer.

community's demand. Suppose we limit to the technical and energy aspects (but a REC in the EU definition is much more than this). In that case, it is clear that in the future, the REC will provide flexibility to the local energy system with a direct impact on the energy balance and the local market price. Anyway, even the REC flexibility and the district/cluster of building potential can be unlocked through buildings and components operations.

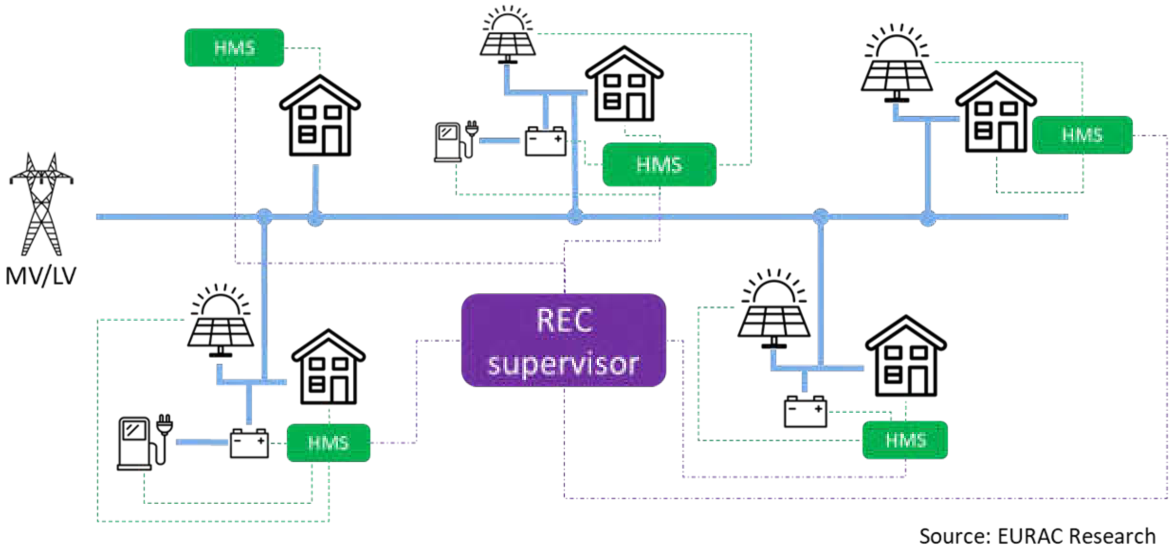


Figure 5 Scheme of a renewable energy community (REC) [15]. The REC is a legal entity that aggregates passive consumers and prosumers who can be equipped with photovoltaics and battery electrical storage systems.

2.3 Building level

The concept of DSM may be moved downward to focus on the building level by moving in two main develop directions:

- Promote a reduction of energy consumption.
- Move consumption behaviour and system utilization according to a target objective.

Concerning the second energy flexibility action identified, the outcomes of the Annex 67 program [4], [5] summarize the property of energy flexibility as follows:

- Time and duration of the change in the energy pattern or behaviour (shredding or shifting).
- Impact on the power profile (reduction or increase)
- Amount of energy that can be moved (shifted or shredded). This property is derived from combining the previous two (how much and how long).

- Evaluate possible impact on the building's performance and the inhabitant's comfort.
- Identifying a target and the relative adopted penalty/control signal to force these objectives.

The latter component introduces the discussion of the controls that enables energy flexibility at the identified levels.

2.3.1 Building Flexibility in a Plus Energy Building Framework

The work of the current document focuses on building energy flexibility. This objective is addressed in a general framework that involves the study of the so-called Plus Energy Houses. The Plus Energy Building (PEB) definition refers to a building that produces from renewable sources more energy than it imports in a year [16], [17].

Developed within the framework of the current project, Hawila et al. [18] work aims to review past literature on PEB and produce their approach for a shared definition and assessment of Plus Energy Building. The work takes up the core definition already reported from [16] and [17]. The positive energy target is considered achieved when annual energy generation exceeds the actual consumption. Simulated or real data may be considered to evaluate such targets. Moreover, in presence of multiple energy carriers, the balance can be formulated in terms of primary energy. All energy uses that ensure the building operation enter the energy balance. Two additional details narrow down the PEB statement proposed in [18], they are:

- an awareness and thoughtful consideration of the physical boundaries at the building scale (building footprint; user interaction; system controllability; infrastructure integration; ownership and management)
- ensure an added value to the final user, indirectly, to the surrounding infrastructure (grid) and finally in environmental terms (accessible, comfortable, and healthy indoor environment; building integration in the surrounding infrastructure; low carbon)

[19] proposes a graphical representation of the production/consumption balance behind the concept of PEB: the "Energy Matching Chart" [19], [20]. This graphical representation serves both as a sizing tool and as a device to allow the qualitative analysis of the performance of a building and fast identification of possible improvement directions. As highlighted in these works ([19], [20]), the only PEB qualification may not be sufficient to also grant an *"optimization"* of other environmental impact and building performance from the other possible KPIs. For example, a positive energy building may present high mismatches between consumption patterns and production profiles. It also may export a high share of the overall renewable production

due to oversizing the production or storage part. In those sketched scenarios, the economic, environmental, and overall technical KPIs may suggest an imbalance or not proper equilibrium between the components of the system, despite meeting the yearly based balance target. This example may bring attention to the proper sizing of the building systems within the solution space allowed by the PEB requirements.

Given a PEB design, an Energy Flexibility Practice may improve the building's economic, environmental, and technical performance and relative plants. By doing so, it is possible to reduce the impact of the building further and enhance the installed energy and technical resources.

The current work explores the Energy Flexibility Practice to improve the impact and effectiveness of the PEB building design regarding the declared objective and driving force reported in section 2.1.

2.4 Component level

From the demand perspective, energy flexibility is achieved by modifying the energy demand and/or on-site generation. For this reason, the heat pump, air conditioner and wet appliances are the most end-user components to exploit flexibility. Associated with these technologies are the building thermal mass, thermal storage tank, battery, PV system and CCHP as facilities to support flexibility. Control strategies for building flexibility and performance metrics

3 Flexibility control logics and performance metrics

This section briefly presents an overview of the different types of control strategies to exploit flexibility in buildings (limited to the ones considered in this task) and a selection of performance metrics to quantify the strategies' benefits. General overview of control strategies

Controls may be characterized as follows [4], [21]:

- **Rule-based control (RBC)**: The most common/ubiquitous example of this is on-off-hysteresis control. This is the control method used in electric water storage heaters. Simply stated, the tank's heating element is turned on when the temperature drops to a certain point (e.g. 65 ℃) and turned off when the temperature reaches an upper threshold (e.g. 70 ℃). Thus, the temperature is kept within the set-point (67.5 ℃). We present some more examples of RBC, operating at "higher levels", i.e. further away from the hardware:
    - Different control actions can be taken depending on external variables, such as electricity price and outdoor temperature. In [22], the setpoints for space heating and domestic hot water, both provided by the same heat pump, are modulated based on an a priori classification of the difference between the maximum and minimum day-ahead (spot) price.
    - In [23], the set-points of 33 distributed DHW-tanks in a neighbourhood are modulated based on pre-defined time schedules, voltage deviations, etc. to yield significant improvements in self-generation and self-production of PV. The case presented shows that the control with the least implementation effort (pre-defined time schedule) performs almost as well as the one with the largest implementation effort associated with it (central intelligent agent, two-way communication required). However, the authors note that the conclusions drawn from this case do not necessarily hold "globally" (i.e. for other "local" cases or system-wide).
    - Rule-based control for a grid-constrained charging site is investigated in [24]. The allocation rule is to divide the available grid capacity equally among charging vehicles, in addition to a preference for emptying stationary batteries if they are present in the system.
- **Rule based predictive Control (RBPC)**. An additional step in the improvement of the "smartness" of controllers is the introduction of predictions (Rule-based predictive controls) that may enter the variation of the basic parameters that the RBC adopts for its operation. An example of this practice is proposed in [25], where to reduce battery aging, the system stores the PV surplus till reaching the amount of energy that is estimated to be used during the following night.
- **Model predictive control (MPC)**:

Definition from [26]: *"MPC is a constrained optimal control strategy that calculates the optimal control inputs by minimizing a given objective function over a finite prediction horizon. The mathematical model of the system together with the current state measurements and weather forecast are used to predict and optimize the future behaviour of the building."* Numerous challenges are associated with the widespread deployment of MPC in buildings, among others:

1. Compatibility of communication interfaces between different hardware and software infrastructures, the lack of which leads to "vendor lock-in".
2. Accurate and computationally efficient control-oriented building modelling. More succinctly: complexity and robustness trade-off, aka bias-variance trade-off.
3. Automated design, tuning, and deployment of MPC (engineering challenge, difficult due to the heterogeneity of the built environment).
4. Plug-and-play implementation, robust operation.
5. Privacy, cyber-security
6. Personnel trained to handle commissioning, and maintenance in practice.

(Bullet points lifted directly from [26]). [27], [28] attempts at least in part to solve the first and next last points. For points 3 and 4 see [29] (Data semantics).

For the MPC system model we distinguish three main modelling paradigms:

White-box modelling: models based on first principles, which can be developed with languages such as *Modelica* [30] (and the open-source *Buildings* library [31] or tools such as DOE-funded *EnergyPlus* [32] or TRNSYS [33]. These models have the potential to be very accurate and realistic and many software tools already exist and are well-developed. Nonetheless, they also require considerable time, effort, and expertise for the development, setup, and calibration, and their optimization may be non-trivial. Successful applications of white-box MPC for building climate control include [34] (mainly shifting cooling loads) and others (to come). In the case of large tertiary/commercial buildings, the overhead incurred by setting up the complicated models is justified by a potential large ROI (especially in grid-constrained spots) and the low ratio of implementation cost compared to other costs such as renovation or construction.

- **Black-box modelling**: Models are based on mathematical constructs such as Artificial neural networks (ANNs) [35], Support Vector Machines (SVMs) [36], multiple linear regression models [37] etc. These models do not encode any physics (i.e. domain knowledge), are completely general, and hence performance could be poor on untrained data. In other words, it is hard to find a good bias-variance trade-off. Parameters are found via system identification and have no physical interpretability. "Data-driven" models.

- **Grey-box modelling**: These are simplified, reduced-order physical models that combine features of both white-box models (physical interpretability, structure) and black-box models (data-driven inference of parameters). Can include stochastic terms to avoid overfitting and accounting for parametric uncertainty. Suitable for MPC in that they e.g. require less data for training than black-box models, and are computationally much lighter than white-box models. For a more detailed overview of modelling paradigms, see [38].

Both rule-based and model predictive control strategies have the potential to work toward an objective. This is what can be reasonably defined as "smart" control. In the case of MPC, this objective is defined explicitly as the objective function of the optimization problem to be solved over the sliding time horizon, subject to constraints and dynamics. With MPC, it is possible to combine objective function targets, in which case it is beneficial with normalization and/or weighting of the separate terms. RBC, on the other hand, relies on some form of logic (exemplified by e.g. if-else clauses or boolean logic) to realize the objective. With a stationary battery and the ability to control the power flow, a simple rule-based control could be based on buying electricity when the spot price is below a certain threshold and selling it when it is above another threshold (with some deadband in between). The main difference between RBC and MPC is in the *optimality* of the action, as well as in the ability to handle *constraints* and *dynamics*. Predictions can be leveraged with both control paradigms, but an MPC is, in theory, able to take better advantage of them.

In the context of smart building control, we want to define two main control levels applied to buildings:

- **High-level/supervisory control**, where the parameters that are controlled are typically setpoints in the HVAC system. Low-level (Automation level) controllers, such as PID controllers, are then used to track the setpoints.
- **Low-level/component control**, where the optimization variables are quantities like valve openings, damper positions (for mechanical systems), or e.g. duty cycles for electrical systems.

These concepts can be combined in different architectures. In [26] and [14], four different architectures are defined, which can be described roughly as either one of the two concepts above, or some combination of the two:

- **Centralized**: a central agent optimizing and feeding setpoints to subsystems that already implement "classical" control. In this way, the system functions fully if the MPC encounters a fault. This is a pure high-level control implementation.

- **Hierarchical**: A supervisory MPC generates setpoints to "local" MPCs (presumably operating with a smaller time step), which determines how to track the setpoints optimally. This is a combination of high-level and low-level.
- **Distributed**: Horizontal architecture. Each agent communicates information about the local state and predictions to others, such that the coupling of systems is accounted for. In principle, this can be both high-level and low-level. Non-cooperative: each controller optimizes its "own" objective function. Cooperative: Each MPC optimizes a global objective function.
- **Decentralized**: Non-cooperative MPC. Each MPC optimizes without awareness of the intercoupling. Same as distributed in that it in principle can be both low-level and high-level.

With the notions presented above, the reader should at least have a basic taxonomy for concepts in control theory/MPC, and thus be able to follow the discussions and presentations in the following.

3.1 Performance metrics

In [39], Deru and Torcelli states their definitions of metrics and indicators in the field of building energy performance evaluation. Several tiers of metrics are identified according to their goal within the entire lifespan of the building (e.g. design state, operational life) and the actual target users (policy makers, owners, designers, operators, raters and researcher). The “Performance Indicators” are defined as: *“a high-level performance metric that is used to simplify complex information and point to the general state or trends of a phenomenon.”* [39].

From the above disambiguation of building metrics and indicators, we can summarise the several flexibility indicators review in literature[5] in two categories:

- **Indicators of flexibility potentials.** These indicators are more related to the characteristics of plant (building) and the sizing of its components (e.g. storage size, maximum power, production capacity, building characteristics) and are more related to a design phase.
- **Indicators of flexibility performance**. These are more related to the operational life of the plant and to potential control objectives. In this sense, they rely on a wider and detailed amount of data (either long-term monitoring data for real plant or derived from extensive simulations based on simplified models of the buildings).

[5] The following literature resources were reviewed and here reported to address the reported metrics: [7], [40]–[44].

For the purpose of the current task, we focus on the latter category of indicators.

We therefore select the following indicators as the most reported in literature and that are also uniquely defined:

- **PV self-consumption** and **self-production** (or self-sufficiency) [7], [40]–[44]

$$SelfConsumption_{\%} = 100 \cdot \frac{\sum_{i=1}^{T} \min\left(E_{PV}(t), E_{load}(t) + E_{toBESS}(t)\right)}{\sum_{i=1}^{T} E_{PV}(t)} \quad (1)$$

$$SelfProduction_{\%} = 100 \cdot \frac{\sum_{i=1}^{T} \min\left(E_{PV}(t) + E_{fromBESS}(t), E_{load}(t)\right)}{\sum_{i=1}^{T} E_{load}(t)} \quad (2)$$

- **Costs** or Energy cost (Operational electricity cost - an estimate [7], [42], [43]): Estimation of the energy price by approximating the energy tariff. A user's energy pricing may depend on national regulations and individual contracts stipulated with suppliers. Providing a reference value for energy billing may be non-trivial. The common approach is to rely on a mean energy price that embeds all the components of a potential billing schema. Another option is to rely only on one component of the price, for example, the external price signal, when present in the case study.
- **Daily equivalent CO_2 emission reduction** [43]

$$CO_{2\_reduction} = 100 \cdot \left(1 - \frac{CO_2}{CO_{2\_noFlexibiltyPractices}}\right) \quad (3)$$

- **Occupant comfort** (Mostly related to the thermal domain of the building)[6]

We also produce additional evaluation on the **final energy balance** (used, production, overproduction) on the overall building (total) and on partial components (e.g. HP, EV – the most energy-consuming devices and on the same time objective of the smart control practices). The latter indicators are often adopted in literature, while several names are proposed to refer to the same (or similar) quantities. Here we adopt the naming proposed by Fink et al. [42], [43], that is "**Load Cover Factor**" (same definition of self-generation but restricted to single devices).

The above indicators are general and hold in all the analysis related to building energy performances. Although the literature proposes plenty of indicators specifically built to evaluate the flexibility practices, it is non-trivial to identify a common approach and

[6] For the implementation and evaluation of this indicator refer to the relative caveat in section 6 related to the actual experimental phase. Flexibility exploitation of the thermal domain is managed in the simulation only through the application of the equivalent electrical profiles derived from the use of thermal resources according to flexibility practices.

provide a cross-comparison among the many formulations. One of the issues is the identification of the actual baseline scenario to evaluate the change in performance of the system due to the introduction of the flexibility practice.

Among the many flexibility-indicators we identify the **Flexibility Factor** [7], [40]–[44]. In different formulation, it tries to represent the quantity of energy that is shifted by the flexibility action from a time of the day that penalizes more the target objective to one with a lower *penalizing potential*. A formulation example may evaluate the amount of energy moved from the hour of the day with a high cost of energy to one with lower costs. Such a formulation follows as defined in [43]:

$$FF = \frac{\int_{LPT} l_{heating} dt - \int_{HPT} l_{heating} dt}{\int_{LPT} l_{heating} dt + \int_{HPT} l_{heating} dt} \tag{4}$$

where H/LPT means respectively *high* and *lower price time* and l is the monitored load (power – in the formulation of eq. (4) the power dedicated to heating, it may be generalized to a specific device or to the whole building energy requirements).

In our work, we explore the following formulation of the flexibility KPI to evaluate the reduction of energy consumed from the grid in high-price hours due to the introduction of flexibility practices. This indicator is particularly suited to evaluate the performance of advanced controllers that has as the objective the minimization of the cost function based on an external price signal. Here we propose a general formulation of this flexibility KPI restricted to the case just described:

$$F^*_{KPI} = \frac{\int_{HPT} p_{optimized} dt}{\int_{HPT} p_{preference} dt} - 1 \tag{5}$$

Where p is the reported power from grid during *high-price* time HPT. Further details and variations related to the formulation and tuning of this and further KPIs will follow in the results sections.

Most of the reviewed indicators that are specifically developed to evaluate the energy-flexibility performance require a baseline scenario [7]. This baseline scenario may be referred to as “inflexible” or “business as usual” and helps to quantify the impact of the proposed practices as relative quantity.

This baseline scenario can also differentiate from the advanced one by the plant hardware equipment. Thermal or electrical storage may not be present (or be smaller in size) in a baseline scenario as they would not be economically or technically. The introduction of those component may be forced by the PEB requirements or to push a further exploitation of any viable energy flexibility source and practice. In this regard, the static electrical storage is an example of component that may not be present in a baseline plant as it presents high investments costs and its performance may be dramatically impacted by geographical factors (climatic factors, e.g., the actual seasonal consumption-production mismatch), inhabitants habits, and regulations on the remuneration of overproduced energy exported to the grid.

According to this remark, we propose the evaluation of the above indicators in several scenarios simulated with different level of plant components (for the electrical side with the presence or not of the static storage) and smartness of control practices (baseline standard controller or advanced flexibility-oriented control logics). To do so, each scenario is simulated (during the preliminary evaluation through simulations) entirely separately and the final yearly results are compared. The practical experimental phase imposes further limitations due to the actual system setup. A preliminary validation of the developed simulation model allows the calculation of indicators for the running experimental phase allowing a relative comparison to a simulated baseline scenario.

4 Sub-Artic geo-cluster (Norway)

This chapter defines possible control strategies for the flexible operation of buildings in the Sub-Artic geo-cluster, represented by Norway. First, factors influencing the flexibility potential and the relevant resources are discussed, and then possible objectives and their impact at both energy system and building levels are evaluated. At the building level, the focus is on multifamily houses related to user behaviour and typically available control methods. In the end, related to the Norwegian demo, the potential and relevant control strategies are discussed in more detail.

4.1 Energy system

In the context of flexibility, the energy system in Norway is characterized by three distinctive features:

1. **Electricity is mainly produced from hydropower**. Not only is this a renewable energy source, but it also has several desirable characteristics from a grid (storage potentials; fast and flexible ramping; balancing capabilities, black start services; frequency stabilization. [45])
2. **Electric resistance heating** is the most ubiquitous heating technology (which can be stated by the previous point). This, in addition to the sub-arctic climate with cool/temperate summers and cold winters, means that the total electric load profile is largely heat-driven [46], as shown in Figure 2.
3. **The highest penetration of EVs in the world per capita**, even coming close to much larger countries in absolute numbers [47]. Due to a combination of factors, but above all, the removal of Value Added Tax (VAT) for EVs, vastly reduced toll, parking rates, and other fees, in addition to cheap electricity and expensive gasoline [48]. By 2030, EV charging is estimated to represent about 3 % of the total energy demand in Norway [49]. However, as most of EV charging is performed at home, the local power grid capacity might be a limiting factor [50]. On the other side, EV charging represents a significant flexibility source.

Energy production flexibility

More than 75 % of the Norwegian production capacity is flexible [51]. This means that production can rapidly be regulated up and down as needed. Combined with the accumulated storage capacity of about 100 TWh, hydropower (the whole system, from water storage to generators) can provide flexibility on a timescale from seconds (frequency regulation) to hours (congestion management, load matching) and months (seasonal flexibility). Historically, this has meant that the need for flexibility in the

Norwegian power system has been low, since hydropower has provided the desirable characteristics.

Grid

While hydropower is a great balancing resource on the transmission level, grid capacity and congestion issues must be solved more locally. With the increasing demand for EV charging and local production, local flexibility resources can be exploited as an alternative to grid investments. A potential source of this flexibility is *buildings*.

A heat-driven electricity profile, combined with an increasing penetration of EVs, leads to a "peaky" total electric load forces stakeholders (especially grid companies) to develop novel ideas on how to handle grid expansion/operation. Traditionally, the business case for expansion has been solid since a high utilization rate has been expected. However, with a "peakier" load, utilizing the potential *flexibility in buildings* could be an alternative to costly expansion and reinforcement of the grid.

Demand side flexibility

Developing technologies that exploit the flexibility inherent in most household loads (in addition to classic measures such as renovation to improve energy efficiency), can contribute to reducing/deferring costly grid investments by reducing the *grid impact* of the building. We can state this as *utilizing demand-side flexibility as an alternative to grid investments*.

4.2 Climate/Weather factors

As discussed in the previous section, the electricity demand in Norway is largely driven by heat demand.

Figure 6 (top), shows the average daily total energy demand (space heating, DHW and electric specific demand) for apartment blocks in Norway, for 3 different efficiency levels, given the weather shown in Figure 6 (bottom). The weather data is an IWEC [52] file for Fornebu, Bærum, near the Norwegian demo case. The profiles are generated by the PROFet tool [53], [54]. The “regular” category is representative for buildings built before 2010, the “efficient” category is representative of buildings built after the current regulations, while the “very efficient” category is representative of buildings built after the “passive house” standard, and with special focus on energy efficiency. One can see the clear seasonal mismatch between the energy demand and the potential for electricity production with solar PV. However, the mismatch is reduced with increasing energy efficiency level. Installation of technologies such as heat pumps, will lower the mismatch further.

However, even with a very efficient building envelope and heating technologies, a high overproduction is needed in summer to compensate for all energy demand with PV panels. Building-level flexibility, such as thermal storage in tanks or batteries, is unsuitable for solving seasonal mismatch.

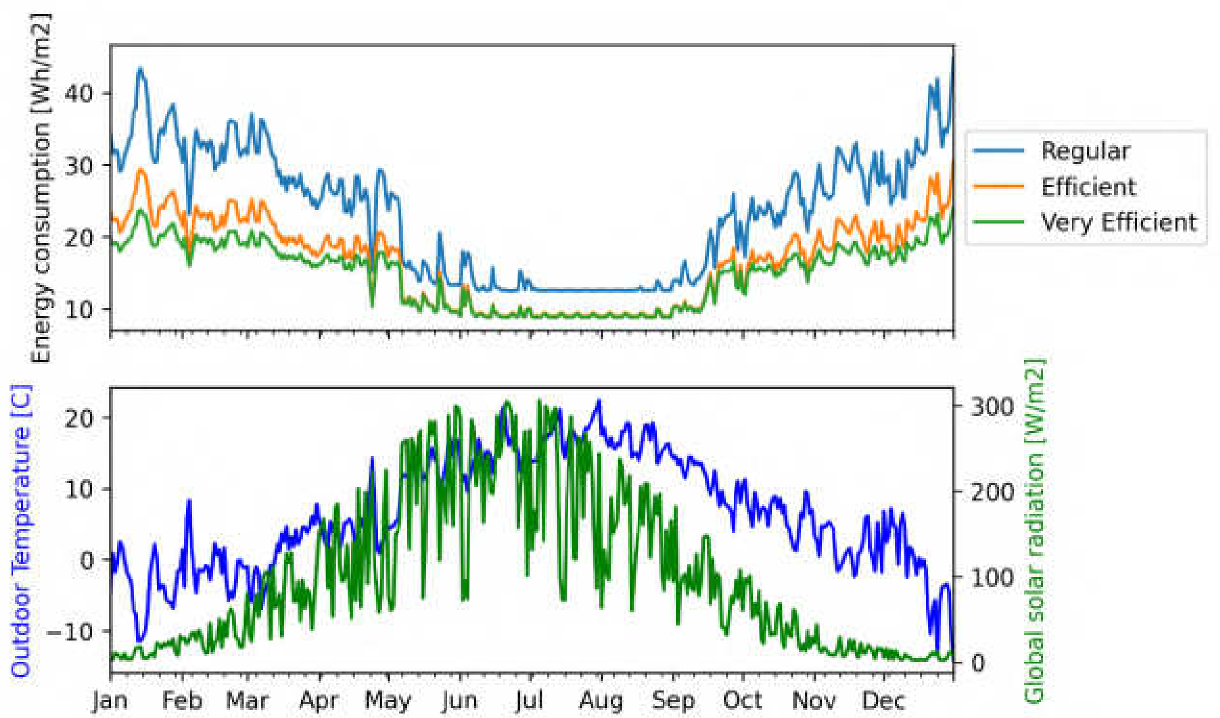


Figure 6: Typical daily energy demand and weather for Norway

4.3 User behaviour and energy consumption patterns

User behaviour related to energy-consuming systems, such as Domestic Hot Water (DHW), comfort preferences and EV-charging habits, influences the energy demand profile, but the consumption is flexible.

This report does not consider Devices like washing machines and cooking equipment.

4.3.1 Domestic Hot water

In Norway, DHW is normally heated by electrical storage water heaters (ESWH) (with storage) or directly with district heating (DH). It is estimated that about 83% of the energy demand for DHW in the residential sector is covered by ESWH and 11 % by DH [46]. For systems with ESWH, the DHW storage system is a significant flexibility resource. Tennback et al. , [55] evaluated the value of flexibility from ESWHs in the European energy system. They found that ESHWs can offer flexibility at multiple levels and markets, enabling peak reduction, increased self-consumption and grid management at both transmission and distribution level. As discussed below, it is also possible to install storage tanks in district heating systems.

DHW consumption is highly stochastic in nature and thus difficult to predict. Figure 7 shows a boxplot for the distribution of energy end-use for DHW per square meter from a measurement campaign conducted by SINTEF Community in the project Varmtvann2030 [56]. This plot shows that although the variability is significant w.r.t. min and max, most values (> 50 %) are contained within a narrow interval. Hence, it is conceivable that prediction models with reasonable accuracy can be developed, enabling flexible operation. Note that the measurements shown in Figure 7 are from social housing. Hence, they are not necessarily representative of most apartment blocks.

In [57], cost savings of ~5 % were reported in a virtual testbed with economic MPC, which was implemented on a storage tank on the secondary/customer side of a district heating system. This cost-saving potential depends on the local conditions and system design, e.g. tariff structures and whether district heating is used or if power is drawn from the grid. A noteworthy finding in [57] is that systems with small loads (i.e. single-family houses) need more accurate forecasting models than systems with larger loads (i.e. neighbourhoods). I.e., for DHW-systems, a larger system is an advantage when it comes to implementing smart control of energy use. Aggregating the loads decreases the *diversity/coincidence factor* and makes the load more predictable.

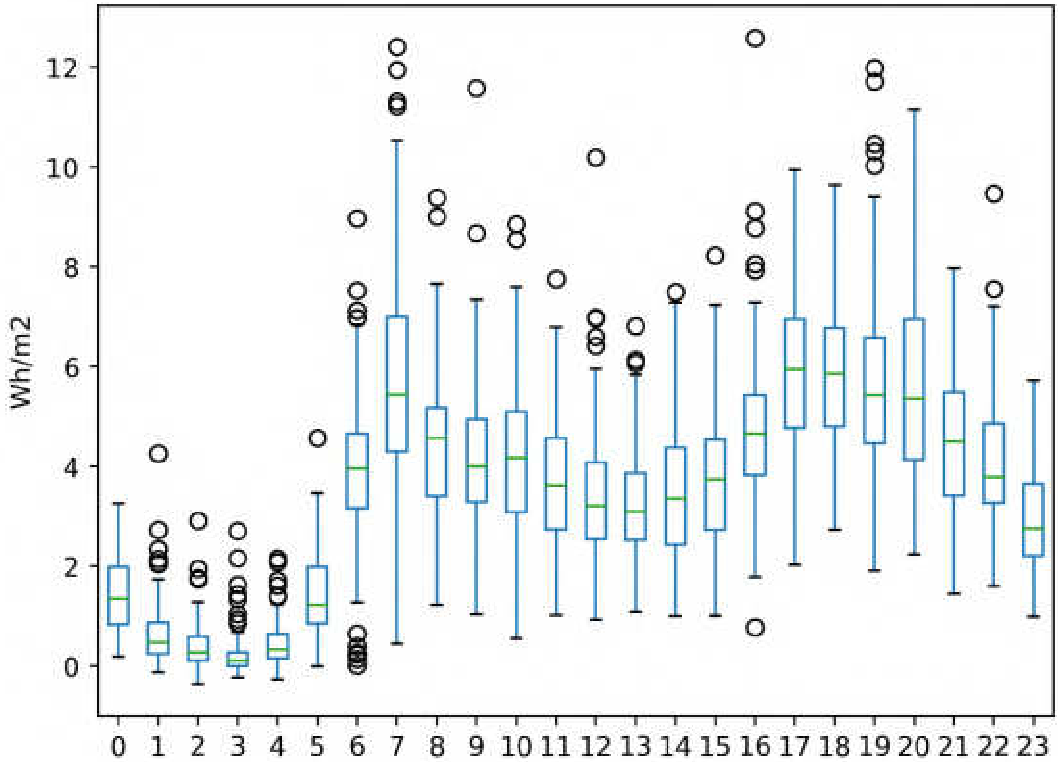


Figure 7: Measured net energy (distribution of daily variation for ca. 8 weeks) for domestic hot water in an apartment block (social housing) for each hour of the day.

4.3.2 Space heating / indoor temperature flexibility

The space heating system can offer flexibility through activation of the thermal mass of the building and operational range in the indoor temperature. Usually, the temperature set point of the heating system is set to a fixed value during occupied hours and sometimes reduced during non-occupied hours (night setback). For residential buildings sleeping hours are considered non-occupied hours. Allowing a span in the temperature setpoint makes it possible to shift energy consumption in time. The high share of electric heating in Norway means that the potential for shifting electricity demand is high at an aggregated level.

The potential for energy flexibility depends on the properties of the building construction (thermal mass that can be activated and insulation level) and the operational temperature span that the user accepts. However, thermal comfort is not only the actual temperature but also the temperature change. Favero et al. , [58] evaluated the comfort temperature during dynamic conditions and found that people are more sensitive to a reduction in temperature than an increase. They also found that the time the participants had lived in Norway influenced the comfort range, indicating cultural differences. Participants who had lived long in Norway had a higher risk of experiencing “warm discomfort”.

Night setback has traditionally been applied as an energy-saving measure for residential buildings. However, this increases the peak demand for the electricity grid in the morning when the heating is turned back on. In addition, the morning hours are normally when the electricity price is highest. From an economic viewpoint, it might be more beneficial to overheat at night when the prices are low. Walnum et al. , [59] demonstrated that it was possible to shift more than 50 % of the energy consumed in the peak price hours compared to a night setback case if the price signal is strong enough. Figure 8 shows how the controller exploits the allowed temperature range to shift the space heating demand. A challenge with preheating the building at night, especially in small apartments, is that Norwegians prefer cold bedroom temperatures [60].

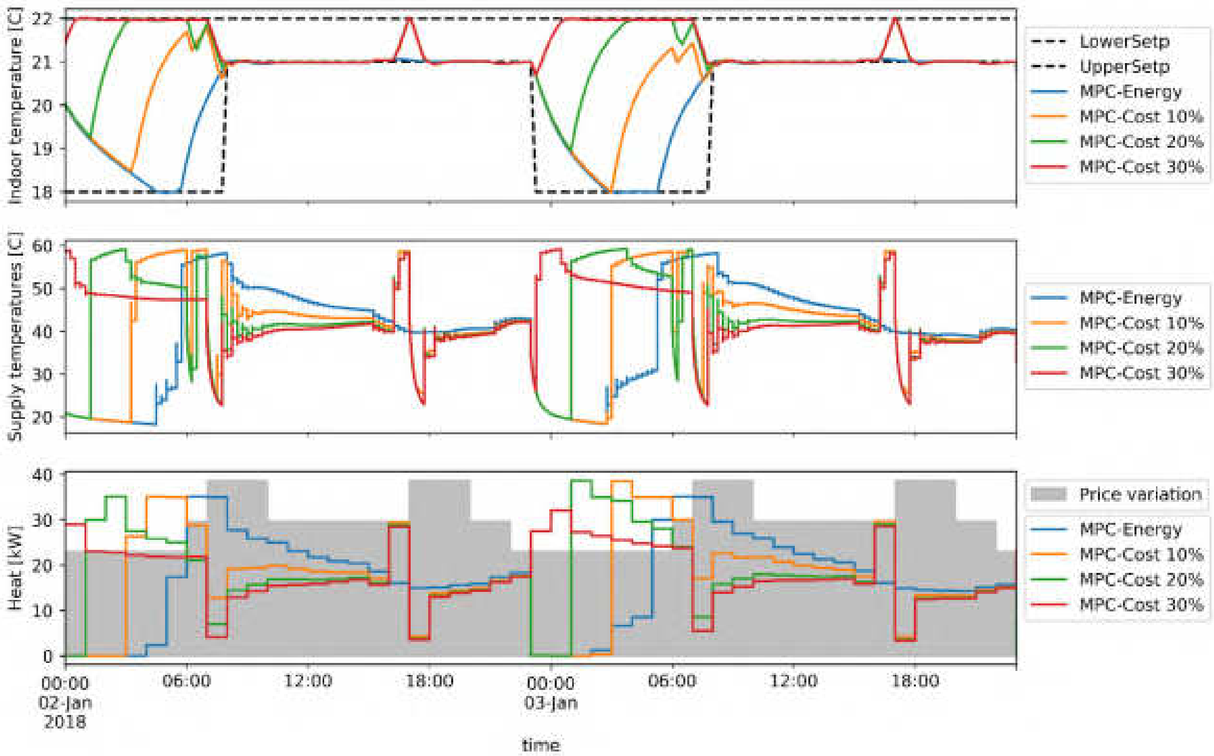


Figure 8: Example of space heating flexibility with energy price as driver [59].

4.3.3 EV-charging

Charging needs and distribution

Another load/energy end-use with a high degree of stochasticity is EV-charging. According to a survey (n=397) reported in [61], almost 90 % of EV-owners in Norway report using home charging daily. This survey is from 2014, when EV batteries were smaller and the public charging (i.e. fast charger) infrastructure was less developed. However, we expect the main trend from this survey to hold today: that most EV-charging takes place at home. Hence, this charging represents a potential source of flexibility from the building point-of-view, even without more technically challenging concepts like Vehicle-to-Grid (V2G). In [62], a report on the significance of EVs in the power system by the Norwegian power regulator NVE, smart/flexible EV-charging, is proposed as an alternative to grid reinforcement. They cite issues such as phase-to-phase voltage imbalances (caused by excessive voltage drops in one phase due to EV-charging) and grid congestion, especially in areas with weak grids (correlated with population density and length of power lines) and a high degree of uniform behaviour, such as cottage areas (areas with many cottages, otherwise remote). The first issue can be alleviated to some degree by three-phase apparatus for charging. The second issue (grid congestion, transformer/line overload on the above hourly timescales) is treated in the following paragraph.

Smart charging

With higher variability in the spot price and/or peak power grid tariffs, end-user savings enabled by smart (predictive) control can drive more efficient grid use. Figure 9 shows the concept for a hypothetical apartment block with an EV penetration of 0.4 EVs/apartment, with historical data from 10 EVs representing the EV load (the green area). The grid tariff in this example is peak power pricing, so keeping the peak below a specific limit is incentivized. The comparison with the baseline shows that the potential for peak load reduction is significant with this setup. While smart EV-charging could benefit from advanced prediction models (using machine learning/statistics), most of this potential on a single-meter level can be realized with one requirement: a user interface for input of *deadline* and *energy need* (driving need, equivalently minimum SOC) by that deadline. This removes a large part of the uncertainty in the charging prediction. Then, earliest-deadline-first (EDF) scheduling will yield the optimal charging pattern in both load flattening and cost [63]. This conclusion holds for meters with EV-charging only; i.e. it is possible that more advanced algorithms can yield better performance with setups like the one shown in Figure 9, where several loads are behind the same meter.

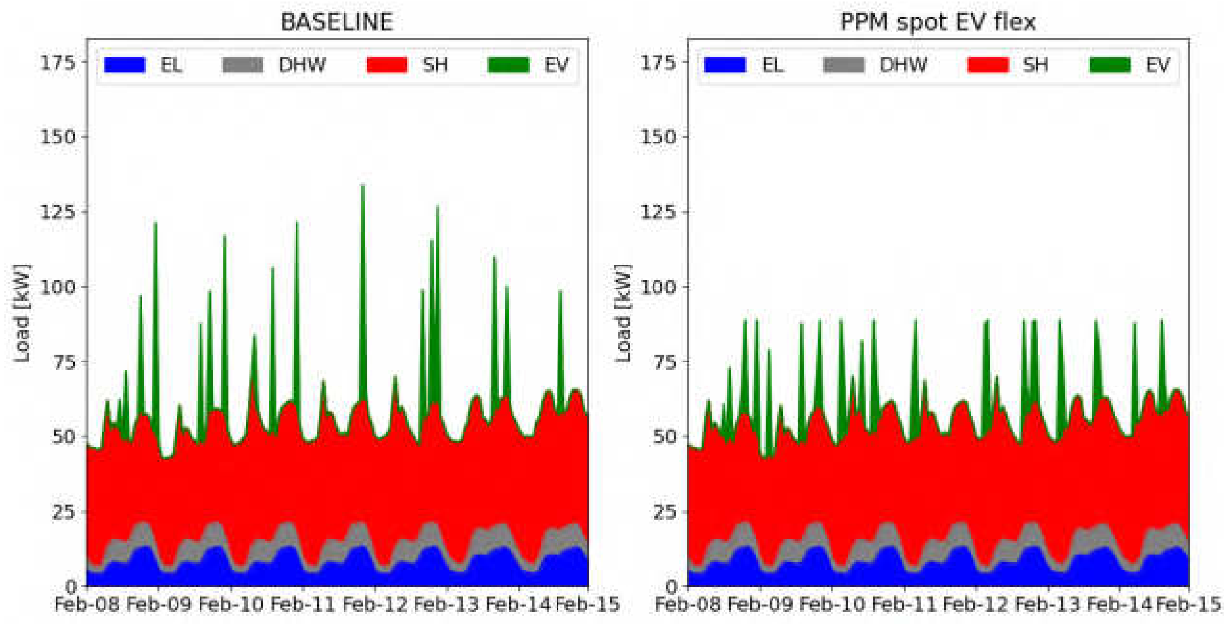


Figure 9: Concept for EV load shifting/peak shaving.

4.4 The objective of the control strategies

This section presents a set of possible objectives for building control. The influence on the energy system and building levels is discussed for each objective.

4.4.1 Minimum cost

From the end-user perspective, electricity spot price volatility is the main forcing factor for utilizing building flexibility. Norway is geographically split into 5 marked areas (NO1-NO5). The energy price can vary significantly between the market areas, both in volatility and average price, especially between the northern (NO3, NO5) and southern (NO1, NO2, NO4) parts of Norway. The southern part has a stronger link to Europe and is more influenced by those markets.

Figure 10 shows the spot price in NO1 during three cold weeks in January-February 2021. The emerging pattern here is that of the morning and evening peaks, which are present every day with varying magnitudes. Four days have morning peaks up to and above 0.2 EUR/kWh, compared to a "base price" of about 0.05 EUR/kWh. It was evident that moving energy use/load from these high-price hours to low-price hours can yield an appreciable economic gain, especially if/when these situations become more common in the Nordic power market. As the Nordic power market becomes increasingly connected to the continental market (esp. Germany and surrounding countries), higher price fluctuations/more volatility can be expected, as well as a higher "base price" (average price). However, with the current energy market (year 2022), political resistance exists against expanding the transmission capacity.

The spot price can be considered the *penalty signal*, embedding information about the power market (supply-demand, marginal costs etc.) at a high level, providing an incentive to shift consumption to hours when it is more beneficial for the system.

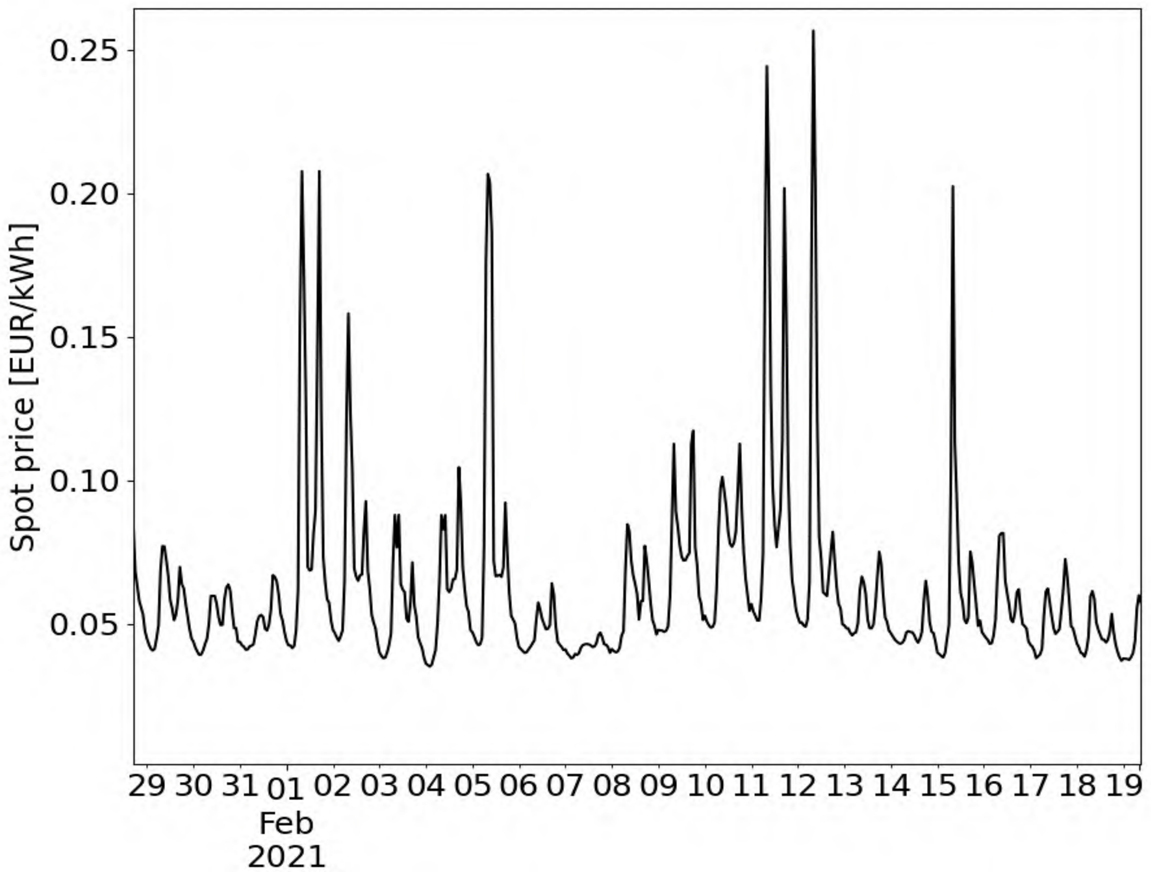


Figure 10: Spot price in NO1 region of Norway during cold/grid-constrained period

A potential weakness of the spot price as a penalty signal is that it only embeds information of the regional (marked) level, i.e. it gives no incentive to act on in the interest of the DSO w.r.t modulation services such as voltage and frequency control or local congestion issues. In other words, if these services are to be provided with the current market structure, it must be done through *direct flexibility/load control*. Alternatively, new market structures and business models are needed. Such markets are under development and have been tested in several pilot projects, e.g. by NODES[7].

A hotly debated issue among commercial actors and government agencies in recent years in Norway has been that of grid tariffs, which are applied to end-users by the DSOs on top of the spot price. These tariffs are supposed to reflect the cost of operation,

[7] https://nodesmarket.com/

maintenance and possible grid expansion [64]. Until recently, the grid tariff for residential customers has consisted of one yearly fixed cost and an energy cost. According to the Norwegian energy regulator NVE, this flat rate is outdated since about 90% of the grid's costs are associated with maintaining grid capacity (i.e. peak power), not marginal losses in the grid (i.e. *energy*). From July 1st 2022, a new structure was introduced. The main differences are that the fixed part should be a function of the peak power demand and that the energy part could be time differentiated, enabling a "time of use" (ToU) tariff. Besides this, the local DSO is quite free in formulating its grid tariff structure. A peak power tariff and a ToU energy tariff are economic drivers for flexibility.

4.4.2 Minimum energy import

Minimising the energy imported from the grid could be interesting to reach a plus energy building target. This would in principle, maximize the self-consumption of renewables produced at the building. This will equal cost minimisation in cases with fixed energy prices and no peak power tariffs. The main advantage of this objective target is its ease of implementation and its interpretability. It does not require any information about the surrounding system in the form of a price signal or a reference signal for tracking. However, as a system objective, it might make less sense in an energy system with significant penetration of intermittent renewables (solar, wind), since it will be desirable to consume as much of this energy as possible when available. Also, it will not be able to consider grid congestion issues. Since it often means applying principles such as night setback, it could increase consumption in the morning hours, when the strain on the grid is at its highest.

4.4.3 Minimum CO_2-emissions

Another possible optimisation target is minimising the CO_2 emissions associated with energy consumption by using the hourly CO_{2eq} intensity of the electricity as the driver. Clauss et al. , [65] described a method for calculating hourly CO_{2eq} intensity for the electricity mix and compared it with the corresponding spot price for selected European electricity bidding zones. It shows that the CO_2 intensity is low when the price is high and vice versa. This is because the Norwegian electricity market is dominated by hydropower. The hydropower plants are operated in a cost-optimal way; increasing production when the price (and demand) is high, exporting electricity to Europe, and "saving" water when the price is low, importing energy from Europe.

This means that operating a building focusing on reduced emissions (on an hourly level) would result in increased use in hours with high strain on the grid. Based on this, hourly CO_{2eq} intensity is not considered a good driving force for flexibility utilization in Norway.

4.5 Flexibility asset evaluation of the Norwegian demo

4.5.1 The technical systems

This section briefly describes the Norwegian demo and its technical systems in relation to the flexibility sources described in section 2.

4.5.1.1 Heating system

The chosen heating system is a common solution for Norway's low-energy buildings. The main heat source is a geothermal heat pump. An electric boiler is used as a peak heating source and backup in case the heat pump fails. A simplified sketch of the system is shown in Figure 11. The heat pump has a small storage tank, and the main function is to avoid frequent start/stop of the heat pump.

The room heating is supplied by hydronic floor heating controlled by temperature sensors in each room. A demand controlled ventilation (DCV) system with a rotary wheel heat recovery unit is installed for the common areas, and the heating system heats the supply air. Individual constant air volume (CAV) ventilation units with rotary wheel heat recovery and electric after-heaters are installed for the apartments.

Domestic hot water is pre-heated with hot water from the heating system and topped up with an electric water heater.

The low temperature of the floor heating allows the heating system to operate at a low temperature the whole year, thereby ensuring good working conditions for the heat pump and a high COP. However, it limits the amount of heat the heat pump can deliver to preheat the domestic hot water.

The internal heater of hot water heater operates with an internal thermostat and is not connected to the local BMS.

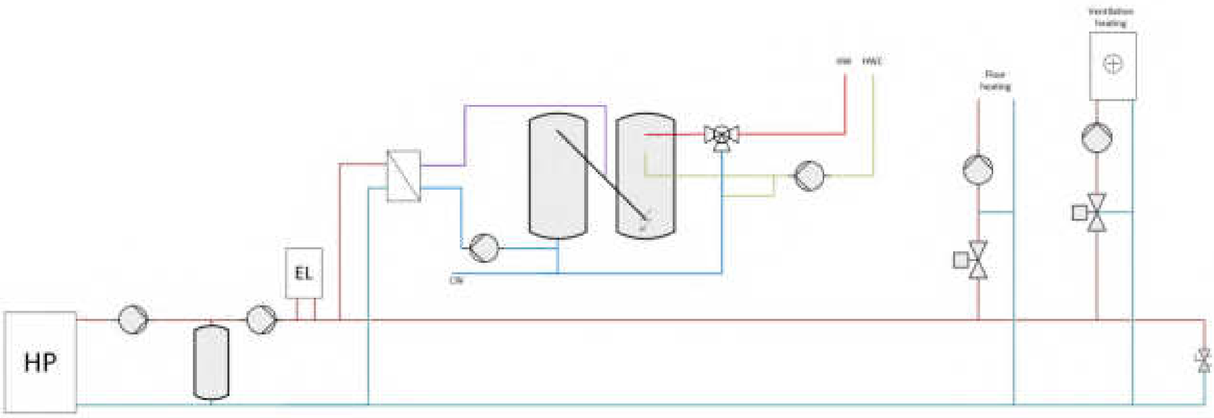


Figure 11: Simplified sketch of heating system in Norwegian demo.

4.5.1.2 Battery

A 7.2 kWh battery is installed. The battery's internal control system is currently not controllable from the BMS. This might change in future, and therefore, the flexibility potential is evaluated.

4.5.1.3 EV-charging

The demo has 4 charging stations for EVs. The total charging energy will be measured but is not controllable and, therefore, not considered a flexibility source.

4.5.1.4 Control system

The building automation system has a hierarchical structure, with local controllers for each unit, communicating via different protocols (Modbus RTU, KNX, BACnet) to a central switch. A BMS system (Niagara) is located on the servers of the Demo owner and manages setpoints and logs measurement data.

4.5.2 Flexibility potential evaluation framework

This section describes the methods and framework used to evaluate the flexibility potential in the Norwegian demo.

4.5.2.1 Method for flexibility potential evaluation

To evaluate the flexibility potential of the different flexibility resources in the building, a SINTEF optimisation tool is applied (FLEXor). The FLEXor tool is under development and is designed to optimize the utilization of flexibility assets within a building, considering external properties (weather, prices) under constraints. The tool considers three levels of flexibility: Fuel-switch flexibility, storage flexibility and comfort flexibility. Fuel-switch flexibility is flexibility in switching between different energy sources, e.g. electricity, district heating or oil. The Norwegian demo is an all-electric system, so fuel-switch flexibility is not an option. Storage flexibility is flexibility in storage systems, such as hot water tanks or batteries. The Norwegian demo has two domestic hot water tanks and a battery. Comfort flexibility is flexibility in allowing an acceptable span in the indoor temperature. This allows for storing energy in the thermal mass of the building. In this study, comfort flexibility is considered for the apartments but not for the common areas.

The heat source components are modelled as steady-state models. To avoid non-linearities, the efficiency of the components (e.g. heat pump COP), is only dependent on properties known as a-priori (e.g. weather), and not properties that are part of the optimization problem (e.g. heat produced).

The thermal storage components are reduced order models formulated as linear and time-invariant (LTI) state space models. A common concept for such models is the RC analogy, where thermal resistances and capacitances are applied analogously to electric resistances and capacities in electric circuits. The general form of the state space formulation is given below.

$$dX(t) = A(\Theta)X(t) + B(\Theta)U(t) + E(\Theta)D(t) \tag{6a}$$

$$Y(t) = CX(t) \tag{6b}$$

where X(t) is the state vector, which in building energy modelling usually represents internal temperatures. U(t) is the vector of controllable inputs (heat from radiator ϕ_h). D(t) are disturbances (solar radiation ϕ_s, internal heat gains ϕ_{ig}). A and B are matrices whose elements are functions of the parameters Θ, while C describes the relation between the model's states (predicted temperatures) and the measured outputs Y(t) (measured temperatures). An advantage of the linear and time-invariant state space model is that it can be reformulated directly into a linear programming (LP) optimization problem [66].

A set of constraints are applied to the problem. The radiant floor heating system is only able to emit a limited amount of heat. This is reformulated into a maximum heat emission ($\overline{u}$). In addition, a constraint on the indoor temperature is added to define a thermal comfort band between the maximum ($\overline{y}$) and minimum ($\underline{y}$). Since there is a risk that the only valid solution to the problem is outside the allowed temperature range (e.g. during warm periods), the temperature constraint is formulated as a soft constraint. The violation of the temperature constraint (δ) is included in the objective function with a penalty factor (ρ). This yields the following optimization problem for a minimum cost objective:

$$\min \left[\sum_{k=1}^{N_c} (c_k^{var} u_k + \rho\delta_k)\,\Delta t \right] \tag{7a}$$

$$s.t. \quad x_{k+1} = Ax_k + Bu_k + Ed_k \tag{7b}$$

$$y_k = Cx_k \tag{7c}$$

$$\underline{y}_k - \delta_k \leq y_k \leq \overline{y}_k + \delta_k \tag{7d}$$

$$\underline{u}_k \leq u_k \leq \overline{u}_k \tag{7e}$$

$$\delta_k \geq 0 \tag{7f}$$

where c_k^{var} is the energy cost for each timestep k.

The parameters for a reduced-order model of a water storage tank can be derived from physical properties. However, for a building envelope, the physics is more complicated. Therefore, the parameters are identified through a statistical method, described in more detail in [67]. For the evaluation of the Norwegian demo case, results from a detailed simulation model are used as input for parameter identification.

In an MPC setting, with a short prediction horizon (typically 24-72 hours), where the model is updated with measurements for each control step, an approach with absolute temperature constraints could give sufficient accuracy. However, when evaluating the flexibility potential in full-year simulations, the linear reduced order model is not considered accurate enough to describe the full physics of the building envelope. As shown by Georges et al. [64], small deviations from a reference can be linearized with reasonable accuracy. Therefore, flexibility in the thermal inertia of the building envelope is evaluated by optimizing a deviation from a fixed baseline.

In the full FLEXor model, the constraints are evaluated individually for each of the submodels, while the objective is evaluated on the total import of the energy vectors (see left side of Figure 15). In addition, balance constraints are used for the connections between the components.

4.5.2.2 Energy prices

The energy prices used in the evaluations consist of two main terms; grid tariff and spot price. The grid tariff again consists of three terms.

1. A fixed yearly cost of 408 €.
2. An energy term of 0.024 €/kWh or 0.021 €/kWh for winter months (November-March) and summer months (April-October), respectively.
3. A monthly demand charge rate of 1.2 €/kW, 0.67 €/kW or 0.22 €/kW for winter months (December-February), transitional months (March and November) and summer months (April-October), respectively.

The applied spot price is shown in Figure 12. Prices are taken from market area NO1 for 2012 and represent spot market prices before 2021.

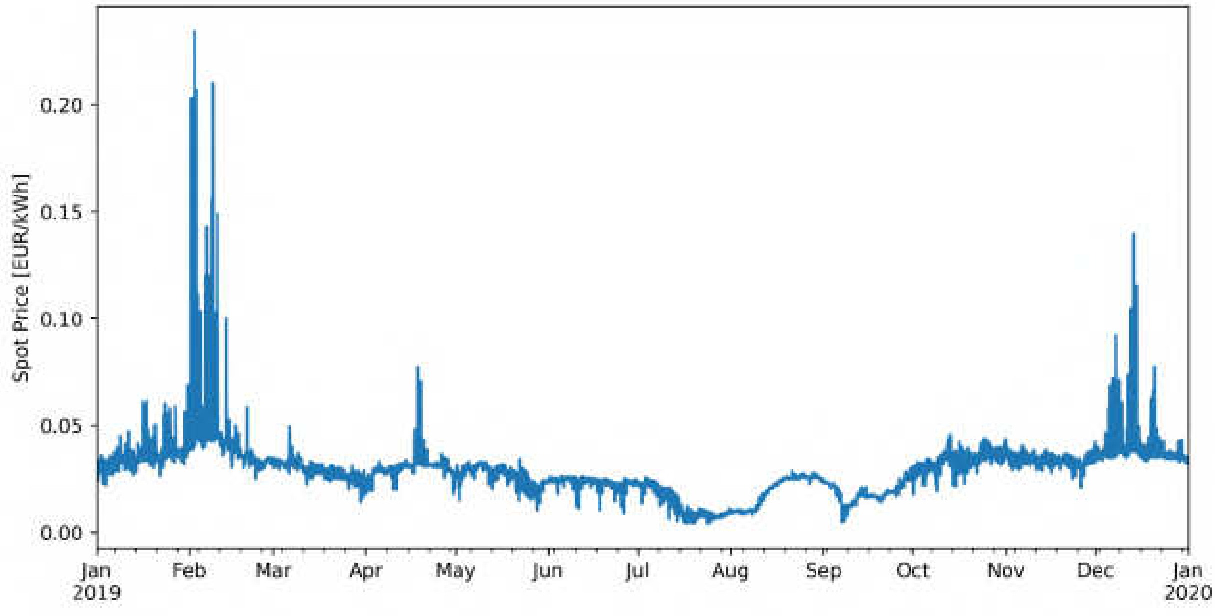


Figure 12: Spot market prices for the Norwegian demo flexibility study.

4.5.2.3 Objectives

The evaluation is run with two objectives: Minimum costs and minimum energy import. The objectives are further discussed in section 4.4.

4.5.2.4 Baseline definition

As no measurements are available from the normal operation of the Norwegian demo, the baseline is calibrated based on the simulation model of the building. The simulation model is a detailed "white-box" model, including physical models for the building construction, heat emission systems and PV production. The model applies standard profiles for electric-specific consumption (lighting, equipment) and DHW. In this evaluation, the electricity production from PV is estimated based on the maximum exploitation of the roof area, which is about 2.4 times the capacity installed in the Norwegian demo.

Figure 13 shows the daily energy demand (top), electricity from PV production (middle) and resulting net electricity import (bottom). Table 6 shows the performance of a selection of KPIs.

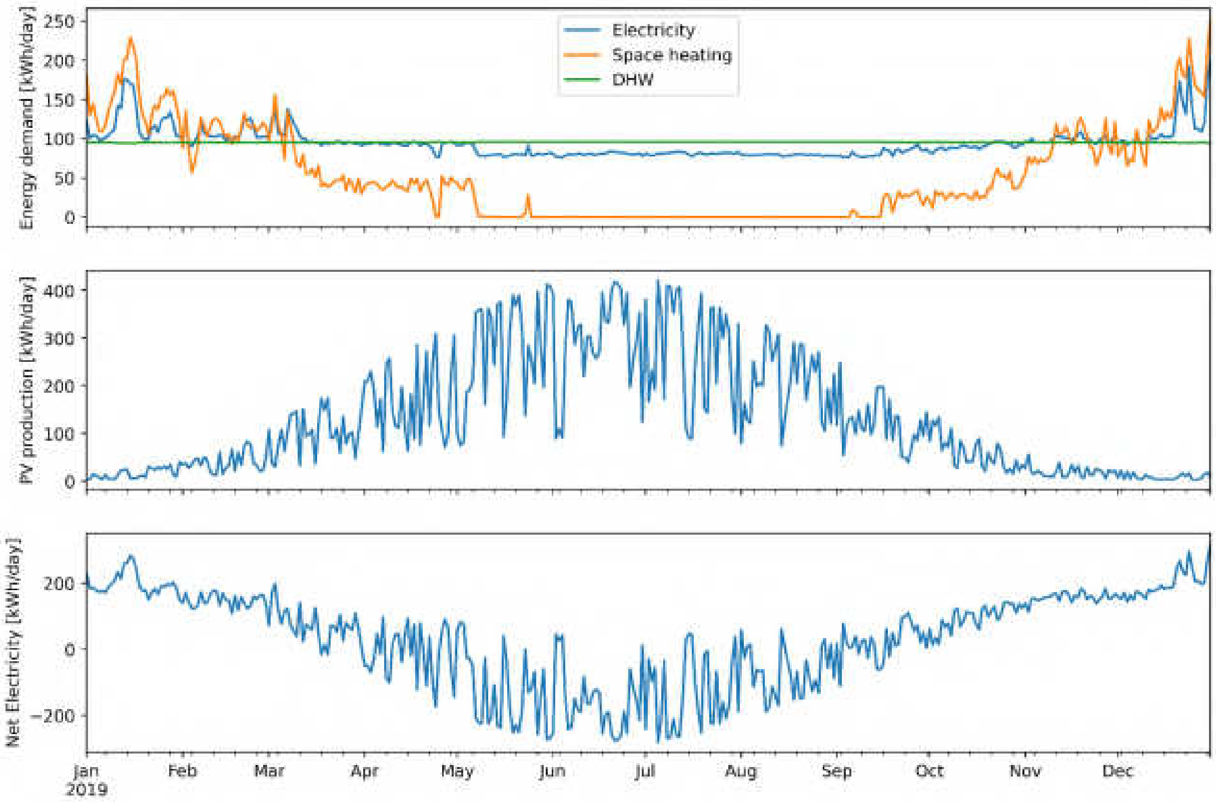


Figure 13: Norwegian demo baseline model.

Table 6: KPI for baseline

KPI	Value
El import [kWh]	37 379
El export [kWh]	25 834
El net import [kWh]	11 545
Energy cost [EUR]	2 977
Max import [kWh/h]	24
Max export [kWh/h]	42
Self-consumption	47 %
Self-Production	38 %

4.5.3 Evaluation of potential and control strategies

4.5.3.1 General implementation of control algorithms

The most feasible architecture for implementing new control algorithms in the Norwegian demo is the centralized approach, where the control algorithm receives measurements from and sends setpoint to the local BMS. As the BMS is located on an internal server of the demo owner, the control algorithm will most likely be installed within the same network. This avoids sending potentially sensitive data out of the internal network. An outline diagram is shown in Figure 11. The control algorithm receives predictions and signals such as weather forecasts and energy prices from external sources through APIs, and measurements from the local BMS. Based on this information, the controller generates setpoints that are sent back to the BMS.

A reason for choosing a high-level control approach with setpoint management is the ease of implementation and avoiding overwriting internal control algorithms. Setpoints, such as room temperature, are human understandable, and constraints can be set in the BMS system avoiding the control algorithm to set invalid setpoints. Comparably, for a valve position, any value between 0 and 100% could be valid, but depending on other conditions, they might give undesirable effects if the control algorithm is not working properly. For components like heat pumps, direct control of internal components, such as compressor speed, will overwrite internal control algorithms and most likely violate the product warranty.

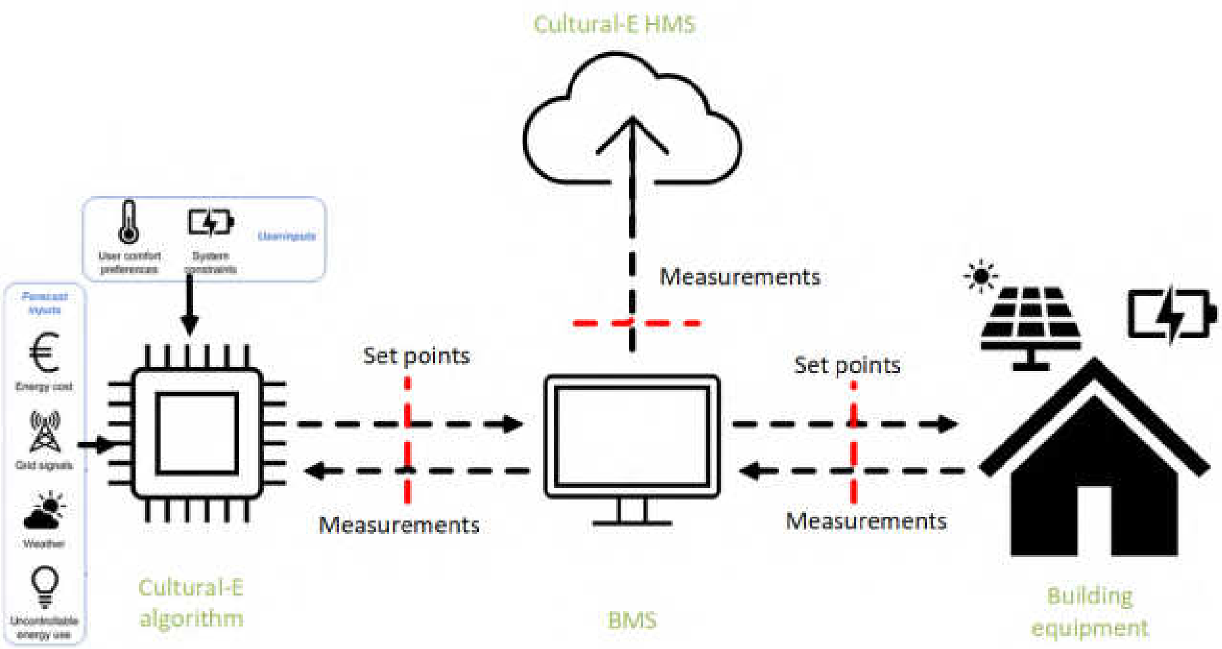


Figure 14: High-level principle for implementation of the controller at Norwegian Demo.

In principle, any algorithm can be implemented in this setup. Figure 15 shows a principle flow sheet of how an MPC controller could be implemented in such a scheme. For each control step (typically 1 hour), the algorithm reads measurements from the building BMS. The state estimator filters the measurements and estimates the value of internal states in the controller model. The controller model (similar formulation to the FLEXor model described below) represents the behaviour of the buildings and the HVAC equipment. Forecasts for energy costs and weather are communicated through external APIs. The optimizer optimizes the energy flows of the control model for the defined objective function with respect to the user-defined constraints. The output from the optimizer is a time series of energy flows, which the regulator converts into setpoints that are sent back to the building BMS. This procedure is repeated for each control step.

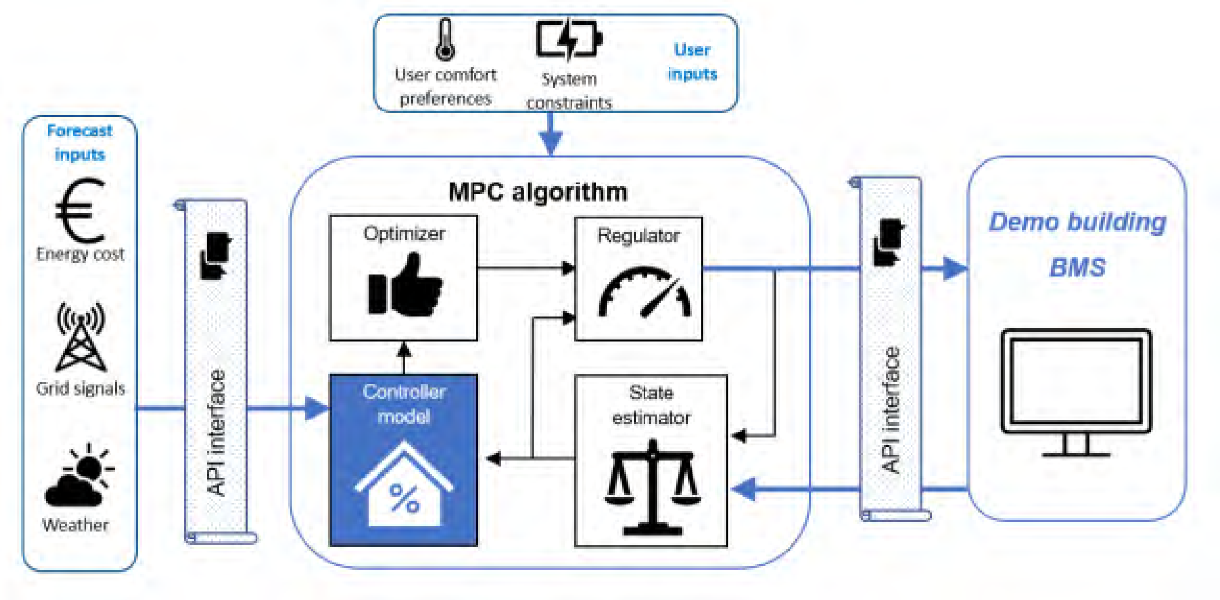


Figure 15: High level principle for an MPC implementation in the Norwegian demo.

4.5.3.2 Indoor temperature control

Shifting or shedding space heating load is possible to enable demand-side flexibility. Because of the thermal mass of the building envelope and the heating system itself, the heating load can be shifted in time while maintaining similar or better thermal comfort [69]. The Norwegian demo is a lightweight, well-insulated construction with limited internal mass. However, the horizontal division is partially concrete, and the floor heating system is cast in a 50 mm concrete slab. This creates some thermal inertia that can be exploited. Only the apartment areas are evaluated for indoor temperature control in this study.

Potential

To evaluate the flexibility potential of allowing indoor temperature variation, the apartments' fixed space heating demand is replaced with an LTI state space model as described in section 4.5.2.1. A 2 Kelvin upward deviation from the baseline is allowed.

Only upward deviation is allowed to avoid the results being influenced by the energy savings of reducing the temperature.

Table 7 shows the resulting KPIs for the two objective functions, both in absolute values and deviation from the baseline. The biggest difference from the baseline is in peak power import. The optimal operation of the heat pump system mainly drives this. Shaving peaks in heat demand means there is less need for the top up electric heater. The main potential of the indoor temperature control is when the space heating demand is high. Therefore, it has little impact on the self-consumption and self-production KPIs. Also, the potential for energy cost savings is limited for a well-insulated building with an efficient heat pump.

Figure 16 shows the net electricity import (upper), indoor temperature deviation from baseline (middle), and space heating delivered to the apartments for a selected winter week. One can see that the peak related to the apartments' space heating is cut by shifting some of the heat demand one hour earlier. The minimum cost case also overheats the apartments slightly, shifting consumption to periods with lower spot prices. The temperature deviation stays within 1 K, so the full flexibility potential is not exploited. With larger fluctuation in the prices, more flexibility could be released.

Table 7: KPIs for indoor temperature control flexibility potential

KPI	Min Energy Import		Min Cost	
	Value	vs. Baseline	Value	vs. Baseline
El import [kWh]	36 831	-1 %	36 890	-1 %
El export [kWh]	25 498	-1 %	25 596	-1 %
El net import [kWh]	11 333	-2 %	11 294	-2 %
Energy cost [EUR]	2 890	-3 %	2 847	-4 %
Max import [kWh/h]	18	-27 %	17	-28 %
Max export [kWh/h]	42	0 %	42	0 %
Self-consumption	47	1 %	47	1 %
Self-Production	38	2 %	38	1 %

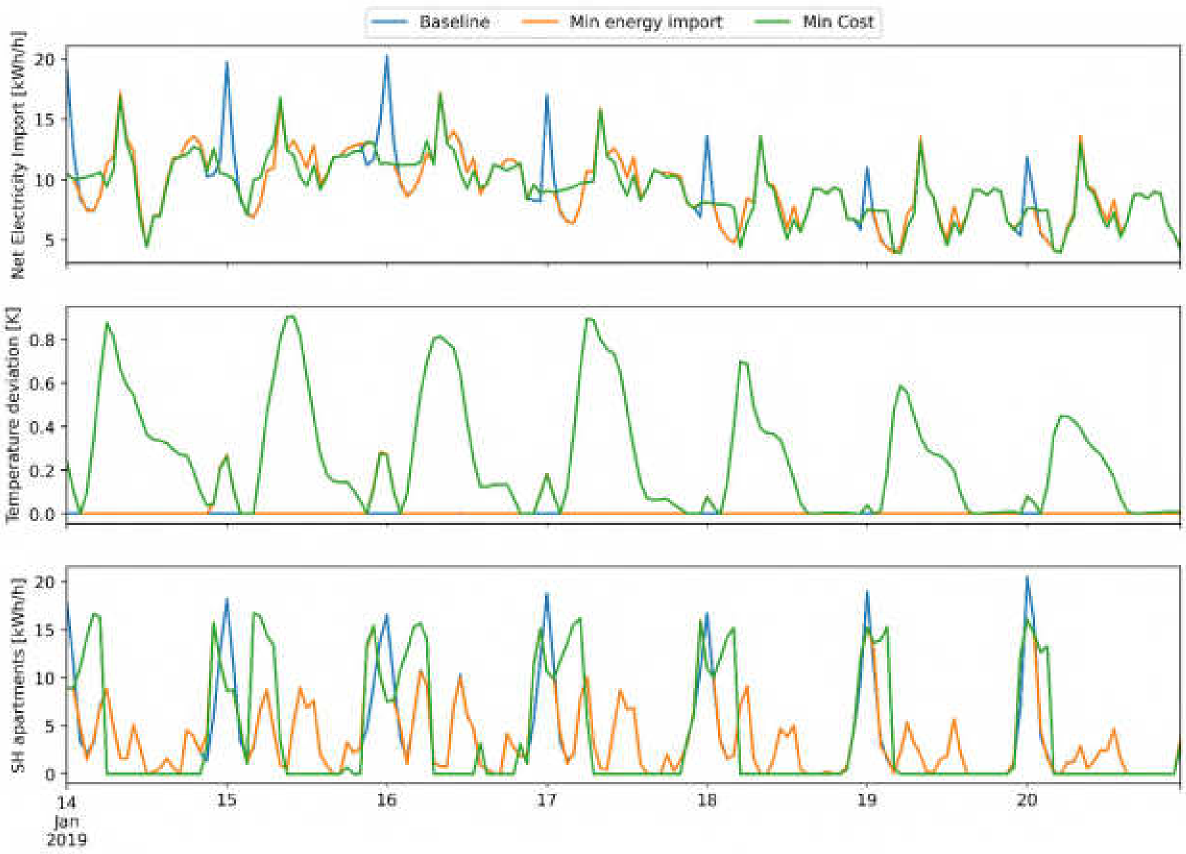


Figure 16: Example winter week for indoor temperature control

Control strategies

Two main variables can be controlled for exploiting the flexibility potential in the thermal mass of the building. Either the actuator controls each circuit's water flow, or the setpoint temperature. In the latter option, the local floor heating controller controls the actuators based on the setpoints. Controlling the actuators would require individual control of each room. As stated above, the safest approach would be a high-level controller setting setpoints for each room, ensuring that the setpoints are always within the allowed comfort range.

Both RBC and MPC approaches can be considered. RBC could be either predictive or non-predictive. In the case of non-predictive RBC, one could e.g. consider rules that increase the indoor temperature when the PV panels are producing more than the electricity demand, and the opposite, to increase self-consumption. With this approach, overheating is risky, as PV production is linked to high solar radiation in the rooms. Predictive RBC might reduce this risk with rules for lowering the temperature before periods with high solar radiation. RBC can also consider day-ahead energy prices by creating high or low prices thresholds. Such concepts are investigated in [22].

For an MPC application, there are several opportunities, both on the control model type (white, grey, or black) and what part of the HVAC system is included in the control model. This work focuses on grey box models for the building envelope. In this case, a linear state space model is usually appropriate. The heat input to the envelope is then normally the “control variable”. However, it is not feasible to directly control the heat input to the envelope in implementation. The inclusion of the HVAC system and control logic will normally make it non-linear. An alternative to include the control system is to use the output of the results from the linear envelope model optimization (heat input and room temperature) in a post-processing algorithm to create setpoints. This could be challenging for systems with high thermal inertia, such as radiant floor heating systems, as the response at room temperature is slower than the control time step. It is also dependent on historical values due to the dynamic behavior of the floor slab.

4.5.3.3 Control of DHW tanks

As shown in Figure 11, the demo has two storage tanks for domestic hot water, each with a capacity of 400 litres. A heat pump mainly charges the first tank through the hydronic heating system, while an internal resistance heater charges the second tank. The heat pump system operates at a temperature of 35 °C, limiting the temperature in the pre-heating tank. This also limits the storage potential in this tank.

Potential

They are allowed to operate within a given temperature span to evaluate the flexibility potential from control of the domestic hot water tanks. For the baseline, the storage tank temperature is constrained to 60 °C, while in the flexibility study they can operate between 50 °C and 70 °C.

Table 8 shows the KPIs for the two objective functions, both in absolute values and deviation from the baseline. Compared to indoor temperature control, the storage tanks will not reduce the peak demands in the same way but can increase the self-consumption and self-production slightly. Allowing a lower temperature than the baseline will increase the estimated potential. Since the energy losses from the tank is a function of the tank temperature, lowering the temperature will result in energy savings. This is not a potential for flexibility itself but more a potential for improved control.

Figure 17 shows the net electricity import (upper), tank internal temperature (middle), and heat fed into DHW tank (lower) in a selected summer week. The minimum energy case has a tendency to stay at the lower temperature limit. It only increases the temperature a few times, to reduce electricity export. To reduce energy losses, this is done as late as possible. For the minimum cost case, the temperature fluctuates more, to reduce peaks and to shift energy consumption to periods with lower spot prices. The peak export is actually increased for the minimum cost objective. This is because, in contrast to peak import, there are no tariff on peak export.

Table 8: KPIs for DHW tanks flexibility potential

	Min Energy Import		Min Cost	
	abs	rel	abs	rel
El import [kWh]	36 108	-3 %	36 155	-3 %
El export [kWh]	24 701	-4 %	24 694	-4 %
El net import [kWh]	11 408	-1 %	11 461	-1 %
Energy cost [EUR]	2 924	-2 %	2 741	-8 %
Max import [kWh/h]	24	-3 %	24	-3 %
Max export [kWh/h]	42	0 %	45	6 %
Self-consumption	49	5 %	49	5 %
Self-Production	40	5 %	40	5 %

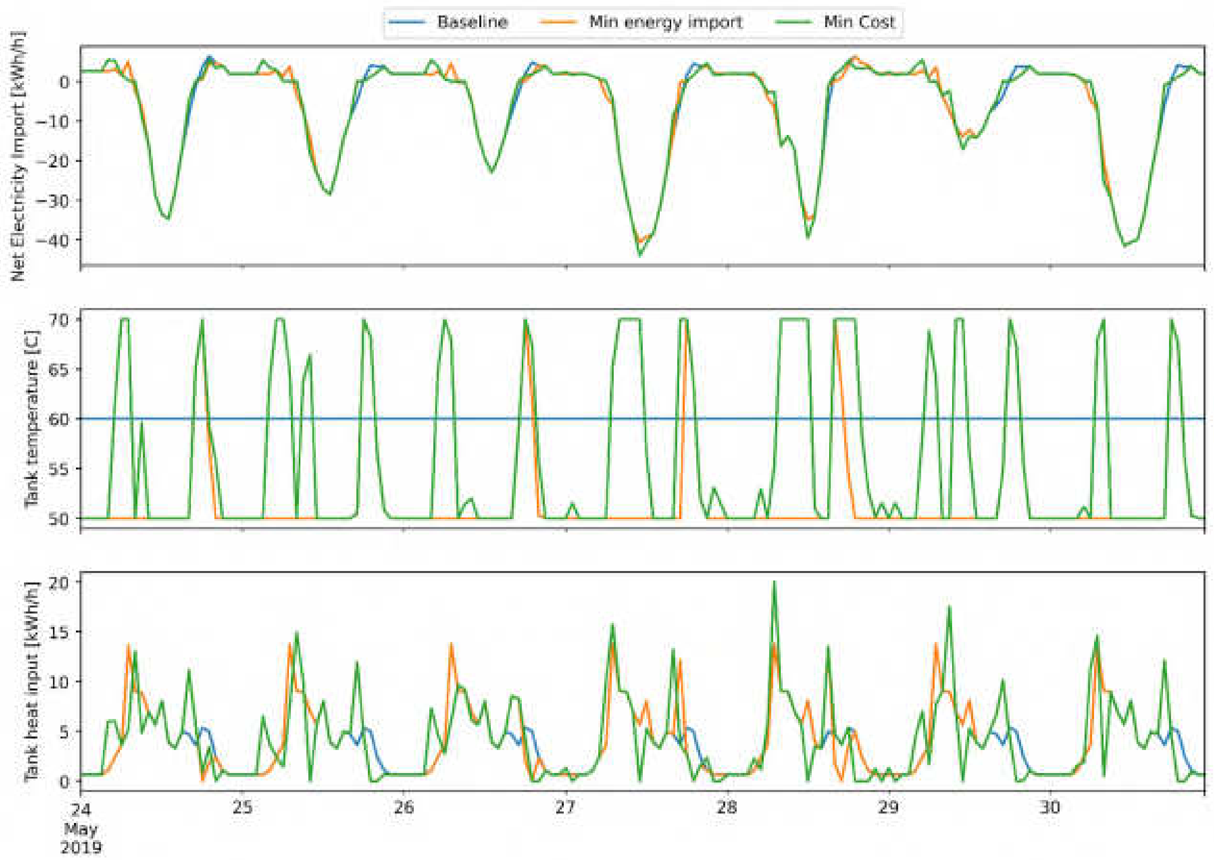


Figure 17: Example summer week for DHW tank control

Control strategies

Two temperature setpoints control the charging of the preheating tank. If the temperature in the tank reaches a set limit, the charging starts. The charging stops when the return temperature from the charging heat exchanger reaches above a set limit. In normal operation, these limits are fixed. These limits could be overwritten for flexibility exploitation to force charging or discharging.

In the second tank, the charging is controlled by an internal thermostat, turning the internal resistance heater on or off. The controller and setpoints are local and completely decoupled from the BMS system. It is, therefore, impossible to alter the setpoint of the thermostat automatically. A possible way around this is to mount a controllable relay on the tank's power supply. If the thermostat temperature setpoint is set to a high level, charging and non-charging can be controlled by cutting the power to the tank. However, it might be challenging to retrofit a temperature sensor, allowing it to measure the tank's temperature (i.e., state of charge). To know the state of charge, the controller would then need to estimate it based on a combination of energy measurements and the outlet temperature.

A simple way to implement a rule-based control would be to operate the DHW tank similar to a battery (see next section). E.g. could charging be activated when there is excess electricity from the PV production. By only allowing "over heating" of the tank, this can be implemented without knowing the internal temperature.

4.5.3.4 Control of battery

The building is equipped with a battery with a capacity of about 7.2 kWh. This is fairly limited compared to the estimated average daily demand of about 120 kWh. Currently, the battery is not controllable from the BMS system, but this should be feasible in the future.

Potential

To evaluate the flexibility potential of the battery solution. A battery model is activated. The battery model is a simple first-order state-space model. The charging and discharging efficiencies are set to 95 % and the maximum charge rate is 0.5, meaning that 50 % of the capacity can be charged or discharged in one hour. The model has been run twice, with the installed and twice the capacity.

Table 9 and Table 10 show the KPI results for the two battery cases. The battery performance characteristics on the KPIs are similar to that of the DHW tanks. It performs slightly better, especially in the self-consumption and self-production KPIs. Adding additional battery capacity increases the relative performance on the KPIs almost linearly, but it is expected that with further increase in battery capacity the increase in performance will flatten out.

Figure 18 shows the operation of the battery for the same week as for DHW in Figure 17. It shows the net electricity import (upper), battery state-of-charge (middle) and the energy balance of the battery (bottom). For the energy balance, positive means charging, while negative is discharging. One can see that the battery and the DHW tank's storage capacity is utilised similarly.

Table 9: KPIs for battery flexibility potential

	Min Energy Import		Min Cost	
	abs	rel	abs	rel
El import [kWh]	35 828	-4 %	35 943	-4 %
El export [kWh]	24 115	-7 %	24 116	-7 %
El net import [kWh]	11 712	1 %	11 828	2 %
Energy cost [EUR]	2 956	-1 %	2 737	-8 %
Max import [kWh/h]	24	0 %	23	-6 %
Max export [kWh/h]	42	0 %	44	5 %
Self-consumption	50	8 %	50	8 %
Self-Production	40	7 %	42	11 %

Table 10: KPIs for battery flexibility potential with double battery capacity

	Min Energy Import		Min Cost	
	abs	rel	abs	rel
El import [kWh]	34 407	-8 %	34 672	-7 %
El export [kWh]	22 541	-13 %	22 543	-13 %
El net import [kWh]	11 866	3 %	12 129	5 %
Energy cost [EUR]	2 927	-2 %	2 538	-15 %
Max import [kWh/h]	24	0 %	23	-6 %
Max export [kWh/h]	42	0 %	48	14 %
Self-consumption	53	15 %	54	15 %
Self-Production	43	13 %	47	23 %

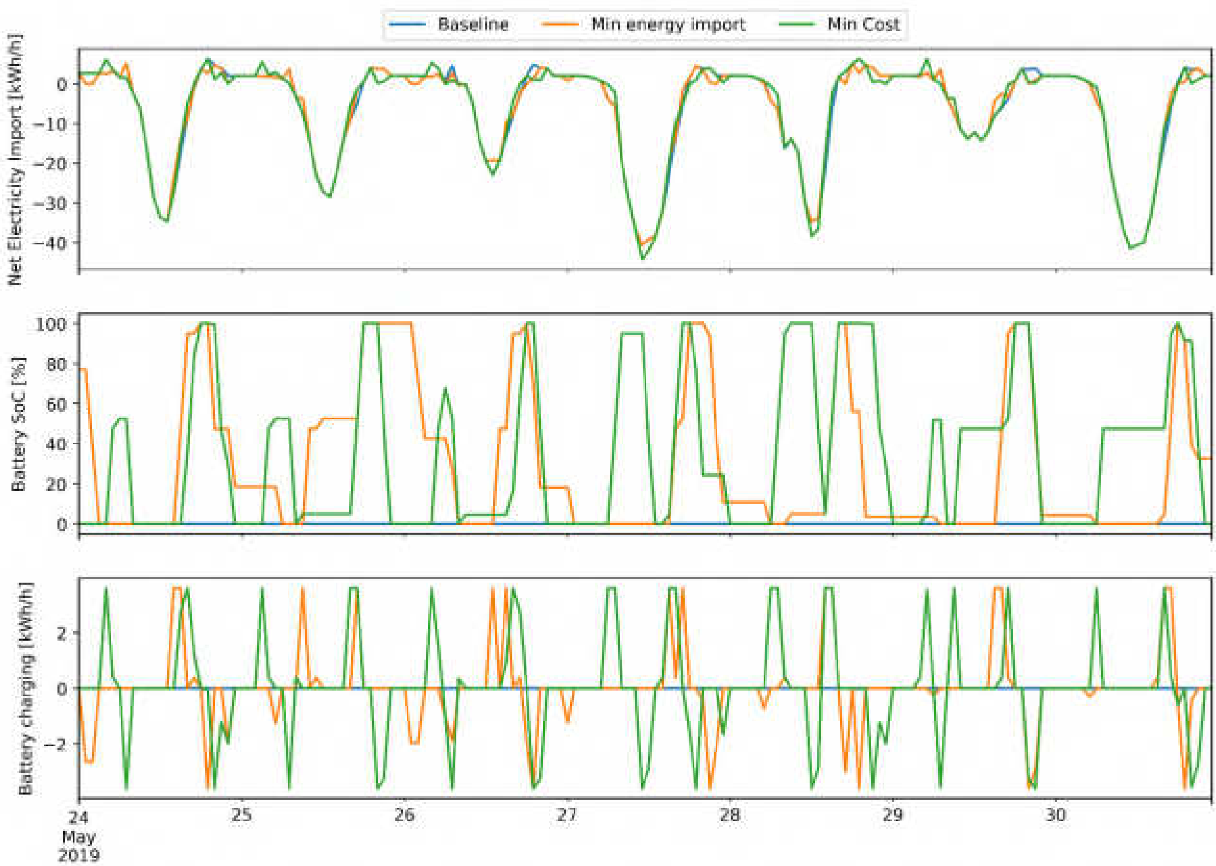


Figure 18: Example summer week for Battery tank control

Control strategies

An approach to high-level control of "electric assets", such as batteries, will be outlined in the following. To illustrate the principles, conceptual sketches of the system is shown in Figure 19. The focus is on high-level "long-term" control, not short-term grid stabilization services, such as voltage support or reactive power compensation.

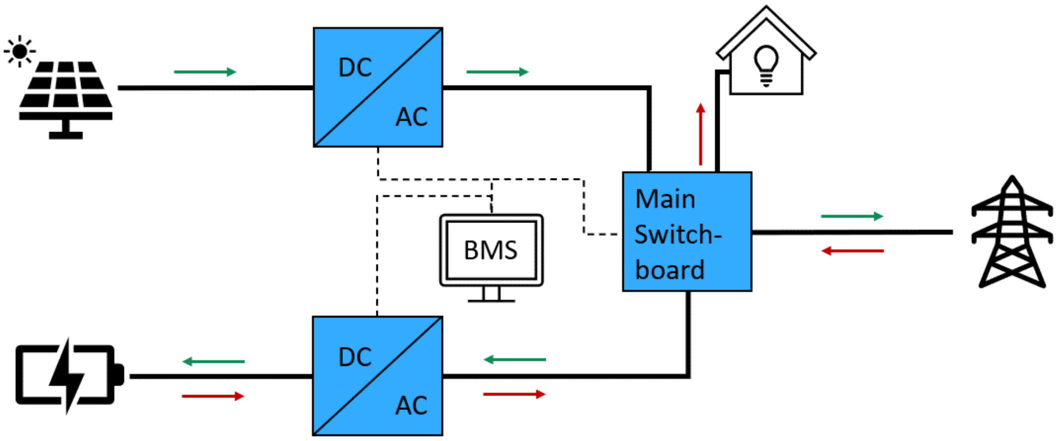


Figure 19: Conceptual sketch of PV/Battery system

For rule-based control, three main principles are considered.

1. **Increase self-consumption.** In this case, rules are implemented so that the battery charges when the PV production exceeds the demand and discharges when the demand exceeds the production.
2. **Energy price control**. In this case, rules are implemented so that the battery charges when the prices are high, and discharges when the prices are low. Thresholds for when to charge and discharge must be defined.
3. **Peak import reduction**. In this case, rules are implemented so that the battery discharges when the import exceeds a set limit. The limit should be set so that one minimizes the risk of exceeding the limit when the battery is fully discharged.

The three principles can be combined, creating more complex rules. While an RBC such as this has the potential to limit grid impact and reduce cost, there is room for improvement regarding flexibility and optimality. The rules are in principle, static, but the optimal thresholds might be dynamic. Provided that the thresholds are controllable via the BMS, it is possible to implement an MPC algorithm on top of the RBC. The output of the MPC can be used to alter the rule thresholds to improve the control. In such case, the MPC works as a supervisory controller on top of the RBC.

4.5.3.5 Control of EV-charging

EV charging is not evaluated as a flexibility source as installed chargers are not controllable.

4.5.3.6 Combining the assets

As shown in the previous sections, the different flexibility assets have different properties and benefits. However, they are also overlapping. Therefore, the potential cannot be added together to evaluate the full flexibility potential of the building.

Potential

The model is optimised to evaluate the total flexibility potential with all the flexibility sources activated simultaneously.

Table 11 shows the resulting KPIs when with all flexibility cases activated (single battery). The results show that including the indoor temperature and DHW tank, has similar performance as including an extra battery, but the flexibility of the indoor temperature also brings peak shaving capacity.

Figure 20 shows an example winter week with all flexibility assets activated. It shows the net electricity input and the "state-of-charge" for all assets. The assets are utilized similar to how they are utilized when activated separately.

Table 11: KPIs for combined flexibility potential

	Min Energy Import		Min Cost	
	abs	rel	abs	rel
El import [kWh]	34 212	-8 %	34 414	-8 %
El export [kWh]	22 854	-12 %	22 921	-11 %
El net import [kWh]	11 358	-2 %	11 493	0 %
Energy cost [EUR]	2 803	-6 %	2 392	-20 %
Max import [kWh/h]	17	-28 %	18	-25 %
Max export [kWh/h]	39	-8 %	48	14 %
Self-consumption	53	13 %	53	13 %
Self-Production	43	13 %	44	17 %

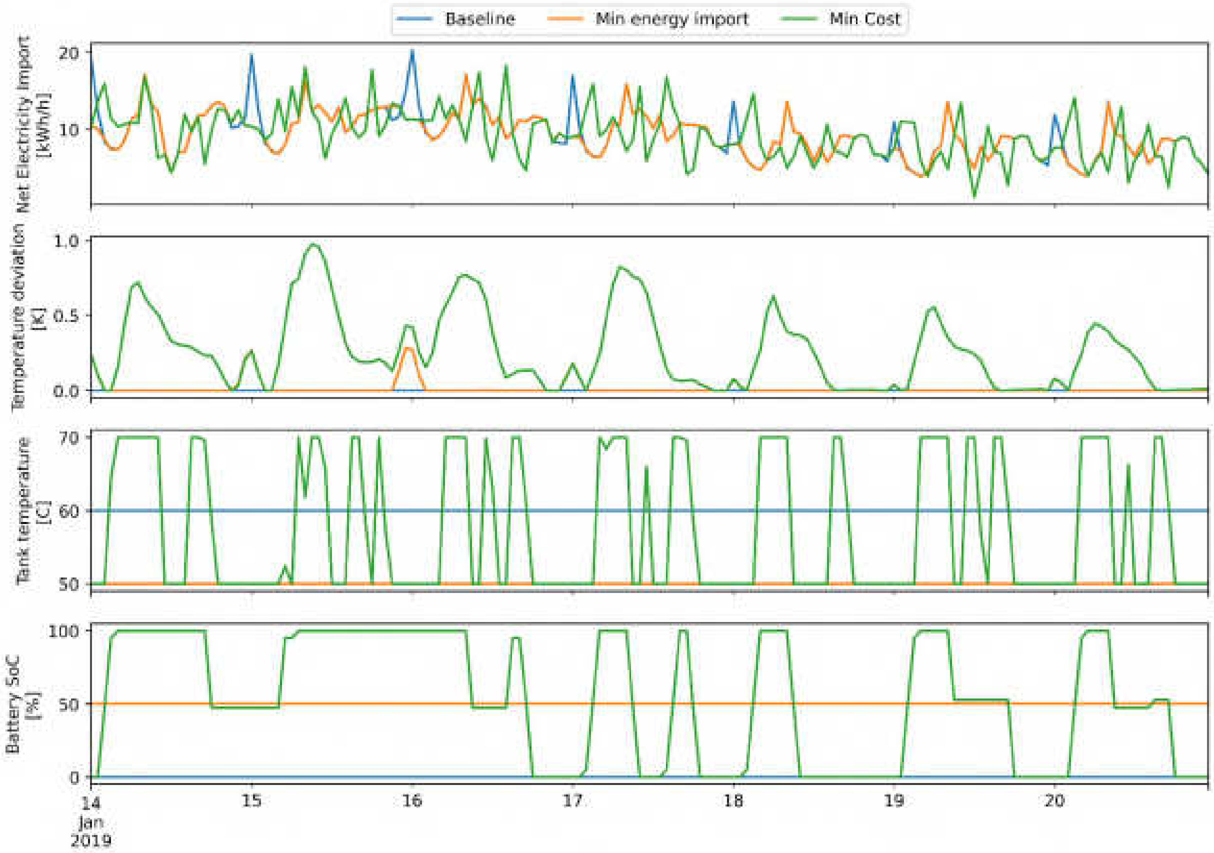


Figure 20: Example winter week with all flexibility assets available.

Control strategies

The individual control approaches described in the sections for the different flexibility assets could in principle also be applied in parallel to exploit all assets combined. However, the challenge is to coordinate the activation among the assets so that they don't counteract each other or create undesired effects. This could be especially challenging regarding peak demand control when all assets are controlled individually to minimize cost.

A strategy to solve the coordination issue is to use optimization-based control, such as MPC, in one of the architectures described in end of section 0.

5 Mediterranean cluster (Italy)

The proposed evaluation of control strategies starts from a standard control approach and will gradually introduce behaviors allowed by smarter controls. In this sense, we want to gradually verify the system performance's expected improvements (from the preliminary baseline simulation phase) according to fixed objectives and external control signals. To justify any additional incrementation of the control complexity, it is mandatory to experience a significant improvement of the system performance first in the simulation phase, then in a potential real DEMO case or, for the Mediterranean cluster, in the planned experimental phase that will take place within the INTEGRIDS' facilities (Section 6).

These possible improvements are measured according to the metrics exposed in section 3.1, given the external forcing signals, mostly energy cost from historical data and capacity penalizing practices that will follow[8]. All the above metrics will be considered to evaluate the impact of the introduced control's variation in the system. In this sense, many factors may influence the actual experienced performance of the proposed practices on the simulated systems. In this regard, the simulation will be first performed according to the buildings' composition and data resulting from the simulations of Task 4.4. Those profiles will be then adapted (rescaled) to the actual capabilities of the experimental facilities as further discussed in section 6.

5.1.1 Prioritization of the two building's domains

The building is the scale of application of the controls for the current work. In this sense, we identify the single available subsystems that act within the building's envelope and operate using electrical energy. Two are the main identified domains: thermal and purely electrical assets. As introduced, we consider electricity the only energy source in both cases.

The control strategies proposed in the current section are organized according to priorities. In this sense, the two concurrent domains (Thermal and Electrical) control are integrated according to given priorities.

[8] Regarding the objectives of the control strategies, the statements produced in Section 4.4 for the Subartictic geocluster holds also for other geoclusters.

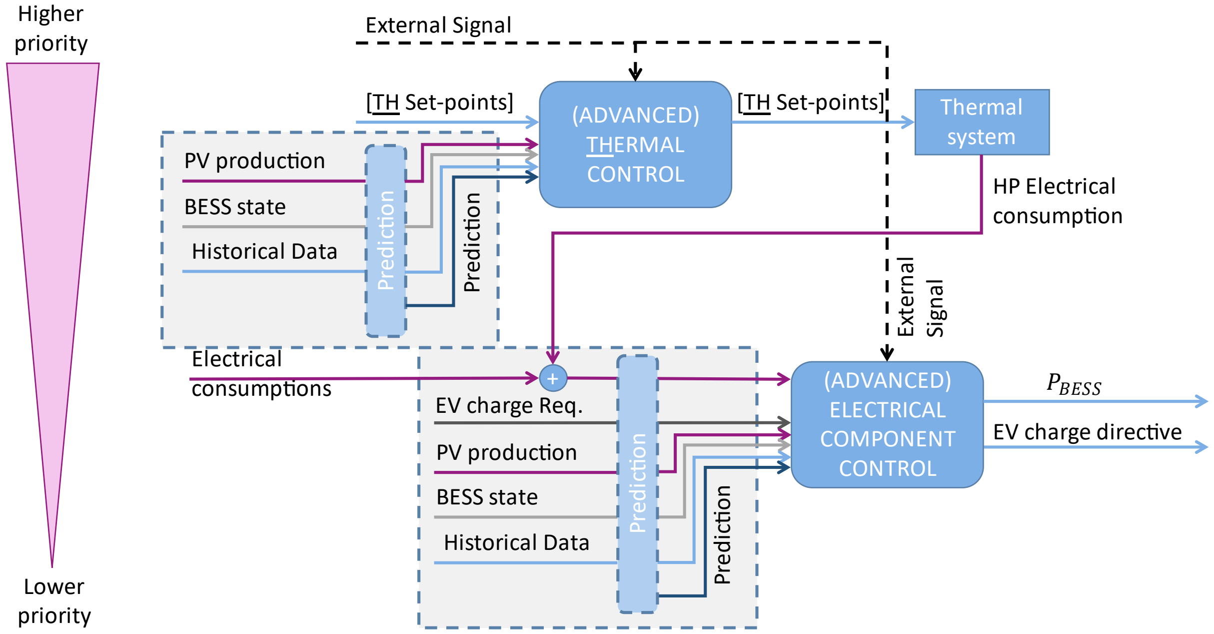


Figure 21 Prioritization of the two energy domains of the building. Thermal and electrical (only) domain. The priority is given to the thermal domain, and the resulting electrical profiles are considered by the controller responsible for the purely electrical components. The qualitative diagram also the more complex scenario with prediction and enhanced controls (the dashed boxes contain the optional components).

Figure 21 shows the priority stack proposed in this work. While the control connected to the thermal domain alters its internal setpoint, the electrical domain control receives the net electrical consumption derived from the operation of the thermal system and all the other electrical assets as input. The control connected to the electrical domain is primarily responsible for the governor of the battery storage system and possibly for the scheduling of EV charges (only in the case of electric vehicles and charging points in the simulations and real cases).

5.1.2 On the consideration of loads components and appliances

For the other electrical appliances, we do not explore an active control algorithm to move their operation periods according to the low impact on the overall electrical power consumption once removed the base load of the building[9]. They still may represent a component of the flexibility included in the electrical domain. Nonetheless, this flexibility contribution is exploitable from a practical point of view with a conscious use of the most energy-intensive electrical appliances. We believe that the simplest practice is to demand this care to a properly educated and sensitized user, that may be helped in the operation of its daily activity according to its needs and possible inputs from the building smart system. For example, the system may indicate to the user the presence of PV production (current and expected) and possible matching appliances, that have an

[9] Similarly stated in the introduction of section 4.3 for the Subarctic case.

electrical consumption pattern compatible with the upcoming electrical production. In this case, the user may be sensitized to operate loads with high electrical consumption (mostly large white appliances that involves heating with resistances and may be considered as deferrable: dishwasher, washing machine, dryers, iron) according to expected PV production or any external signals (e.g. low electricity prices).

This suggestion may not be easily translated into a simulation domain and its impact is expected to be small but not insignificant, overall, from the point of view of a pursued consumer awareness. For both these reasons, the exploration of such flexibility is not ported into simulation or the experimental setup.

Many are the factors that may impact the energy consumption of inhabitants. Among the others, it is possible to identify social demographic, different appliances, and personal attitudes. It is possible to produce a statistical analysis of the behaviour of consumers depending on such factors and time parameters (hour of day, day of week, seasons). This classification may highlight groups of populations with similar consumption behaviours and the so-called “archetypes” (consumer segments) as done in [9]. The same analysis may be extended at the country level as in [9], [70], providing significant information on consumer segments in each geo-clusters.

Further analysis of the typical composition of the residential load may be explored to understand the contribution of each appliance to the electrical profile and the relative cycles that the operation of the appliances under analysis may reproduce in the power consumption [71], [72]. Excluding HP and EV contribution, it is possible to identify a baseline load that may show slow changes in amplitude during the day and more random contributions or spikes that enters that base static consumption.

Due to the reported characteristics, only a few **appliances** are eligible to implement smarter automatic control strategies. These should be the ones that have a higher impact on the overall consumption (**HP, DHW, EV**), that are naturally equipped with controllers to properly operate in what we consider a baseline behaviour, and that are somehow deferrable and can be modulated. The only source of **production** (**PV**) is not actively controllable unless we operate it curtailing the actual production capability, a practice not suggested at the residential/building level. This holds considering the size of the plant that typically matches by design the order of magnitude of the expected local consumptions of the inhabitants. The final component is the **battery**, which operates buffering power and therefore behaves as an additional load or production source. In this sense, it is extremely important to remember both the cost of this technology (expected to decrease [69]) and the non-ideal efficiency that characterize the component of the system. Any electrical work involves losses and the typical operational life of the battery is expressed by producer with a maximum number of cycles or an age in years (5-15 years, while 10 years is a common warranty value for commercial products[10]).

5.1.3 Thermal Domain

The thermal domain scheduling may act on the thermal energy storage (TES) set-point considering the building and its thermal systems as storage. Such control will act on large masses and therefore storage capabilities with slow dynamics. It has therefore large potential in the amount of the shifted energy but less flexibility. It should also be noted that the losses are a function of temperature and therefore pushing the system to operate at a temperature too far from the reference (suggested by user comfort) may induce higher losses not justified by the benefits in terms of energy flexibility except to increase the exploitation of the local overproduced energy resource. The approaches discussed in section 4.3.2 hold for all the geoclusters considered in this work.

The baseline approach differentiates target setpoints according to hours of the day and the inhabitants' relative expected habits and activities. The differentiation of the heating/cooling intensity in the rooms of dwellings and the building areas may introduce an additional dimension. This may match user comfort according to the activities carried out in each environment. The dedicated hardware facilities should be present in the building to accommodate each variation of the proposed control approaches. The complexity of the final system should result from a trade-off-driven design.

According to the review of Figure 2 (section 2.1), for the Mediterranean geocluster, room temperature control is critical both during winter and summer.

This makes the thermal domain a useful source of energy flexibility for the whole year, but especially during winter and summer.

In general, these controls have a higher impact during high load periods. In winter (cold season) the space heating load is mainly concentrated during the night when there is no PV production. It is almost always possible for buildings with high thermal inertia to overheat the environment and shut the HVAC system off overnight. Usually, the total produced heat is higher. However, it increases the COP of the heat pump as it operates mainly during the day when the air temperature is higher. Thus, the electrical consumption is lower but concentrated when the PV modules are producing more electricity. In summer (hot season) the load is already concentrated in the central part of the day. It is possible to subcool the building in the morning when the air temperature is lower and there is already PV production to increase the EER of the heat pump. Finally,

[10] Respectively https://www.sunrun.com/go-solar-center/solar-articles/what-is-the-life-expectancy-of-a-solar-battery, and https://www.cleanenergyreviews.info/blog/home-solar-battery-cost-guide.

during mid-seasons, the building's heating/cooling needs are reduced; the same is the impact in terms of energy flexibility.

The thermal work shifting action is undertaken to improve the matching between consumption and local renewable production profiles. It is worth noting that it is possible to operate successfully in this direction. Nonetheless, this approach may increase the overall consumption of the building (a critical component in the evaluation of the PEB characteristics).

All the work done in the thermal domain is translated into electrical usage that may be easily considered in controlling the next components that act exclusively in the electrical domains.

5.1.4 Electrical domain (battery storage control)

The battery operates as an electrical energy buffer. The standard rule-based (RB) control approach is the so-called "**Own-Consumption**" and acts to maximize the exploitation of the local energy resource. Figure 22 proposes the diagram with the basic adopted approach for this control mode. In this mode, the control requires the battery to absorb the PV overproduction. Once production is less than the net consumption, the electrical storage is discharged according to the reported mismatch.

Typically, the battery storage system covers all the loads in the building. Nonetheless, in special cases, it is possible to limit its operation to serve only certain. In this case, the P_{load} Figure 22 is composed by the electrical load of the single supported device (a component of the total building load). For example, it is possible to dedicate the electrical storage to support only HP or EV, given explicit requirements from the user.

Finally, A less strict approach may operate by reserving virtual quotas of the total battery capacity for each group of appliances (EV, Thermal work, all other appliances of the building).

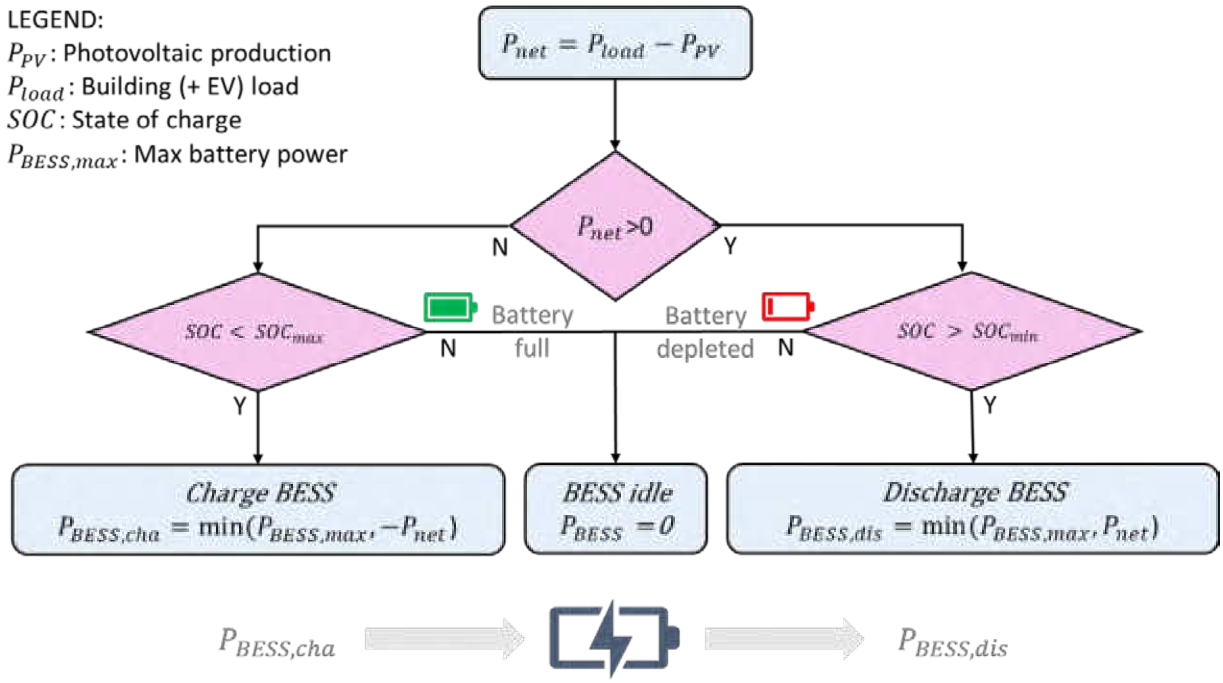


Figure 22 Example of RBC logic with own-consumption optimization that is considered as the base to develop the tested control strategies.

The "**Own-Consumption**" logic (Figure 22) is embedded in most commercial products and requires only monitoring the real-time production and consumption of the building. It is possible to design further variations to the current procedure, first exploiting the basic functionalities commonly available in the commercial battery inverter and then exploiting the possibility to fully alter the power profile applied to the electrical storage. The latter option requires the control of the battery management system from an external energy manager within the boundaries offered by the standard firmware provided onboard of the devices by the producer. Among the most common option provided by manufacturers, there are the following logics (here summarized by function even if they may be slightly different according to the specific product[11]):

- De-facto standard "**Own-Consumption**" (Scheme on Figure 22 for more details)
- **Time of Use**. Work forcing charge or discharge within certain time ranges according to given thresholds. In the remaining time holds the previous control.
- Prioritize the EV charge[12].

[11] Some of the product's link explored to review the above listing follow. (Access date March 2022). https://www.zcsazzurro.com/inverters/storage-inverters https://www.solaredge.com/products/ev-charger#/ https://www.fimer.com/string-inverters/react-3646-tl https://www.sma-italia.com/prodotti/inverter-per-batteria/sunny-boy-storage-37-50-60.html https://kaco-newenergy.com/products/blueplanet-hybrid-10.0-TL3/ https://solar.huawei.com/eu/Products/FusionSolarResidential

[12] https://www.solaredge.com/products/ev-charger#/ (Access date: August 2022)

- Operate in partial or total islanding mode (as backup during the grid loss and instabilities or continuously in the absence of connection to the grid)
- Operate in a custom mode according to the external tuning of the battery inverter parameters[13].

In the current work, we explore several approaches to interacting with the battery inverter according to the function mode described in the above listing. These solutions are compared with the reference standard case of the plant without the battery system (as the battery installation may be exclusively required to explore the energy flexibility) and with a battery with standard "**Self-Production**" control. An effective improvement of the monitored metrics during the simulation phase may suggest the possible advantages of such solutions and justify the control framework required to support such a logic.

From the configuration described in Figure 21, it is expected that the thermal domain is potentially capable to introduce the largest reallocation of energy according to the size and dynamics of the thermal storage. On the other hand, it is expected smaller flexibility exploitation and therefore smaller margin of improvement from the electrical domain given the above priority stack. In this domain, the only element that can act as explicit storage is the battery. The basic logic is already well optimized for the operation of such a device. Moreover, the battery is always sized according to the building's needs, and most of the time it is limited in dimension due to its costs. This system will so work at the maximum of its capabilities (bounded by capacity, actual max power, and the amount of overproduced energy). Given these premises, here we want to explore the possible margins for improvement linked to a different battery use according to an external forcing signal. Further discussion about EV charges will follow in section 5.1.5.

5.1.4.1 Advanced objectives

The alteration of the standard control logic may be induced according to observation produced starting from common practices, historical, or reference (simulation) data or literature work [25].

A more advanced approach is to identify the target objective to be minimized from the advanced control routine. These objectives are achieved considering external signals that enter the control loop.

Price signals are built during simulation and experiments according to historical records of energy price (despite the high variation observed at the time of writing due to the complex geopolitical dynamics in progress). Moreover, we explore in simulation the potential introduction of capacity penalties on the energy price to act as an external

[13] https://www.zcsazzurro.com/inverters/storage-inverters

price signal to encourage the reduction of consumption peaks. This practice will alter the energy price by applying a penalty whenever a given power threshold is exceeded. More details will follow the section 6 related to the experimental setup and relative results.

We will first rely on simulation to evaluate the effectiveness of the proposed control rules. These will be held according to electricity profiles from the simulation model of the mediterranean high-rise/low-rise building in deliverable [15], [73]. Building characteristics, dwellings aggregation, and system sizing are all factors that may heavily affect the performance of the proposed control strategies. For these reasons, here we sketch several proposes and we will test some of them in simulation and compare those results to the actual case study. Moreover, more details will follow about the approach adopted in the experimental setup in section 6.

5.1.4.2 Introduction to the prediction and advanced control frameworks

More advanced controls require the construction of a prediction of the system's behaviour in the next future. The prediction aims to provide information on the future evolution and state of the system and allow proper computation of the advanced control. Figure 23 states the main concepts that allow a proper tuning of such a tool according to the review provided in [26].

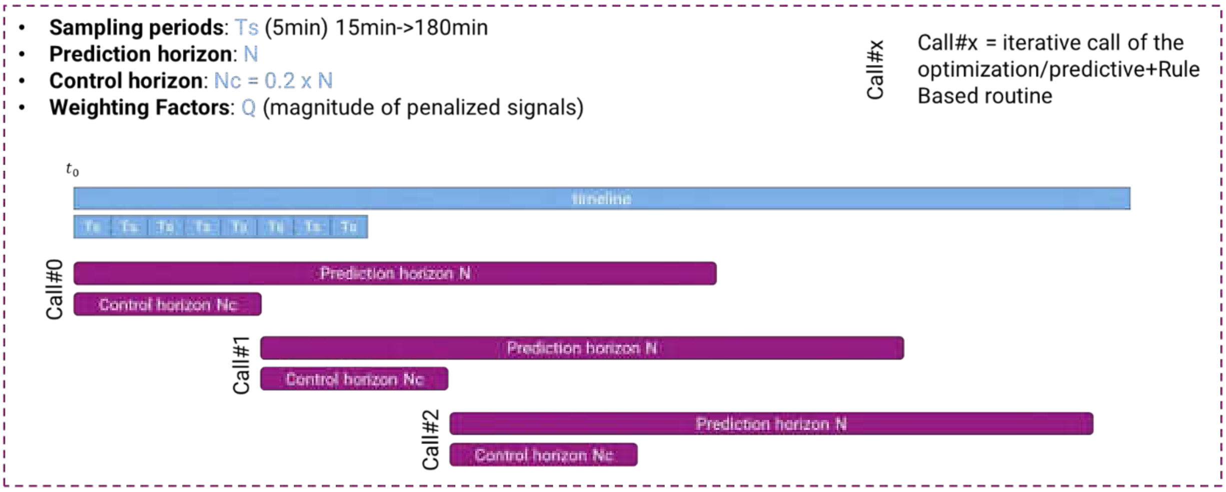


Figure 23 Statement of prediction's parameters. Timing and Horizon [26].

Timing and method of prediction are two of the main parameters of such a process:

- **Timing**. The prediction is performed for the window of time called "Prediction Horizon". The process will output an estimation of the system's future state for the whole horizon. During operation, the control is updated and adopted for a shorter horizon that typically lasts 20%-25% of the main prediction horizon. Doing so makes it possible to operate well within the time limits covered by the prediction. The subsequent predictions that follow one after the other are also overlapped. A sampling time of 15 to 180 minutes is adopted in such computations during the simulation phase. This timestep keeps simple the computational complexity while allowing the exploration of advanced control logic. Finally, privacy concerns suggest that such time ranges are considered acceptable by the final users in case local data (overall consumption behaviours) are collected and reported to external infrastructure or entities to allow the processing of both prediction and advanced control logic.

- **Method of prediction**: In a simulation framework, the first practice is to adopt the so-called "perfect prediction". In other words, as the future system conditions are typically almost known, future data are adopted to evaluate the control logic performances under ideal conditions (a perfect prediction of the future system state). Suppose the logic under evaluation would report satisfactory results in this best-case scenario. In that case, it is possible to implement a more practical prediction practice which will certainly worsen any result obtained from the previous ideal case. A further step is to adopt the so-called "Persistence prognosis" [25] (holds as worst-case scenario or simply worst prediction). According to this approach, the prediction is built from a combination of past history records that must be retained and updated by the control (locally or remotely when demanded to an external platform). The simplest approach is to reconstruct future load according to the mean of the *n* past matching days (distinguishing among weekdays and weekends). Production may be also assumed to be constant within the last couple of days, with possible improvements brought by the introduction of external weather data. Further models and approaches may be deployed to construct the actual prediction. This is also strictly related to the availability of past data and other information related to factors that may change the actual production and consumption behaviour. In a real implementation, prediction complexity is related to the actual complexity of the energy controller and the availability of an external infrastructure responsible for such advanced control strategies.

5.1.4.3 From reference Self-sufficiency controls to advanced controls frameworks

Section 5.1.4 reports a list of operational modes allowed from the battery control units. It is possible to overcome the standard control logic to improve the control approach.

The first improvement in this direction is to alter the standard operation mode by introducing limits on Power, Daily Energy, or Hour of the day within the electrical storage should operate. A more complete listing of such operations will follow:

- Fix the <u>maximum power value</u> in charge and discharge.
- <u>Bound battery operation above/below given thresholds expressed in available capacity (energy) or equivalent SOC thresholds.</u> This may be exploited to reduce

battery cycling and aging by storing only the expected share of energy not covered by production during the next day (until the next peak in production) [25]; or to reserve a quota of the total capacity to a specific load or function (e.g. to enter in backup in case of grid instabilities on critical loads).

- Define specific fixed time ranges when charge/discharge should take place. This is done to match the input of the external signals that may suggest forcing operation at a specific time of the day that is recurrent for long periods (e.g. during the weekend, or the night in the entire year or seasons).
- Disable the battery standard operation within certain periods of the day (for example delay the start of the charge from overproduction to afternoon, instead of loading as soon as available energy from PV).
- Finally, the more advanced solution will force a custom power profile on the battery storage system. In this case, the onboard controller tries to match the required setpoint feed from the external advanced control at each iteration of the control update computation (refer to Figure 23).

These parameters may be fixed according to rule-based controls built on top of the returned prediction or programmatically by deploying advanced control or model predictive controls MPC [26] (refer to the functional scheme provided in Figure 15).

In the simpler case, it is possible to introduce the tuning manually. For example, once a month or once a season, according to the results of preliminary evaluation over the entire season. This may adapt to seasonal variation in the load consumption still relying on the only interface that equips the commercial battery management system. It may be possible to fix maximum operational power, SOC to grant in the presence of overproduction, and actual Time of Use settings.

A more advanced solution may require the proper interaction between the onboard battery management system and an external energy manager. In that case, intercommunication capabilities should be granted, and proper external control must produce and apply the variation of the standard operating parameters.

Both offline and online tuning of such parameters requires all the components introduced above: a modelling framework, a prediction tool, an optimization tool, and the external signal or information needed to tune the whole process. Regarding the optimization techniques, in this work, we will exploit heuristics techniques and more precisely evolutionary methods (such as Genetic Algorithms and Particle Swarm Optimization) to simulate and evaluate the system's model and identify within the solution space a good solution to pass as set-point to the base controller of the system.

The complexity of the problem is connected to its dimension. According to the above listing of possible parameters to tune, the dimension of the optimization problem may be limited to a couple of variables (to tune the standard operation mode). On the extreme side, it may extend till reaching the actual number of samples that compose the battery power profile in the explored prediction horizon. In the latter case, each sample of the battery power profile should be fixed to optimize the objective in the overall prediction horizon.

5.1.5 Electrical vehicle charge (whenever present)

Figure 4 introduced the share electric vehicle in European Countries. In Italy, the share of new electric vehicles in the year 2021 is 9%, according to [47], while EVs are still 0.3% of the total of circulating cars in the same year, according to data from ACI[14]. Despite the current low diffusion, here we sketch possible solutions for that resource with a view to future adoption expansion.

Working in a framework of Plus Energy Building (PEB), the presence of electric vehicles may significantly impact the overall balance [74]. Whenever considered or not in the total building energy use [18], it may consistently increase the electric power consumption of a building. Moreover, this will depend on the actual annual mileage, the vehicle type, and the driving style. The variability of the energy consumption connected to the drive may be somehow consistent with the ICE counterpart. Nonetheless, electric vehicles may enter and dramatically impact the energy balance of a residential building.

Charging habits and locations are also significant in evaluating the building's energy performance. If a personal parking space is available, it can be expected that most of the charges will be made at home while the vehicle is parked. Depending on personal habits and work conditions, this may include the night but also other periods of the day. In any case, the charge is performed at relatively high power if compared to the overall power consumption of a single housing unit. The actual power may vary from the characteristic of the charging point and the connected EV or PHEV. Nonetheless, the charge profile is typically kept constant at the rated power value till it approaches the state of full charge.

A vehicle's charge can occur whenever the EV is plugged into the grid. A standard approach is to perform the charge at the nominal power, starting just after the vehicle is plugged into the charger and proceeding until the vehicle is unplugged or the battery is fully charged. This approach may be called "Fast Charge".

A smarter charging approach is to modulate the charge according to the availability of renewable resources directly from the PV source (preferably) or indirectly from the electrical storage. The basic approach may externally operate on/off the charging point according to the presence of PV overproduction. Nonetheless, this way of operating will

[14] https://opv.aci.it/WEBDMCircolante/ (Accessed August 2022).

not take into account any deadline in time or requirement in energy transferred to the vehicle.

To introduce these parameters, smarter scheduling of the charges is required. The charging device should allow the input from the user of an expected time deadline (or departure time) and a target SOC of the vehicle (or a range in kilometers) to the granted at the end of the charge. Such an approach allows smarter scheduling of the charges. The following possible logic may be applied:

- Charge modulating power according to the availability of renewable energy,
- Charge at the lower admitted power to match the available mileage target within the given time deadline,
- Reschedule the charge from early evening to the night-time in case the vehicle is plugged after the workday and remains parked until the following .

Whenever the adoption of the proposed logic does not achieve the required energy/time deadline, it is possible to fall back to a more aggressive and standard charge of the vehicle to match these requirements. Such a logic requires the physical ability of the charging point to provide a modulation in the charge power and proper integration with the building system (for example, to estimate the actual energy availability during the present and future time).

A final solution can operate beyond the input time/energy requirements, removing the need for the active interaction of the users and operating according to statistical analysis built on past charge events data. Such a solution requires a significant increase in the logic complexity and may eventually not result in an equivalent proportional improvement in the final user experience. However, keeping the user in the control loop may be significant to both provide a sufficiently smooth user experience and keep the control simpler yet more effective.

6 Experimental test and validation of energy building flexibility control strategies in Mediterranean climate

6.1 The simulation campaign focused on the Mediterranean geo-cluster

6.1.1 Simulations definitions and objectives

A simulation campaign preceded the experimental phase. Given the approach introduced Section 5, we setup a simulation environment to provide a simplified model of a system composed by the component that we are going to find in the upcoming experimental setup. The tool combines simplified model of electrical batteries, PV systems and the relative power electronics. The other component of the building enters the simulations as electrical loads. In this regard, we take as inputs the outcomes of the simulations explored in previous project activities[15], [73] for the Mediterranean geocluster and one of the identified reference buildings (Low-Rise). By doing so, we can provide a simplified modelling of the building, having the ability to tune the use of the battery electrical storage.

In previous work [15], the optimization of controls in thermal and electrical domain aims at improving the system performances and bringing to a better exploitation of the available renewable resources working on the energy performance parameters (SP, SC). In the current task, we start from this already *advanced* condition, and we move toward a different direction in the search for the optimization of an objective based on an external price forcing signal. This objective is pursued trying at the same time to maintain the good energy performance achieved and demonstrated in the work carried out in [15]. According to the statements provided in Section 5.1.4, here the focus is on the electrical domain and therefore the control of the battery. This same configuration is found in the experimental chapter that will follow in Section 6.

Working only with the BESS has many limitations and the starting point (a standard RB control) should already provide an almost optimal, or at least good, performance in terms of exploitation of the local renewable resources. Acting on an HP and on other possible loads may further improve indicators such SP and SC that clearly summarize this call to the improvement of the local exploitation of the renewable resources. In these cases, the increase of total consumption of loads is tolerated as they are supported by the locally generated renewable resource and its further exploitation.

On the other side, two qualitative remarks should be made in the introduction of the work here done: first, sizing matters, and here the sizing was done within the framework of positive energy building and discussed in detail in the relative task report [15], [73]. Second, the operation of the battery has rigid limits that correspond to the fully charged and discharged state of the device. It is not possible to operate the device to charge more when it is fully charged and to discharge more when it is fully depleted. This is a huge difference compared to a smarter operation of an HP (or other loads with similar characteristics), that can be pushed to operate more (increasing the target temperature values) accepting possible reductions in efficiency, but potentially shifting the load of the device in the present time or in the future. Moreover, we decide not to charge the battery from the grid, both for regulatory concerns and from an efficiency point of view. In this sense we focus on the exploitation of the local energy resources, even widening the objective of our optimization action.

Giving these operation limits of the BESS, in combination with the latter remark, the factors induced by the mismatch between the consumption and production profiles matters. PV production, if present thanks to the proper weather condition, has a highly peculiar shape that typically mismatch with the consumption and moreover peak consumption of residential uses. This issue is widely analysed and discussed in literature [75], [76] and is here only recalled providing a better interpretation of the context in which we are moving. This regards, a qualitative consideration may suggest that rarely it is possible to perform more than one charge/discharge cycle a day in a system typically sized for a residential building and given the photovoltaics as an energy resource.

That said, our work explores if it is possible to move and alter the *finite* work of the battery within a prediction horizon (a near future) to reduce an objective function that responds to external forcing signal coming from the grid. This, in details, converts into an external price signal that enter the cost function and penalize more the use of energy from the grid in times with high energy prices. We want to explore such target preserving the performance summarized by the indicators computed in the reference task, and therefore preserving the capability of the building system to exploit at best the local renewable resource for the operation of its plants. This aim masks a deeper objective connected to the capability to interact and react to stimuli that come from the external system to be also able to accommodate and responds to its potential needs.

6.1.2 Overview on the simulation implementation

In the work, we use a simplified model of the system (PV, battery, building) in which we are able to control the use of the electrical storage system. The resulting electrical profiles from report [15] are the input of our analysis and define in the specific case the behaviour of the building and the PV production.

The modelling framework allows us the setup of an optimization problem which has as objective the reduction of the cost of the energy imported form the grid computed considering only the reference national energy price with hourly time resolution (we select a year assumed as reference). The same resolution was kept for the whole simulation analysis.

A heuristic approach explores the space of parameters of the optimization problem and identify the values that provides better performance. By doing so, we can operate the battery adopting a model predictive control MPC. Such a control approach is compared to the reference case in which the electrical storage is operated with the standard rule-based approach. Two are the approaches that show better performance and therefore were implemented in the final simulations. They differ by the way the battery operation is altered. In the first case, we let the MPC define the power profile to be applied to the electrical storage along the whole prediction horizon. In the second case, we define the time slots within the day in which the battery is allowed or not to operate in charging or discharging mode. Perfect prediction is adopted to explore the best-case performance of the provided tools.

The simulations are repeated for each set of profiles resulting from report [15] exploring different prediction and control horizon of the MPC tool. This allows us to understand the magnitude of the improvements of the cost function we can expect from such an approach.

6.1.3 Simulation results

The provided MPC is able to react to the external forcing signal provided from the grid reducing the cost function. We developed an indicator that highlight the effects of the applied MPC in terms of the stated target (Figure 24).

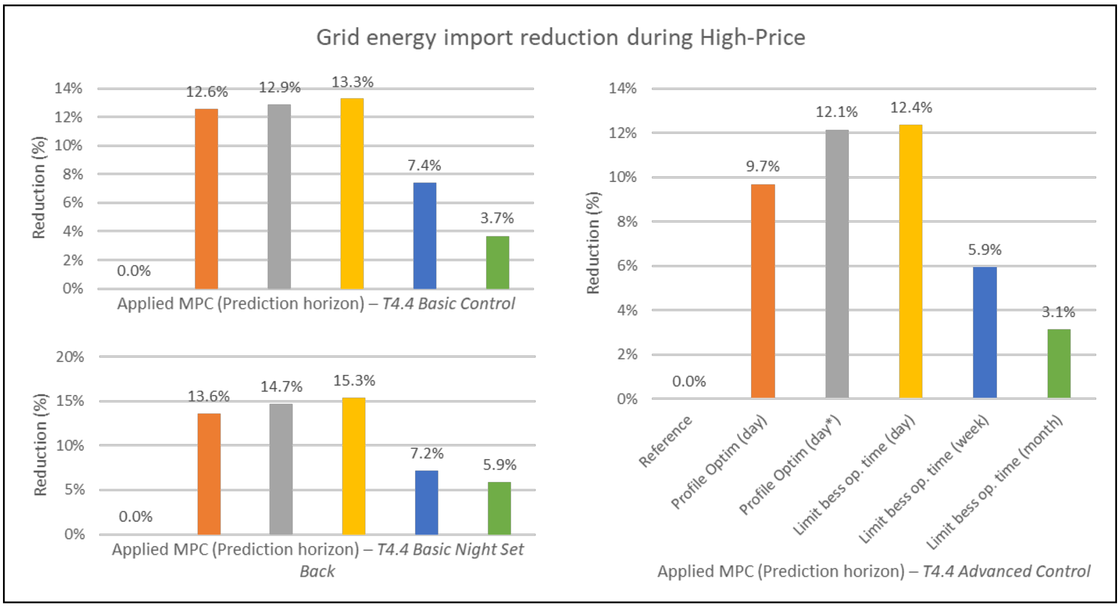


Figure 24 Different MPC simulation results applied to the resulting profiles described in [15]. In figure, the custom indicator developed to highlight the effects of the applied MPC in terms of energy import reduction during high-price hours.

This indicator shows the reduction of energy import of the building system from the grid during the time of high energy prices. From a mathematical point of view, high energy prices are defined fixing a threshold value that corresponds to the 85 percentiles of the forcing external signal (PUN).

In all cases the MPC does not significantly worsen the performance obtained in the optimization done in [15]. In this sense, all the KPIs that does not enter the optimization objective are retained and therefore the system performs very similar from a perspective of SC, SP, CO_2 reduction, energy import and export from and to the grid, and so on.

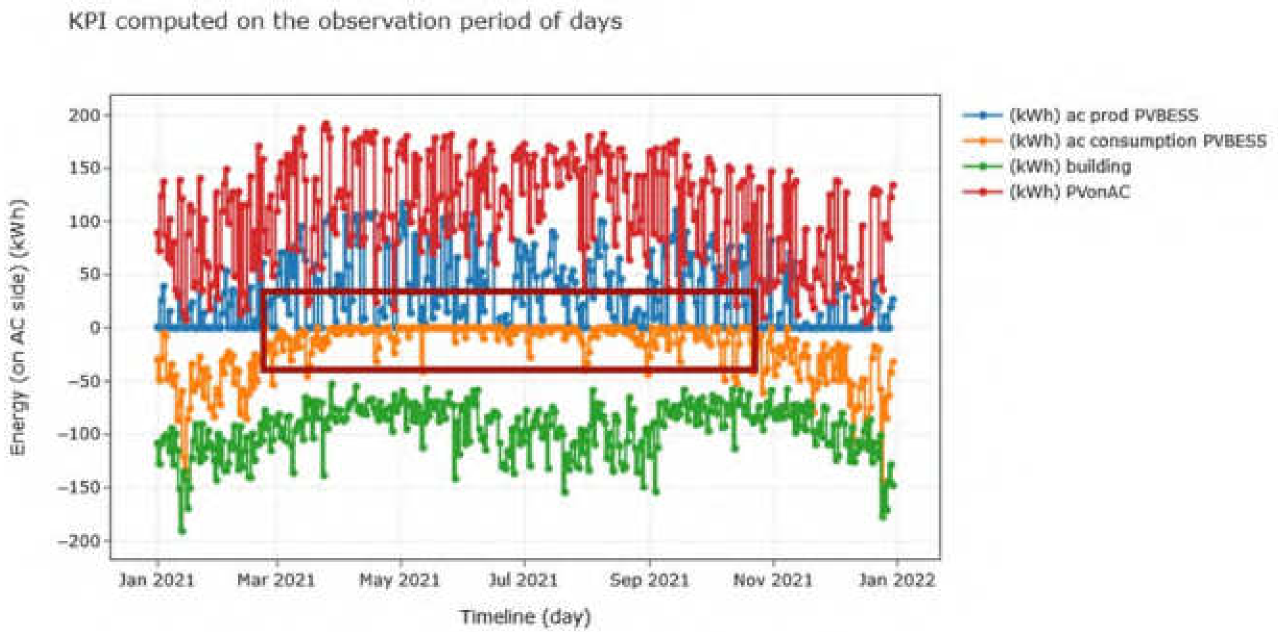


Figure 25 Example of daily energy consumption and production from one of the simulated control and scenarios. Focus on the near to zero consumption from grid during good-weather seasons thanks to the high local renewable production and the installed system.

Many days of the year are characterized by a net positive energy balance (Figure 25). In that condition the systems always export energy to the grid and is perfectly able to cover its need. This happens mostly in the warm season due to the sizing of the system and the consequently massive PV production. In such days we do not expect a change in the cost function as it is already equal to zero having no import from the grid. In such days, the only presence of the BESS normally operated is able to bring to zero the imported energy requirements and the relative costs. In the other seasons, lower rates of self-production give the optimizer potentially greater room for manoeuvre and improvement, which means a cost of energy import greater than zero. In such a scenario, the MPC tries to move the energy import away from high-price hours in order to minimize the relative target by proper operation of the electrical storage. An analysis of the indicator aggregating data in smaller windows of time suggests this behaviour and the actual seasonality of the performance of the system.

6.2 INTEGRIDS' facilities

INTEGRIDS[15] is a framework developed to provide a heterogeneous set of facilities to explore the concept of energy flexibility in buildings and districts under the FEDR funding between 2017 and 2020.

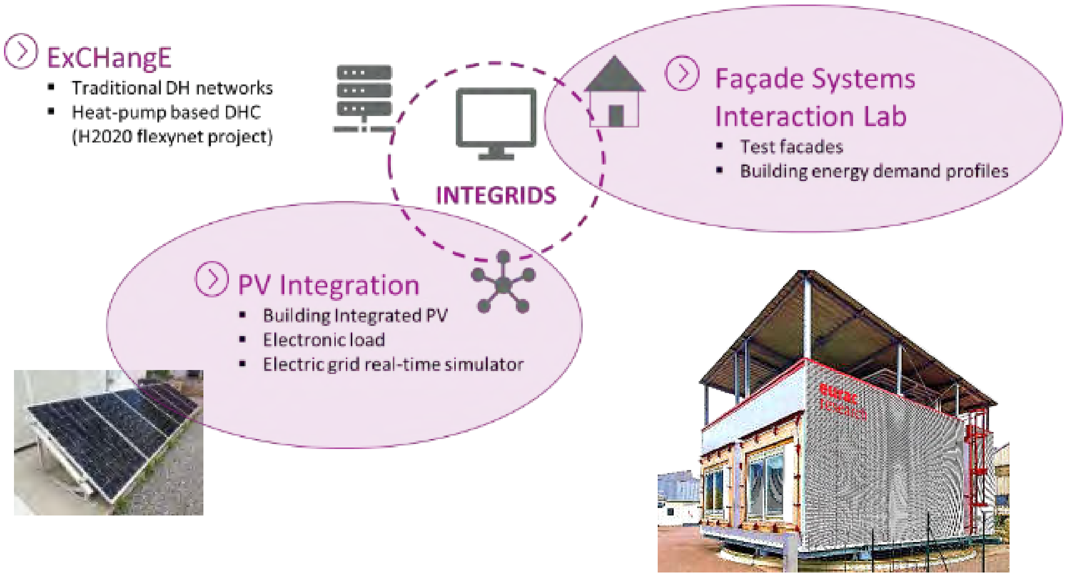


Figure 26 INTEGRIDS laboratories schematic. INTEGRIDs is a network and set of tools that allows the integration of the available outdoor facilities present at EURAC research. In red, the areas interested by the setup proposed in section 6.3.

The laboratory provides an integration between each system and plants present in the EURAC research laboratories. Figure 26 provides an overview of the main outdoor facilities exploited in several tasks of the current project. The infrastructure allows a connection between laboratories, data acquisition and storage, and enables controls over the several facilities.

6.3 Laboratory setup

Figure 27 proposes a simplified schematic of the devices of the system. The components are physically present inside the outdoor EURAC facilities[16], while the laboratory infrastructure ensure communication among them even if not physically installed in the same facility[17].

[15] INTEGRIDS project resources https://www.eurac.edu/en/institutes-centers/institute-for-renewable-energy/projects/integrids (Accessed March 2022).
[16] https://www.eurac.edu/en/institutes-centers/institute-for-renewable-energy/pages/laboratories-facilities.
[17] https://www.eurac.edu/en/institutes-centers/institute-for-renewable-energy/pages/pv-integration-lab.

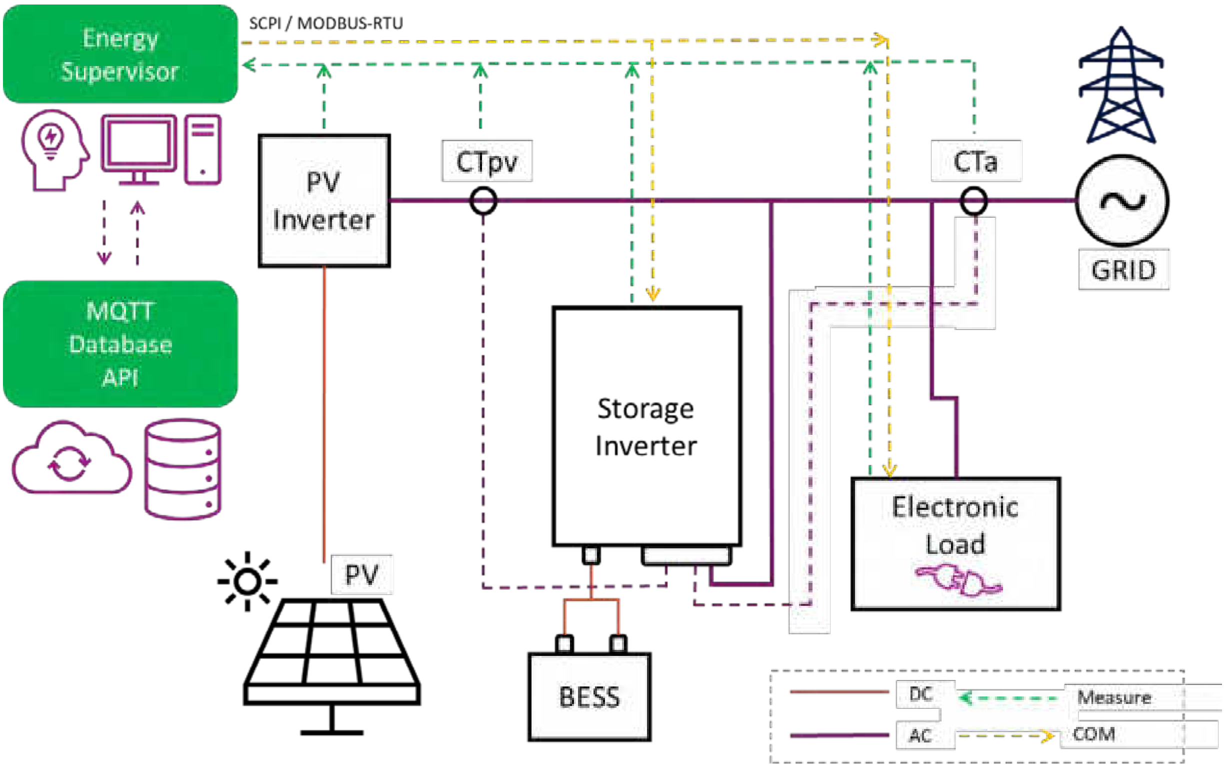


Figure 27 Design of experiment. Simplified schematic of the component involved in the final system as regards the electrical domain.

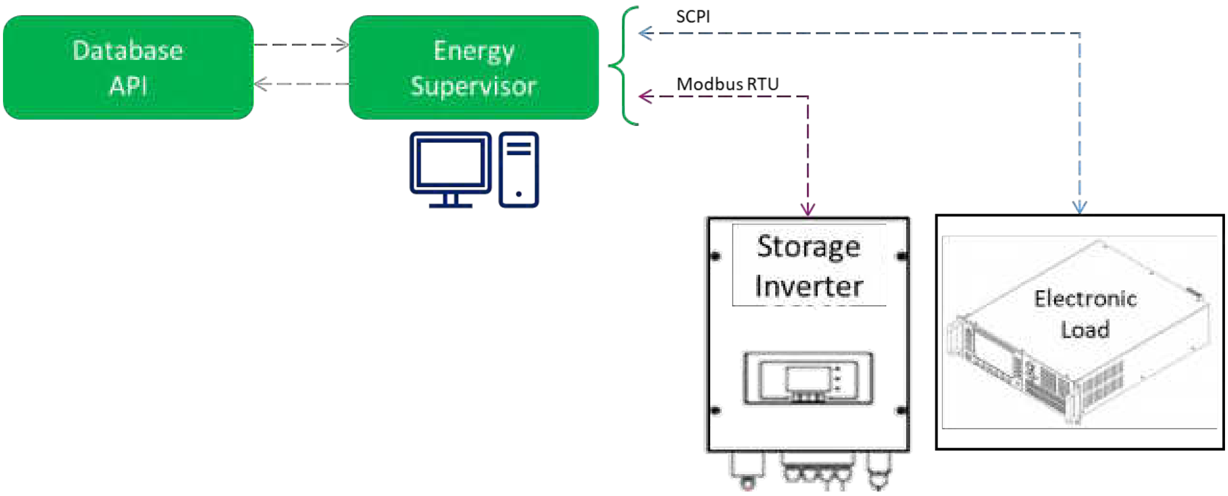


Figure 28 Communication protocols within plant components.

The active component, responsible for renewable energy production, is provided by photovoltaic systems (Several PV DEMO plants are present inside the laboratories equipped with modules and inverter of different technologies). A storage system is composed by three modules with a total capacity of 7.2 kWh and an inverter responsible for the interface of the battery modules with the grid. Finally, an electronic load emulator enables the simulation of arbitrary load profiles that can represent a scaled version of the building's electrical load profiles. The availability of Electronic Load enables the generation of customized profiles on the basis of simulated energy requirements and intrinsically allows basic load-shifting practices.

According to the systems topology and available resources at the outdoor facilities, the following components may be controlled or simply monitored:

- PV production (nominal 4.4 kWp), live production of several demo plants is present. In case the experiment requires it, these production values may be virtually summed up or scaled to match the required amount of produced power. No active control is available on these sources.
- Battery energy storage system (nominal 7.2kWh). Several levels of external controls on the battery inverter may be applied according to the implemented control logic and requirements of the experiment.
- The electronic Load (max 1800 VA) mimics the expected electrical load profile behavior and potentially enables some level of load shifting according to the experiment requirements.

Figure 28 reports the basic communication protocols that are operating to allow intercommunication between the Supervisor (an industrial computer) and the single devices within the systems. Such protocols allow to collect from the devices the monitoring data and state. They also allow to act by altering the internal operative settings of the devices and editing the work setpoints of each device. The collected data are processed locally and delivered for storage to a database on the EURAC ICT infrastructure that serves the laboratory. Storage is delocalized to ensure robustness, and reliability to the conservation and visualization of data[18]. On the other hand, the compute is retained on the local supervisor PC as it offers sufficient spare computational capability for the purpose of this setup.

6.4 Implemented Control Strategies

The aim of the experiment is to provide a test setup that allows the researcher to potentially apply the simulated advanced control strategies on a setup that mimic the behaviour of a dwelling or building. Starting from a basic Rule-Based Control (Figure 22) strategy it is possible to introduce and test a component of prediction (RBC + Prediction) by properly tuning some parameters of the RBC controller according to the optimization of some objectives (Refer to section 4.4 for more details about the possible control

[18] Refer to the images produced in Section 6.5 as examples of produced dashboard to monitor the plant operation and the a-posteriori evaluation of the results.

strategies). The final target is to encode the model predictive control (MPC) in order to apply it to the real test plant.

These objectives may match with the explored KPIs monitored on a time window compatible with the experiment. These are:

- Self-Consumption (SC) and Self-Production (SP), describe the actual exploitation of the locally produced renewable resource.
- Energy to/from the grid (from a cumulative consideration of the mismatch between produced power and consumptions);
- evaluation of a daily cost function based on the reference grid energy cost (the introduction of a variable external price signal may further suggest the performance of a control logic focused on the minimization of that objective);
- daily CO_2 reduction (also connected to self-exploitation of the local renewable resource).

The control approaches that passed the preliminary simulation condition in ideal conditions will then be implemented into the experimental setup. By doing so, the modelling and control framework developed for the simulation purpose is adapted to the experimental plants according to its constraints in size, operation parameters and controllability constraints. The simplified model adopted in the simulation should also mimic the behaviour of the real plant. Such a setup will finally enable the operation of the MPC on real hardware.

6.5 Experimental results and future perspectives

The experimental setup was finally implemented according to the indications of Figure 27 and Figure 28. The existing infrastructure of data collection was expanded to grab the operation status and measurements of the battery inverter through the implementation of the custom Modbus communication provided by the inverter producer. The same path was followed for a proper integration of the bench-top electronic programmable load that simulate the building load. The infrastructure has also been redesigned to operate controls of the controllable parameter of the newly introduced devices. Such a feature requires extensive testing and allows the researcher to collect useful information for proper observation of the operation of the devices. This process was aided by a set of dashboards developed to allow better control on the plant during testing, operation, and final evaluation of the test period. The dashboards allow live visualization of data and a basic capability to evaluate qualitatively the behaviour of the system. All the developed tools feed the database of all the relevant generated data, in order to have in the same bucket and with a compatible data-structure both data from real plant operation, from the iteration that MPC requires to update the control and finally, some a-posteriori evaluation and simulations performed on the whole operation period observed and considered for the current analysis. Figure 29 proposes an example of a dashboard dedicated to the live monitoring of the plant operation, it exposes both live data from the plant and some insight on the past 24h history trends of monitored values. Examples of dashboards dedicated to the actual evaluation of the MPC operation are proposed in Figure 30 Figure 32, and Figure 33.

The provided framework allows to proper operate the electronic load by applying the required building load profile and the battery inverter. In the latter case was possible both to alter the working parameters with partial control on the device and also operate a full device control by forcing the application of a specific value of power from and to the electrical storage.

Figure 29 Grafana[19] dashboard to monitor the operation of the experimental plant. Live data and past 24h overview of main collected measures (image taken the day 2023-08-11).

From the practical point of view, the applied profile was derived from the simulation of report [15]. The *IT-LR Basic-control* profile was adopted in the experimental setup and applied rescaled by a ratio of 7. Such a ratio allows to stay in the operation parameters that the experimental test facility was able to reproduce[20] and at the same time was able to reproduce a ratio between the sizing present in the simulation of IT-LR case reported in the deliberable [15] and the experimental plant.

[19] https://grafana.com/oss/.

[20] Refer to Section 6.3 for the actual nominal size of the component of the experimental facility. The evaluation is done on hour time series from simulation T4.4 and device max power and size and involves the following parameters: nominal *PV* (kWp) power, *BESS* size (kWh), the ratio *PV/BESS* (kWp/kWh), max power of Eload (*MaxLoad* kW), ratio *PV/MaxLoad* and ratio *BESS/MaxLoad*.

All the adopted time-series (both from the simulation results and PUN price[21] taken as reference) were shifted forward to align with the current year, while PV production reflect the live weather condition and plant topology available in the external laboratory facility in the periods in which the test was performed.

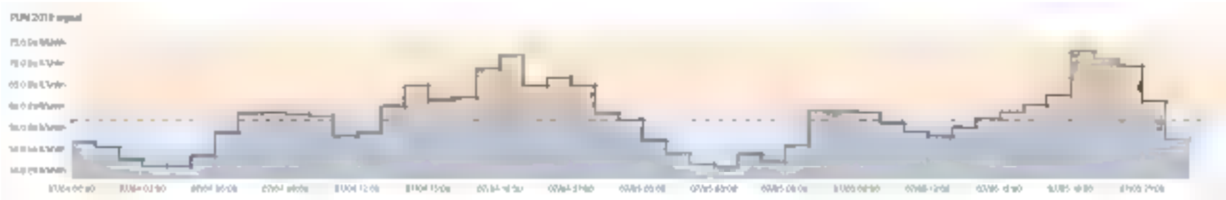


Figure 30 Component of the dashboard reporting the adopted PUN price from *PUN2019*. In orange (above threshold line - the 85 quantile) the value considred as high price.

A period of one month is selected for the purpose of the anlysis proposed in this work (between end of June 2023 and end of July 2023). Most of the charts reports only two sample days (2023-07-04 and 2023-07-05). Such a selection improves the visualization of data and behaviors of the actual control.

A single MPC logic was selected to be implemented into the actual experimental facility to allow a longer monitoring period for the test plant and to focus on a single solution. The applied control logic was adapted to the limitations present in a real plant and that may emerge from the application of a control logic developed and theoretically tested in a simulation environment with approximation in modelling and a long simulation horizon. The selected logic *("Limit bess operation")* scores among the best combination of logic and control horizon MPC in the graph of Figure 24. It consists of the limitation of the standard bess operation (either charge or discharge) during certain hours of the day to move the operation of the battery in hours with higher/lower PUN values. Such control decision is derived from the MPC execution according to the known future load, a trivial prediction of PV production and the same modelling suite that try to mirror the behaviour of the real system through a set of simplified models of the devices.

After a preliminary period run with the automatic RBC control rule, the device was tested with the actual MPC run on the supervisor controller. The latter testing period was carried out at the end of July. According to what is highlighted in Figure 24, such a period is characterized by massive renewable production that typically almost covers the total load demand of the building in such period. In this condition, the MPC has a low-to-no margin to introduce an improvement in the objective function that may be equal to its minimum (zero) already with the RBC standard control (refer to the first graph of Figure 31, where the cost function is zero in some days of the observed period).

[21] PUN-price refers to the year 2019 as done for the simulations. Data obtained from https://www.mercatoelettrico.org/It/Download/DatiStorici.aspx. Example in Figure 30.

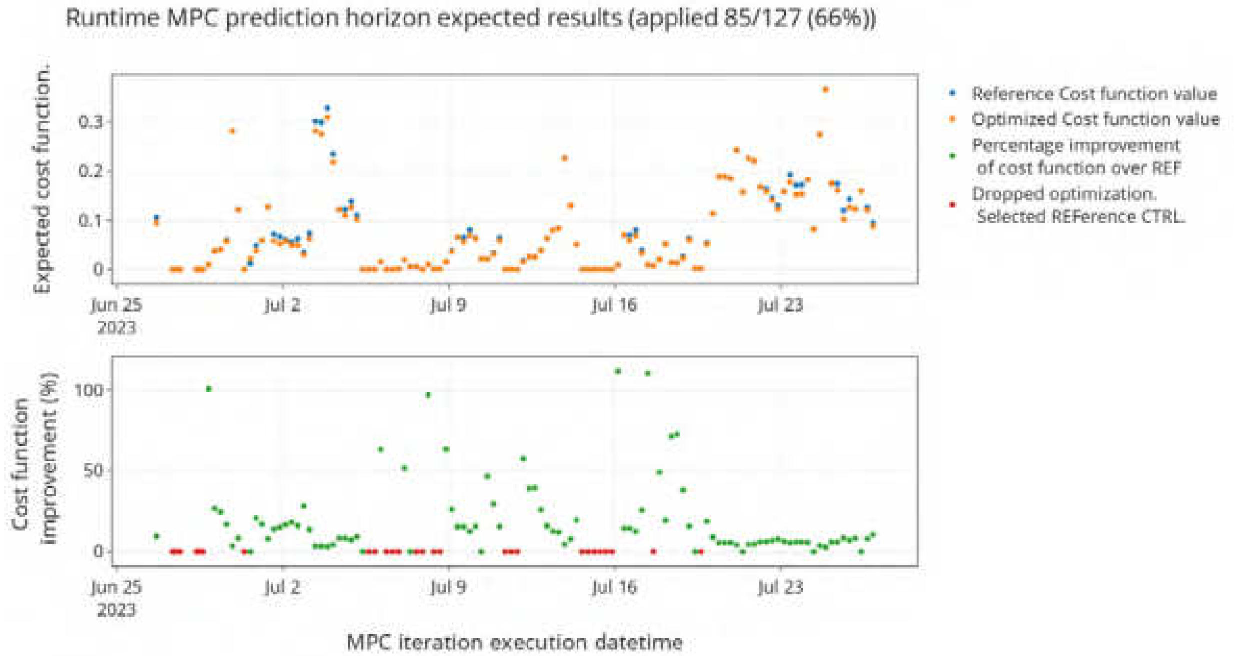


Figure 31 Data resulting from the runtime computation of each iteration of the MPC in the observed periods. A total of 127 iteration computations are reported, from which 25% were rejected (ref dots in chart below) bringing no improvement over the reference RBC operation. (Above) The expected reference cost-function value and the one expected from the application of the MPC in the next prediction horizon window. (Below) Percentage improvement of cost function, in green non-zero improvement.

Figure 31 reports the expected improvement of the cost function during the experiment for each MPC iteration computation and shows that still some of the MPC iteration produces and allows an expected improvement of the cost function. Nonetheless, according to the simulations, higher results should be expected in seasons with a lower irradiance and therefore without the capability of the combined system photovoltaic and storage to cover the total load demand of the forecoming days.

Figure 32 Dashboard example visualizing 2 reference days of MPC applied to the real system. The first chart reports the time-series of applied load (blue), PV production (green), operation of battery (red) and resulting metered net

load (orange). All values are reported with the producer sign contention (Production is greater than zero, consumption/absorption is less than zero). The other three charts report a timeline respectively of *battery SOC*, *Inverter operation Status* and *Mode*. MPC application may be extrapolated by the *Inverter operation Status*.

Figure 32 shows an example of the daily applied load profile (blue time series) and the MP produced controls[22] and the data derived from the actual application of such control. The information relative to the inhibit of charge and discharge operation in certain time hours is here reworked in combination with the information of the actual operation of the device and converted in a complete halt of the device (put in *standby* state) in such inhibited hours. The conversion of the MPC output into one single ON/OFF signal was possible as we know the predicted production and load and the system operates either charging or discharging according to the actual presence of photovoltaic production. Notice finally that the devices fall back in the standby state also in case of the complete charge of discharge of the electrical storage.

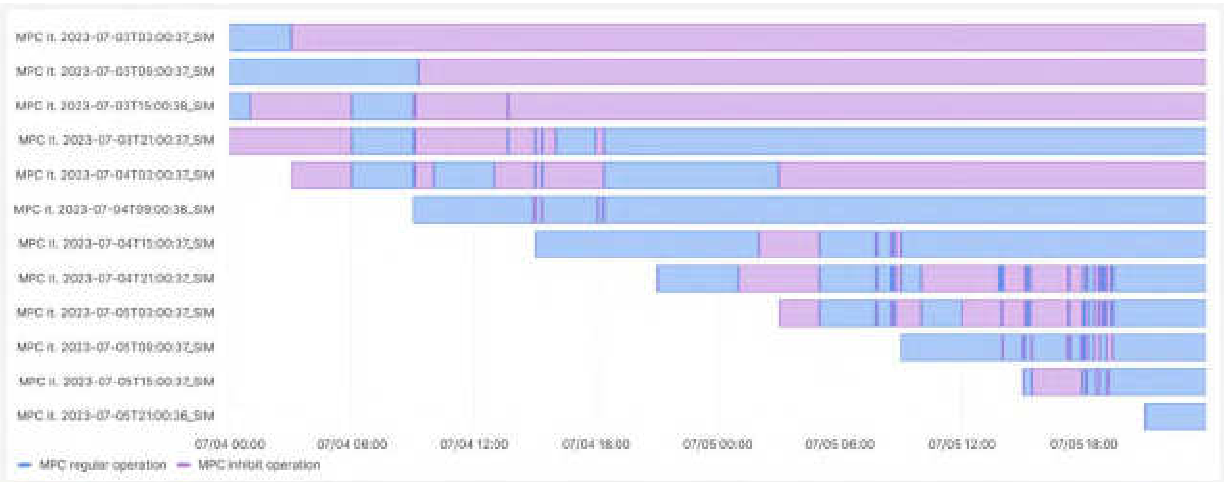


Figure 33 Example of the runtime MPC iteration outcomes for the selected days for visualization. Here it is possible to understand the difference between the prediction and the control horizon introduced in Figure 23. The MPC outcome is translated in order to be compatible with the inverter logic.

From the observed month of operation, it was possible to compute the real plant KPI[23] reported in the Table reported in Figure 34.

[22] It is possible to extrapolate the MPC operation control through the *Inverter operation mode* parameter or more directly in the representation produced in Figure 33.
[23] The KPI where computed on the acquired data with a resolution of 30 seconds over the observation period of one month. Energy is estimated by integrating the power time-series with 30 seconds resolution.

KPI	Experiment MPC (1 month 06-07 2023)
Self-Consumption (SC)	58.7%
Self-Production (SP)	83.1%
Energy to grid	39.7%
Energy from grid	17.0%
Total production PV	592 kWh
Total load	-381 kWh
Energy Balance	170 kWh
BESS charged energy	-167 kWh
BESS discharge energy	149 kWh
BESS losses	11 %
Energy from grid in high price periods	-6 kWh
Energy from grid in low price periods	-59 kWh
Price threshold (computed on whole year)	62.332 EUR / hour / megawatt
Time series samples in high price periods	15%

Figure 34 Table reporting KPIs computed for the experimental setup in the observation period.

The application of the logic required the components and communication infrastructure set up in the context of the laboratory facilities and described in section 6.3. On the hardware side, a PV production and storage system which can be interfaced for reading and writing. These operations are carried out by a third device, in this case, a computer (a consumer product with medium-low specifications), also responsible for carrying out the simulations. In the laboratory implementation, we then rely on the existing ICT infrastructure for data storage and consequent visualization and consumption during simulations. The simulations require at least parameters such as building load, PV production and battery state of charge. The implementation of an adequate forecasting system has not been investigated in detail in this work. Nonetheless, on the basis of this, a certain history of these states of the system is required and, potentially, further external parameters may be required to improve the forecast of the main states. This moreover holds in the case of the adoption of more sophisticated prediction techniques in place of the mere persistence approach employed for the demonstrative purposes in this work. The final key component is a software simulation framework able to reproduce the controlled system behaviour and guess a logic to potentially better operate the system in the near future. In this case, the software is tailored to the technical specifications of the operated test system.The produced experiment shows that it is possible to apply flexibility practices on real systems, as it was done on the experimental setup within the laboratory facilities. Significative improvements are still possible overall in a more precise validation of the modelling framework on the specific installation and on the device behaviors. Such a setup opens the possibility to test and evaluate further advanced control approaches.

The produced experiment suggested that there might be further improvement in the control performance with the improvement of the modelling framework and with the introduction of a more precise prediction stack (both for PV, here only accomplished with the simplest persistence-based approach, and overall for the load, not addressed in current work having available a perfect prediction). Regarding the modelling framework, the computation of the MPC may be executed with a simplified model but a more detailed validation of the modelling framework is required to produce the most precise reproduction of the system behavior to generate comparable simulations and produce a proper comparison between the actual monitored performance and the expected under standard (RBC) operation of the plant. The testing phase of the experimental facilities allows the collection of several data relative to the operation of the battery system and the actual inverter under the forced non-standard condition that may help to further improve the modelling framework and to improve the performance of both of the sketched control strategies. The work suggests that further effort should be put into the actual increase of knowledge on the behavior of these two components (battery and power electronics for power conversion).

MPC practices and optimization of a problem of small dimension[24] may finally be ported to the real application on a test facility as the one setup for the purpose of the current task. MPC - even if limited to only battery management - may boost small margins of improvements by increasing the system performance against certain properly designed objectives. System sizing and geographical conditions (mainly due to weather factors in this case) are important factors in the actual success of such strategies and the adoption of such technologies. Finally, as shown in the simulation domains in the work committed in the report [15], the consideration of more domains (mostly including the thermal domain) may further expand the flexibility potential that characterizes the exploitation of renewable resources and technologies in positive energy buildings.

[24] For dimension we intend the number of controlled parameters and the possible explorable space of solutions, in the explored case the 4 hours that defines the ranges in which to operate the inhibition of the device functionality.

7 Conclusions

Buildings account for 40% of final energy use and 36% of greenhouse gas emissions in Europe. To achieve decarbonization goals, renewable energy sources must be adopted widely. Wind and solar power, despite being intermittent, must play a significant role. Energy flexibility on the demand side is crucial to manage demand and reduce penalties associated with price, CO_2 emissions, and grid congestion. Buildings must be able to manage demand and generation based on local climate, user needs, and grid requirements. The report discusses the focus on building energy flexibility, particularly within the framework of Plus Energy Buildings. Plus Energy Buildings (PEBs) generate more renewable energy than they consume annually. PEB qualification alone may not optimize environmental and performance factors. Energy Flexibility Practice is explored to enhance economic, environmental, and technical aspects of PEBs.

Two of the four EU geo-clusters identified within the H2020 Cultural-E project are specifically analyzed to demonstrate this concept: the Sub-Artic and the Mediterranean. For both of them, different flexibility factors are considered based on the predominance of the energy system composition. The flexibility potential and the corresponding control strategy to be applied are described by showing the benefits through simulation results. For the Mediterranean geo-cluster, an implementation in a laboratory experiment demonstrates the validity of the proposed approach. While for the Sub-Artic geo-cluster the flexibility potential will be demonstrated in the Norwegian demo-case. The summary and main conclusions for the Sub-Artic and Mediterranean geo-clusters are reported in the following.

The Sub-Artic geo cluster and, in particular, the Norway energy system is characterized by electricity mainly produced from hydropower, electric resistance heating and the highest penetration of EVs in the world pro-capita. The energy production is flexible for 75% of the production capacity. Hydropower mainly provides this flexibility at the transmission level by performing different global ancillary services (from frequency regulation to seasonal flexibility).

From the local flexibility point of view, the necessity to adapt the producer's condition to the system requirements is given by the high penetration of EVs. To this aim, the building can provide a significant contribution in terms of flexibility, mainly through the user behaviour related to energy-consuming systems, such as domestic hot water (DHW), comfort preferences and EV-charging habits. In this regard, the report analysed the potential of the demo case multi-family house[25] considered in the Cultural-E project by focusing on this level of flexibility.

[25] https://www.cultural-e.eu/norwegian-demo/.

Different possible objectives can be considered, and each objective's influence on the energy system and building levels is discussed. In the simulation performed considering the characteristics of the demo case, different flexibility potentials are evaluated separately and then all together. Considering as the objectives both the minimization of the energy imported and the minimization of the cost, three flexibility factors are considered: the indoor temperature, the DHW tanks control, and the battery system. The results show that the indoor temperature control exhibits a higher flexibility potential by reducing maximum import to 27%. On the contrary, both the DHW control and the use of battery (even of high capacity) tend only to increase self-consumption and self-production slightly, reducing the energy imported from 3 to 4%. By combining all these flexibility potentials and considering the related logic that properly managed their effect, the benefits of exploit the flexibility factors are a reduction of 8% in electricity import and 6% in energy cost.

The Mediterranean geo-cluster, where the Italian demo case[26] is considered, is mainly focused on the flexibility potential provided by electrical components such as the combination of PV and battery and the EV charger. After a general presentation of the possible benefits of these devices' flexibility, the focus is mainly on the PV+ battery system, and the presentation of a model predictive control which tends to minimize the cost of the energy exchanged with the grid. A comparison considering different prediction horizon and battery rule-based control show that the maximum benefits in terms of energy reduction reduction, considering the energy consumption profile of the low-rise building simulated in [15], can be achieved from 10% to 13% based on the control used.

The simulated concept has also been tested at the Eurac outdoor facility, where within the Cultural-e project, a system composed of PV+battery and electronic load and the corresponding monitoring and control system has been implemented. The results achieved in the experimental campaign, even with a duration of one month, confirm the flexibility potential achievable and the effectiveness of the proposed flexibility strategies.

Additional tests and studies should be undertaken in order to highlight not only the potential of the building to provide flexibility to local ancillary services to the grid but also to emphasize how this potential can be improved by the plus energy building and the active role that they will play in the future of the decarbonized energy system.

[26] https://www.cultural-e.eu/italian-demo/.

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