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Direct and indirect energy flexibility interactions at the building and community scale: From system to the human-interfaced system

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THÈSE

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Interactions directes et indirectes de la flexibilité énergétique à l'échelle du bâtiment et de la communauté : Du système aux systèmes à interface humaine

Direct and indirect energy flexibility interactions at the building and community scale: From system to the human-interfaced system

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The beautiful thing about learning is nobody can take it away from you. Education is the passport to the future, for tomorrow belongs to those who prepare for it today.

– Malcolm X

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Abstract

In the context of the energy transition and the need for decarbonization through the use of renewable energies (i.e., the energy transition), the building industry assumes a pivotal role due to its potential to generate local renewable energy and its substantial energy consumption. Buildings (and by extension the energy grid) have two key components which are central to this thesis, the energy subsystem (i.e., the technical component and in essence the direct flexibility) and the human occupants (i.e., the social, indirect flexibility, component, which is key to determining the energy performance of any building). In most cases, the emphasis is placed on controllable direct flexibility. However, there is a need for the two components to work together to produce flexibility services both for the grid and the building (in the context of self-consumption).

This thesis explores the potential synergy that exists between the human occupant and a building's energy subsystem in the context of energy flexibility using the Predis-MHI platform (a living lab within the GreEN-ER building) and its users as an experimental setup. This setup was constituted by a 22kWp solar PV station, the demand of the building, EV charging stations, and a 50kWh battery. For this research, we identified EV charging (in particular the plugging in and unplugging) as an indirect flexibility resource.

Our investigation follows a three-part methodology to address the challenges associated with human-interfaced buildings, first, we propose a Mixed Integer Linear Programming optimization approach to assess the available potential of indirect flexibility and subsequently to dimension direct flexibility. The second aspect entailed the control of direct flexibilities, for this, we proposed and implemented a Machine Learning based Model Predictive Controller. Lastly, to gain insight into the interplay between the direct and indirect flexibilities, we propose a co-simulation approach based on a Mixed Integer Linear Programming optimization and a Multi-Agent System simulation of the stochastic behavior of EV users concerning charging their vehicles. This co-simulation is envisioned to allow for the testing of different scenarios (and rules, especially in the context of a local energy community).

Our findings show that indirect flexibilities are not only essential to the energy transition, but they are quantifiable, with a discernible impact on the overall performance of the building system. In the case of our test bed, the estimated potential of the indirect flexibility in terms of self-consumption is approximately 8% (1,700.00 kWh) annually. The Machine Learning-based Model Predictive Controller combined with the reactive controller of the 50kWh battery also showed promise despite a decreased performance particularly attributed to the low quality of EV demand forecasts. Lastly, the co-simulation indicates that if mobilized, indirect flexibility can be utilized as a primary energy flexibility resource contrary to current practice where direct flexibility is the preferred resource for providing energy flexibility.

Résumé

Dans le contexte de la transition énergétique et du besoin de décarbonisation par l'utilisation d'énergies renouvelables ("la transition énergétique"), l'industrie du bâtiment joue un rôle central en raison de son potentiel de production d'énergie renouvelable locale et de sa consommation d'énergie significative. Les bâtiments (et par extension le réseau énergétique) ont deux composantes clés qui sont au cœur de cette thèse, le sous-système énergétique ("la composante technique" et par essence la flexibilité directe) et les occupants humains ("la composante sociale", la flexibilité indirecte, qui est essentielle pour déterminer la performance énergétique de n'importe quel bâtiment). Dans la plupart des cas, l'accent est mis sur la flexibilité directe contrôlable. Cependant, il est nécessaire que les deux composantes travaillent ensemble pour produire des services de flexibilité à la fois pour le réseau et pour le bâtiment (dans le contexte de l'autoconsommation).

Cette thèse explore la synergie potentielle qui existe entre l'occupant humain et le sous-système énergétique d'un bâtiment dans le contexte de la flexibilité énergétique en utilisant la plateforme Predis-MHI (un laboratoire vivant au sein du bâtiment GreEN-ER) et ses utilisateurs comme dispositif expérimental. Cette configuration était constituée d'une station solaire photovoltaïque de 22 kWc, de la demande du bâtiment, de stations de recharge pour VE et d'une batterie de 50 kWh. Pour cette recherche, nous avons identifié la recharge des VE (en particulier le branchement et le débranchement) comme une ressource de flexibilité indirecte.

Notre étude suit une méthodologie en trois parties pour relever les défis associés aux bâtiments à interface humaine. Nous proposons tout d'abord une approche d'optimisation par programmation linéaire en nombres entiers pour évaluer le potentiel disponible de flexibilité indirecte et, par la suite, pour dimensionner la flexibilité directe. Le deuxième aspect concerne le contrôle des flexibilités directes, pour lequel nous avons proposé et mis en œuvre un contrôleur prédictif de modèle basé sur l'apprentissage automatique. Enfin, pour mieux comprendre l'interaction entre les flexibilités directes et indirectes, nous proposons une approche de co-simulation basée sur une optimisation de programmation linéaire en nombres entiers et une simulation de système multi-agents du comportement stochastique des utilisateurs de VE en ce qui concerne la recharge de leurs véhicules. Cette co-simulation est conçue pour permettre de tester différents scénarios (et règles, en particulier dans le contexte d'une communauté énergétique locale).

Nos résultats montrent que les flexibilités indirectes sont non seulement essentielles à la transition énergétique, mais qu'elles sont aussi quantifiables, avec un impact perceptible sur la performance globale du système de construction. Dans le cas de notre banc d'essai, le potentiel estimé de la flexibilité indirecte en termes d'autoconsommation est d'environ 8% (1 700 kWh) par an. Le contrôleur prédictif de modèle basé sur l'apprentissage automatique combiné au contrôleur réactif de la batterie de 50 kWh s'est également avéré prometteur malgré une baisse de performance attribuée en particulier à la faible qualité des prévisions de la demande des VE. Enfin, la co-simulation indique que si elle est mobilisée, la flexibilité indirecte peut être utilisée comme une ressource de flexibilité énergétique primaire, contrairement à la pratique actuelle où la flexibilité directe est la ressource préférée pour fournir une flexibilité énergétique.

Nomenclature

BESS	Battery Energy Storage System.
BMS	Battery Management System.
CAES	Compressed Air Energy Storage.
CCUS	Carbon Capture Utilization and Storage.
CO ₂	Carbon Dioxide.
DSEF	Demand Side Energy Flexibility.
EDF	Electricité de France.
ENSE3	École Nationale Supérieure de l'Énergie, l'Eau et l'Environnement.
ESS	Energy Storage System.
EV	Electric Vehicle.
G2ELab	Grenoble Electrical Engineering Laboratory.
GAM	Generalized Additive Model.
GHG	Greenhouse Gas.
GreEn-ER	Grenoble Énergie - Enseignement et Recherche).
GWP	Global Warming Potential.
HICS	Human-in-the-Control System.
HVAC	Heating Ventilation and Cooling.
IEA	International Energy Agency.
IPCC	Intergovernmental Panel on Climate Change.
KPI	Key Performance Indicators.
LGBM	Light Gradient Boosting Machine.
LOH	Level Of Hydrogen.
MAE	Mean Absolute Error.
MAS	Multi-Agent System.
MHI	Monitoring and Habitat Intelligence.
MILP	Mixed Integer Linear Programming.
ML	Machine Learning.
ML-MPC	Machine Learning based Model Predictive Controller.
MPC	Model Predictive Control.
MSE	Mean Squared Error.
NaNiCl	Sodium Nickel Chloride.

NaS	Sodium Sulfur.
NASA	National Aeronautics and Space Administration.
NEEG	Net Energy Exchange with the Grid.
NiCd	Nickel-Cadmium.
NZEB	Net Zero Energy Building.
obFMU	Occupant Behaviour Functional Mock-up Unit.
OmegAlpes	Generation of Optimization Models As Linear Programming for Energy Systems.
PCM	phase change material.
PHS	Pumped Hydro Storage.
PID	Proportional Integral Derivative.
PV	Photovoltaic.
RED	Renewable Energy Directive.
RER	Renewable Energy Resources.
R ²	Coefficient of Determination.
RTE	Réseau de Transport d'Électricité.
SCES	super Capacitor Energy Storage.
SEM	Small and Medium-sized Enterpris.
SMES	superconducting magnetic energy storage.
SOC	State of Charge.
SOH	State of Health.
SVM	Support Vector Machine.
TCM	Thermo-Chemical Material.
TES	Thermal Energy Storage.
TRL	Technology Readiness Level.
UML	Unified Modeling Language.
V2G	Vehicle to Grid.
V2H	Vehicle to Home.
V2V	Vehicle to Vehicle.
XGBoost	eXtreme Gradient Boosting Machine.

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Thesis Structure

 **The thesis is structured as follows:**

- ▶ **Chapter 1:** This chapter is a foundation chapter and as such provides essential definitions, and introduces and explains key concepts that are essential for understanding and addressing the main theme of this thesis.
- ▶ **Chapter 2:** In this chapter, we discuss the scientific lock of this thesis and pose our research questions. Additionally, we introduce our experimental setup (a living lab).
- ▶ **Chapter 3:** This chapter addresses the scientific lock related to indirect flexibilities. We introduce a framework for quantifying indirect flexibilities and further demonstrate a battery dimensioning methodology that takes into account the identified indirect flexibility in our experimental setup.
- ▶ **Chapter 4:** This chapter focuses on direct flexibilities and is made up of two parts, the first addresses the question of the complexity of control systems for direct flexibilities. The second part details the implementation of a Model Predictive Controller for a 50 kWh battery in our experimental setup. This chapter provides a first insight into the interaction between direct and indirect flexibilities in (smart) buildings.
- ▶ **Chapter 5:** This chapter builds on the work proposed in chapters 2 and 3. We propose a Multi-Agent System based simulation for evaluating the implications of the interactions between direct (the 50kWh battery) and the indirect (a local energy community) flexibility on the global energy performance of the building under study.
- ▶ **Chapter 6:** This is the concluding chapter of the thesis. In this chapter, we provide a global conclusion of the work presented in this thesis, our perspectives, the limitations of our work, and the future works that we envision as a continuation of this work.

Towards a Sustainable Future: Socio-Technical Solutions for the Grid

1

The purpose of this chapter is to present an introduction to the subject matter, the chapter starts by giving a brief overview of why energy flexibility is important and the role it plays in the transitioning of our current electrical networks to the smart Grid (i.e., the grid 2.0). Thus, this chapter puts together fundamental concepts and essential definitions that are central to the global theme of the thesis.

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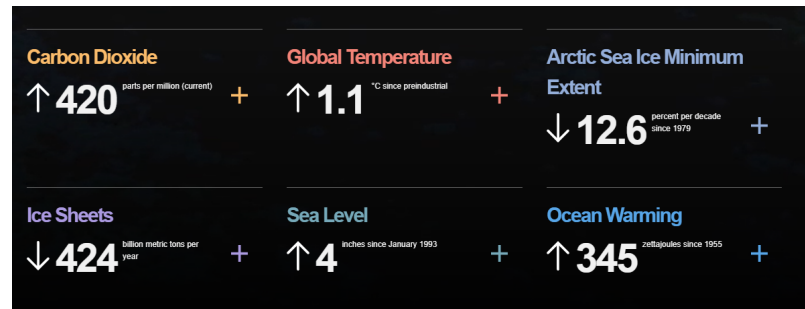
1.1 The Energy Transition

Today, climate change is one of the most significant challenges faced by humankind [1]. Studies indicate that these anticipated changes are primarily due to an increased (and still increasing) concentration of Greenhouse Gases (GHG), such as carbon dioxide (CO₂), methane (CH₄), etc. These GHGs trap heat energy in the atmosphere, resulting in rising global temperatures. Thus, by adding more GHGs to the atmosphere, humans are in effect enhancing the greenhouse effect. Current estimates point to an average increase in temperature of 2.7°C by the end of the century. More alarmingly, The Intergovernmental Panel on Climate Change (IPCC) [2] confirms that barring any positive change in GHG emissions, the global average temperature would be 1.5°C hotter than pre-industrial times by 2040. NASA [3] estimates that current CO₂ concentrations are approximately 420 ppm and the global average temperature is approximately 1.1°C above pre-industrial levels, see Figure 1.1. Thus, we have already exceeded the initial 350 ppm target proposed by James Hansen [4].

If not mitigated, global warming and consequently climate change is expected to result in rising global temperatures, increased frequency and intensity of extreme weather events, and changing weather patterns, which pose significant risks to human health, biodiversity, and ecosystems at large [5]. Many studies have identified human activities, mainly the extraction and use of energy for industrial, domestic, and transportation purposes (which usually involves the burning of fossil fuels) as a major source of greenhouse gasses, and consequently a major contributor to the global warming phenomenon [1, 6].

In this thesis, we endeavor to harness the potential energy flexibility inherently available in buildings and local energy communities. Our primary objective is to maximize the use of local Renewable

Figure 1.1: Vital signs of the planet (source [3])



Energy Resources by capitalizing on both technical and social interventions (i.e., the direct and indirect flexibilities respectively) to establish a socio-technical approach to harnessing energy flexibility at the building and local community level.

This chapter provides insights into how direct and indirect energy flexibilities play a pivotal role in our decarbonization efforts. We discuss in particular energy storage systems which are direct flexibilities and the role of human actors (individually and collectively as local energy communities) in transitioning towards a sustainable low carbon energy future. Furthermore, this chapter lays the foundation for the ensuing discourse by introducing and discussing pivotal concepts, defining key terminologies, and highlighting the rationale behind the need for these socio-technical solutions. Through this research work, we hope to contribute to the advancement of research in a sustainable energy transition which should ultimately lead to a more resilient and adaptive energy landscape¹.

1: A low-carbon energy landscape that capitalizes on both technological (such as Renewable Energy Resources) and social interventions (such energy sobriety) to ensure reliable, sustainable and efficient delivery of energy (using different vectors) to the end user).

1.1.1 The Energy Transition and the Future Grid

Given the identified cause of climate change (increased concentration of GHGs due to human activities), it is undeniable that avoiding the impending dangers of climate change would require a shift towards more sustainable and ecological practices, particularly in the energy sector (since it is the single largest contributor of GHGs). The energy transition has been conceived and developed to address this impending crisis as a key solution to reduce GHG emissions from the energy sector [7].

The energy transition is a vital tool in the quest to alter the current trajectory of a global climate crisis (i.e. climate change) by replacing existing fossil fuel-based energy systems with more sustainable, environmentally friendly, and low-emissions alternatives (these are usually Renewable Energy Resources (RERs)) whilst also consciously reducing our energy demand (through energy efficiency and conservation means) [8]. According to Olave et al [9], the energy transition is not only restricted to a technology change

from fossil fuels to RERs, but also encompasses social, economic, and environmental aspects of the development of clean energies. This transition also offers a range of other environmental benefits, which ultimately translate to a safer and cleaner environment and by extension a healthier eco-system.

There is no doubt that the energy transition is critical to climate change mitigation and should be treated with utmost urgency. Despite the emphasis on technology transformation and energy efficiency [10], these two are not the only core pillars of the energy transformation, discussed below are solutions that are critical for achieving the energy transition:

- ▶ **Increasing Renewable Energy adoption:** The transition to a low-carbon or carbon-neutral energy system requires a significant increase in the adoption of RERs, such as solar, wind, hydro, geothermal, and biomass. This is possibly the foundation on which the other pillars of the energy transition are built. RERs by nature are intermittent and less predictable, these qualities present a myriad of problems such as low inertia, degraded power quality, and high-level uncertainties for the grid operator [11]. The smart (and more resilient) grid, which is the grid of the future (i.e., grid 2.0) has been conceived as a possible solution for mitigating the above-mentioned issues.
- ▶ **Improving Energy Efficiency:** The term energy efficiency emphasizes using less energy to do at least the same work or to produce the same results [12]. For this reason, energy efficiency is often referred to as the fifth fuel, following traditional fuels coal, natural gas, nuclear, and RERs [13]. Energy efficiency is not only linked to environmental benefits, but also has positive implications with regard to commercial, and industrial competitiveness and energy security [14]. The goal of energy efficiency measures is to reduce the energy demand (without affecting the quality of services) and consequently reduce GHG emissions. Several measures exist for achieving energy efficiency, these include but are not limited to; upgrading building insulation and, using more efficient electrical appliances.
- ▶ **Decarbonization:** Engie [15] defines decarbonization as “all measures through which a business sector, or an entity – a government, an organization – reduces its carbon footprint, primarily its greenhouse gas emissions, carbon dioxide (CO₂) and methane (CH₄), in order to reduce its impact on the climate”. Again, this process involves a shift towards low and zero-carbon alternatives, however, Carbon Capture Utilization and Storage (CCUS) is critical here. The IEA estimates

that for 95% of carbon capture and 5% of carbon utilization in 2050 (used for synthetic fuels, as is the case with [16]), the currently identified global geological carbon storage capacity largely exceeds the estimated storage requirement. CCUSs are crucial as they imply removing GHGs from the atmosphere and consequently will aid in climate change mitigation.

- ▶ **Electrification:** Here, the concept is to use low or zero-emissions electrical energy in place of fossil fuel-based options. A typical and highly visible example would be the ongoing electrification of the transportation sector, or the electrification of heating (using efficient heat pumps) in buildings [17]. Electrification allows sectors that are highly dependent on energy to provide services to transition towards low-carbon energy alternatives (in this case, electricity). Here the gains are usually twofold; efficiency gains, as the electric alternatives are usually offered with relatively higher efficiencies [18] and reduced environmental impact, especially if the electricity is sourced from RERs.
- ▶ **Smart Grids:** Often described as the grid of the future, smart grids are one of the key pillars of the energy transition. The smart grid has emerged as a solution to new energy carriers and the decentralization of generation. Smart grids have been conceived to utilize advanced communications, control, optimization, and automation technologies to provide intelligent and often real-time responses to changes in grid parameters [19]. Smart grids offer improved efficiency, resilience, and overall effectiveness of energy systems.
- ▶ **Energy Flexibility:** Energy flexibility, according to Lund et al [20], can be defined as the ability of an energy network to adapt its generation or demand in response to external signals. Flexibility can be provided from the demand side, supply side, or by using energy storage systems. Energy flexibility is essential because it offers a solution to one of the fundamental problems of any electrical grid; maintaining equilibrium between demand and supply. Energy flexibility provides services such as load shifting, valley filling, and peak shaving, two concepts that could improve RER utilization and ultimately reduce the need for peaking plants (which are usually fossil fuel based and expensive). Demand-Side Energy Flexibility (DSEF) is particularly important as it bolsters an often-ignored pillar of the energy transition, behavioral change.
- ▶ **Behavioral Change:** Behavioral change is perhaps the single most important pillar after RER adoption but is often over-

looked. Human behavior is the driving factor for the demand for all energy-related goods and services. That is to say, individual choices and the norms of society will play a key role in reducing energy demand and achieving energy conservation [13] and energy sobriety [21]. The IEA [17] estimates that 55% of emissions reduction measures and initiatives require at least a mixture of low-carbon technology and active engagements from the citizenry. The IEA has identified 3 main types of behavioral change that would yield the highest results:

1. **Reducing energy waste:** here the emphasis is on using energy wisely, especially in buildings; bordering on energy conservation, energy sobriety, and energy efficiency.
2. **Switching transportation mode:** Using non-fossil fuel-based solutions for short trips (bicycles, walking, etc.) and using public transport and ride sharing for longer trips as opposed to using cars (which become even more inefficient if their passenger capacity is under-utilized).
3. **Materials efficiency gains:** here, the message is simply to consume less and can be expanded to mean improving the design to improve product longevity, using materials that reduce energy requirement (building insulation for example), reuse and recycle, etc.

1.1.2 2050: Carbon Neutral Scenarios

The energy transition by its very definition implies a vision of the future in which 100% of our energy requirements would be sourced from RERs (such as solar, geothermal, and wind). To achieve this goal sustainably we must simultaneously reduce our energy demand through energy efficiency and conservation² (including energy sobriety) efforts. Multiple studies [22, 23], have been conducted to evaluate 100% renewable energy scenarios and ultimately conclude that a change in technology and grid infrastructure is required to ultimately achieve this goal. For example in France Dubilly et al [22] estimate that there would exist a rooftop potential of 1,268 TWh³ per annum for solar PV with a corresponding demand of 750 TWh [24] by 2050 (Figure 1.2).

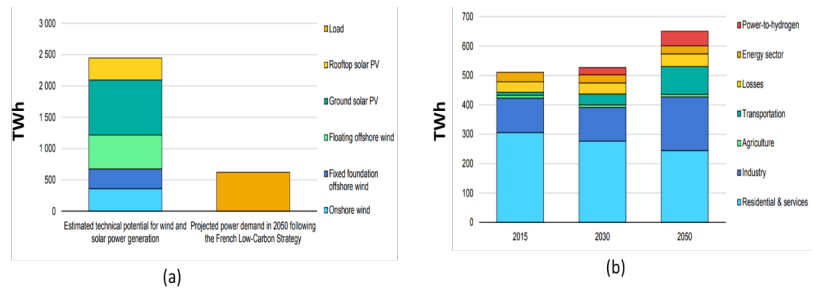
Using rooftops means we optimize the use of land resources (and do not exploit otherwise unused land resources). However, there is still a high energy requirement for manufacturing and replacing these solar panels. Arguably, as the energy mix becomes less carbon intensive, and the technology improves, the associated energy and environmental costs are expected to reduce in the future. Additionally, owing to the nature of solar PV technology, it

2: Conservation effort here refers to the conscious decisions individuals or groups of individuals make to use less energy.

3: This would represent a 69.07% excess in energy production relative to the energy demand)

is intermittent, very susceptible to extrinsic factors, and available for a limited period of the day, a 100% solar scenario would typically require storage infrastructure to be deployed in the network.

Figure 1.2: 2050 Energy Projections for France (a) Technical potential for wind and solar power generation in France compared with estimated load level by 2050, (b) Evolution of annual electricity demand in the National Low-Carbon Strategy (including French overseas departments) (source [24])



Storage is a fundamental requirement of the future grid, Katie Fehrenbacher [25] emphasizes this point in her statement: “A next-generation smart grid without energy storage is like a computer without a hard drive: severely limited”. Thus, pointing to the fundamental need for energy flexibility services (in the form of energy storage systems or any other). In the case of a 100% solar PV scenario as proposed by Dubilly et al [22], both short-term (intraday, interday, etc.) and long-term (seasonal) storage. The short-term storage would be required to deal with intermittency and nighttime unavailability whilst the long-term storage would serve the seasonal supply-demand paradigm that exists in most of Europe (higher solar production in summer coupled with lower demand and conversely lower generation and increased demand in winter).

Additionally, A recent study by Hodencq et al [26] which considered the sizing of a solar PV system (solar PV panels and batteries) for an energy community with 20 houses in France and Germany found that 100% self-sufficiency does not translate into a reduction in carbon emissions reduction. The study considered a positive behavioral response (i.e., reduction in demand in response to having solar PV as an energy source) from the participant in the community and a battery usage period of 8 years. Results from the study, illustrated in Figure 1.3, indicate that for France (as is the case with most countries), the reduction in carbon emissions becomes negative beyond self-sufficiency of between 24% and 35% (depending on the Global Warming Potential (GWP) of the solar PV components). The results for Germany were the same, however, the inflection point was between 74% and 80%, which was relatively higher and was attributed to the higher carbon intensity of the German grid relative to the French one. It is key to note that this study did not account for future changes in the GWP of solar PV panels and batteries (a downward trend is anticipated owing to the increasing RER penetration in grids where these components are manufactured). Thus, there is a need to reevaluate the efficacy of such scenarios in the face of changing energy mixes.

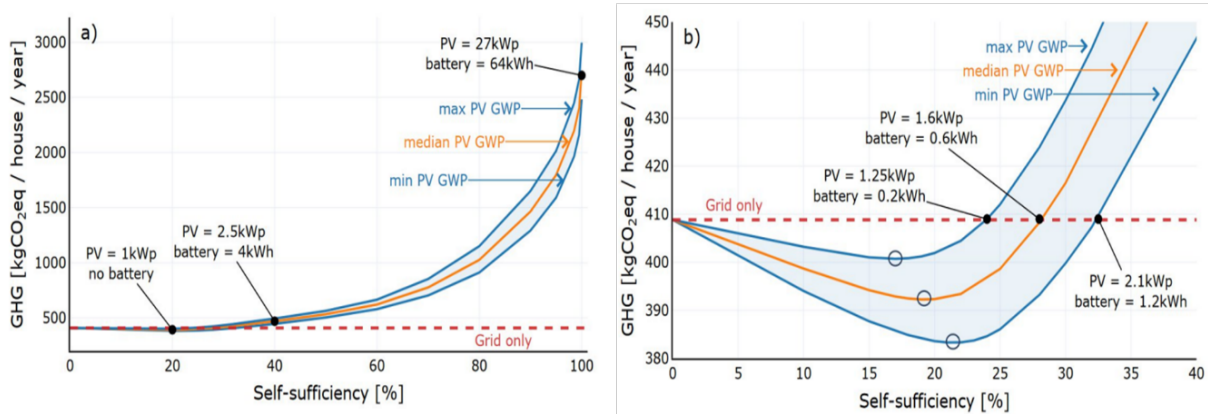


Figure 1.3: (a) Yearly greenhouse gas (GHG) emissions of the energy consumption of a household in France as a function of self-sufficiency rates for minimal, median, and maximal PV panels Global Warming Potential (GWP), with associated batteries and PV sizing, (b) zoomed in between 0 and 40% of self-sufficiency (source: [26])

1.1.3 Self-Consumption and its Role in the Energy Transition

An examination of the concept of self-consumption is highly relevant to the scope of this thesis, as self-consumption is pivotal to the central theme, which revolves around improving building (and by extension local energy communities’) self-consumption by mobilizing both direct and indirect flexibilities.

Self-consumption is a concept that has become increasingly necessary given the increased adoption of RERs, especially distributed energy resources and the advent of the prosumer (producer and consumer of electrical energy). The concept emphasizes the local consumption of energy produced from on-site resources. Luthander et al [27] define self-consumption (in the context of solar PV) in simple terms as locally produced electricity that is consumed directly by the producer (as illustrated in Figure 1.4, which often is the owner of the PV system).

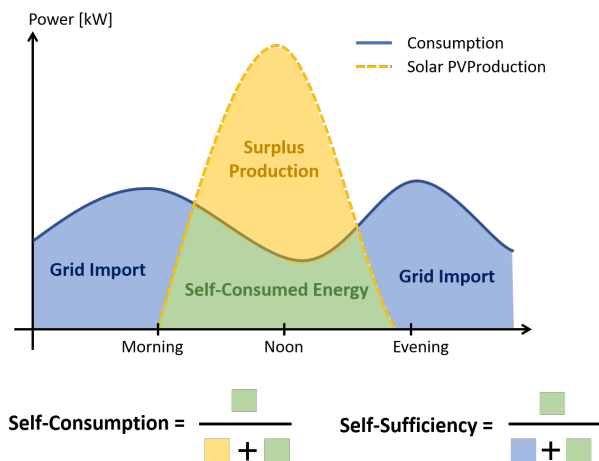


Figure 1.4: Self-consumption definition with storage (source: [28])

The concept contrasts with the traditional vertically integrated

approach where production is distant and separated from consumption. As RERs become more prevalent in the energy mix, especially where they are integrated into buildings or at the community scale, self-consumption becomes more necessitated.

Consuming at source (i.e., self-consumption) would mean that the intermittency is not seen on the grid and that buildings and communities become more energy independent. The concept was initially conceived on an individual scale (usually a single building) but has evolved beyond the individual's boundary to the boundary of a local community as depicted in Figure 1.5. The main drawback for the individual scale was that it required storage infrastructure (which at the building scale is usually chemical storage in the form of batteries) which can be financially and environmentally expensive. Collective self-consumption was thus conceived to reduce or potentially eliminate the need for storage by taking into account the different demand profiles within a community.

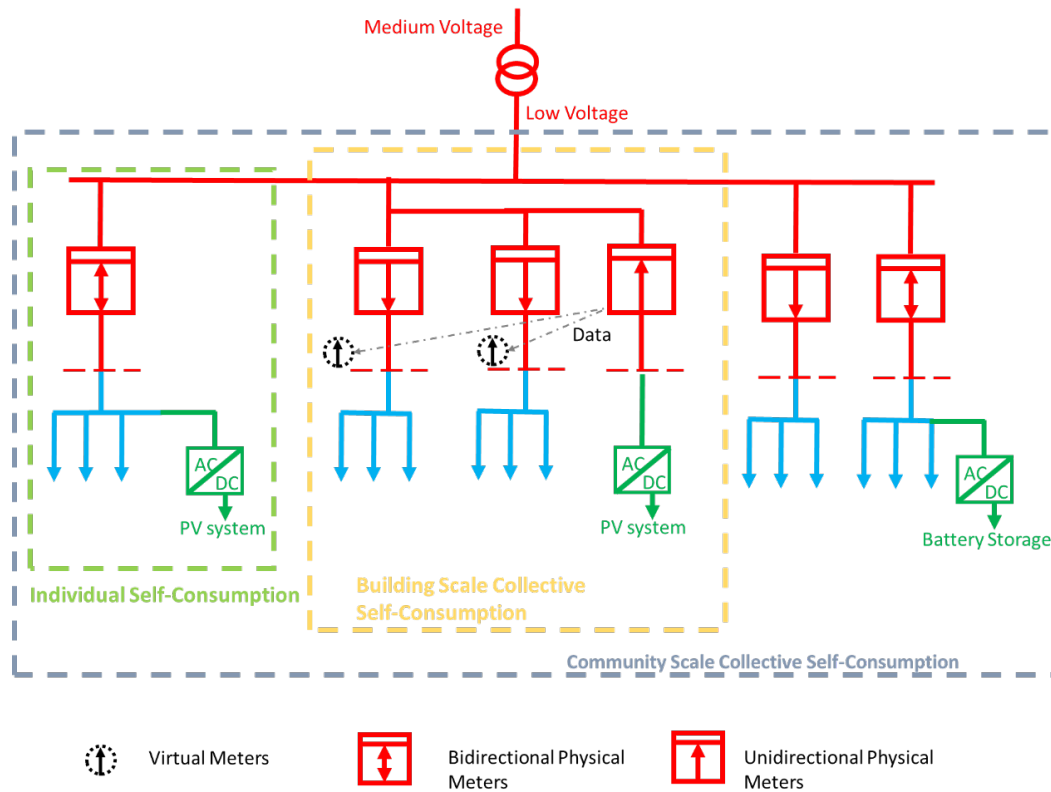


Figure 1.5: Self-consumption at various scales (from individual to community scale collective), (source: [29])

Thus, the individual self-consumption definition given by Luthander et al [27] has been expanded to take into account a community of different types of actors. According to Electricité de France (EDF) [30] (and by extension the French government), “*Collective self-consumption is a system governed by laws and regulations. It allows locally produced electricity to be shared between producers and consumers connected to the public distribution network, within the same geographi-*

cal area". These local consumers or producers can be residential, commercial, or local authorities.

1.2 Demand-Side Energy Flexibility

Energy flexibility is not a new concept and has indeed been in use for a few decades, as identified by Ehrhardt-Martinez et al [31]. Energy Flexibility represents a foundational component of a building's energy sub-system which we mobilize in this thesis to improve self-consumption (both at the building and community scale). Demand-Side Energy Flexibility (DSEF) can be described as measures and actions that facilitate a change in the demand in response to external signals from the grid (mainly imbalance as a result of high RER penetration) [32]. Because buildings constitute a large proportion of energy consumption (approximately 43% [33] in Europe, and 44% [34] in France), DSEF in the context of this document will focus on buildings and communities. As already mentioned in chapter 1.1.1, energy flexibility is an essential pillar for achieving our energy transition goals. DSEF often implies a change in energy users' behavior and is often associated with changing consumption patterns in response to changing supply, changing price [35, 36], or social signals (i.e., nudges) [37]. DSEF is usually implemented to achieve either an upward modulation of the load (i.e., valley filling) or a downward modulation of the load (i.e., load curtailment, peak shaving) [38], see Figure 1.6.

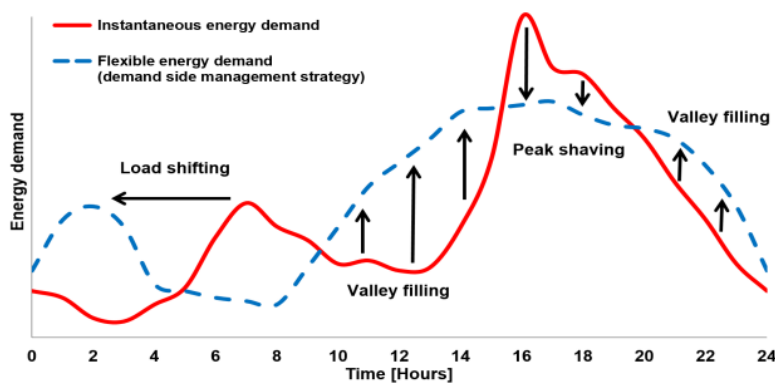


Figure 1.6: Benefits of Demand-Side Energy Flexibility (source: [39])

Based on how these flexibilities are activated and used for providing flexibility services to the energy network, DSEFs can be classified into three main groups, encompassing both the social and technical dimensions of the socio-technical system upon which this thesis is based. In the subsequent subsections, these classifications will be comprehensively discussed, bringing to light the distinct characteristics of each classification as well as their significance to a building's energy system (and by extension the grid).

1.2.1 Direct Flexibilities

Direct flexibility refers to the ability of an energy system to rapidly and directly respond to changes in energy demand or supply. We [40] defined direct flexibilities as “devices within the global energy system that can be fully automated/controlled using software or a control signal and can significantly affect the overall performance of the global energy system”. For this type of flexibility, the user is typically not involved in the process and consequently, there is no cognitive strain on the user (as they have no decisions to make concerning the external signals).

Since this type of flexibility involves the use of smart or connected devices to take measurements and actuate in response to signals their performance is guaranteed, however, there is a high capital expenditure associated with their initial acquisition [41]. Additionally, a high level of computation is required to aggregate data from multiple devices, compute an optimal strategy and resend the control signal to the devices. Batteries are a typical example of direct flexibilities; they can act as a consumption or production unit in response to an external signal and deal with fluctuations (provided the battery can meet the requirements).

Direct flexibilities are often but not exclusively implemented at the lower levels of the grid (i.e. at the demand side such as at the building and community levels) and can be integrated with smart grid technologies to optimize energy use and reduce costs. By enabling a more responsive and adaptable energy system, direct flexibility measures can help to facilitate the integration of renewable energy sources and reduce the need for new energy infrastructure.

1.2.2 Indirect Flexibilities

From literature [40, 41] indirect flexibilities can be described as “actors in the global system (in this context the building or member of an EC) who cannot be controlled directly using software or control signals”. Here there is a reliance on human behavior to achieve upward or downward modulation of the demand, hence the use of actors in the definition. Thus, these energy flexibilities are dependent on the end consumer (i.e. the human in the loop [42]) altering their consumption in response to some form of signal (these could be price signals [35, 36], or social signals [37]). Compared to direct flexibilities, which can react in a short time scale, indirect flexibilities typically involve some amount of cognitive strain on the end user to first comprehend the signal and subsequently decide which kind of action to take, thus indirect flexibilities typically have a relatively slower reaction time [40]. Unlike direct energy

flexibility, there is a large range of devices that can be used for this kind of flexibility, as it does not require specialized devices but rather a conscious effort to use or not use energy (or a device) at a specific time.

There are many implementations of indirect energy flexibilities; these include real-time pricing and time-of-use tariffs which use pricing signals to encourage behavioral change to achieve changes in energy demand. Additionally, more recent studies have focused on using social signals to influence end-user behavior, usually to reduce the demand (peak shaving) [38]. These social signal implementations of indirect flexibilities usually have feedback as a key element in their design. According to Shahid et al [38], Social Signal based DSEF can be classified into three main groups; (i) comparative Norms, (ii) Injunctive Norms, and (iii) Pro-Environmental nudges. Figure 1.7 below provides an overview of available signaling used for indirect flexibility.

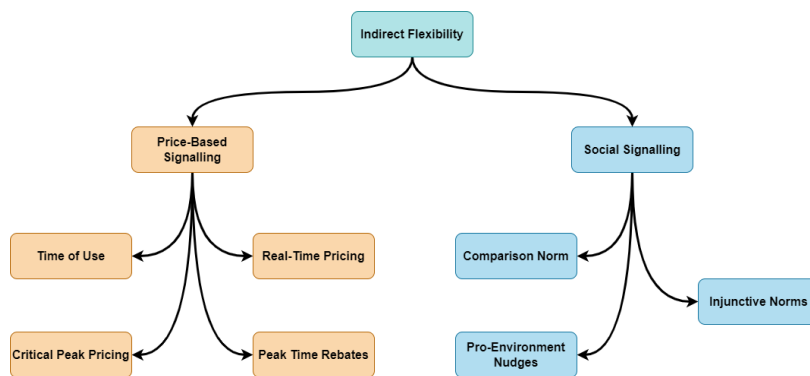


Figure 1.7: Types of signaling used for Indirect Flexibilities (source: [38])

1.2.3 Hybrid Flexibilities

These Flexibilities as their name suggests are a hybrid of direct and indirect flexibilities. Hybrid flexibility is usually a controllable device that is dependent on the human in the loop to make it available for direct control. Thus, there are two components to this type of flexibility; the first is the human, who for example has to plug in their electric vehicle in response to a pro-environmental nudge (i.e., the indirect flexibility component).

The second component is the directly controllable aspect of flexibility, thus, for the EV example, once the vehicle is plugged in it is possible to use control signals to further optimize the charging of the vehicle to further maximize the benefit from charging the EV (this could be maximizing the self-consumption rate of the building). Hybrid Flexibilities bring into the fold devices that otherwise would be difficult to use as direct flexibility but have the capability. For example, a dishwasher or washing machine could be directly controllable but its availability is subject to the washing

schedule of the human actor, thus these devices are not ideal for use as direct flexibilities.

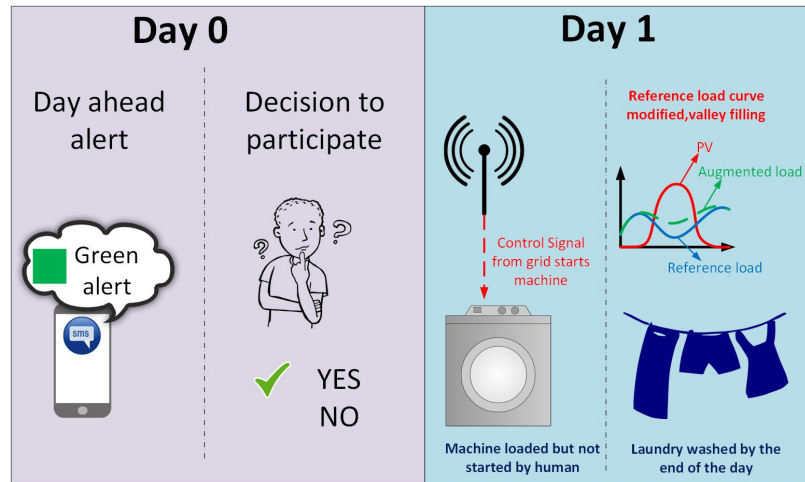


Figure 1.8: Indirect Flexibility Use case of nudges, using a washing machine as direct flexibility

However, The Human in this case could be nudged to schedule their laundry for days on which there is a high RER production on the grid (using a day ahead alert as was done in [43]). This would imply that the end user would only have to decide the day to do their laundry and not the hour or minute as the washing machine could be programmed to start on the reception of a signal, thereby reducing the cognitive strain associated with a purely indirect implementation, Figure 1.8 illustrates this example.

💡 Highlights:

- ▶ **Direct Flexibility** is directly controllable and provides high-performance guarantees since they do not require human interactions to activate them. For this type of energy flexibility, the end-user of the energy is not expected to do much and their energy needs are still met.
- ▶ **Indirect Flexibility** is dependent on the human in the control system, in this regard their performance is not guaranteed, and their response time is slow. Because humans cannot be controlled, and we can only encourage them to change their behavior, we need to use signaling that can be processed easily without introducing a cognitive strain in order to effectively harness this flexibility. For this type of Flexibility, the end-user of the energy is expected to change their energy usage patterns (change the time of use or reduce their demand etc.).

1.2.4 Impact of Human Behavior on Building Energy Consumption

Buildings have been identified as one of the main consumers of energy in most economies. The IEA [44] estimates that buildings accounted for 30% of final energy consumption and consequently 27% of emissions attributed to the electrical sector. Janda [45] in 2009 described human behavior as a key parameter that is often ignored during the conception of building systems. Studies show that the physical properties of a building and the equipment or appliances used in the said building account for approximately 50% of a building's energy demand, while the other 50% is largely influenced by occupants and their behavior [46]. Thus, occupant behavior is undoubtedly one of the key factors in determining how effective any energy subsystem in a building would be [47, 48].

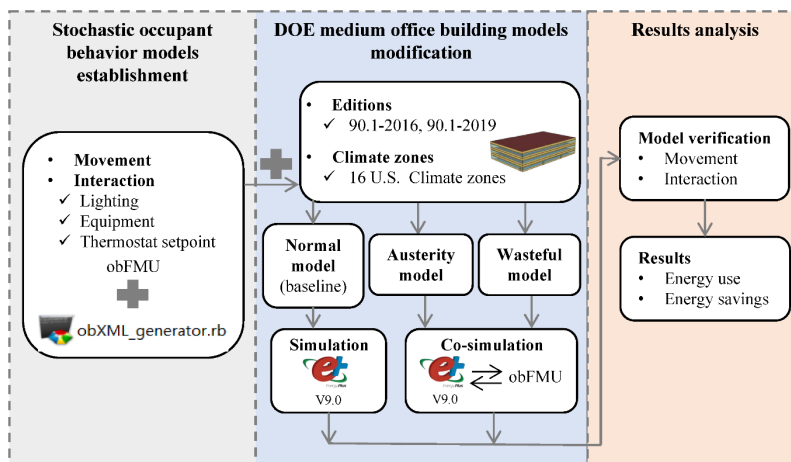


Figure 1.9: Proposed framework (based on prototype building models suite) for simulating occupant behavior (stochastic) in American buildings – based on Occupant Behaviour Functional Mock-up Unit (*obFMU*) (source: [49])

In recent times, the importance of human behavior has been acknowledged and implemented in widely used building energy efficiency models such as the suite of prototype building models [50] which was initially based on deterministic models but has been upgraded to stochastic models as was proposed by He et al [49], see Figure 1.9. These prototype models classify occupants into three behavioral styles; austerity, normal, and wasteful. Further, some work has been done to use Multi-Agent System (MAS) based simulation to model the stochastic behavior of human occupants in relation to energy systems in buildings [51–53]. Additionally, some research has been carried out on the application of agent-based simulation for modeling participant behavior in Local Energy communities [54, 55].

Energy models can be improved to better reflect the ground truth by factoring human behavior into these energy models. This would not only imply simulation results that are closer to reality but would also serve as a stepping stone to better understanding the role of humans in control systems.

1.3 The Position of Humans in Control Systems

This sub-chapter is essential as it addresses the complex socio-technical system, which is embodied within buildings and their subsystems, with specific emphasis on the energy subsystem. Because humans (i.e., the occupants) represent the social component of a building's energy subsystem, which we desire to operate in an optimal manner, it is imperative to understand the role of the human in the system. This sub-chapter provides insight into how humans interact with and influence control systems.

Control engineering has mostly been focused on the research, development, and implementation of automation and control solutions for machines and devices. For many systems, this approach is well warranted and effective, however, for systems whose performance is dependent on humans (e.g., buildings), it is imperative to factor the human into the control strategy, and thus the Human-in-the-Control System (HICS) concept. HICS in the context of control theory refers to the inclusion of the actions of humans into a control system in order to improve the performance of the said system. Whilst the definition of HICS provides a general overview of the concept, the question of where the human should be placed (i.e., the role of the human) in the loop arises. Tariq Samad [56] proposes four categories of HICS which he basis on the fundamental closed-loop control architecture with controller and plant (system under control) as depicted in Figure 1.10.

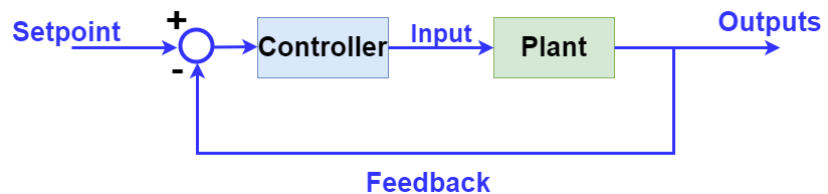


Figure 1.10: Fundamental closed-loop control architecture (source: [56])

These four categories proposed by Samad [56] are:

- ▶ **Human-in-the-Plant:** In this category, the human is part of the plant and is only subject to the control actions taken by the controller (i.e., the automation). Thus, the human here does not directly affect change to the control system but is, however, a consideration in the control strategy, see Figure 1.11 (a). A typical implementation of this is seen in many buildings where the temperature set-point is managed centrally, and the environmental conditions within the building are controlled to minimize energy use, reduce equipment stress, and ensure occupant comfort.
- ▶ **Human-in-the-Controller:** For this category, the human is in the controller and actively contributes to the actions taken by

the controller. Thus, the human can directly provide input for the control system, Figure 1.11 (b). This can be illustrated using buildings equipped with temperature control interfaces, in such buildings, the occupant can directly change the temperature set-point thereby causing the control strategy to change in order to meet their thermal comfort requirements.

- ▶ **Human-Machine Symbiosis:** Here, the human is both a part of the control system and the subject of the control (see Figure 1.11 (c)). According to Samad, “*The control of these devices must also integrate human actions with computerized reactions*”. Abbink et al [57] further describe this human-machine shared control as “*humans and robots interacting congruently in a perception-action cycle to perform a dynamic task that either the human or the robot could execute individually under ideal circumstances*”. This type of control can be illustrated using neuroprosthetics which utilize sensory feedback to the brain coupled with neural electrode measurements to control the movement of the prosthetic.
- ▶ **Humans-in-Control-loops:** Here, the emphasis is not on a single system, which could be in any of the three categories highlighted above interacting with each other as a singular system (Figure 1.11 (d)). Thus, there are multiple loops with humans interacting with both the plant and the controller that interact with each other to form one system. Thus, such systems typically incorporate both the human-in-the-plant and the human-in-the-controller as subsystems of a larger system. A typical example would be an airplane, here the pilot would be the human-in-the-controller, whilst the passengers would be the humans-in-the-plant.

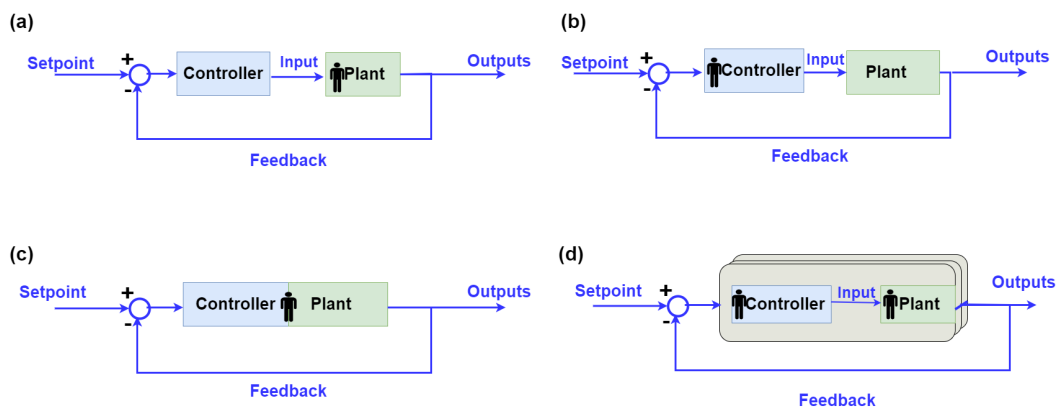


Figure 1.11: Four categories of Human-in-the-Control System (HICS) control systems based on the Fundamental closed-loop control architecture (a) Human-in-the-Plant, (b) Human-in-the-Controller, (c) Human-Machine symbiosis, and (d) Humans-in-Control-Loops (source: [56])

1.3.1 Energy Storage Systems and Their Role in the Energy Transition

Energy Storage Systems (ESS), a typical example of direct energy flexibilities, as highlighted in chapter 1.1.1 are a key element for the future grid allowing for the integration of intermittent and distributed RERs. Different technologies exist for ESSs, however, they can largely be classified as mechanical storage, chemical storage, thermal storage, and electromagnetic [58], Figure 1.12 shows various types of energy storage technologies and their maturity as of 2017. In the context of buildings, and even at the community scale, chemical storage in the form of batteries (lead acid and much recently lithium-based chemistries) is the most often used and available storage solution [38]. This has largely been influenced by their compactness, and recent development in lithium-based technologies [40], driving a drop in the financial cost of energy storage even to the point of grid parity in some economies [59].

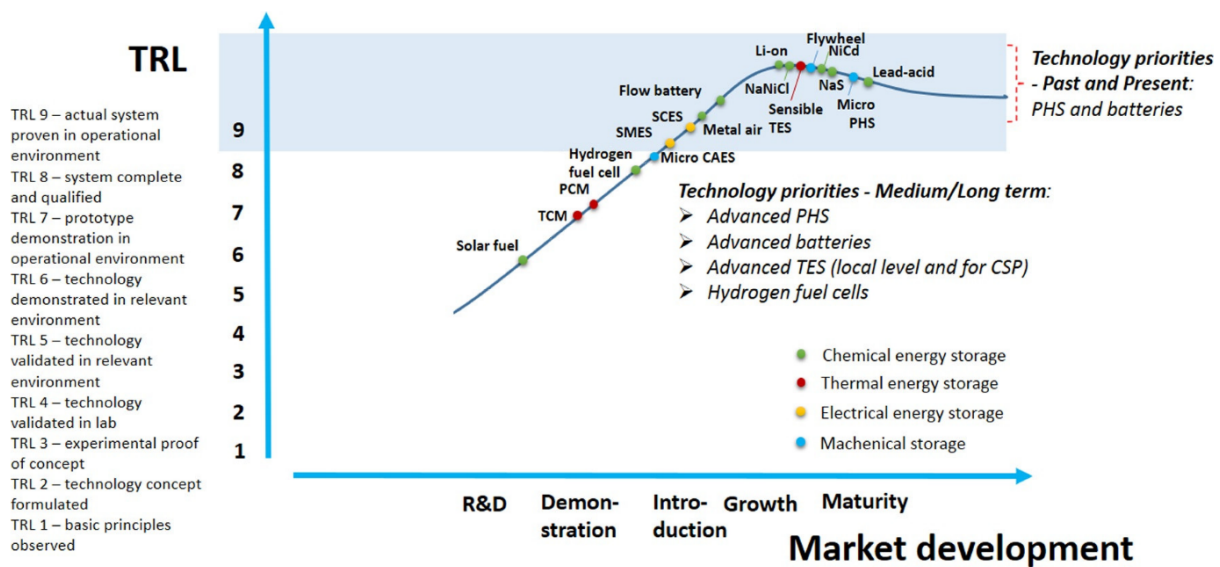


Figure 1.12: Overview of the maturity of energy storage technologies (Thermo-Chemical Materials (TCMs), phase change materials (PCMs), Super Conducting Magnetic Energy Storage (SMES), Super Capacitor Energy Storage (SCES), Sodium Nickel Chloride (NaNiCl) batteries, Thermal Energy Storage (TES), Nickel-Cadmium (NiCd) batteries, Sodium Sulfur (NaS) batteries, and Pumped Hydro Storage (PHS)) as of 2017 with Technology Readiness Level (TRL) on the y-axis and market development on the x-axis

(source: [60])

Battery Energy Storage Systems (BESSs) enable and encourage self-consumption at both the building and community scale by allowing these buildings and communities to reach higher rates of self-consumption, which would have otherwise been difficult to achieve. Thus, BESSs offer flexible services to buildings and communities and can be used for DSEF services such as peak shaving and valley filling services [61, 62]. Additionally, BESSs

are scalable and are capable of dealing with rapidly changing demand or production (i.e., highly responsive) making them ideal for managing and mitigating the issues associated with high RER penetration in the grid. BESS can be used as distributed resources, thus they can be aggregated and used for grid-scale services such as maintaining equilibrium (and providing ancillary services) [63].

Battery Energy Storage Systems despite being widely used are limited in that they are only useful for providing short-term energy storage, and evidently might not be the most efficient ESS for providing other forms of energy besides electrical energy. For example, other ESSs such as Pumped Hydro Storage (PHS) and Compressed Air Energy Storage (CAES) are more suited for long and medium-term energy storage requirements. Similarly, a BESS would suffer efficiency losses in converting from electrical energy to heat energy whereas a heat battery would not. Thus, the choice of Energy Storage System is dependent on factors such as (but not limited to) the duration of energy storage, the final energy desired, and the quantity of energy to be stored.

The recent development in battery technology has accelerated the transition to electric mobility (Electric Vehicles (EVs)). As pointed out in chapter 1.1.1, EVs are essential to the energy transition. However, EVs, because they typically are equipped with BESS and directly consume electrical energy represent a new paradigm for mobilizing energy flexibility at the building and community scale (and even at the grid scale).

The rapid development and improvement of the energy density of Battery Energy Storage Systems have played a pivotal role in driving the transition to electric vehicles (EVs). EVs have emerged as a key component of the energy transition, offering a sustainable and efficient alternative to traditional combustion engine vehicles. With their ability to store and deliver electricity, batteries empower EVs to reduce greenhouse gas emissions, promote energy independence, and contribute to a cleaner and greener transportation ecosystem.

1.3.2 Electric Mobility as an Energy Flexibility

Global EV adoption has soared exponentially, with the IEA [64] estimating that approximately 10 million EVs were sold in 2022 (i.e., 1 in every 70 cars sold), similarly, RER uptake in buildings is also growing.

The Electrification of the transportation sector translates to an increase in electrical energy demand, with particular challenges for grid operators especially given the increased uptake of BEVs. The storage potential of EVs if untapped would be underutilized, as it is estimated that vehicles remain parked for 95% of the

time. Underutilizing EV batteries would consequently reduce the benefits of electrifying the transportation sector. Tertiary buildings offer an interesting prospect for utilizing EV batteries. Most EV owners would typically go to work and park their EVs on the premises or nearby, the otherwise untapped storage potential of such EVs could be harnessed to offer flexibility services to the building. These Flexibility services include charging with solar PV electricity to maximize self-consumption and can be achieved by activating additional services related to the storage capacity such as Vehicle to Grid (V2G), Vehicle to Vehicle (V2V), Vehicle to Home (V2H) [65, 66](see Figure 1.13) which translate into benefits such as peak shaving, load shifting and valley filling.

For any of these additional services to work, bidirectional charging must be enabled, this implies that both the vehicle and the charging infrastructure must be capable of bidirectional energy flow. The key benefit of these services is that the energy storage component of a BEV becomes an extension of the grid (this is the case only when the vehicle is plugged in). At the grid scale, these batteries are capable of reducing the effects of having intermittent and distributed RERs on power quality and can be used to reduce peaks in demand. Typically, some form of aggregation is required to scale up the capacity of individual batteries to meet the requirements of the larger grid. Uncertainties such as the availability of vehicles, available capacity to discharge (from the vehicle), etc. imply that control systems need to be in place to fully realize the potential of V2G [67]. For V2H and V2V, the need for an aggregator might not be warranted, however, there is still a need for coordination between vehicles (for V2V), and buildings (for V2H).

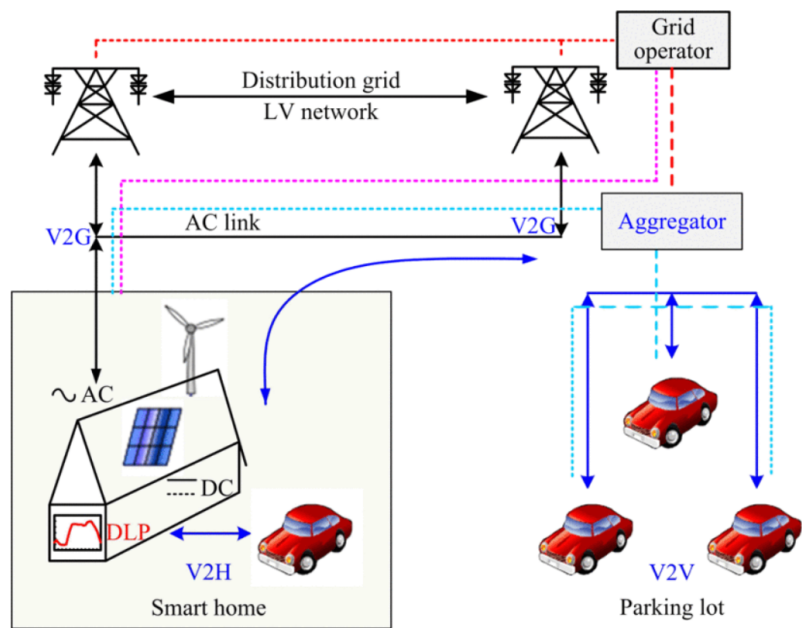


Figure 1.13: Framework for Electric Vehicle Charging, including Vehicle to Grid (V2G), Vehicle to Vehicle (V2V), and Vehicle to Grid (V2G) (source: [66])

1.3.3 Environmental Impact of Battery Storage Systems

Due to the proliferation of BEVs, Lithium-based batteries (which have a high energy density) have seen a high uptake in the last decade. Skarvelis-Kazakos et al. [68] estimate that EVs have the potential of producing between 3.6 GWh and 17.6 GWh of waste battery capacity by 2030 in Scotland alone. Mrozik et al [69] further point out that a large fraction of end-of-life lithium-based batteries ends up in landfills. Additionally, the technology available for recycling these batteries is not in itself eco-friendly (high energy requirements) or efficient thus implying high financial costs⁴ and in some cases making sourcing new materials a more feasible solution [70–72].

4: Recycling of some components (particularly the precious metals) is typically financially more viable compared to other components.

Whilst current battery storage technology presents environmental concerns, second-life applications for lithium-based technologies in particular hold a lot of promise. Martinez-Laserna et al [73] defined the second-life usage of batteries as the repurposing batteries that may no longer be considered viable for their originally intended purpose for alternative and usually less demanding operations. Thus, batteries that would have otherwise been described as expended can be repurposed and used for renewable energy purposes, thus extending the life of these batteries, and reducing their environmental impact as is being implemented by Nissan [74] and Renault [75].

Additionally, research is being carried out to develop more sustainable storage technology alternatives such as Sodium batteries [76] and solid-state batteries [77]. Alternatively, Alami et al [78] have proposed a small-scale, modular compressed air energy storage system, whilst some research has also been directed at small-scale pumped-hydroelectric systems [79] that could have potential applications in buildings and energy communities.

Extending the boundary from the individual building to the local community implies a mix of different energy demand profiles (especially when the community is comprised of both residential and commercial buildings), which would imply a better utilization of the local RER and consequently translate to lower storage requirements and the lower associated carbon footprint.

1.4 Local Energy Communities

Local energy communities have emerged as a means to re-structure our current vertically integrated energy systems and facilitate active citizen participation in the energy transition as these communities encourage the adoption of RERs [80]. Furthermore, Local energy

communities can be effectively mobilized as a response to the need for energy flexibility services from the demand side of the grid. According to the European Commission, “Energy communities organize collective and citizen-driven energy actions that help pave the way for a clean energy transition while moving citizens to the fore. They contribute to increasing public acceptance of renewable energy projects and make it easier to attract private investments in the clean energy transition.” By participating in local energy communities, individuals can potentially benefit from a reduced energy bill (due to consuming local RER or energy conservation), increased energy efficiency and conservation, and an increased level of energy awareness [27, 81].

The EU’s Renewable Energy Directive (RED II) provides two definitions for energy communities, the renewable energy community [82], and the citizen energy community [83]. Frieden et al [84] provide a comparison of the two definitions, which are highlighted in Table 1.1.

Energy communities are essential for the energy transition as they enable concepts such as collective self-consumption and consequently influence individual behaviors (participants subscribe to a common goal, which is usually sustainability). Local energy communities are not restricted to renewable energy production, but could also provide services such as aggregated demand, and aggregated storage services (using conventional batteries and BEVs). One major merit for energy communities for the energy transition is that because it involves the active participation of individuals in the energy economy, it allows for a restructuring of the energy sector (to a more prosumer/citizen-focused energy sector).

Table 1.1: Comparison of renewable energy communities, and citizen energy communities

Renewable Energy Community	Citizen Energy Community
<p><i>"A legal entity:</i></p> <ol style="list-style-type: none"> <i>1. which, in accordance with the applicable national law, is based on open and voluntary participation, is autonomous, and is effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity.</i> <i>2. the shareholders or members of which are natural persons, SEMs, or local authorities, including municipalities</i> <i>3. the primary purpose of which is to provide environmental, economic, or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits."</i> 	<p><i>"A legal entity that:</i></p> <ol style="list-style-type: none"> <i>1. is based on voluntary and open participation and is effectively controlled by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises.</i> <i>2. has for its primary purpose to provide environmental, economic, or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits.</i> <i>3. may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders."</i>
Requires geographical proximity (defined at the national level)	No geographical limitation applied
Large companies are excluded from membership	Large and medium-scale companies can participate but are excluded from effective control
Restricted to renewable energy sources only	Technology neutral, not restricted to renewable energy sources.

1.5 Conclusion

The energy transition is undoubtedly a key instrument in averting the impending climate crisis, and as discussed in chapter 1.1.1, the concept not only entails the use of technology but also includes a fundamental change in how we view, generate, transport, and use energy. Thus, a fundamental change in mindset and behavior is also required from all stakeholders in the energy system, including the end-user. The end-user is particularly important, especially in the residential (building) sector, because the occupant (end-user) ultimately consumes the energy, not the building. Additionally, since buildings account for a large proportion of energy demand in most countries, it is not a far-fetched idea to emphasize efforts in this sector.

E-mobility presents an excellent opportunity to solve two issues at the same time, i.e., sustainable transportation and energy storage,

the latter being pertinent to the high penetration of RERs in the electric grid. The concept of self-consumption, both at the community and building scale, can benefit from the use of E-mobility solutions as energy flexibilities (indirect in this case).

Energy flexibilities, both direct and indirect, exist in any building system and should not be viewed independently of each other. Perhaps the emphasis has remained on the control of direct flexibilities due to their very nature, they can easily be controlled using software or a control signal. Indirect flexibilities on the other hand depend on the end user, the human, and cannot be controlled (not in the same sense as machines and devices). Thus, the leveraging of indirect flexibilities would require the use of communication channels such as feedback indicators and nudges to effect a change in behavior towards a desired optimal.

The scientific lock of this thesis is therefore on mechanisms and concepts, which facilitate the use of both direct and indirect flexibilities in a non-residential building (and by extension local energy communities). The subsequent chapter will provide more insights into the problem being explored and ultimately present the scientific questions that this thesis seeks to answer.

Harnessing Flexibilities as a Sub-Service of the Smart Building

2

This chapter has two main parts; the first focuses on the scientific lock of this thesis and presents our main research question (from which we derived four sub-questions). The second part presents the experimental setup, a living lab, which allows us to study the building (a socio-technical system) and its sub-systems, with specific emphases on the energy sub-system.

2.1 Introduction: The Smart Building - A Conduit for Improving Building Energy Performance using the Human-in-the-Control-System

Smart buildings (a building with a decision-aided energy system), similar to smart grids, play a crucial role in achieving the energy transition by utilizing data (often real-time) related to the use of the building and the behavior of occupants (this can usually be inferred from sensor data) to efficiently manage the various sub-systems within the building to achieve high energy performance.

Since buildings are typically end nodes (and can be described as micro-grids) in the electrical network, smart buildings essentially enable innovations and concepts higher up in the network such as smart communities and by extension smart districts. Earlier definitions of smart or intelligent buildings were centered around reducing human inputs (or interactions) with the building, however, this definition has evolved to include the building occupant's (i.e., the human-in-the-system) interaction and its consequence on the global building system (and by extension the energy sub-system) [85], see Figure 2.1.

Building on this notion, Wurtz et al [42] describe the smart building as an adaption of the smart grid concept at the level of the building micro-grid, one with an energy sub-system equipped with multi-source, multi-demand, and multi-storage sub-systems, which are coordinated and managed using information and communication technology. A definition that ultimately focuses on the technical aspects of the building.

From a social and environmental point of view, Clements-Croome [86] describes a smart building as “one that is responsive to the requirements of occupants, organizations, and society. It is sustainable in terms of energy and water consumption besides being lowly polluting

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2.5	The Experimental Setup: Living Lab - a Tool for Investigating the Interactions Between the Social and Technical Components of a Building	29
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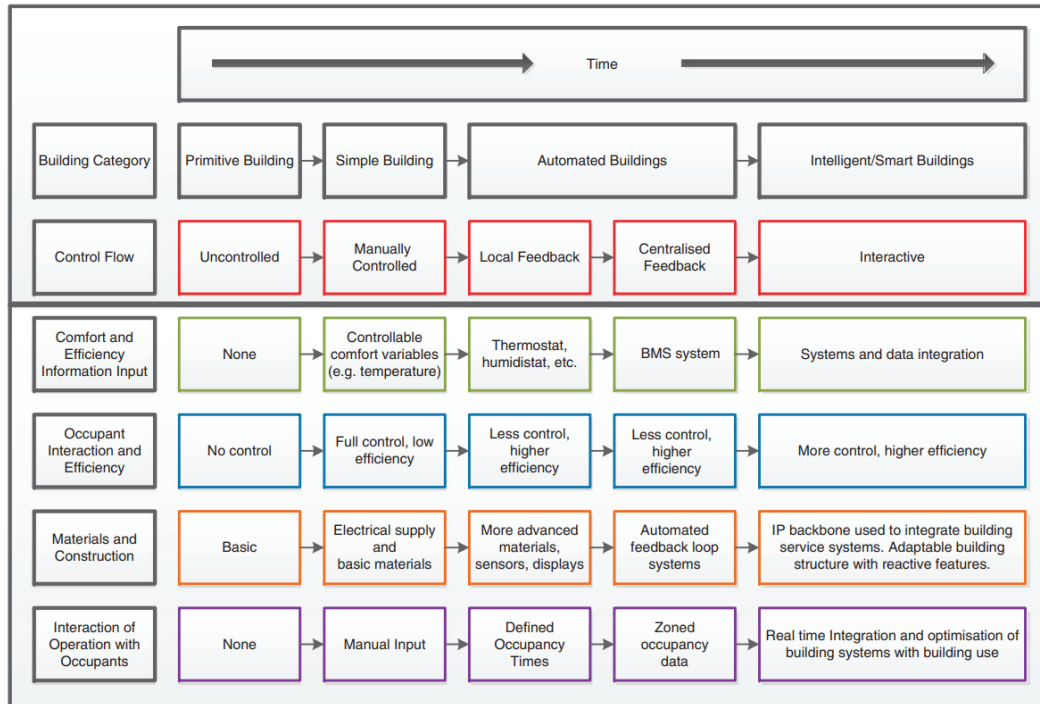


Figure 2.1: The evolution of buildings. (Source: [85])

in terms of emissions and waste: healthy in terms of well-being for the people living and working within it; and functional according to the user needs”.

Buckman et al [85] described such an advanced functioning building as a building whose performance, occupant’s comfort (environmental and visual), and occupant’s satisfaction are maximized whilst simultaneously minimizing its energy consumption over a long lifetime.

The smart building is a technological solution to energy management at all levels of the grid (buildings will be expected to be grid responsive [88] and should be able to adapt to changing boundary requirements [87]) however, the concept should not be viewed as only a technical solution but as a socio-technical solution [89]. Indeed, the concept requires the use of sensors and actuators (largely facilitated by the Internet of Things) and presents an opportunity for energy efficiency and conservation gains using information and automation [90].

Automations, however, typically are unable to fully take into account the behavior of humans, Wurtz et al [42] point out that their experience and experiments with smart buildings and occupants show that occupants will try to defeat automation (and smart systems) if they do not fully understand them. Therefore, there is a need for occupant engagement (i.e., indirect flexibility) in addition to automation (i.e., direct flexibility) in realizing the full potential of smart buildings in optimizing building demand.

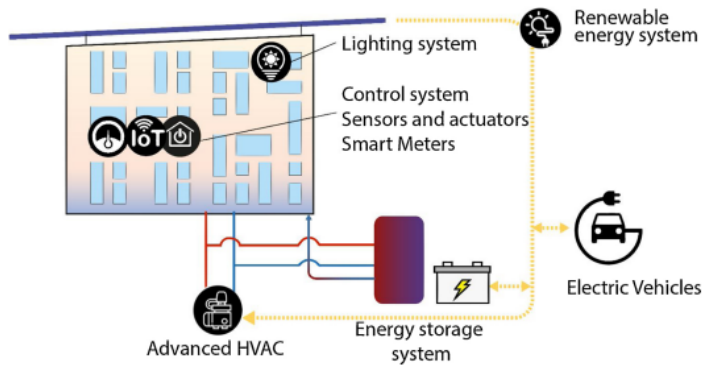


Figure 2.2: Key technologies in smart buildings (IOT – Internet of Things, HVAC- Heating Ventilation and Airconditioning) (Source: [87])

Furthermore, the smart building presents the opportunity to harness and assess the interaction of the direct (sensors, actuators, and controllable loads) and indirect (the occupants) flexibilities. Since real-time monitoring is a core feature [87] of the smart building’s concept, it provides the opportunity to optimize all parameters effectively and efficiently within the building’s system (comfort, satisfaction, energy efficiency, etc.).

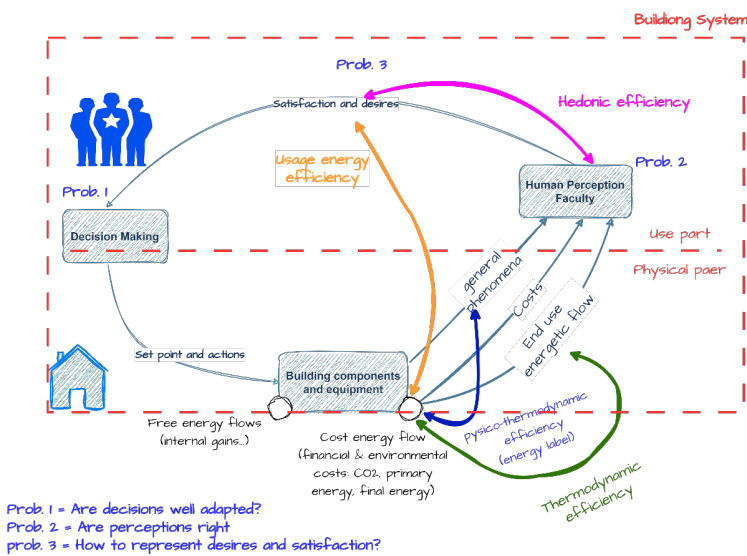


Figure 2.3: Qualitative model representing smart buildings with the human-in-the-loop (source: [89])

Consequently, there is a need for a multi-disciplinary research approach towards the development of the smart building concept to yield models such as the one depicted in Figure 2.3, which allow for the physiological (comfort and satisfaction) and psychological (perceptions and feelings) aspects of the occupant to be accounted for [42].

The smart building allows for the real-time monitoring and control of the technical components (i.e., the direct flexibility) of the socio-technical system (the building system). Additionally, the meters in such buildings allow for the estimation of the impact of occupant behavior, which brings us to the main scientific question on which the central theme of this thesis is based:

Main Research Question

“To what extent can human (occupant) behavior, which is the social component of the building system, be effectively mobilized and integrated with technical and highly controllable solutions to facilitate the delivery of energy flexibility services at the building and local energy community scale”.

Thus, the main objective of this thesis is to evaluate the interaction between both the indirect and direct flexibility which may be present in a building (and by extension a local energy community) with the goal of providing services at both the community and building scale. We decomposed this main question as will be highlighted in the subsequent sub-chapters.

2.2 Indirect Flexibilities in Buildings

Engaging Occupants in the micro-grid that is the building provides a means of activating indirect flexibilities. Indeed, these devices (which without human intervention are unavailable for flexibility purposes) exist in most buildings (i.e., commercial, residential, etc.), for example, the electric oven in a residential building whose usage is dependent on the cooking schedule of the occupant or EV charging stations attached to a tertiary building. Once a device or service has been identified as having the potential to provide indirect flexibility services, the question then arises:

SQ.1

“What methodologies can be employed to validate the potential and accurately quantify the impact of an identified indirect flexibility on the energy performance of a building?”

To realize the full benefit of the available indirect flexibility, it is essential that we can quantify and model it. This allows for said indirect flexibility to be accounted for in the conception and operational planning of building systems. However, since there is a high dependency on the human actor (occupant), and at the building scale this could be just one person, it is not a far-fetched idea to add a direct flexibility to provide (in a support sense) the same services as the indirect flexibility.

2.3 Battery Storage as Direct Flexibilities in Smart Buildings

Given the definition of direct flexibility (chapter 1.2.1), battery storage can be a direct flexibility in buildings. Batteries are, however, not without costs (both financial and environmental), and as such there is a need to ensure that they are optimally sized.

Undoubtedly an oversized battery will yield the desired results but would not merit the cost, especially the environmental costs (there is the possibility that the cost might outweigh the benefit), conversely an undersized battery will not meet the performance requirements of the system and ultimately lead to shortfalls in the overall performance of the system. Literature shows that a lot of work has been done to propose optimal sizing approaches for battery storage systems for buildings. Typically, these sizings are done using data related to the demand and the production (if any exists) or grid electricity pricing with the objective to either minimize environmental impact [26, 91], minimize financial cost [92, 93] or to maximize the buildings self-consumption [94, 95].

Despite varying methodologies and objectives, literature generally has one thing in common; indirect flexibilities are not considered for the sizing of direct flexibilities at the building scale. Thus, we will tackle the question:

SQ.2

“How does one effectively account for indirect flexibility in the optimal dimensioning of direct flexibilities (battery storage)?”

In the context of storage, it is also imperative to effectively control the charging and discharging of the battery to ensure optimal performance of the energy system whilst minimizing the degradation of the battery. In this regard, we will tackle the question:

SQ.3

“Given an energy system, what is the appropriate level of complexity and computational cost that ensures optimal and efficient use of a battery energy storage system?”

Storage is a key component of the smart building concept (both residential and commercial buildings) as illustrated in Figure 2.2, and just like any other subsystem in the building, its usage is highly dependent on occupant activity and behavior. As both the human and storage (i.e., battery) are present in the building microgrid and

there exists some co-dependence between these two actors it is also imperative to study the interaction between them.

2.4 Interactions Between Direct and Indirect Flexibilities: A Socio-Technical Problem

Both direct and indirect flexibilities can be utilized at the building scale, with the direct flexibility being easier to control and with better performance guarantees, however, the indirect flexibilities are less expensive and easier to implement. Due to the stochastic nature of indirect flexibilities, we must be able to evaluate and assess their interactions both from a technical and social point of view. Thus, we arrive at the question:

SQ.4

“How do we evaluate and quantify the impact of the synergy between direct and indirect flexibilities on a building’s energy performance?”

Furthermore, energy communities (see chapter 1.4) present an interesting opportunity to harness indirect flexibilities, in that, they are typically composed of individuals who share a common goal, which is typically to reduce their environmental impact. Participants in such energy communities would typically be more willing to adjust the consumption patterns (i.e., load shifting, valley filling, etc.) or conserve energy altogether. Thus, these participants can be considered as potentially ideal candidates for mobilizing indirect flexibilities.

Modeling human behavior is a complex task as there is no hard fast rule to achieving a representative model. This complexity is perhaps increased in commercial/office buildings or in an energy community where there are multiple human actors with varying levels of interest and enthusiasm to participate.

Living labs provide the opportunity to design, test, and optimize ideas and concepts. Thus, for the work presented in this thesis, we consider a living lab setup as elaborated in the next sub-chapter.

2.5 The Experimental Setup: Living Lab - a Tool for Investigating the Interactions Between the Social and Technical Components of a Building

The Living lab concept presents a space for conception, development, testing validation, and co-creating during the various stages of both the design and commercialization process [96]. According to the European Network of Living Labs [97], “Living Labs are real-life test and experimentation environments that foster co-creation and open innovation among the main actors of the Quadruple Helix Model¹”. Indeed, the concept has not been standardized and it is therefore unclear how to operationalize living labs and further how to measure their outcomes [98]. However, for applications in the energy domain, the results are quantifiable and measurable.

1: The Quadruple Helix Model of innovation is an innovation model which stipulates that there are four major actors in the innovation system: science, policy, industry, and society

2.5.1 The Predis-MHI Platform

The Predis – MHI (Monitoring and Habitat Intelligence) platform is a living lab that is housed in the GreEn-ER building. This is a smart building, commissioned in 2015, that is owned and operated by Grenoble Institute of Technology’s school of Energy, Water, and Environment (École Nationale Supérieure de l’Énergie, l’Eau et l’Environnement - ENSE3). It houses the Grenoble Electrical Engineering lab with a total floor area of approximately 27000m² (6 floors, each with 4500m²).

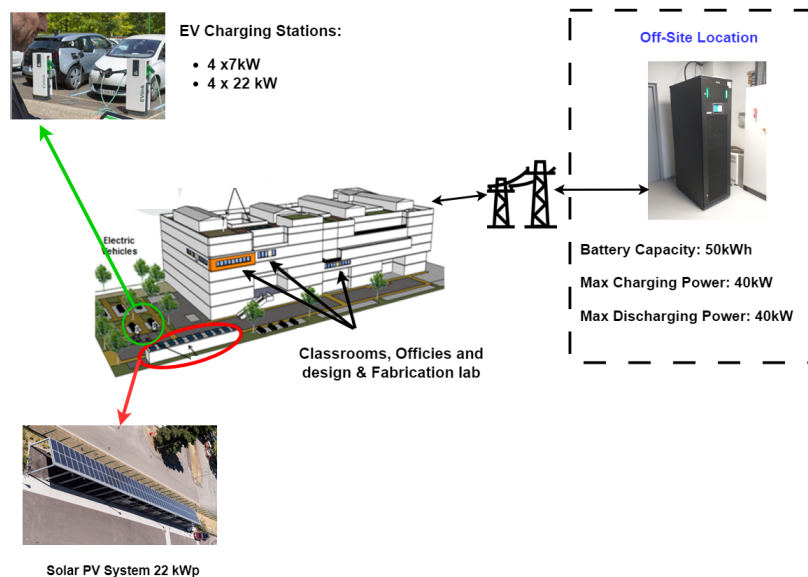


Figure 2.4: Pictorial view of the GreEn-ER building highlighting the parts dedicated to the Predis-MHI platform (source [99])

The platform which is the demonstration zone of the GreEn-ER building was conceived to achieve net-zero energy status. The platform is constituted of 600m² of floor space composed of

offices, lecture rooms, and experimental rooms which make up the demand, a Heating Ventilation and Cooling (HVAC) system, 22kWp of solar PV, four EV charging stations (each with two charging leads) and a 50 kWh lithium-ion battery (see Appendix A for more information) [40, 99], see Figure 2.4. Typically, the demand for the platform is comprised of lighting, HVAC, electrical outlets (typically computers), and EV charging stations. The platform not only allows for innovation and experimentation of technological solutions but also allows for the evaluation of the human element (i.e., the building's occupant). Thus, allowing for the development and testing of solutions in real-life settings.

For the rest of this chapter, the Predis-MHI platform is considered to be a tertiary building with an energy system as depicted in Figure 2.5.

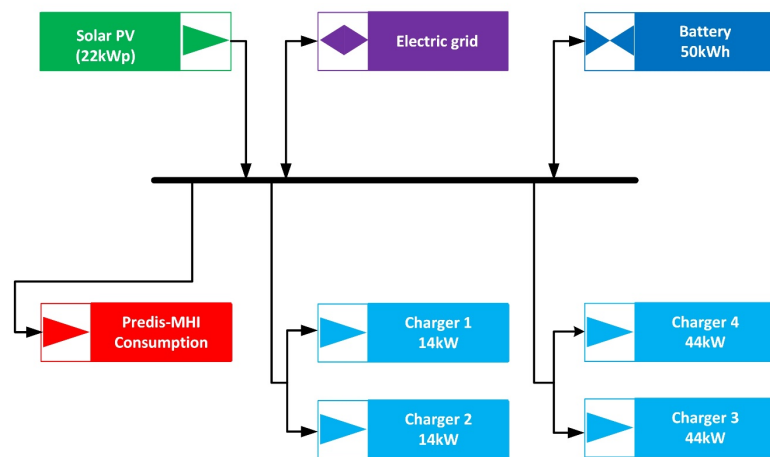


Figure 2.5: Electrical System of the Predis-MHI platform (diagram inspired by the OmegAlpes graphical representation [100]) (source: [99])

2: Jupyter Notebook can be found online at [GitLab: Predis-MHI Data Analysis](#)

Hourly Data from the platform is considered for the case studies presented in subsequent chapters of this thesis (Figure 2.6 shows the annual energy consumed and produced, see Appendix B.3²). The data collected and used consists of:

1. Consumption data: data related to consumption of the platform; this consists of lighting, HVAC, and electrical outlets.
2. solar PV data: hourly data related to the on-site 22kWp solar PV system.
3. EV charging station data: This data provides the energy consumption of the 4 charging stations present on-site. These charging stations are considered as the indirect flexibility for the building.

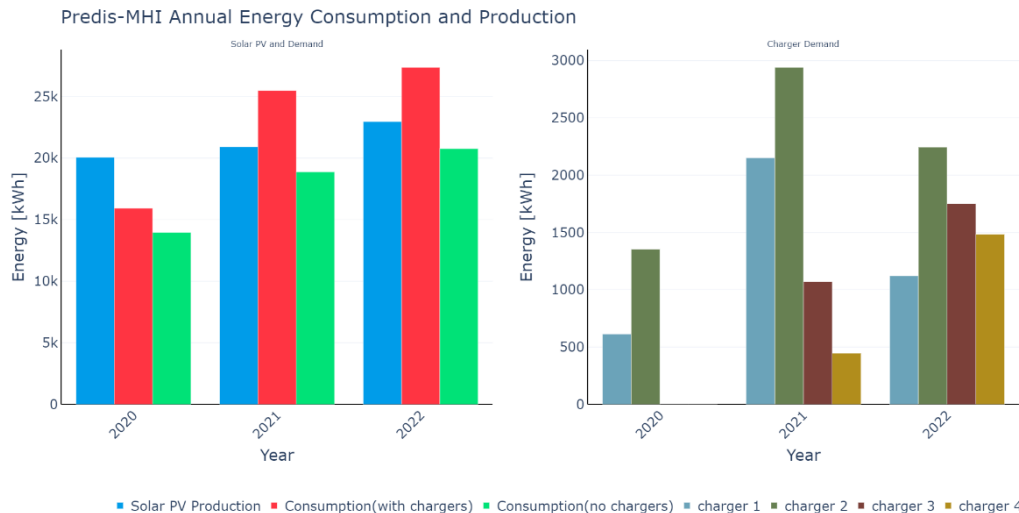


Figure 2.6: Summary of Predis-MHI energy data (a) energy demand and production (b) demand for the 4 individual chargers (Available online: [GitLab: Predis-MHI Data Analysis](#))

2.6 Conclusion

In this chapter, we have posed our main research question:

To what extent can human (occupant) behavior, which is the social component of the building system, be effectively mobilized and integrated with technical and highly controllable solutions to facilitate the delivery of energy flexibility services at the building and local energy community scale.

This central question borders on the interaction between the social and technical components of the socio-technical system which is the energy subsystem of a building. Delving further, we further decomposed this main question into four sub-questions which are summarized below:

1. What methodologies can be employed to validate the potential and accurately quantify the impact of an identified indirect flexibility on the energy performance of a building?
2. How does one effectively account for indirect flexibility in the optimal dimensioning of direct flexibilities (battery storage)?
3. Given an energy system, what is the appropriate level of complexity and computational cost that ensures optimal and efficient use of a battery energy storage system?
4. How do we evaluate and quantify the impact of the synergy between direct and indirect flexibilities on a building's energy performance?

Furthermore, we introduced the Predis-MHI platform, a living lab within G2ELab, which for this work is considered to be an office building. Since the platform is part of a smart building and was designed to be a Net Zero Energy Building (NZEB)³, it can

3: NZEB refers to a prosumer building with a high energy performance that yields an annual energy balance (produced energy - consumed energy) of zero (or close to zero)

4: Performance here is subject to occupant behavior as well as the effectiveness of the energy management strategies put in place within the building.

Gitlab Repository

A Jupyter Notebook with data analysis for Predis-MHI is available online at [GitLab: Predis-MHI Data Analysis](#) Additionally, see Appendix B.1 for a list of all available notebooks

be described as already having a high energy performance⁴. This platform allows for the testing of different strategies (occupant engagement, nudging, model predictive controllers) and provides real-time feedback regarding the effectiveness of such strategies.

Additionally, the satisfaction and comfort of occupants can be estimated to an extent (using occupant feedback). To address the research questions posed, the subsequent chapter will address the first two questions. Thus, the subsequent chapter will address the question related to quantifying and validating identified indirect flexibilities and will also delve into the sizing of direct flexibilities with indirect flexibilities as a consideration.

Indirect Flexibility: A Conduit for Maximizing Self-Consumption

3

In this chapter, we address two out of the four sub-questions we stated in chapter 2. Thus, the chapter has two main parts, the first part presents a framework for quantifying the potential available from an identified indirect flexibility. In the second part, we proposed a methodology for dimensioning direct flexibilities (i.e., stationary batteries) which considers the available indirect flexibility. Furthermore, in each of these two parts, we applied our proposed methodologies to our experimental setup as a use case and present the results obtained.

3.1	Introduction	33
3.2	Quantifying Indirect Flexibility in Buildings	35
3.3	Mobilizing Indirect Flexibility for the Optimal Dimensioning of Stationary Battery Energy Storage Systems	46
3.4	Conclusion	50

3.1 Introduction

Self-consumption can be increased by reducing the size of the local on-site generation or by increasing the demand, both solutions contradict the objectives of the energy transition. In this light, an often-proposed solution to increase a building's self-consumption is to use storage (usually battery storage) as it is directly controllable and allows for the intermittency associated with renewable energy resources to be mitigated if not eliminated. Batteries despite their usefulness and role in the energy transition are not without drawbacks, especially when one considers the environmental impact related to the manufacturing and recycling of these battery storage devices and the safety risks associated with their use (albeit mitigated by Battery Management Systems). However, in this chapter, we explore the concept of indirect flexibility, especially from the perspective of a smart building.

Self-consumption was originally conceived on an individual scale, where the owner (or the building for which the RER is installed) of the RER was the only consumer of the on-site energy production. For a lot of buildings, the demand profile does not allow for the maximum utilization of the on-site energy resource without socio-technical interventions. Collective self-consumption was thus conceived as one such socio-technical solution which allowed prosumer buildings to share any excess energy with other nearby buildings. The concept draws on the different demand profiles (residential, commercial, and tertiary profiles) that may exist in a community, mobilizing the diversity in demand profiles as an asset to better utilize the energy from local RERs. In France for example, collective self-consumption has been possible since 2017 and allows locally produced electricity to be shared amongst members of the collective self-consumption community as long as they are within

the defined geographical limits (i.e., within a 2 km radius [84]) [30].

A third alternative, changing consumption patterns to follow the generation profile of the available RER (i.e., indirect flexibility), allows for the further increase of self-consumption even in the face of other technological or socio-technical solutions. This solution is less emphasized, largely because it requires the participation of humans (often in the form of behavioral change). However, recent literature shows a growing interest in harnessing this indirect flexibility to improve self-consumption [101, 102] and also to provide ancillary service for the extended grid [37, 103]. Since humans cannot be controlled but can be aided to take informed¹ decisions, harnessing this flexibility requires the use of signals, there is, however, no hard fast rule to designing and implementing such signals.

At the building scale, these indirect flexibilities do exist and there is no precise rule for identifying them; however, a good rule of thumb is to mobilize devices with high demand and frequent usage (frequent usage might have high priority). For example, in a household where there is minimal cooking, an oven despite being a high-power device will have very little impact, lighting on the other hand could be more useful as a flexibility since it is more frequently used. Once identified, the next step would be to quantify the potential impact of the indirect flexibility.

The significance and impact of indirect flexibilities at the grid scale have been emphasized by the French Ecowatt/Eco-gestes initiative which was scaled up to a national level in the face of the energy crisis of 2022 (winter). The French administration [104] describes Ecowatt as a citizens' initiative which has been set up and is solely managed by the French transmissions system operator RTE². Ecowatt in effect is a mobile application (also available as a web page) that provides real-time forecasts of electricity demand in France and signals users based on a color scheme³

if there is a need to reduce their consumption. Eco-gestes (eco gestures) are recommended actions that can be taken by users to effectuate the demand reduction (i.e., demand response using indirect flexibilities). According to the French administration, the service had as of December 1st, 2022, the service had 470,000 SMS subscribers and the application had been downloaded by approximately 300,000 users, which grew to 700,000 by December 4th, 2022 [104] (133.33% growth in 3 days). Ultimately, an 11% reduction in demand was achieved and the anticipated energy crisis⁴ was averted in France [105]. Several hypotheses can be ascribed to this significant reduction, key amongst them are:

1: decisions that are based on knowledge and ultimately benefit the global system

2: Réseau de Transport d'Électricité ("Electricity Transmission Network") the French Transmission Network Operator

3: Based on forecasts established by RTE on electricity consumption, each day is classified according to a color code where

- ▶ green: "reasonable" level of consumption
- ▶ orange: "high" consumption
- ▶ red: "abnormally high consumption, with risk of power failure".

4: The energy crisis refers to an anticipated electricity supply deficit of approximately 10% in France. This crisis was a result of the shut down of nuclear plants for maintenance, design flaws identified in a generation of nuclear reactors and the gas and oil supply issues associated with the Russia-Ukraine war.

- ▶ **The success of the Ecowatt campaign:** That is to say, the Ecowatt application was effective and influenced users to reduce their demand (this could have been by energy sobriety [21] or energy conservation [13]).
- ▶ **Increased inflation:** During the winter of 2022/2023, inflation in France was approximately 5.2%, a doubling of the previous year's value of 2.8% [106]. That is to say, the reduced purchasing power influenced the demand for power
- ▶ **Higher tariffs for industrial and commercial users:** Domestic users in France were shielded from the volatile electricity tariffs, however, this was not the case for commercial and industrial users, thus, with soaring energy prices, these sectors could have reduced their electricity demand in response to the increasing cost of electricity.

Whilst self-consumption is central to this thesis, the Net Energy Exchange with the Grid (NEEG) indicator is also of particular interest. By definition, NEEG represents *"the absolute quantity of energy that is either injected or extracted from the grid"* [54]. Thus, by decreasing the NEEG, the self-consumed energy would be effectively increased. Simoiu et al [107] demonstrated that, minimizing the NEEG is more effective as an objective than maximizing the self-consumption⁵.

3.2 Quantifying Indirect Flexibility in Buildings

To make responsible choices with regards to the consumption of energy and the management of energy-dependent services within any building, it is important to have useful information. Thus, there is a need to quantify the impact of the available indirect flexibility (this is the available potential of the flexibility) on the building's energy performance. Li et al [108] in their article "Ten Questions Concerning Energy Flexibility in Buildings" assert that energy flexibility is often quantified using Key Performance Indicators (KPIs) such as the financial cost of electricity [109]. Self-consumption given its important role at all levels of the grid is one of such KPI [110].

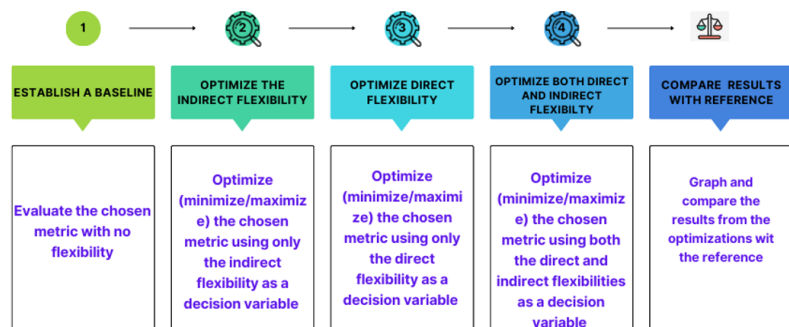
We propose a methodology for quantifying an identified indirect flexibility resource using self-consumption as a metric. The proposed methodology utilizes a Mixed Integer Linear Programming (MILP) approach and was applied to the Predis-MHI platform (living lab within the premises of G2ELab) as a use case. This methodology consisted of four key steps (Figure 3.1) ; (i) estimate the metric with no flexibility to serve as a baseline (in our use case this is the natural self-consumption⁶), (ii) optimize the met-

5: The self-consumption definition does not penalize export and as such the optimizer maximizing self-consumption as an objective function consequently represents minimizing the import from the grid. This is especially true when battery efficiency and self-discharge are taken into account

6: Natural self-consumption refers to the self-consumption before any external influences such as batteries or demand side flexibility.

ric (self-consumption) using the indirect flexibility as decision variables, (iii) optimize the metric with the direct flexibility as a decision variable, and (iv) optimize the metric with both direct and indirect flexibilities as decision variables. The first two steps are usually sufficient to indicate how much indirect flexibility potential exists. Step (iv) provides an indication of how the two flexibilities interact from a technical standpoint. It should be noted that self-consumption was chosen as a metric for our experimental setup, as there exists a solar PV system, however, other metrics such as carbon emissions can be considered.

Figure 3.1: Summary of methodology for evaluating indirect flexibility potential)



3.2.1 Mixed Integer Linear Programming for Energy System Scheduling and Sizing

Mixed Integer Linear Programming (MILP) optimizers are regarded as a capable, effective, and reliable tool for finding the global optimal provided the problem to be solved is linear (or can easily be linearized). MILPs are often used in the literature [100, 111, 112] for optimizing problems related to energy systems (production and consumption scheduling, equipment sizing, etc) related to energy systems. Marocco et al [111] state that, energy dispatching problems can be handled using rule-based energy management strategies, however, second-layer scheduling which may require more advanced methods may rely on MILPs. In this regard, Moretti et al [113] proposed a single layer MILP based algorithm for the predictive design and optimal dispatching of microgrids, their solution was compared to existing rule-based strategies (heuristic approach) and was found to not only result in cheaper electricity cost but also higher system reliability and RER penetration in the energy mix. MILPs have also been effectively applied to the sizing of different types of energy systems [26, 100, 111, 112, 114]. One key advantage of MILPs is that given a well-formulated problem, a MILP will converge and produce a global optimum⁷ [116].

Additionally, MILP problems are relatively easier to formulate⁸ (resulting in relatively faster and less costly computations), with Arcurie et al [117] asserting that a MILP problem only become

7: It is possible to have a set of solutions that provide the same value for the objective function (The W effect as described by [115]). This method provides the solution in the set on which it converges first

8: MILP problems are easier to formulate when the problem is already linear. For problems that have non-linear components, linearization approaches need to be applied and these can increase the complexity and difficulty in formulating the MILP problem

infeasible under two conditions; (i) when the defined objective function can be improved without limit (i.e., the optimal solution is unbounded), and (ii) when at least two of the defined constraints contradict one another.

Since by definition linear programming requires the problem to be linear, non-linear parts of a system (or problem) cannot be represented without some form of linearization, MILP however can account for some linearities some linear phenomena using integers. Further, non-linear components of the system such as efficiencies and failure probabilities can be accounted for as a constant value or by applying linearization techniques such as decomposition [118] and piecewise linearization [117, 119]. Further, Urbanucci et al [118] point out that MILPs when dealing with system sizing problems require a single optimization of the problem for the entire time horizon which can be computationally costly. These issues can be solved using different approaches as proposed by literature, including: (i) simulation period reduction [114], (ii) problem decomposition methods [120, 121], and (iii) the sliding window technique (usually applied to scheduling problems) [122].

To further emphasize the usefulness and suitability of MILPs for modeling and optimizing energy systems, modeling tools such as OMEGAAlpes utilize MILPs. OMEGAAlpes is an open-source multi-carrier energy modeling tool developed in Python to aid in the preliminary design of energy systems at the building-district scale [100].

Radet et al [121] propose in their work a methodology that makes use of both simulation period reduction (i.e., using clustering) and decomposition, allowing for both the investment (slow) and operational dynamics (relatively faster) to be accounted for in the planning and operation of microgrids. This work introduces two-time scales (i.e., one for dynamic investments and the other for operations) and proposes a method for bridging the gap between the two timescales.

For this study, a battery was the recurring investment, thus, the State of Health (SOH) at the end of each year was used as a decision variable to determine if a new investment was warranted. In the event of an investment, the subsequent year (i.e., the start of a new time block) would have a new battery, fully charged and capable of discharging its full capacity. This approach consequently allowed for cost evolution to be accounted for in the model and also enabled the control of the system (i.e., a battery) aging using the SOH of the battery. Additionally the use of clustering and decomposition to reduce the size of the problem allowed for the simulation of a horizon of 20 years without incurring high computational costs [121].

3.2.2 A Mixed Integer Linear Programming Approach for Indirect Energy Flexibility Potential Assessment at the Building Scale

9: Self-consumption is the ratio of self-consumed energy to the total energy produced on-site. This formulation does not constrain or penalize export and in the face of battery efficiency, will essentially really maximize self-consumption.

10: Minimizing the exchange with the grid consequently implies maximizing the self-consumption as discussed in chapter 3.1. Thus we consider NEEG as the objective function but use self-consumption as our evaluation metric outside of the optimization

11: $P_{export}(t)$ is considered to be a negative value following node notation

12: Considering the definition of self-consumption, then the self-consumption would in effect be increasing whilst the NEEG is decreasing.

Using the Predis - MHI platform as a test case, a MILP formulation was developed to assess the available potential of indirect flexibility to maximize the building's (i.e., the platform's) self-consumption. The EV chargers (more specifically the charging of EVs) were identified as a potential source of indirect flexibility. In this regard, the objective of the MILP was to maximize the self-consumption of the building, given the 22kWp solar PV system. The MILP formulation employs a sliding window approach (i.e., the optimization is done for a 24-hour sub-horizon for a horizon of 1 year). The formulation for self-consumption did not employ the classical definition⁹ as proposed by [123], but used the Net Energy Exchanged with the Grid (NEEG)¹⁰ [54] formulation. Thus, the objective function of the MILP was defined as [40]:

$$\text{objective} = \min \sum_t [P_{\text{import}}(t) - P_{\text{exports}}(t)] \times \text{timestep} \quad (3.1)$$

Where:

- ▶ $P_{export}(t)$ is the power exported from the Predis-MHI platform to the electric grid at the time t ¹¹.
- ▶ $P_{import}(t)$ is the power imported from the grid at the time step t .

The NEEG indicator was chosen as it represents the dependence of the building on the grid (the sum of energy injected into or extracted from the grid). Consequently, minimizing the NEEG of the building would result in maximum self-consumed energy¹² [107]. It is also noteworthy that sizing of solar PV systems with an objective function to maximize self-consumption would not yield an optimal solar PV size as no solar would imply 100% self-consumption. Thus, for sizing applications also, the NEEG proves a more suitable objective function compared to self-consumption.

Given the objective defined in eqn 3.1 above, there was the need to define constraints to ensure that the system operated within technically feasible limits. The optimization was therefore subject to the constraints defined below:

1. A battery state of charge(SOH) limit constraint confines the battery SOH within the defined maximum (i.e $\leq 100\%$) and minimum (i.e., $\geq 0\%$) boundaries:

$$SOC_{\text{Min}} \times Cap_{\text{bat}} \leq E_{\text{bat}}(t) \leq SOC_{\text{Max}} \times Cap_{\text{bat}} \quad (3.2)$$

where $SOC_{\text{Min}} \times Cap$ and $SOC_{\text{Max}} \times Cap_{\text{bat}}$ are the minimum and maximum energy allowed in the battery respectively (given the battery capacity Cap_{bat}) and E_{bat} is thus, the energy in the battery (given in kWh) at time step t and is denoted by:

$$E_{\text{bat}}(t) = E_{\text{bat}}(t-1) \times [1 - \Delta_{sd}] - \left[P_{\text{bat}_{\text{in}}}(t) \times \eta_{\text{charge}} + \frac{P_{\text{bat}_{\text{out}}}(t)}{\eta_{\text{discharge}}} \right] \times \text{timestep} \quad (3.3)$$

- ▶ $P_{\text{bat}_{\text{in}}}$ and $P_{\text{bat}_{\text{out}}}$ refer to the charge and discharge power of the battery respectively.
- ▶ η_{charge} and $\eta_{\text{discharge}}$ refer to the efficiency associated with charging and discharging the battery respectively
- ▶ Δ_{sd} is the self-discharge rate of the battery.

Given that self-discharge is a consideration, and the problem is decomposed into 24-hour sub-problems, it is important to ensure the SOH at the end of each 24 hours is high enough to ensure that the constraint in eqn 3.1 is not violated in the next 24-hour period¹³. This was formulated as:

$$E_{\text{bat}}(T+1) \geq 1.1 \times SOC_{\text{Min}} \times \text{Battery}_{\text{Capacity}} \quad (3.4)$$

where T is the last time step in the set $[1, 2, 3, \dots, T]$ and the final battery energy $E_{\text{bat}}(T)$ is bounded by the constraint defined in eqn 3.3:

2. For safety and technical reasons, charge and discharge power limits were defined as:

$$P_{\text{bat}_{\text{in}}}(t) \times \text{State}_{\text{battery}}(t) \leq P_{\text{bat}_{\text{Max}_{\text{in}}}}(t) \quad (3.5)$$

$$P_{\text{bat}_{\text{out}}}(t) \times [1 - \text{State}_{\text{battery}}(t)] \geq P_{\text{bat}_{\text{Max}_{\text{out}}}}(t) \quad (3.6)$$

Where:

- ▶ $P_{\text{bat}_{\text{Max}_{\text{in}}}}$ and $P_{\text{bat}_{\text{Max}_{\text{out}}}}$ are the maximum charge and discharge power of the battery.
- ▶ $\text{State}_{\text{battery}}$ is a binary value, used to ensure that simultaneous charging and discharging of the battery does not occur in the same time step. For this purpose, the battery is considered to be charging when $\text{State}_{\text{battery}}(t)$ has a value of 1 and discharging when $\text{State}_{\text{battery}}(t)$ has a value of 0.

3. Given that the grid connection to the building has a limit, a maximum connection capacity was added as a constraint.

13: Charging with energy from the grid is not allowed and as such, there is a possibility that the energy in the battery goes too low before the solar energy is available due to self-discharge.

Additionally, to prevent the use of grid-sourced electricity for charging the battery a grid constraint was defined as:

$$P_{\max_{\text{import}}}(t) \geq P_{\text{import}}(t) \leq P_{\text{load}}(t) \quad (3.7)$$

4. In the MILP, EV chargers have to provide the same quantity of energy that was originally used for the 24-hour sub-problem under consideration, this was ensured by:

$$E_{\text{Charger}_x_{\text{historical}}} = \sum_t^T P_{\text{Charger}_x}(t) \times \text{timestep} \quad (3.8)$$

where:

- ▶ $E_{\text{Charger}_x_{\text{historical}}}$ is the energy originally consumed by charger X (where X belongs to the set of charger IDs 1, 2, 3, 4) for the optimization 24-hour horizon.
- ▶ P_{Charger_x} is the output power of charger X at the time t .

The building and by extension the chargers are not accessible 24 hours a day, and as such, it is necessary to account for the building's operating hours in the optimization. This is given by:

$$\sum_t^T P_{\text{Charger}_x}(t), \text{ if } t < T_{\text{open}} \text{ or } t > T_{\text{close}} \quad (3.9)$$

Where T_{open} and T_{close} refer to the opening and closing hours of the GreEn-ER building respectively.

5. To ensure a power balance in the energy system:

$$P_{\text{bat}_{\text{in}}}(t) + P_{\text{bat}_{\text{out}}}(t) - \left[P_{\text{load}}(t) + \sum_X P_{\text{charger}_X}(t) \right] + P_{PV}(t) + P_{\text{import}}(t) + P_{\text{export}}(t) = 0 \quad (3.10)$$

Since self-consumption (see Figure 1.4) is the KPI used to assess the available indirect flexibility potential, it was defined mathematically as [123]:

$$\text{Self-consumption} = \frac{\int_t^T \min [P_{PV}(t) - P_{\text{bat}_{\text{in}}}(t) - P_{\text{bat}_{\text{out}}}(t) - \xi(t), P_{\text{load}}]}{\int_t^T P_{PV}(t)} \quad (3.11)$$

where $\xi(t)$ refers to the losses in the energy system.

The MILP formulation above was solved using the commercially available solver Gurobi [124] and was applied to the case study described in the subsequent

3.2.3 Case Study: Evaluating the Indirect Flexibility Available in the Predis-MHI Platform

As already indicated above, the charging stations (here it is the plugging-in and unplugging of EVs) were identified as a potential indirect flexibility that could be harnessed to provide load-shifting services for the building, the objective being to improve the building's self-consumption. Given that the building is smart and equipped with multiple sensors, the data related to the production, consumption, and EV chargers was extracted from the building's Building Management System, a summary presented in Table 3.1.

Table 3.1: Summary of Predis-MHI energy data

DATA	2020	2021	2022	TOTAL
Charger 1 demand [kWh]	614.00	2,151.05	1,122.00	3,887.04
Charger 2 demand [kWh]	1,345.00	2,940.00	2,244.00	6,538.00
Charger 3 demand [kWh]	0.00	1070.00	1750.00	2,820.00
Charger 4 demand [kWh]	0.00	446.00	1,484.00	1930.000
Total charger demand [kWh]	1,968.00	6,607.00	6,600.00	15,175.04
Predis-MHI demand (no chargers) [kWh]	13,957.00	18,874.00	20,761.00	53,592.00
Total demand [kWh]	15,925.00	25,481.05	27,361.00	68,767.04
PV Production [kWh]	20,062.00	20,910.00	22,960.00	63,932.00

There is no data related to the 50kWh battery as its role will be modeled in the MILP adhering to the technical constraints of the battery storage unit. The technical parameters used in the MILP optimization are detailed in Table 3.2. Power export to the grid and charging power (of the battery) are considered to be negative for this optimization.

Analyzing the existing behavior, which can be inferred from the time of charging (extracted from the charging station data). It was observed that the preferred time to charge was 08:00 – 11:00 AM, Figure 3.2. Figure 3.3 reiterates this and further shows that EV users plugged in the most at 09:00, this is likely the time EV users arrive on-site.

Considering Figure 3.2, it can be seen that this behavior of EV users is less than ideal, as the peak sun hours are between 11:00 and 15:00. Figure 3.2 also shows that charging took place when the building was not accessible, a plausible explanation for this phenomenon is the charging of the school's EV which remains on-site. Additionally, one of the EV users in the building arrives around 06:00 and accounts for the higher charge rates between 05:00 and 08:00.

Table 3.2: Technical parameters for the Predis-MHI use case optimization

Parameter	Unit	Value
Battery Energy Storage Unit		
Nominal capacity	kWh	50
Maximum charge	kW	40
Maximum discharge	kW	40
Maximum SOH	%	100
Minimum SOH	%	20
Efficiency	%	95
EV Chargers		
Nominal Capacity	kW	14
Start of availability	hour	8
End of availability	hour	20
Grid		
Grid connection capacity	kW	20

Figure 3.2: Charger Utilization against annual mean PV Production for the period 1st January 2020 – 31st December 2022 (3 years)

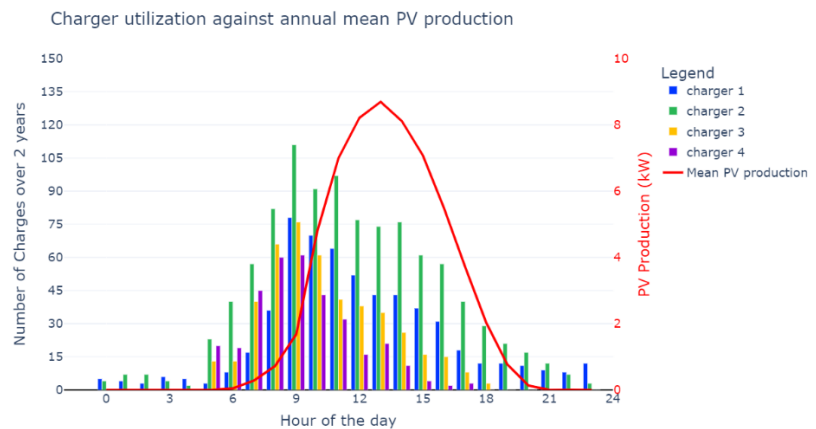
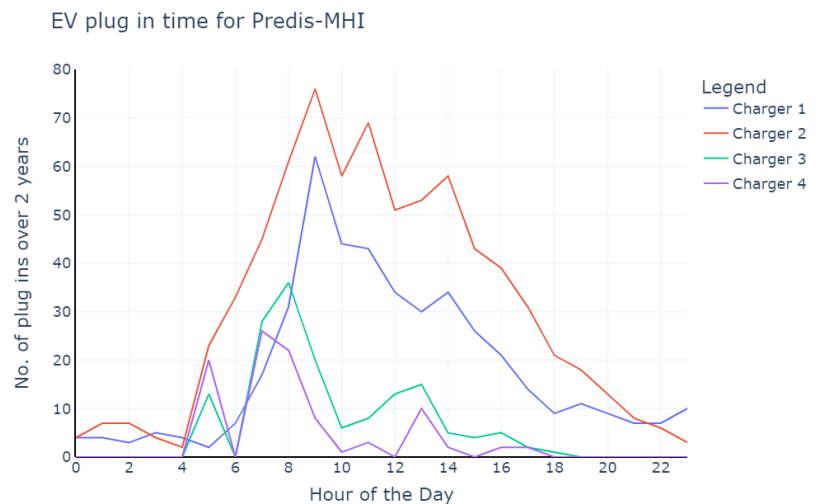


Figure 3.3: EV Plug-in time for the four chargers installed on the GreENER site for the period 1st January 2020 to 31st December 2022



Since self-consumption is the metric for evaluating the available potential for the identified indirect flexibility; an evaluation of the data (solar PV production, and demand) for the period 1st January 2020 to 31st December 2022 (3 years) show that there exists a significant potential to improve the self-consumption of the platform as shown in Figure 3.4¹⁴. This potential is at its highest during the summer months (when production is high, and demand is relatively low) and lowest during the winter months (when production is lowest, and demand is relatively high).

14: For a detailed monthly evaluation, see the Jupyter Notebook available online at: [GitLab: Indirect Flexibility Assessment](#)

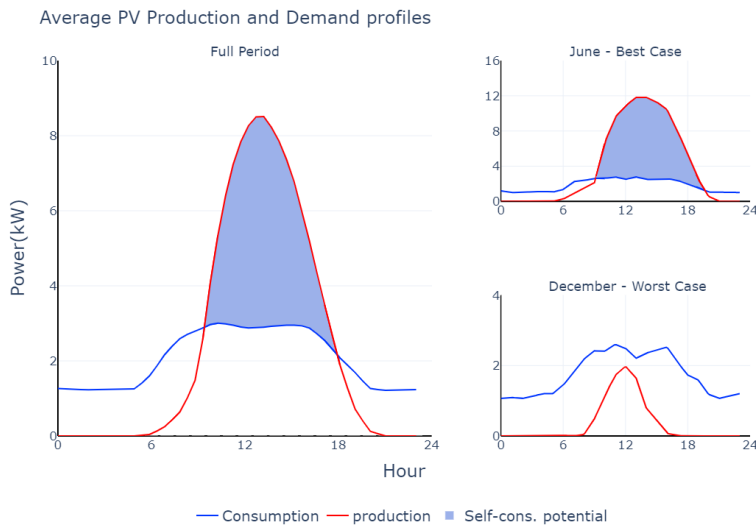


Figure 3.4: Average self-consumption potential for the Predis-MHI platform (a) Full period, (b) Best case (June), and (c) Worst case (December)

Three Scenarios were considered as follows:

- ▶ **Scenario 1 – EV chargers only (Indirect):** This scenario was intended to evaluate the full potential of the available indirect flexibility from the EV charging stations. Thus, in this Scenario, we did not consider the direct flexibility (i.e., the 50kWh battery was excluded). In this scenario, we maximized self-consumption by optimizing the charging of EVs only.
- ▶ **Scenario 2 – Battery only (Direct):** This scenario was intended to indicate the magnitude of gain associated with the use of the 50kWh battery (i.e., the direct flexibility) as a strategy to maximize self-consumption (which is the defined objective function). Thus, for this scenario, we make use of the historical demand curves for the EV charging stations and only optimized the scheduling of the battery charging and discharging to maximize the building's self-consumption.
- ▶ **Scenario 3 – Battery and EV Chargers (Indirect + Direct):** This was a hybrid scenario; for this use case, we exploited both the batteries and EV charging to maximize the building's self-consumption. The goal here is to provide an insight into how the two flexibilities would interact and provide a first

insight into how optimally dimensioned our system is in the face of the identified indirect flexibility.

Before assessing the potential indirect flexibility, the natural self-consumption of the building was evaluated for each of the 3 years in the study period to serve as a reference. The natural self-consumption was found to be 28% in 2020, 46% in 2021, and 44% in 2022. The lower performance in 2020 can be attributed to the COVID-19 confinements in France which resulted in lower energy consumption in the building¹⁵.

15: see Jupyter notebook available at [GitLab: Predis-MHI Data Analysis](#) for more details on the effect of Covid on the energy system

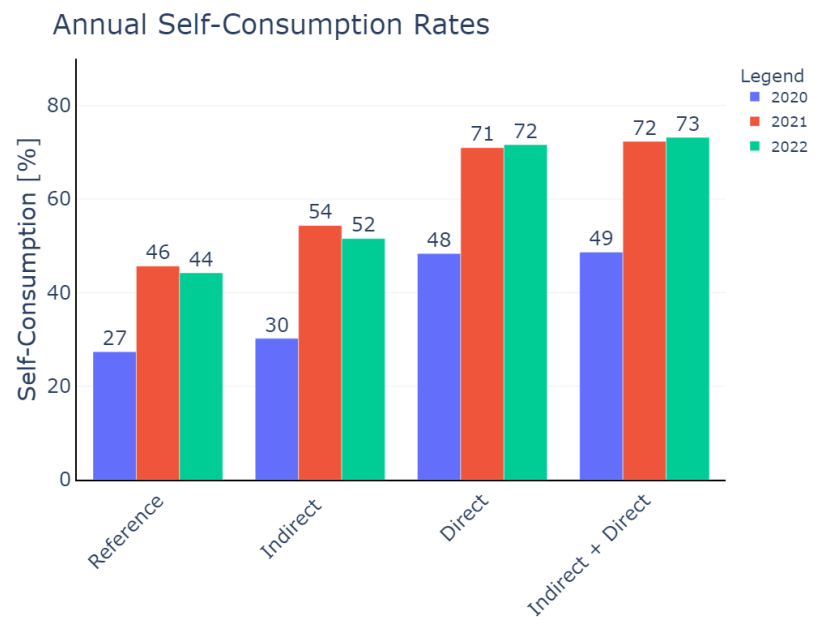


Figure 3.5: Summary of Predis-MHI self-consumption resulting from indirect flexibility potential assessment (Jupyter Notebook available online at: [GitLab: Indirect Flexibility Assessment](#))

Figure 3.5 shows a summary of the self-consumption achieved for each of the scenarios in 2020, 2021, and 2022. The results indicate that using only the EV chargers, it was possible to increase the self-consumption of the platform by approximately 2.81% (i.e., 563.94 kWh) in 2020 and approximately 8.65% in 2021 (i.e., 1,810.81 kWh) and 7.34% in 2022 (i.e., 1,687.56 kWh). In the case of the battery-only scenario, the self-consumption increased by 20.85%, 25.27%, and 27.40% for 2020, 2021, and 2022, respectively.

Combining the battery and EV charging however did not provide any significant improvement over the battery-only scenario, 0.34% and 1.36% and 1.56% in 2020, 2021, and 2022 respectively, see Table 3.3. This reduced influence (see Figure 3.5 and Table 3.3) of the indirect flexibility on the building's self-consumption (from 2.81% to 0.34% gain in 2020, 8.65% to 1.36% gain in 2021 and 7.34% to 1.56% gain in 2022) when both the direct and indirect flexibilities are mobilized in the direct + indirect scenario relative to the gains in the indirect flexibility only scenario could be the result of one of the two phenomena described below:

- ▶ Given the consumption profile and the demand of the EV chargers, the self-consumption has reached its maximum and will not be increased further even if the demand for EVs increases.
- ▶ The Battery is potentially oversized and is overcompensating, thus, not allowing for the full potential of the indirect flexibility to be realized.

A parametric study was carried out where the EV demand was increased by applying a growth coefficient) and applied to the Direct + Indirect scenario (i.e., scenario 3) and maintaining the current 50 kWh battery. The results, see Figure 3.6, show that by doubling the current consumption (applying a growth coefficient of 2) the self-consumption could be increased from 72.32% (in the reference case with a growth coefficient of 1) to 76.17%, representing a 3.85% increase in 2021 and 73.17% to 75.81% representing a 2.64% increase in 2022. The results indicate that the building's platform has not been maxed-out and consequently the battery could be oversized.

Additionally, from Figure 3.6 (b and c) it is observed that, beyond a coefficient of three¹⁶, the improvements in self-consumption provided by the EV chargers begin to plateau (i.e., the self-consumption rate has reached a point where any further significant increase would require an exponential increase in battery storage capacity).

16: The coefficient is a multiplier that is applied to the original demand curve to represent an increase in demand. Thus, 3 in this case implies using three times the original EV demand

Table 3.3: Summary of flexibility potential assessment results

Year	Reference Self-consumption [%]	Optimal Self-consumption [%]	Gain from reference scenario [%]	Gain from direct only scenario [%]
Indirect Flexibility only				
2020	27.38	30.20	2.81	-
2021	45.68	54.34	8.65	-
2022	44.21	51.56	7.34	-
Direct Flexibility only				
2020	27.38	48.24	20.85	-
2021	45.68	70.96	25.27	-
2022	44.21	71.61	27.40	-
Direct + Indirect Flexibilities				
2020	27.38	48.54	21.15	0.30
2021	45.68	72.32	26.64	1.36
2022	44.21	73.17	28.96	1.56

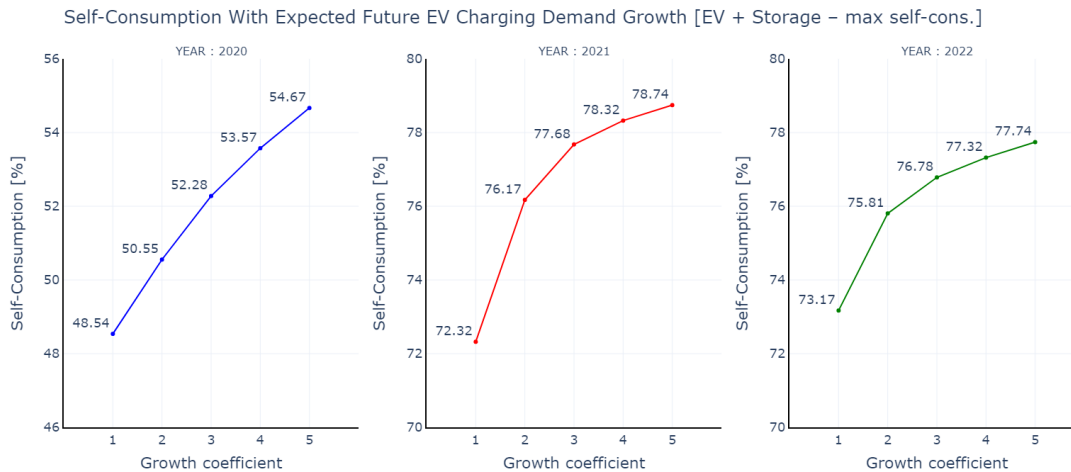


Figure 3.6: Sensitivity of Predis-MHI’s self-consumption to growing EV demand (i.e., the indirect flexibility) considering the use of both the direct and indirect flexibilities (i.e., scenario 3) for (a) 2020, (b) 2021 and (c) 2022 (growth coefficient is a multiplier applied to the existing EV demand) (Jupyter Notebook available online at: [GitLab: Indirect Flexibility Assessment](#))

3.3 Mobilizing Indirect Flexibility for the Optimal Dimensioning of Stationary Battery Energy Storage Systems

From the assessment carried out in chapter 3.1.3, we concluded that the battery was potentially oversized. This was not a far-fetched conclusion since the sizing was done following sizing methodologies proposed in literature such as [26, 92, 94] which do not take into account any indirect flexibilities. These approaches typically take into account the load and available on-site RER production and apply optimization over a given horizon to arrive at an optimal size. In most cases, the demand is not disaggregated, and this approach yields good results. In the case of Predis-MHI (which is a smart building), the demand is disaggregated, and it is possible to take into account any identified indirect flexibilities.

To account for indirect flexibility, it is prudent to first account for the dynamics associated with the problem. In most cases, there will be two-time scales, the shorter time scale which accounts for the human interest in using the device associated with the indirect flexibility, and the longer time scale which will consequently affect the optimal size of the battery (or direct flexibility being sized). Thus, there is a need to apply a time-scale decomposition method as was applied by Radet et al [121].

3.3.1 Case Study: Considering Indirect Flexibility for the Optimal Sizing of a Battery for Predis-MHI

A MILP approach that builds on the formulation defined in chapter 3.2.2 was developed. For this sizing, the objective function was defined as:

$$\text{objective} = \min[Cap_{\text{bat}}] \quad (3.12)$$

Where Cap_{bat} is the battery capacity. Since the optimization here has two distinct time scales (in this case 1 day and 1 year – 365 days) eqns 3.2 to 3.10 were modified such that they accounted for these two time scales. For example, eqn 3.2 was modified based on the decomposition method used in [121] such that [125]:

$$SOC_{\text{Min}} \times Cap_{\text{bat}} \leq E_{\text{bat}}(pd, t) \leq SOC_{\text{Max}} \times Cap_{\text{bat}} \quad (3.13)$$

Where pd is the long-term time scale (i.e., 365 days), referred to as the period, and t represents the short-term time scale (24 hours) referred to as the timestep. Because there was a need to ensure continuity over the entire long-term horizon for the battery in terms of SOH (i.e., the energy in the battery), the starting energy in the battery for each sub-horizon (short-term problem) was formulated as:

$$E_{\text{bat}}(pd, t) = \begin{cases} E_{\text{bat initial}}, & \text{if } pd = 0 \text{ and } t = 0 \\ E_{\text{bat}}(pd - 1, T + 1), & \text{if } pd > 0 \text{ and } t = 0 \end{cases} \quad (3.14)$$

Where $E_{\text{bat}}(pd - 1, t)$ is the energy in the battery and T is the final step of the previous period, $pd - 1$ and $E_{\text{bat initial}}$ is the energy at the start of the optimization (i.e., $pd = 0$ and $t = 0$) and is denoted by:

$$E_{\text{bat initial}} = E_{\text{bat}}(0, 0) = E_{\text{bat}}(PD, T) \quad (3.15)$$

Where PD is the final period in the set of periods defined as $\{0, 1, 2, \dots, PD\}$. The starting SOH for any period except the initial period 0 is the final SOH for the previous period $pd - 1$, denoted by $E_{\text{bat}}(pd - 1, T + 1)$.

Because self-consumption is a metric for evaluating this sizing, a target self-consumption was added to the optimization as a constraint and defined as:

$$SC_{\text{target}} = \frac{\sum_{pd}^{PD} \sum_t^T P_{\text{load}}(pd, t) - P_{\text{import}}(pd, t)}{\sum_{pd}^{PD} \sum_t^T P_{pv}(p, t)} \quad (3.16)$$

Thus, the optimal battery size should yield a self-consumption rate equal to the target provided as an input.

17: Lower threshold determined by the natural self-consumption and the upper determined by the plateau depicted in Figure Figure 3.6

Based on the problem formulation detailed above, two optimizations were run, the first only considered the battery as a flexibility and followed conventional sizing, whilst the second included the EV chargers as an indirect flexibility. This study considered the period 1st January 2021 to 31st December 2021 and considered target self-consumption rates from 44% to 78%¹⁷, and considered the same technical parameters listed in 3.2.

Table 3.4: Summary of battery sizing results using the direct only (conventional) and the proposed direct + indirect approaches

Target self-consumption [%]	Battery Capacity - Direct Flexibility only [kWh]	Battery Capacity -Direct and Indirect Flexibility [kWh]	Capacity Difference [kWh]	Percentage Reduction Achieved [%]
46.00	0.19	0.00	0.19	100.00
48.00	1.50	0.00	1.50	100.00
50.00	3.07	0.00	3.07	100.00
52.00	4.77	0.00	4.77	100.00
54.00	6.65	0.00	6.65	100.00
56.00	8.65	1.54	7.11	82.17
58.00	10.84	3.77	7.08	65.25
60.00	13.28	6.16	7.13	53.66
62.00	16.21	8.64	7.56	46.65
64.00	19.76	11.37	8.38	42.43
66.00	24.00	14.63	9.36	39.02
68.00	29.49	18.99	10.51	35.62
70.00	36.49	25.57	10.92	29.92
72.00	46.05	37.54	8.51	18.49
74.00	61.34	55.59	5.74	9.37
76.00	86.84	81.26	5.58	6.43

The results as depicted in Figure 3.7 and summarized in Table 3.4 reiterate the results of the assessment carried out initially in chapter 3.2.3. From Figure 3.7 it can be seen that for a target self-consumption of 54%, the conventional approach required a 6.65 kWh battery whilst the proposed method required 0 (Zero) kWh. Further, to achieve a 70%¹⁸ self-consumption, the direct-only

18: 70% was chosen as it represents the point with the highest difference in capacity between the 2 approaches

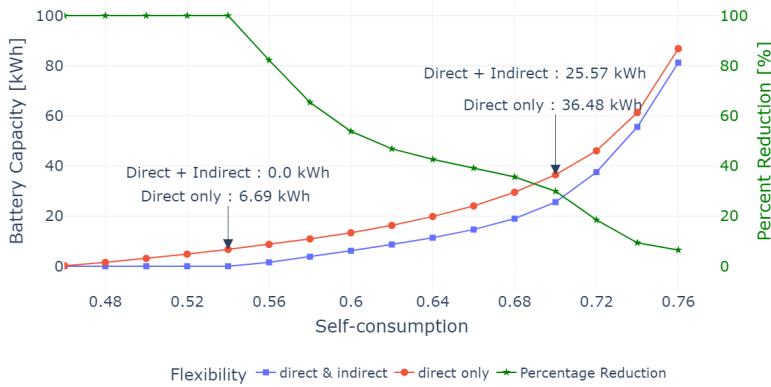


Figure 3.7: Optimal sizing of battery for Predis-MHI using direct flexibility only (red curve), direct and indirect flexibilities (blue curve), and the associated percentage reduction in battery capacity (green curve). (Jupyter Notebook available online at: [GitLab: Optimal Battery Sizing](#))

approach resulted in a battery size of 36.49 kWh whilst the direct + indirect approach resulted in a relatively smaller battery size of 25.57 kWh (representing a reduction of 29.92% in the required battery capacity).

Further, by applying the battery capacities resulting from these two strategies to the EV charger and battery scenario (scenario 3) in chapter 3.2.3 and studying the optimal charging behavior proposed by the optimizer, we see that having the smaller battery capacity implies less flexibility in terms of human behavior in order to achieve the set target of 70% (see Figure 3.8, where indirect + direct requires more charging at peak sun hours).

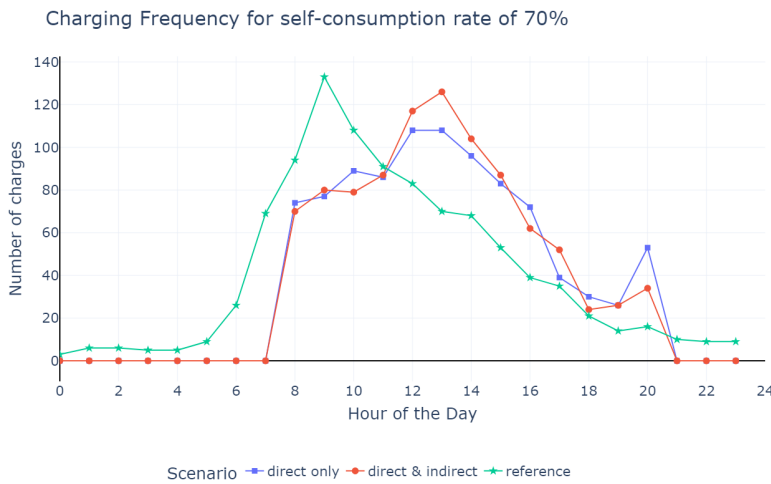


Figure 3.8: Comparison of charging frequency for direct only and direct & indirect sizing strategies (target self-consumption rate=70%) using both direct and indirect flexibilities for optimizing the Predis-MHI building’s self-consumption. (Jupyter Notebook available online at: [GitLab: Optimal Battery Sizing](#))

💡 Highlights:

- ▶ Mobilizing Indirect flexibility has little to no costs associated, thus, for Predis-MHI we could improve our self-consumption from approximately 46% to 54% (considering 2021) using only human behavior and therefore avoid a substantial financial investment.
- ▶ Since this flexibility is highly dependent on the behavior of humans in the control system, its performance is not guaranteed and consequently, a hybrid system with both direct and indirect flexibilities is recommended.
- ▶ For our use cases, we considered self-consumption as the key metric of evaluation. Other metrics such as Carbon emissions, self-production, and financial cost can also be used (the proposed methodology is not restricted to self-consumption).

3.4 Conclusion

In this chapter, we identified EV chargers, particularly the plugging-in and the unplugging of EVs as a potential indirect flexibility. In this instance, the human actor is the driver (i.e., owner of the EV) who is required to plug in their vehicle to charge it and unplug it to stop the charging as a load-shifting service to the building with the goal of maximizing the use of energy from the on-site 22 kWp solar PV system. Building on this idea, we proposed a methodology for assessing and quantifying the indirect flexibility potential using self-consumption as an evaluation metric. Self-consumption is, however, an effective metric for scenarios where a solar PV system already exists.

Whilst the evaluation of available potential and sizing were evaluated using self-consumption, the Net Energy Exchanged with the Grid was considered more effective as an objective function. The proposed methodology can, however, be applied using different objective functions and is not limited to the self-consumption metric, for example minimizing the carbon impact related to the building's energy use and is not restricted to usage in tertiary buildings only.

Additionally, a new approach to sizing direct flexibilities, in particular battery storage was also proposed. This approach considers the available indirect flexibility and was found to reduce the need for high storage capacity.

The Predis-MHI was considered a tertiary building and used as a case study for the proposed approaches. We found that the building's self-consumption could be increased by up to 9% using indirect flexibilities only. This was particularly interesting since it meant no financial investment from the building owner, cheaper or no cost energy for charging the EV (benefit for the EV user), and a reduction in the carbon intensity of the building's operations. With regards to the sizing of the battery, we found that depending on the self-consumption target set the battery size could be reduced by up to 100% (typically only using the indirect flexibility). For a self-consumption rate of 70%, the reduction achieved was 30.15%, in this case, this meant a 30% reduction in the financial and carbon cost related to the acquisition of the battery.

Whilst the proposed methods utilize the available indirect flexibility, they do not fully account for the "human-in-the-loop" since they assume 100% compliance. In reality, this might not be the case and the system may not be able to reach this theoretical optimum. This can however be mitigated by implementing strategies to influence humans toward the desired optimal such as nudges and feedback using indicators.

In this chapter, we have addressed two of our research questions:

- ▶ How does one validate the available potential and quantify the impact of the identified indirect flexibility on the energy performance of a building?
- ▶ Given the availability of a quantifiable indirect flexibility in a building, do current battery sizing approaches ensure an optimal sizing of direct flexibilities in the said building?

To follow up on this, chapter 4 will deal with the topic of direct flexibilities in buildings, particularly battery storage. The focus will be on control strategies for harnessing direct flexibilities at the building and community scale.

Gitlab Repository

The code and associated notebooks for the solutions proposed in this chapter can be found in the following repositories:

1. Assessment of indirect flexibility potential: [GitLab: Indirect Flexibility Assessment](#)
2. Sizing of direct flexibility (stationary BESS) with consideration for indirect flexibility: [GitLab: Optimal Battery Sizing](#)

Additionally, see Appendix B.1 for a list of all available notebooks

Direct Flexibility for Individual and Collective Self-Consumption

4

This chapter delves into the control of direct flexibility particularly centered on battery storage systems, which are direct flexibility often used at the building scale (both residential and non-residential). We delve into the topic of control complexity and further demonstrate using our experimental setup that a complex control scheme is required for the efficient and effective control of our battery storage system. We go a step further to propose a Machine Learning based Model Predictive Controller (ML-MPC) for the battery system.

4.1 Introduction: Battery Storage as a Building Scale Direct Flexibility

Given the uptick in demand for clean and sustainable energy sources and the consequent pivot towards a decentralized energy system, buildings (i.e., end nodes within the electrical network) play a crucial role in the transition towards RERs (see chapter 1). A new paradigm shift has emerged which pivots buildings to the forefront of the future energy network. The role of the building has shifted from a strict consumption role to that of a prosumer (i.e., buildings can now be producers and consumers) with distributed energy resources being one of the key factors influencing this pivot.

While RERs offer a cleaner and more sustainable alternative to fossil fuel-based energy sources, their availability and productivity are often susceptible to external and often uncontrollable factors (particularly the weather). Thus, to have a resilient and efficient electric grid, storage systems at all levels of the network are needed.

At the Building scale, Battery storage is one of the most frequently used energy storage options as it is compact and relatively simple to operate. For the most part, battery storage is highly controllable and capable of effectively dealing with the intermittency problems often associated with RERs (solar PV and wind in particular). Additionally, battery energy storage systems serve as an enabler for active participation in demand-side energy flexibility, are capable of providing other ancillary services for the grid and can be used as a backup system for critical infrastructure.

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4.3	Control Strategies for Battery Energy Storage Systems	55
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4.5	Conclusion	82

This chapter focuses on direct flexibilities at the building scale, specifically emphasizing battery storage. Thus, in this chapter, we seek to address our third research question:

SQ.3

“Given an energy system, what is the appropriate level of complexity and computational cost that ensures optimal and efficient use of a battery energy storage system?”

As was the case in chapter 3, we considered the self-consumption indicator as our evaluation metric for the performance of the building. Thus, we consider the battery as a means of increasing the utilization of the on-site solar PV energy and delve into the topic of effective control of direct energy flexibilities

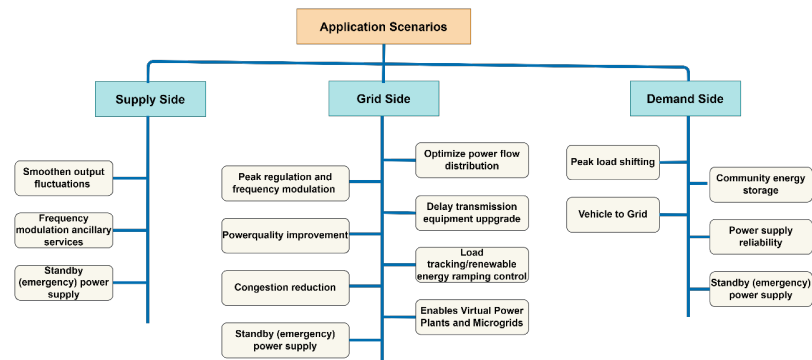


Figure 4.1: Application scenarios for battery energy storage systems at different parts of the energy system (source [126])

4.2 Battery Energy Storage Systems: a Conduit for Direct Energy Flexibility

To address this emerging need for storage, several storage technologies have been developed (and still many are being developed), see Figure 1.12. Chemical energy storage (i.e. battery storage), has emerged as the most favored storage technology (especially with the recent development of higher-energy dense Lithium-based batteries and the increased proliferation of EVs), particularly at the lower levels of the grid (buildings, districts, cities, etc) and in micro and nano grids [127], see Figure 4.1 for application scenarios. Two battery chemistries are usually utilized for most power applications: lead-acid and lithium-ion batteries. Table 4.1 details a comparison of the two technologies (valve-regulated lead acid and lithium iron phosphate batteries) based on four criteria; efficiency¹, cost, life cycle, and charging/discharging performance [128].

1: Efficiency here referring to the ratio of energy discharged from the battery to the energy charged into the battery

Whilst EVs are essential and effective for decarbonizing the transportation sector and have effectively contributed towards the rapid

Table 4.1: Comparison of valve-regulated lead acid battery and lithium iron phosphate battery chemistries (source: [128, 129])

Metric	Valve Regulated Lead Acid Battery	Lithium Iron Phosphate Battery
Efficiency	Low efficiency (55% - 75%) at low C-rates (0.25 - 4). A self-discharge rate of approximately 0.1% per day at an operating temperature of 25°C	High efficiency 88% - 98% for low C-rates of between 0.25 and 4. Self-discharge rate of approximately 0.01% per day at a standard operating temperature of 25°C.
Life Span	Expected lifetime of 2-5 years depending on the depth of discharge Longer life span	Expected lifetime of 12-16 years at 100% SOC and standard working temperature of 25°C which can be extended to 20-25 years considering a 50% SOC.
Charging/ Discharging performance	A comparably lower number of charge/discharge cycles to reach its end of life. Efficiency deteriorate when discharging at higher current rates Slower charging as the charging is usually around 0.25C	A higher number of charge/discharge cycles (at least by a factor of 2 times that of lead acid) Efficiency is sustained when discharging at high current rates Can be charged at much faster speeds (>1C)
Financial Cost	Can safely be charged at lower temperatures (as low as -20°C at a maximum current rate of 0.3C) Lower initial capital cost. However, for long-term applications, the total cost per kWh of storage is higher owing to factors such as efficiency and lifespan	Not possible to charge at temperatures lower than 0°C as irreversible damage happens on the anode. Higher initial capital cost, considering long-term applications, the total cost per kWh of storage is relatively lower due to factors such as efficiency and lifespan.

development of battery technology, there is still the question regarding their end of life. In most cases, these batteries can be repurposed as storage for use in alternative and less demanding operations (second-life battery usage) [73]. In any of such applications (second-life or new) there is the need to operate the battery in a manner that encourages the longevity of the battery and does not pose any danger to the immediate environment where the battery is installed (this includes humans and property).

4.3 Control Strategies for Battery Energy Storage Systems

Depending on the battery chemistry and application scenario, different control strategies can be applied. Some battery chemistries (such as lithium-based chemistries) require a Battery Management System (BMS) to ensure they perform optimally and safely. BMSs are however essential in the face of multiple battery packs being

combined to be used as one large pack. This is necessitated since batteries are dynamic in nature and are constantly operating outside their equilibrium state during cycling [130]. The BMS (Figure 4.2) is often the first layer of control (and in many applications the only one) and can be simple, smart, or predictive/adaptive (these are essential for large battery packs utilized in applications such as EVs and grid integration [131]) [130].

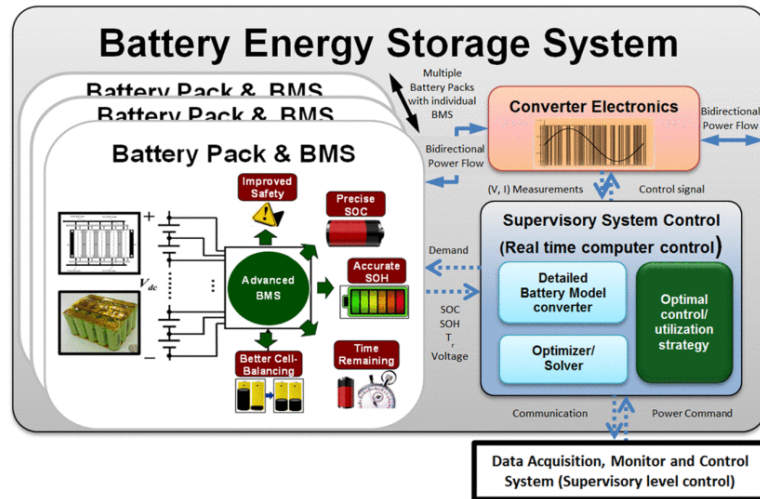


Figure 4.2: General schematic for Battery Energy Storage System (BESS) based on a battery pack managed by a Battery Management System (BMS) (source: [130])

However, irrespective of the existence of a BMS, the charging and discharging actions of the battery have to be controlled to reach a set objective while ensuring the efficient and safe functioning of the battery storage system. At the grid scale, the available battery storage may not be available in a central location but might be distributed (cited in different locations,). Thus, there is a need to coordinate these battery storage resources in order to maximize the potential benefit of having them. Alternating Direction Method of Multipliers [132] is one of the most frequently used approaches used for the coordinated and optimal control of these distributed storage resources [126]. This optimization approach divides the problem into a set of sub-problems and solves the local problems with the global objective in view. Additionally, such distributed battery storage resources can be controlled using the consensus-based method which in itself is based on the consensus protocol [133].

Distributed storage systems can in fact be found and managed at all levels of the grid, for example in different houses of a community, or in different apartments within the same building. However, in this thesis, since our boundary is limited to the community scale, we focus on the management of a single storage resource particularly at the building and community scale. For this purpose, we identified two control mechanisms that are applied to battery storage systems

at the building and community levels, the rule-based (heuristic) control and Model Predictive Control (MPC).

4.3.1 Rule Based Control

As the name implies, this is a control approach that utilizes a set of predefined rules to direct decisions in order to achieve a set objective. This approach is particularly useful for problems that are simple in nature and do not warrant the computational cost of complex control algorithms. Given that this approach is based on predefined rules, there is a possibility that these predefined rules are not adequate (for example, in the face of seasonal variations) and as such do not guarantee an optimal solution. Additionally, in the face of the increasing complexity of the control problem, such a rule-based approach will also increase in complexity and there is an elevated risk of further deviating from the set of optimal solutions.

Rule-based control schemes typically require that some rules be put in place to respect the technical constraints of the system being controlled. For batteries, these parameters are, the State of Charge (SOC), the charging and discharging power limits, and the depth of discharge of the battery [134]. In addition, rules that are focused on delivering the desired objective also need to be put in place. Salpakari and Lund [135] applied such a rule-based control algorithm to maximize the self-consumption of a low-energy house in southern Finland over a one-year horizon. Their application considered flexible (shiftable) loads and used battery and thermal energy storage systems for storing excess energy.

A comparison of the rule-based with a dynamic programming-based² optimization approach showed that the optimization-based approach performed significantly better than the rule-based approach [135]. Figure 4.3 (a) shows that the optimization-based approach resulted in a 13 – 15% reduction in electricity cost relative to the reference whilst the rule-based only achieved a 0 – 2% reduction relative to the reference. Further, Figure 4.3 (b) also shows a reduction in export of between 36% and 88% in the case of the optimization-based approach and 18% and 88% in the rule-based control approach.

The results here indicate that either the rule-based approach as was used was not sufficiently defined to deal with the dynamics of the system or the problem warranted more complex algorithms that could handle both long-term and short-term constraints optimally.

2: The underlining principle behind the theory of dynamic programming is that of viewing an optimal policy as one determining the decision required at each time in terms of the current state of the system.

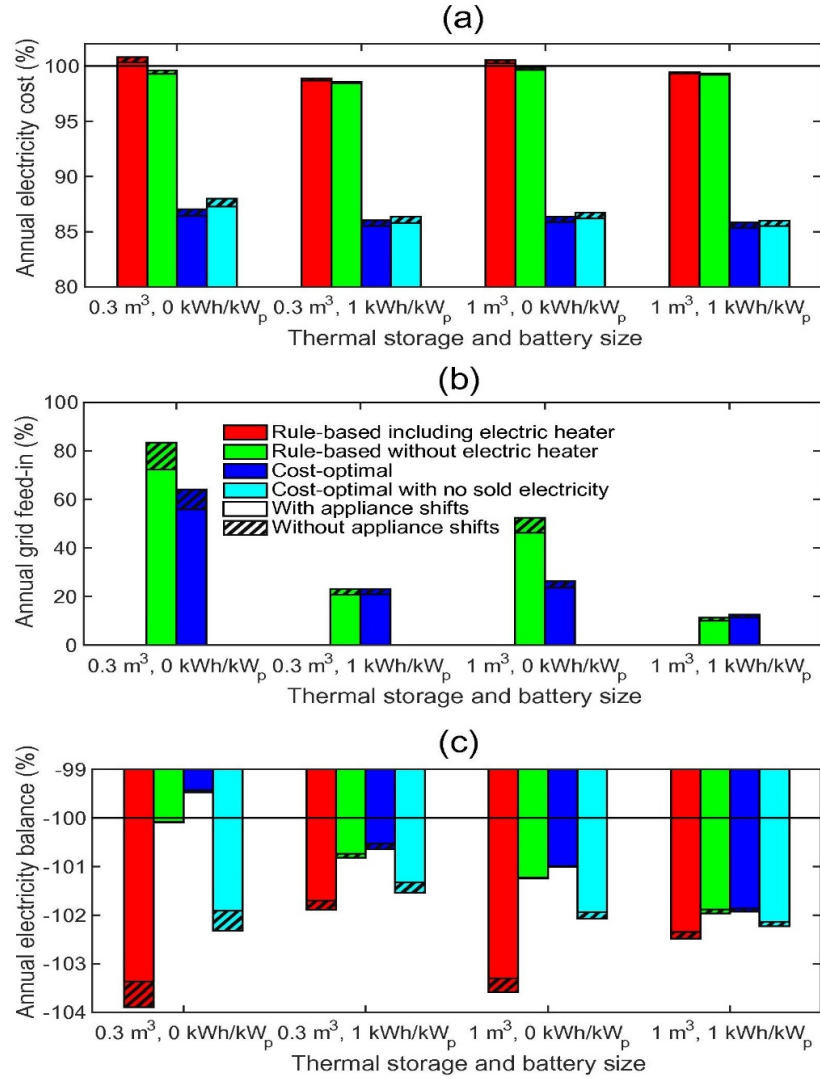


Figure 4.3: comparison of a rule-based control with dynamic programming based approach for the control of a building's energy system (3kW_p solar PV, with varying thermal (in m³) and battery (in kWh) storage of varying capacities – see x-axis) based on (a) the percentage difference in annual electricity cost relative to the reference case and (b) the percentage difference in annual grid feed-in (export from the building) relative to the reference case (Source: [135]).

4.3.2 Model Predictive Control: A State of the Art

Model Predictive Controllers (MPCs) are advanced control mechanisms that are based on a predictive model of the system to be controlled and are applied to dynamic systems to minimize a cost function over a finite, receding, horizon [136]. Holkar et al [137] in their description of an MPC state that, "MPC uses the range of control methods, making use of an explicit dynamic plant model to predict the effect of future reactions of the manipulated variables on the output". The basic concept of an MPC (see Figure 4.4) can be outlined in four steps, these are [137]:

1. Predict the future state of the system using a representative model of the system to be controlled.
2. Based on the predicted state, estimate a control input that minimizes the cost function.
3. Send the control signal and measure the output of the system as feedback

4. At each timestep, the horizon is moved towards the future by one timestep (a receding horizon strategy) and consequently a control signal is calculated (steps 1 – 3).

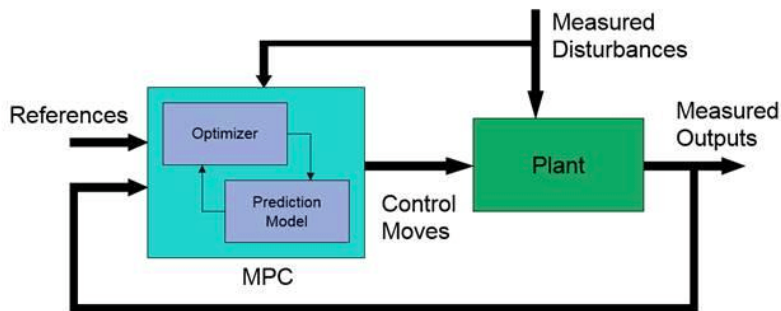


Figure 4.4: Basic control loop of a Model Predictive controller (MPC) – the plant is the system to be controlled (source: [136])

MPCs allow for the optimal control of more complex and dynamic systems. These dynamic systems are often represented using state space³ representation. State space is often considered for representing the physical system as it can comprehensively and concisely represent the dynamics of the system, allowing for the mathematical representation (using first-order differential equations) of both the internal states and the input–output relationship of the system (this allows for estimating of the system’s future state) [138].

Following this strategy, Gonzalez et al [139] in their works proposed a state space model-based MPC to control a hybrid power plant for a building which was composed of a 20.88 kWp solar PV, a 14.4kWh battery, and a hydrogen fuel cell with a nominal power output of 3.2kW (with associated electrolyzer and hydrogen tank), see Figure 4.5(a). The controller’s objective was to maximize the building’s self-consumption whilst considering the lifespan of the individual components. Their proposed MPC used the battery to deal with fast-changing variability from the demand and production whilst the hydrogen fuel cell was used for slower variations, see Figure 4.5(b).

In recent times, robust and effective Machine Learning (ML) algorithms that are capable of dealing with non-linear problems have been developed and have consequently led to the development of machine learning-based MPCs [140]. For example, Martin et al [141] applied ML algorithms for daily energy solar energy prediction using weather models, similarly, Robinson et al [142] also used ML algorithms to forecast the demand of a commercial building whilst Amayri et al proposed an ML-based approach to characterize available flexibility from residential buildings using aggregated consumption data collected using smart-meters with low-sampling rates. Building on these applications of ML to non-linear problems, Cai et al [140] applied an ML-based MPC for the control of a pumped storage system (made up of a pump-turbine, a generator, a penstock, and a servo mechanism). The ML-MPC

3: The state-space representation is a mathematical model of a physical system with the input, output, and state variables composed by first-order differential equations. The state-space representation gives a suitable and compact way to model and analyze systems with multiple inputs and outputs.

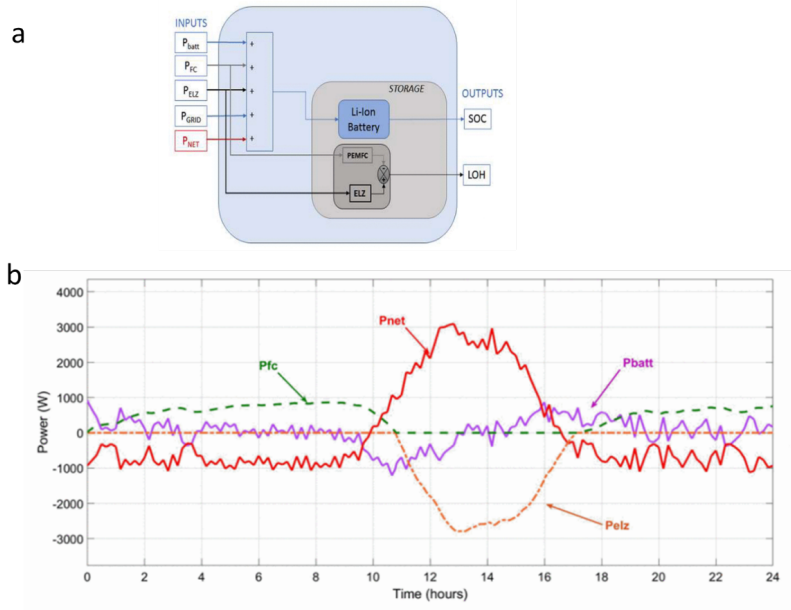
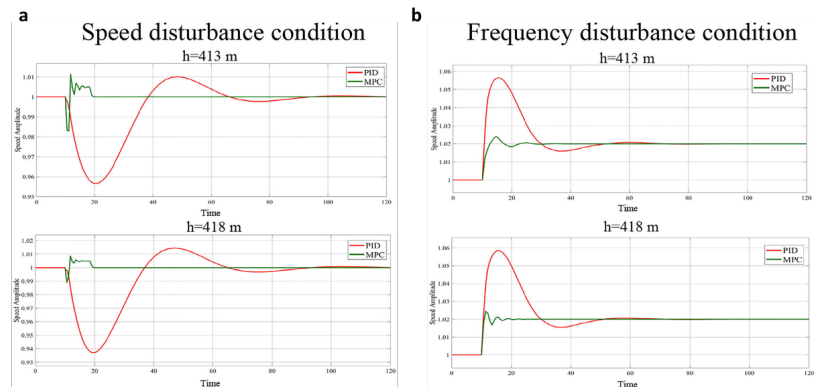


Figure 4.5: (a) block diagram representation of hybrid power plant controlled using MPC by Gonzalez et al (b) typical sunny day results applying the MPC to the energy system, where P_{batt} , P_{FC} , P_{ELZ} , P_{Grid} , and P_{NET} are the power of the battery, fuel cell, electrolyzer, grid, and a disturbance term respectively. LOH and SOC are the level of hydrogen and state of charge respectively) (source: [139]).

structure was decomposed into three parts, the controlled system, the data collection component, and the control component.

Figure 4.6: comparison of the system response for the machine learning based model predictive controller (ML-MPC) and a proportional integral derivative (PID) controller applied to a pumped storage system with different water heads (h). (source: [140])



Four ML models based on Koopman theory were developed and used for each of the individual components of the system and the results show that the proposed ML-MPC performed better in comparison with a PID controller applied to the same setup given a speed and frequency disturbance as illustrated in Figure 4.6 (a) and (b) respectively.

We have thus shown that model predictive controllers are effective for managing energy systems and that both state space-based (white box approach) and machine learning-based (black box approach) are effective tools to be utilized for such a control strategy. In the following sub-chapters, we will demonstrate the need for an optimal control strategy and advance to a real-life implementation of an ML-MPC for the experimental setup.

4.3.3 Maximizing self-consumption for the predis-MHI platform: a comparison of rule-based with an optimization-based energy management control strategy

As highlighted in the previous sub-chapters (4.3.1), rule-based energy management strategies are typically effective for simple problems. To demonstrate this, and highlight the need for an optimization-based energy management approach for the experimental setup (i.e., Predis-MHI), we compared a rule-based strategy to an optimization-based approach (this could be considered as an MPC with perfect prediction) for the 2021 period. In this use case, the indirect flexibility was not considered (i.e., no shiftable loads), thus only the direct flexibility (50 kWh battery) was considered for improving the platform's self-consumption, see Figure 4.7.

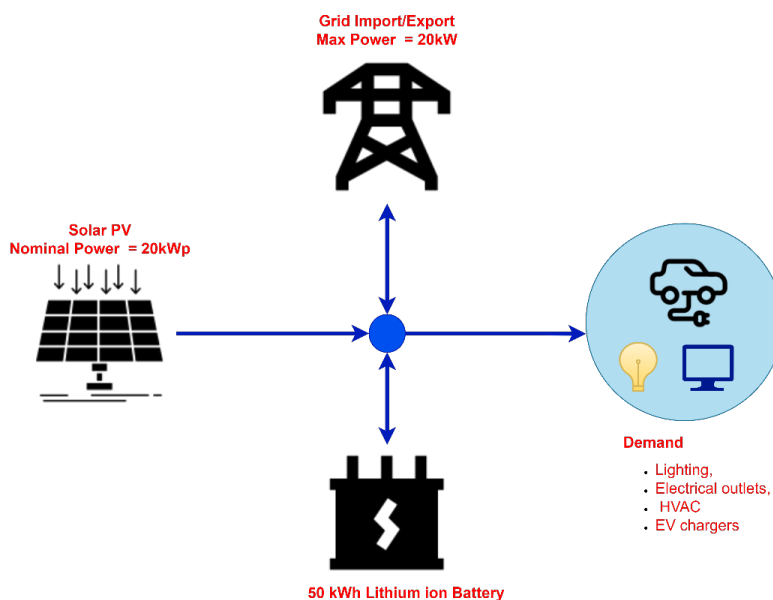


Figure 4.7: Graphical representation of the Predis-MHI platform as considered for the control strategy comparison study

The rule-based method prioritized local consumption of the onsite production and is outlined below (a flow diagram of the method is depicted in Figure 4.8):

1. If there is energy from the solar PV panels, it is first fed to the load.
2. If any excess exists (i.e., PV energy exceeds the demand), the excess is stored in the battery.
3. If all or part of this excess energy directed towards the battery cannot be stored in the battery due to physical constraints of the battery (battery at capacity or charging power exceeded) then any further excess is exported onto the grid
4. If the solar PV is not sufficient to supply the load, energy is taken from the battery to make up for the difference. Energy

is subsequently imported from the grid if the solar PV and storage system cannot supply the demand.

5. If there is no solar PV production, energy is taken from the battery to supply the load. If the battery cannot meet the demand, the proportion of the demand not satisfied by the battery is imported from the grid.

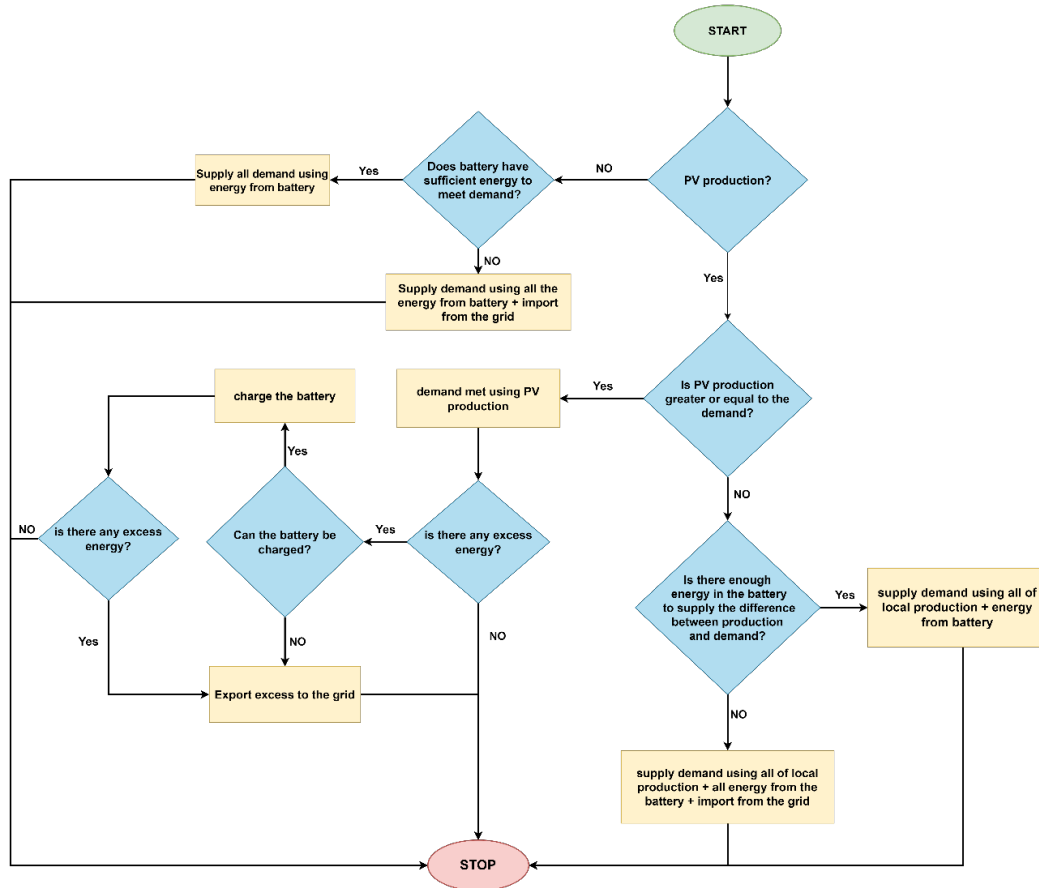


Figure 4.8: Flow diagram of rule-based energy management approach for maximizing the self-consumption rate of the Predis-MHI platform.

For the optimization-based approach, we considered an MPC with perfect prediction with a Mixed Integer Linear Programming optimization as proposed in chapter 3.2.2.

The MILP was represented mathematically using eqns 3.1 - 3.7 and eqn 3.10.

Computing the self-consumption on a monthly basis as depicted in Figure 4.9, the results show that the optimization-based approach does not have a significant advantage over the rule-based approach. The improvements (see the Jupyter Notebook available at: [GitLab: Comparison of control strategies](#)) were negligible and did not warrant the complexity or added cost of adopting an optimization-based approach. Thus, it can be inferred that for a problem of similar complexity (as the system in Figure 4.9), a rule-based solution is

effective, and complex algorithms would not be merited.

However, since our use case involves the use of shiftable loads (indirect flexibilities) as was the case in [135], an MPC is warranted and consequently described in the subsequent sub-chapter.

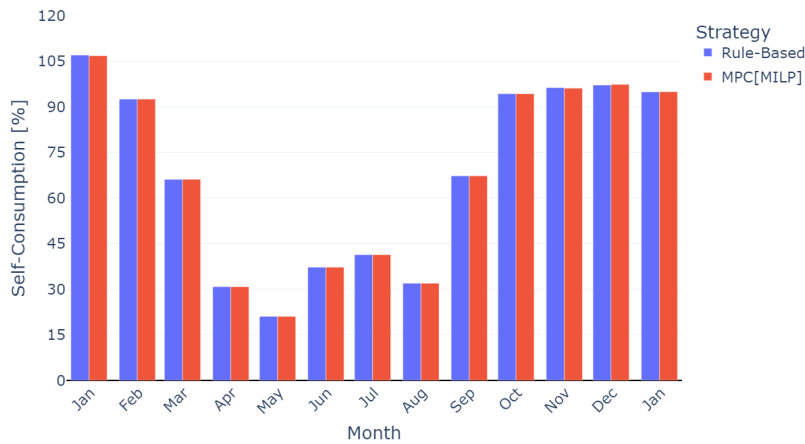


Figure 4.9: Comparison of a rule-based energy management strategy with an MPC (considering perfect prediction) for the Predis-MHI platform using monthly self-consumption as a metric (available online at [GitLab: Comparison of control strategies](#))

💡 Highlights:

- ▶ Rule-Based control may be effective for simple systems such as the one described in Figure 4.7. However, it is important to note that for this approach, the defined rules must capture all possible scenarios; long, medium, and short-term. This can become increasingly difficult as the system increase in complexity.

4.4 Optimal Mobilization of Direct Flexibility using a Machine Learning Based Model Predictive Controller

Building on the discussions on Model Predictive controllers in sub-chapter 4.3.2, MPCs are capable of effective control by utilizing optimization and prediction models. In this sub-chapter, we consider our experimental setup (i.e., the Predis-MHI platform), with emphasis on the direct flexibility (i.e., the 50-kWh battery) which due to legislative constraints pertaining to occupant safety necessitated an off-site installation. The installation of the battery in another geographical location (i.e., another building of the university in a different district of the city) implies that the battery would have to be operated using an energy community model (the grid would have to be used to allow for the sharing of the delivery of energy between the two buildings).

We propose a predictive control approach to optimize the scheduling of the battery as well as the charging of EVs (i.e., the indirect flexibility), utilizing Machine Learning (ML) models for forecasting and MILP as an optimizer. Figure 4.10 provides a visual representation of the framework of the proposed MPC.

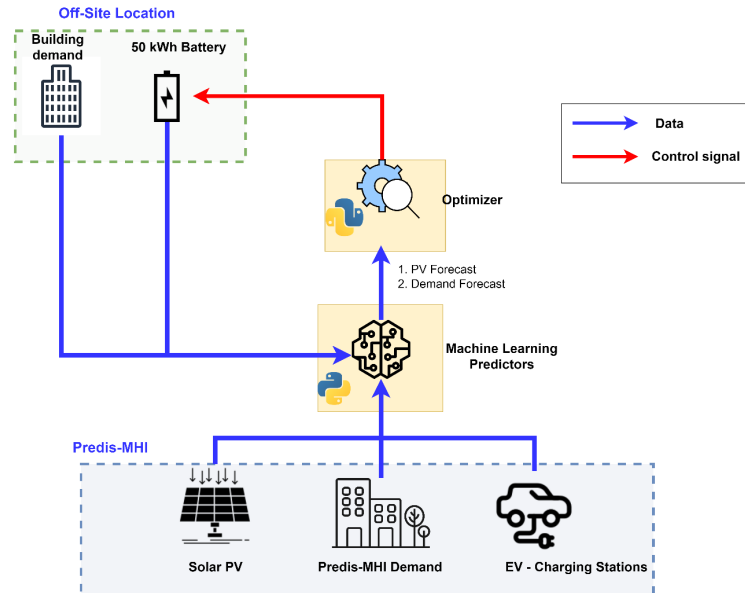


Figure 4.10: Framework of proposed Machine learning based Model Predictive Controller

The (ML-MPC) described in Figure 4.10 requires the prediction of the demand profile of the Predis-MHI platform and the production profile of the solar PV system. The ML methods for forecasting these profiles are discussed in the next sub-chapter.

4.4.1 Forecasting Demand and Production profiles for Predis-MHI

Machine learning techniques have in recent times been effectively used for electricity consumption and solar PV profile forecasting as demonstrated in [141–144]. As previously highlighted, the proposed ML-MPC would require forecasts of both the production and demand (the building and EV Charging station profiles). For this application, we employed supervised learning techniques which have been defined by Cunningham et al [145] as “learning a mapping between a set of input variables X and an output variable Y and applying this mapping to predict the outputs for unseen data”.

Load and solar PV forecasting approaches can be classified into 3 main groups, based on the prediction horizon, which is consequently determined by their functionality and purpose, these three groups are [146]:

1. Short-Term Load Forecasting: these are predictions that are made for a time horizon of one week ahead or less and are

typically applied to real-time control and security assessment in electric utilities.

2. **Medium-Term Load Forecasting:** this approach considers a horizon greater than one week but less than one year and is applicable for maintenance scheduling, coordination of load dispatch, and price settlement in electrical networks.
3. **Long-Term Load Forecasting:** This approach focuses on a horizon greater than a year and typically has applications in the planning of electric grid infrastructure.

Since our application considers a horizon of 24 hours, we will focus on Short-Term Load Forecasting approaches. For this purpose, we considered supervised machine learning approaches for forecasting the solar PV production, building demand, and EV charger demand as discussed below

- ▶ **Extreme Gradient Boosting (XGBoost):** XGBoost, a supervised learning ML approach, is a scalable and efficient implementation of the gradient boosting approach proposed by Friedman [147]. XGBoost has been demonstrated to be a highly capable and effective algorithm for forecasting across several domains [148]. The method is an ensemble algorithm that utilizes several models (typically decision trees) to produce a strong predictive model. The global model is based on sequentially arranged weaker models, with each subsequent model attempting to improve the error of the previous model (i.e., boosting), illustrated in Figure 4.11.

The method works by minimizing a given loss function, typically using a gradient descent approach. XGBoost is especially suitable for demand forecasting because it can efficiently handle both structured and unstructured data and can incorporate diverse features. For both demand and solar PV forecasting this is essential since both of these are dependent on many factors which include but are not limited to, weather, time of day, and the day of the week. Furthermore, XGBoost is capable of dealing with both missing data and outliers (both of which are typically present in many datasets) in the data in an effective manner and has been designed to identify and handle sparse data [148]. The performance and generalization capabilities of XGBoost are enhanced by incorporating regularization techniques (typically L1 and L2) which penalize the complexity of the model and prevent overfitting [148]. By controlling the complexity of the model, XGBoost achieves a good balance between bias and variance, leading to robust and accurate predictions.

- ▶ **Generalized Additive Models (GAMs):** According to Hastie et al [150], “Generalized additive models have the form $\eta(x) =$

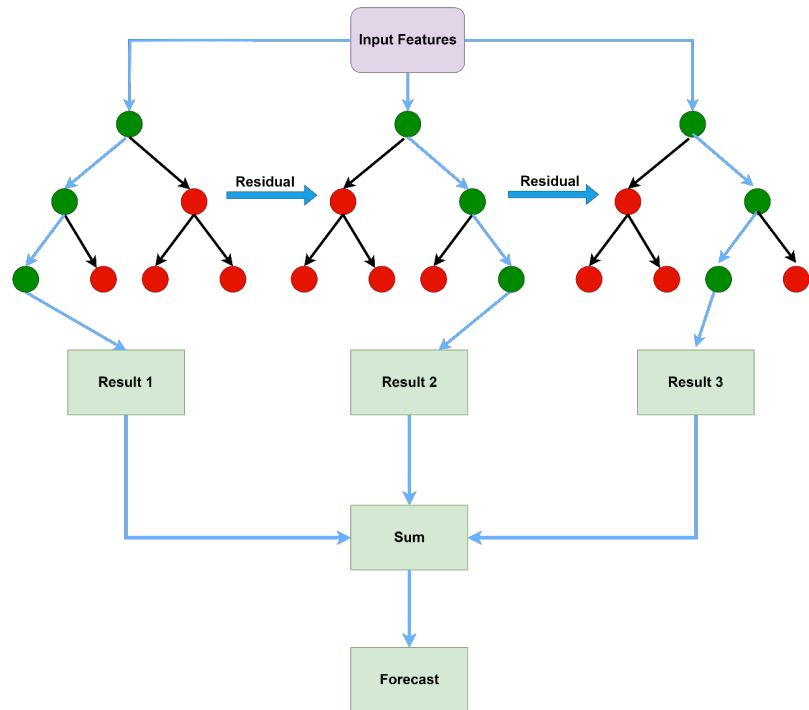


Figure 4.11: Fundamental working principle of the XGBoost framework (source: [149])

$\alpha + \sigma f_j(x_j)$, where η might be the regression function in a multiple regression or the logistic transformation of the posterior probability $pr(y = 1|x)$ in a logistic regression. In fact, these models generalize the whole family of generalized linear models $\eta(x) = \beta'x$, where $\eta(x) = g(\mu(x))$ is some transformation of the regression function". In simplified terms, A generalized additive model (GAM); [151]) is a generalized linear model with a linear predictor involving a sum of smooth functions of continuous independent variables [152].

Thus, GAMs are a statistical modeling-based approach that enables the fitting of a familiar family of non-linear functions [153].

Typically, in a GAM, the response variable is a sum of smooth functions (these can take many forms, such as splines⁴) of the predictor.

GAMs improve the general linear regression by facilitating a framework that captures both the linear and non-linear effects of the problem in a unified manner. Furthermore, GAMs are capable of relatively higher accuracy predictions due to the use of their non-linear fits [154] and can further provide the merit of automatic smoothness function selection [155]. On the other hand, GAMs typically have high computational complexity and as such are prone to overfitting [156]. Further, because GAMs are additive some important interactions can be missed, this can however be remedied by manually adding interaction terms [154].

4: Splines are piecewise polynomials that join smoothly at specific points

- **Light Gradient Boosting Machines (LGBMs):** Like XGBoost, LGBM is an ML approach that utilizes a gradient boosting framework that is built on tree-based machine learning algorithms [157]. The main distinguishing factor is that whilst other tree-based algorithms grow trees horizontally, LGBM grows trees vertically (i.e., leaf-wise as against level-wise growth, see Figure 4.12) [158]. Additionally, the method uses a histogram-based algorithm as described in [159], which results in faster training, and lower memory usage and also facilitates the use of advanced network communication to optimize parallel learning (Parallel voting DT algorithm [158]) [160].

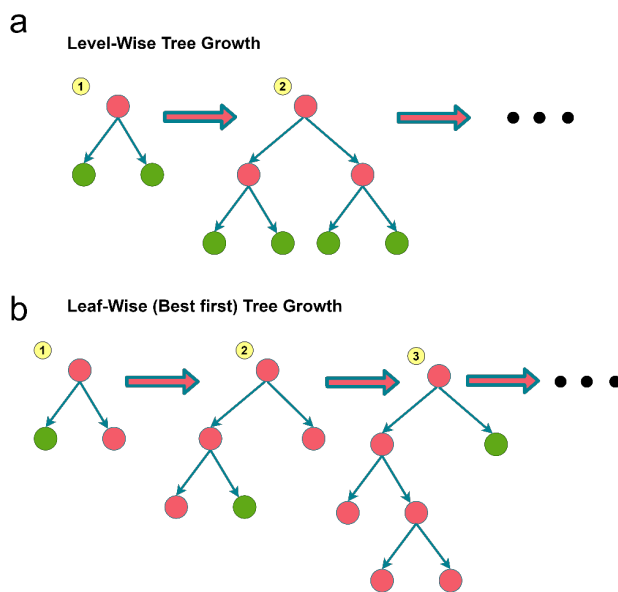


Figure 4.12: Graphical depiction of (a) level-wise growth as applied in other gradient-boosted tree applications) and (b) leaf-wise (best-first) tree growth as applied in Light Gradient Boosting Machines (source: [157])

- **Physical Model:** This method is only applied to the prediction of solar PV generation and uses a deterministic method to evaluate solar PV production based on physical phenomena (geographical position, zenith, azimuth, day of the year, time of day, etc). In this work, we consider the Python package PVLib⁵ [161]. The model also takes into account weather factors such as solar irradiance, wind speed temperature, and nebulosity as well as the physical characteristics of a solar PV module to estimate solar PV production.
- **Rule-Based (Naive) Predictors:** These are predictors that are based on a simple rule (such as tomorrow's consumption is the same as today's consumption). The goal of these naive predictors is to use them as a baseline for assessing the performance of the more complex forecasts made with the algorithms discussed above.

5: PVLib is a python package proposed by NREL for modeling PV systems based on a physical model of such systems

Since the building demand and solar PV production are dependent on external factors, particularly the weather, it was imperative to

have forecasts of the weather parameters, several approaches have been proposed for short-term forecasts of the weather [162, 163], however for this thesis we considered the [tomorrow.io](#) weather API. In order to quantitatively assess the models proposed, we considered three performance metrics:

1. Mean Squared Error (MSE) is a measure of the squared difference between the predicted and measured values. The lowest value for this metric is zero (perfect prediction), there is however no upper bound. Typically, lower values are desired as this is an error term and lower values imply the predicted value is closer to the ground truth. It is defined mathematically as [164]:

$$\text{MSE} = \frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2 \quad (4.1)$$

2. Mean Absolute Error (MAE) is an estimate of the average of the absolute error between the predicted and measured values (i.e., the ground truth) [165]. For this indicator, the lower bound is 0 and indicates perfect prediction (i.e., no errors), however, there is no upper bound, and typically the higher this value the more the predicted value has deviated from the ground truth. It is expressed mathematically as:

$$\text{MAE} = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (4.2)$$

3. Coefficient of Determination (R^2) which represents the proportion of variance in the outcome variable that is explained by the predictor variables in the sample. This metric has an upper bound of 1 which indicates an ideal predictor and has no lower bound. It is expressed as:

$$R^2 = 1 - \frac{\sum_{t=1}^N (y_t - \hat{y}_t)^2}{\sum_{t=1}^N (y_t - \bar{y}_t)^2} \quad (4.3)$$

Where y_t and \hat{y}_t are the measured and predicted values respectively, \bar{y}_t is the mean of the measured values (ground truths), and N is the total number of observations. It should be noted that LGBM and GAM do not support sequence-to-sequence regression and are only capable of sequence-to-point. To get around this constraint, 24 models were trained, such that each model predicted the demand corresponding to a specific hour of the day. For the MSE and MAE metrics, lower values indicate a good fit whilst the opposite is true for the R^2 metric.

In the subsequent sub-chapters, we will apply these algorithms to forecast the required profiles for the proposed ML-MPC.

4.4.1.1 Demand Profile Forecasting

In this sub-chapter, we will present a comparison of the discussed ML (black box) approaches for forecasting the demand profile. For this purpose, we employed a naïve predictor as a baseline against which the more complex ML algorithms were compared. For the demand profiles, the naive predictor considered was the consumption of the previous week, this allowed for the recurring patterns in the dataset (i.e., reduced consumption on weekends) to be accounted for by this predictor.

In the ML approaches considered, various features were used to effectively learn the complex relationships and dependencies that exist between the proposed features and the building's energy consumption. These input features can be classified into three main classes:

1. **Calendar features:** These are features that can be extracted from a calendar and were constituted by:
 - ▶ **Day_of_year:** this is a value between 1 and 365 that indicates which day of the year it is
 - ▶ **Day_of_the_week:** this is a numerical value that represents which day of the week it is (1 for Sunday and 7 for Saturday).
 - ▶ **Is_holiday:** This is a Boolean value that indicates if the day for which the forecasted profile is to be generated is a holiday or not with 1 indicating a holiday and 0 indicating it is not a holiday
 - ▶ **Is_weekend:** This is a Boolean value that indicates if the day for which the forecasted profile is to be generated is a weekend, with 1 indicating a weekend and 0 indicating a weekday.
2. **Temporal features:** these account for exogenous factors that have an impact on the energy demand within the building. For the purpose of this application, only the external ambient temperature was considered.
3. **Engineered features:** These were lagged variables, specifically:
 - ▶ **consumption_lag_1_day:** This is the previous day's consumption profile and allows for the model to capture immediate historical context for the forecast.
 - ▶ **consumption_lag_7_days:** This is the previous week's consumption profile and allows for the model to have a medium-term insight into the demand patterns



Figure 4.13: Comparison of Predis-MHI building’s energy demand ML forecasts with the ground truths for (a) summer (5th July – 12th July 2022) and (b) winter (5th January – 12th January 2022) week (Jupyter Notebook available online at [GitLab: Comparison of forecasting models](#))

Figure 4.13 shows a visual comparison of the results from the considered ML algorithms with the ground truths for summer (5th – 12th July 2022) and winter (5th– 12th January 2022). The results show comparable performance in the summer, however in the winter (Figure 4.13 (b)) the GAMS algorithm showed a tendency to under-predict. The evaluation of these algorithms using the performance metrics discussed in sub-chapter 4.4.1 (considering a one-day (24-hour) evaluation period) indicates that for all three metrics, LGBM produced the best daily predictions with lower error values and the highest R^2 value achieved. Also, to be noted is that the naïve approach, despite being simple yielded results that were not very far from those of the ML algorithms considered.

Furthermore, when the entire horizon of 11 months (18th January – 18th November 2022) was considered, LGBM remained the best-performing algorithm for all the metrics considered (see Table 4.2). However, since the difference in MAE between XGBoost and LGBM was 0.05kW and given the added complexity of using 24 models (since LGBM only supports sequence-to-point regression), we considered XGBoost as the forecasting algorithm for the demand curve.

	DAILY MIN	DAILY MAX	FULL PERIOD
MEAN ABSOLUTE ERROR (MAE)			
GAMS	0.36	1.76	0.74
LGBM	0.24	1.42	0.68
XGBoost	0.28	1.78	0.73
Naive	0.33	2.58	0.86
MEAN SQUARED ERROR (MSE)			
GAMS	0.20	4.97	0.96
LGBM	0.14	3.37	0.81
XGBoost	0.12	5.53	0.97
Naive	0.38	9.58	1.59
COEFFICIENT OF DETERMINATION (R ²)			
GAMS	-9.47	0.85	0.63
LGBM	-8.42	0.89	0.69
XGBoost	-8.24	0.86	0.63
Naive	-20.82	0.87	0.39

Table 4.2: Comparison of demand forecasts for the considered machine learning algorithms for a 1-day sub horizon over an 11-month horizon and the full horizon (18th January – 18th November 2022).

4.4.1.2 Solar PV Production Profile Forecasting

In this sub-chapter, we apply both the Physical model and the ML algorithms discussed in chapter 4.4.1. For this prediction, we consider a naïve predictor with a lag of 24 hours (1 day) as there are no weekly patterns that will be captured by considering a 7-day lag. As was the case in sub-chapter 4.4.1.1, this naïve predictor would serve as a baseline for evaluating the other predictors.

The considered algorithms used the following as input features to establish relationships and patterns between the proposed features and the solar PV production (i.e., the desired output):

1. **Day_of_year:** this is a value between 1 and 365 that indicates which day of the year it is
2. **Temperature_lag_1_day:** This is the temperature profile for the previous day
3. **Temperature_lead_1_day:** This is the temperature profile for the next day
4. **Production_lag_1_day:** This is the solar PV production profile of the previous day.

Additionally, for the physical model some additional environmental inputs are also required, these are:

1. **Wind_speed_lead_1_day:** this is the wind speed profile for the next day

2. **Nebulosity_lead_1_day**: this is the cloud cover (in percentage) of the next day (however, this data was available only until the end of 2021)

A comparison of the results from the three ML models and the physical model is shown in Figure 4.14. These results show that the GAM model suffers from a tendency to predict negative values (as can be seen in Figure 4.14 (b)), whilst XGBoost and LGBM were able to effectively capture the relationship between the input features and the solar PV production. The physical model, however, did not yield good results, particularly in the winter months, possibly due to a lack of nebulosity (cloud cover) and potential shading from the building.

Based on the results of the performance metrics however detailed in Table 4.3, the GAM approach yielded the least MAE and MSE and had the highest R^2 value both for the one-day horizon and full horizon assessments. Also of interest is that, for all the models, with the exception of the physical model, the daily minimum MAE was less than 0.02 whilst the minimum MSE was less than 0.05. For the maximum error, however, LGBM and the GAM approach proved to be relatively better than the other models (the maximum MAE was 2.21).

Table 4.3: Comparison of solar PV forecasts for the considered machine learning algorithms for a 1-day sub horizon over an 11-month horizon and the full horizon (18th January – 18th November 2022)

	DAILY MIN	DAILY MAX	FULL HORIZON
Mean Absolute Error (MAE)			
GAMS	0.10	2.21	0.76
LGBM	0.13	2.21	0.78
XGBoost	0.12	2.27	0.84
Physical Model	0.55	5.42	2.04
Naive	0.04	3.46	0.98
MEAN SQUARED ERROR (MSE)			
GAMS	0.03	13.09	2.25
LGBM	0.05	15.14	2.48
XGBoost	0.05	16.01	2.83
Physical Model	1.29	72.86	13.76
Naive	0.04	36.13	5.32
Coefficient of Determination (R^2)			
GAMS	-34.11	1.00	0.90
LGBM	-59.28	1.00	0.89
XGBoost	-78.78	1.00	0.88
Physical Model	-627.90	0.92	0.39
Naive	-230.65	1.00	0.77

Despite the better performance shown by the performance metrics,

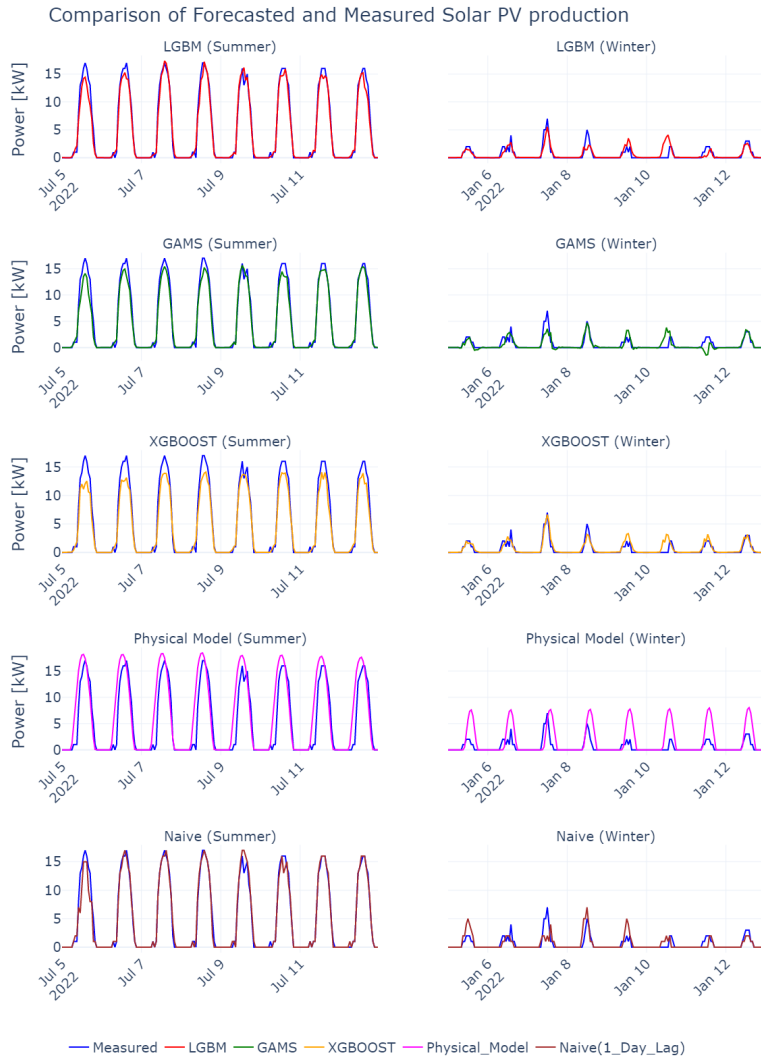


Figure 4.14: Comparison of ML and Physical model solar PV production forecasts with the ground truths for (a) summer (5th July – 12th July 2022) and (b) winter (5th January – 12th January 2022) week (Jupyter Notebook available online at [GitLab: Comparison of forecasting models](#))

GAM still showed the tendency to forecast negative values and was also computationally the costliest. Further, because the LGBM approach forecasting errors were comparable to that of the GAM approach (see Table 4.3), we considered the LGBM model for the forecasting of solar PV production for the ML-MPC.

4.4.1.3 Electric Vehicle Charger Demand Forecasting

Unlike the demand and solar PV data, the data for the EV chargers are sparse (see Table 4.4) and very random (due to the demand being highly dependent on user behavior). Additionally, from Figure 4.15, it can be seen that the monthly load factor (i.e., the ratio of hourly average load to peak load, during the operating hours of the building) was never over 5%, indicating that the chargers were not used for a great proportion of the time. Aggregating the demand profiles only improved the sparseness by approximately 2-4%. However, for the ML-MPC application, only the daily charg-

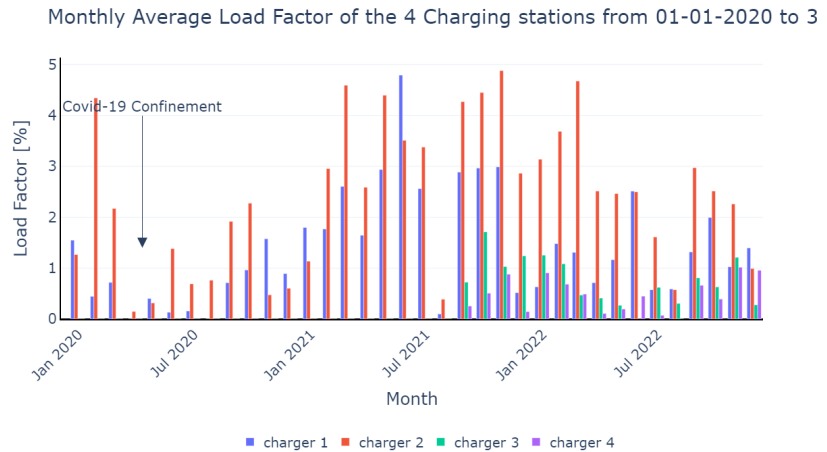


Figure 4.15: Monthly load factor for the four charging stations present at the Predis-MHI building (Jupyter Notebook available online at [GitLab: Indirect Flexibility Assessment](#)).

ing energy demand is required, thus the demand profiles were resampled from an hourly time step to a daily time step. This further reduced the sparseness to approximately 64% in the case of the aggregated consumption (see Table 4.4.).

Table 4.4: Summary of the sparseness of EV charger data for hourly and daily timestep

	Hourly Sparseness	Daily Sparseness
Charger 1	99.13%	87.03%
Charger 2	98.44%	83.01%
Charger 3	99.36%	95.54%
Charger 4	99.59%	97.31%
Aggregated Chargers	96.83%	76.08%

Due to the sparse nature of the data, a Support Vector Machine (SVM) approach was also considered in addition to the already discussed ML algorithms. For this application, the naïve predictor was considered to be the daily energy demand of the previous week. The input features for this application were:

Temporal features: the feature considered in this regard was the daily demand lagged from 1 day to 14 days.

Calendar features: two features related to the calendar were considered, these were:

1. **day_of_the_week:** this was represented as an integer value between 1 (i.e., Sunday) and 7 (Saturday).
2. **Is_holiday:** this was a Boolean value, with 1 (True) indicating the day for which the demand is to be forecasted is a holiday and 0 (False) indicating it is not a holiday.

No weather or external features were considered since the use of the chargers was not dependent on external factors such as weather.

	DAILY MIN	DAILY MAX	FULL HORIZON
Mean Absolute Error (MAE)			
GAMS	0.21	73.25	13.59
LGBM	0.00	73.42	12.92
SVM	0.00	81.03	12.56
XGBoost	0.02	76.21	11.88
Naive	0.00	94.99	15.14
Mean Squared Error (MSE)			
GAMS	0.04	5366.16	365.74
LGBM	0.00	5390.71	328.69
SVM	0.00	6565.83	395.03
XGBoost	0.00	5807.23	328.21
Naive	0.00	9023.53	601.34
Coefficient of Determination (R ²)			
GAMS	-	-	0.15
LGBM	-	-	0.23
SVM	-	-	0.08
XGBoost	-	-	0.24
Naive	-	-	-0.40

Table 4.5: Comparison of EV charger demand forecasts for the considered machine learning algorithms for a 1-day sub horizon over an 11-month horizon and the full horizon (18th January – 18th November 2022)

From Figure 4.16, none of the forecasting approaches performed particularly well, however, given the sparse nature of the data (Table 4.4 and the high degree of randomness in the data, we considered the best predictor for our ML-MPC application. Thus, given the results in Table 4.5 for both daily and full horizon, the performance of LGBM was found to be the best and as such was considered for the forecasting of EV charger demand.

 **Highlights:**

- ▶ **EV Demand Forecasts** did not have high accuracy, however, did is not a result of the models but rather the data set itself. As shown in our work, the data was very sparse and in addition charging events were very random (even after aggregation). These issues with the data are largely because these chargers are only available to occupants of the building and as such the ratio of EV users to the number of chargers is low. Potentially, as EV penetration increases, the predictability of charging is also expected to increase.

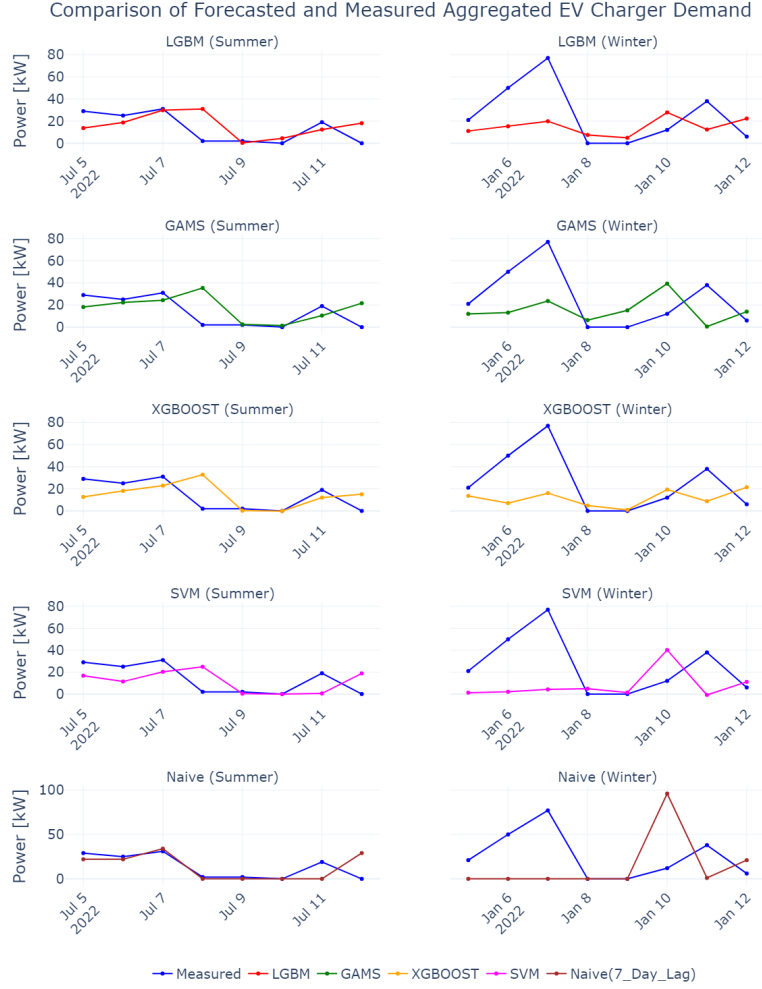


Figure 4.16: Comparison of ML and Physical model EV charger demand forecasts with the ground truths for (a) summer (5th July – 12th July 2022) and (b) winter (5th January – 12th January 2022) week (Jupyter Notebook available online at [GitLab: Comparison of forecasting models](#)).

4.4.2 Optimal Dispatch of Direct and Indirect Flexibilities

Having developed the forecasting component of the ML-MPC, we now focus on the optimization component which we developed using a Mixed Integer Linear Programming (MILP) approach as was discussed in chapter 3.

In this instance, the objective function was to maximize self-consumption which was achieved by minimizing the Net Energy Exchange with the Grid (NEEG)⁶.

Thus the MILP optimization approach considered utilized the same formulation described in chapter 3.2.2. (eqn 3.1 - 3.11). However, because the forecasts considered an aggregated EV charger demand equations 3.8 - 3.11 were modified such that:

$$E_{aggregated_charger_original} = P_{chargers}(t) \times timestep \quad (4.4)$$

Where $E_{aggregated_charger_original}$ is the predicted aggregated daily energy consumed by the EV chargers and $P_{chargers}(t)$ is the

6: Minimizing the NEEG implies maximizing the self-consumed energy as explained in chapter 3.1. We only consider the NEEG as an objective function for the optimization.

decision variable for the aggregated charging stations (i.e., the shiftable load) and is defined as:

$$\sum_x^X \sum_t^T P_{charger_x}(t) \quad (4.5)$$

And consequently, the operating hours of the building were integrated such that:

$$P_{chargers}(t) \times timestep = 0, t < T_{open} \text{ or } t > T_{close} \quad (4.6)$$

Given that T_{open} and T_{close} are the opening and closing times of the building. The energy balance (eqn 3.10) was modified to:

$$P_{bat_{in}}(t) + P_{bat_{out}}(t) - [P_{load}(t) + P_{chargers}(t)] + P_{PV}(t) + P_{import}(t) + P_{export}(t) = 0 \quad (4.7)$$

Such that $P_{bat_{in}}(t)$ and $P_{bat_{out}}(t)$ are the battery charging and discharging power, $P_{load}(t) + P_{chargers}(t)$ is the total consumption of the building (i.e. the sum of building demand and charger demand respectively). P_{PV} , $P_{import}(t)$ and $P_{export}(t)$ are the power output of the solar PV system, the import power from the grid, and the export power from the grid respectively. Lastly, the main indicator self-consumption (eqn 3.11) was redefined as:

$$\text{Self - consumption} = \frac{\int_t^T \min [P_{PV}(t) - P_{bat}(t) - P_{bat_{out}}(t) - \xi(t), [P_{load}(t) + P_{chargers}(t)]]}{\int_t^T P_{PV}(t)} \quad (4.8)$$

Where $\xi(t)$ refers to the system losses of the solar PV system.

Having defined both the forecasting and optimization components required for the ML-MPC, in the subsequent sub-chapter we apply the ML-MPC to the battery in our experimental setup.

4.4.3 Case Study: Model Predictive Controller for the Direct Flexibility in the Predis-MHI Building

Having developed both the forecasting and optimization components of the ML-MPC, the approach was implemented using the battery of the Predis-MHI building. However, because the battery was installed off-site, and there is no existing contract that permits the export of energy from the off-site building onto the grid, the tests carried out only permitted a maximum discharge of 1kW as can be seen in Figure 4.17. The Measurements show that the BMS of the battery generally respected the control signals and allowed

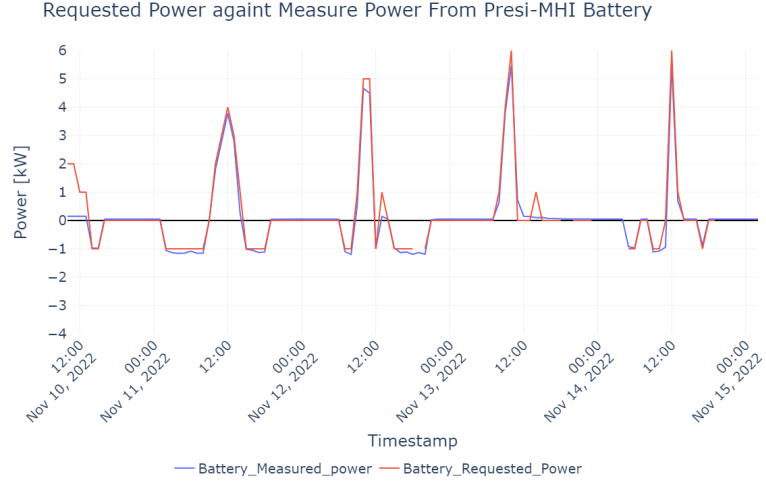


Figure 4.17: Comparison of the control signal (requested power) and measured power from the Predis-MHI battery (available online at [Git-Lab: MPC implementation](#))

for the design of a Digital Twin of the battery to be implemented (Figure 4.17).

From Figure 4.17, we can deduce that the control signals are treated as maximum and minimum energy thresholds, as such, we implemented the digital twin such that:

$$P_{\text{battery}_{DT}}(t) = \begin{cases} \min[P_{\text{battery}_{MILP}}(t), P_{PV_{\text{measured}}}(t)], & \text{if } P_{\text{battery}_{MILP}}(t) > 0 \\ \max[P_{\text{battery}_{MILP}}(t), -P_{\text{load}_{\text{measured}}}(t)], & \text{if } P_{\text{battery}_{MILP}}(t) \leq 0 \end{cases} \quad (4.9)$$

Where $P_{\text{battery}_{DT}}(t)$, $P_{\text{battery}_{MILP}}(t)$, $P_{PV_{\text{measured}}}(t)$ and $P_{\text{load}_{\text{measured}}}(t)$ are the battery power from the digital twin, the battery power computed by the MILP, the measured solar PV power, and the measured demand of the building for timestep t respectively. Additionally, to ensure the lower and upper state of charge limits were respected:

$$P_{\text{battery}_{DT}}(t) = \begin{cases} E_{\text{battery}_{\max}} - E_{\text{battery}_{DT}}(t-1), & E_{\text{battery}_{DT}}(t) > E_{\text{battery}_{\max}} \\ E_{\text{battery}_{\min}} - E_{\text{battery}_{DT}}(t-1), & E_{\text{battery}_{DT}}(t) \leq E_{\text{battery}_{\min}} \end{cases} \quad (4.10)$$

Where $E_{\text{battery}_{\min}}$ and $E_{\text{battery}_{\max}}$ are the minimum and maximum allowed energy in the battery (i.e. the minimum and maximum SOCs) respectively and $E_{\text{battery}_{DT}}(t)$ is the energy in the battery at step t .

Using this formulation, we devised three scenarios for evaluating the performance of the ML-MPC, these are:

1. **Perfect Predictor Scenario:** For this scenario, we assumed that the solar PV, demand, and EV Charger demand profiles for the next day were perfectly predicted. Hence the results from this scenario could be considered the global optimal

2. **ML-MPC Scenario:** this scenario considered the ML predictors discussed in this chapter for the prediction of the solar PV, demand, and EV Charger demand profiles for the next day. Thus, the optimal solution here integrates the prediction errors.
3. **ML-MPC and Digital Twin Scenario:** in this scenario, the battery charge/discharge schedule computed by the MILP in the ML-MPC scenario is used as control signals for the digital twin of the battery. Thus, this scenario allows us to assess the performance of the ML-MPC.

Given the above scenarios, the results shown in Figure 4.18 were obtained. The battery power from the digital twin (blue curve) is seen to charge and discharge lower amounts of energy relative to the perfect predictor and ML-MPC scenarios. This behavior is due to the reactive nature of the BMS of the battery which, to an extent reduces the errors associated with the forecasts of the ML-MPC.

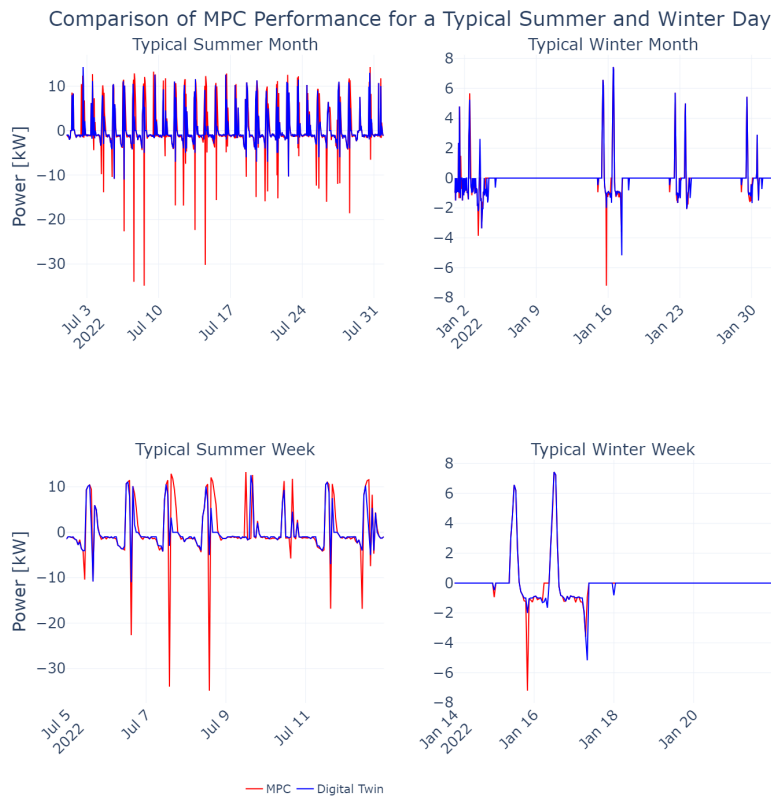


Figure 4.18: Comparison of the battery output for the Machine Learning based Model Predictive Controller (ML-MPC) (red) and ML-MPC and digital twin scenarios (blue) for (a) a typical summer day and (b) a typical winter day (available online at [GitLab: MPC implementation](#))

Comparing the monthly self-consumption of results from the three scenarios (see Table 4.6 and Figure 4.19) and in addition, an MPC which only used Naïve predictors, the perfect predictor was seen to have achieved higher self-consumption rates relative to the other three scenarios. Figure 4.19 also shows that the use of the ML-based forecast improved the performance of the ML-MPC in most of the studied months (January being the exception). Furthermore, the

Table 4.6: Summary of Monthly self-consumption results for the studied scenarios

Month	Natural Self-Consumption	Perfect Predictor	ML-MPC	ML-MPC and Digital Twin	Naive
January	59.27%	84.75%	70.36%	72.54%	70.78%
February	51.46%	70.85%	56.69%	59.65%	59.59%
March	50.98%	72.24%	61.54%	64.45%	60.73%
April	39.56%	65.28%	53.22%	56.24%	48.05%
May	37.39%	57.92%	47.57%	51.09%	45.55%
June	35.41%	51.91%	38.33%	45.15%	35.90%
July	28.90%	47.53%	39.06%	41.41%	37.13%
August	26.18%	47.23%	36.36%	39.08%	35.59%
September	38.99%	60.65%	54.30%	56.92%	48.15%
October	53.23%	74.40%	60.08%	66.81%	58.32%
November	65.19%	89.40%	70.75%	77.97%	68.95%
Full Period	39.01%	59.75%	48.64%	52.27%	46.51%

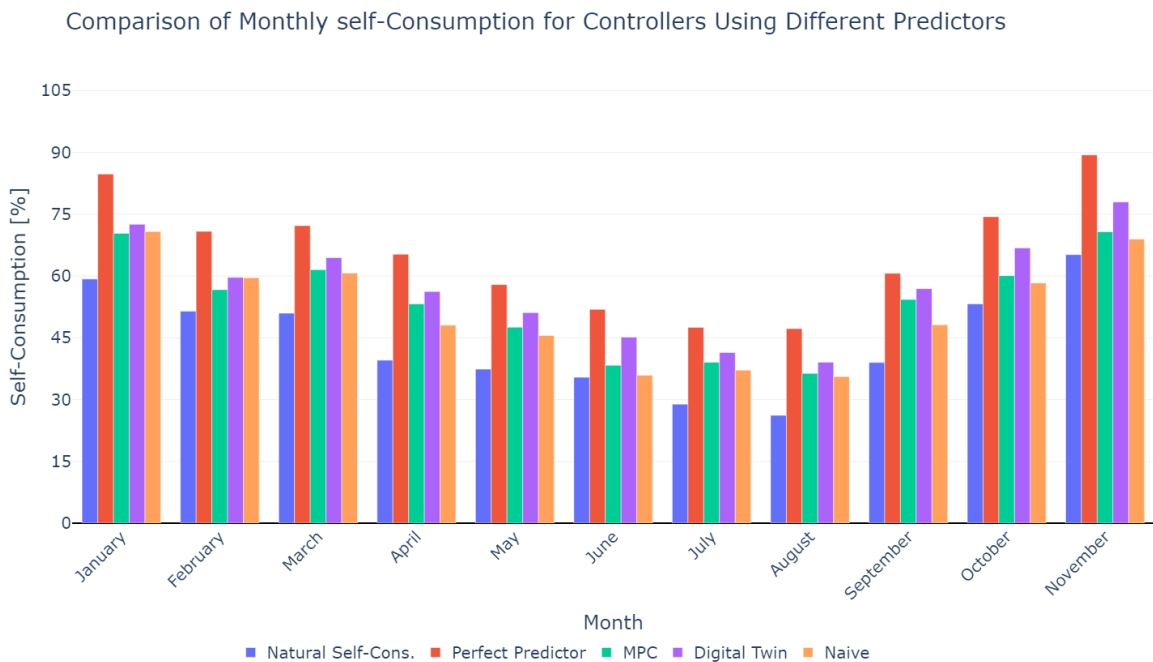
ML-MPC and digital twin scenario was observed to have surpassed the ML-MPC scenarios (ML and Naïve predictors) as well. This phenomenon could be attributed to prediction errors (see Table 4.7). Given the mathematical expression of self-consumed energy:

$$E_{\text{self-consumed}} = \min [P_{pv}(t) - P_{\text{battery}}(t), P_{\text{load}}(t)] \times \text{timestep} \quad (4.11)$$

Where $P_{pv}(t)$, $P_{\text{battery}}(t)$, and $P_{\text{load}}(t)$ are the solar PV power, battery power and the load power at timestep t . Thus, an overprediction of the solar PV output would have the tendency to result in a battery charging power that is higher than the actual solar PV output, consequently resulting in a negative self-consumed energy value which would reduce the self-consumption rate.

Table 4.7: Comparison of monthly energy predicted to monthly measured energy for PV production, building demand, and EV charger demand

	Consumption [kW]		Solar Production [kW]		EV Chargers [kW]	
	Predicted	Measured	Predicted	Measured	Predicted	Measured
January	1730.82	1929.00	732.11	928.00	544.42	766.97
February	1686.39	1796.00	1033.09	1267.00	591.78	694.96
March	1897.91	2194.00	1976.67	2083.00	661.74	632.92
April	1699.84	1952.00	2231.72	2477.00	441.44	350.96
May	1661.03	1875.00	2903.25	2969.00	447.55	378.96
June	1405.30	1650.00	3069.72	2988.00	448.51	479.98
July	1440.47	1692.00	3295.63	3467.00	420.22	305.97
August	1211.62	1427.00	2853.19	2872.00	167.43	150.00
September	1479.35	1664.00	2124.15	2144.00	558.61	633.98
October	1591.45	1776.00	1640.75	1379.00	609.59	554.95
November	980.62	978.00	384.48	270.00	356.80	408.98

**Figure 4.19:** Comparison of monthly self-consumption for the perfect predictor, Model Predictive Controller, and ML-MPC and digital twin scenarios (available online at [GitLab: MPC implementation](#))

Gitlab Repository

The code and associated notebooks for the solutions proposed in this chapter can be found in the following repositories:

1. comparison of rule-based and optimization-based control strategies: [GitLab: Comparison of control strategies](#)
2. Implementation and comparison of machine learning forecasting models for consumption and production profiles of Predis-MHI: [GitLab: Comparison of forecasting models](#)
3. Implementation of Machine Learning based Model Predictive Controller (ML-MPC) for Predis-MHI: [GitLab:ML-MPC implementation](#)

Additionally, see Appendix B.1 for a list of all available notebooks

4.5 Conclusion

In this chapter, we have examined the mobilization of direct flexibility within the energy system of buildings, with an emphasis on battery storage as direct flexibility. We addressed concepts related to the control of batteries, in particular the increasing complexity and computational cost related to the control of battery energy storage systems.

Furthermore, we propose a machine learning-based Model Predictive Controller for the control of the 50 kWh Battery in our experimental setup (the Predis-MHI building). Despite being flawed (forecasting errors), the ML-MPC yielded promising results by achieving an overall self-consumption rate of 48.64%, thus a shortfall of 11.11% from the global optimal (i.e., using the perfect predictors only).

Due to constraints regarding the installation of the battery in the Predis-MHI building, the battery was located off-site restricting the practical implementation of the ML-MPC. A digital twin of the battery was however implemented and when the control signals from the ML-MPC were applied to this digital twin, an increase in the building's estimated self-consumption from 48.64% to 52.27% (a decrease in the deviation from 11.11% to 7.48% from the global optimal). Further, the results showed an improvement in self-consumption of 2.13% resulting from the use of ML predictors in place of the Naïve predictors.

Furthermore, the ML predictors for solar PV and the demand yielded high accuracy predictions, however, when applied to the EV charging demand the predictions had high levels of error and consequently low accuracy. This problem was not a result of the ML methods, but rather the data itself. As already indicated, the data was sparse and very random in nature. Both issues are the result of a low number of EV users relative to the number of available charging stations, and the data's predictability is expected to improve as the number of EV users increases. Additionally, data augmentation methods can be applied to the data as a means to improve the predictability of the data, this is however not covered in the scope of this thesis.

The use of the ML-MPC allows us to gain an initial insight into the intricate interplay between indirect and direct flexibilities (in this context by considering the demand of EV chargers as shiftable and flexible loads). To delve deeper into this interaction between direct and indirect flexibilities, the subsequent chapter considers an Agent-Based simulation approach to simulate the behavior of EV drivers and assess the consequence of human actions (the indirect flexibility) on the building's energy performance.

Simulation Tools for Direct and Indirect Flexibilities in Local Energy Communities

5

In this chapter, we simulate the behaviour of EV users with respect to the charging of the vehicles (indirect flexibility). This simulation approach allowed us to examine the effect of the interplay between direct and indirect flexibilities in a building and how this interplay impacts the energy sub-system of a building. Our proposed approach was a co-simulation tool consisting of a Mixed Integer Linear Programming optimization and Multi-Agent System based simulation components that allow us to have a first insight into the interplay between these two types of energy flexibilities.

5.1 Influencing Human Behavior: Collective Self-Consumption and Local Energy Communities as a Vector for Change

Collective self-consumption allows for the pooling and sharing of local (usually renewable) energy resources. This is, however, one of the many services that a local energy community can provide. Detailed below are some key services that local energy communities can provide:

1. **Generation:** In this scheme, members typically do not consume any of their locally produced energy and as such act as energy generators. Thus, this type of community sells all the generated energy (usually from solar, biomass, and wind) to an energy supplier [166].
2. **Energy Sharing:** In this scheme, the goal is to pool and share the available local energy resources. Thus, self-consumption is a central theme for such a local energy community [166]. This approach embodies collective self-consumption and enables concepts such as peer-to-peer energy trading [167].
3. **Demand Side Energy Flexibility:** In this scheme, the objective is to provide energy flexibility services to the utility operator (or even a building). The services (typically achieved by aggregating resources) provided by such communities include but are not limited to; peak-shaving, valley filling, and both upwards and downward modulation of demand [166], [168].
4. **Electric Mobility:** In such an energy community, the goal is to provide sustainable transportation and energy management (i.e., flexibility) services. Services provided in this scheme

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include but are not limited to car-pooling, ride sharing, and charging station operations.

In this Chapter, we explore the interaction between direct flexibility (i.e., Battery Energy Storage System) and indirect flexibility (i.e., plugging in and unplugging of EVs). Our primary focus centers on addressing the fourth sub-question posed in Chapter 2 which involves studying the impact of the interaction between the direct and indirect flexibilities on the global energy performance of the Predis-MHI building.

In an ideal situation, such a study would require a comprehensive study with human participants (as it involves and is directly impacted by human behavior) which would ultimately provide valuable insights into actual human behavior and real-life results. The scope and the limitations of our work do not however allow for such a study, and thus, we defaulted to a simulation-based study using Multi-Agent Systems (MAS) to model both the human behavior and the socio-technical interactions between the social and technical components of the system.

In the subsequent sections, we delve into existing literature concerning the intricate topic of modeling and simulating energy communities and proceed to discuss the MAS-based simulation considered.

5.2 Modeling Local Energy Communities: A State of the Art

Local energy communities undoubtedly are a socio-technical system, and their effectiveness is directly influenced by both the individual and collective behavior of participants in the community. Thus, in order to model the community, it is imperative to first model the individual participants (these are the building blocks of the community).

Huruax [169] in his work describes human activity as a complex system composed of a combination of several entities whose interactions result in a global behavior that is difficult to accurately predict. Albouys-Perrois [170] further emphasizes that several elements characterize this complex system that is human activity, however, key amongst them is variability (different people will make different choices given the same scenario). This variability can be expanded to include intra variability, that is given the same scenario, the same individual may make a different decision when one or more factors¹ change.

1: Factors here include but are not limited to their emotional state, the people and environment around them and their immediate past interactions.

Soto et al [171] in their review of peer-to-peer energy trading identified six² main classifications for approaches used in the literature on peer-to-peer³ energy trading. However, of particular interest to us in this thesis are game theory, simulation, and optimization since these focus on modeling the system. Interestingly, Soto et al [171] point out that some works have used simulation approaches to validate game theory models [172], indicating that it is possible to use a combination of the 6 categories they outlined. Thus, considering our use case, two main possibilities exist to simulate our system as indicated by Simoiu et al [55]; optimization and Game theory. These approaches are detailed in the subsequent subsections.

2: These classifications are:

- ▶ Trading platforms
- ▶ Blockchain
- ▶ Game theory
- ▶ Simulation
- ▶ Optimization
- ▶ Algorithms

3: Direct energy trade between consumers and prosumers

5.2.1 Optimization as an Approach for Modeling Local Energy Communities

Optimization approaches are mathematical representations of systems that are usually relevant for either maximizing or minimizing a parameter of that system. The use of optimization-based approaches for modeling local energy communities has largely been focused on maximizing financial benefits (minimizing costs for example) and balancing supply and demand in an energy system [173]. Whilst these approaches will result in a theoretical optimal, they either ignore the human behavior component or assume optimal behavior from humans. Hodencq et al [26] used a mixed integer linear programming optimization approach to dimension a solar system for a local energy community composed of 20 residential buildings, their model considered positive behavioral feedback, which was modeled as a linear annual decrease in demand. Coignard et al [174] using the same local energy community from [26] modeled and included demand-side energy flexibility services by using a MILP optimization to modify the demand curve such that a target natural self-sufficiency⁴ was achieved.

4: self-sufficiency (self-production) of a building (or community) evaluated using a local on-site production capacity that results in a net zero energy balance (consumed energy equals produced energy). In simple terms, this natural self-sufficiency is a measure of how well a load profile is adapted for an energy generation source

Simoiu et al [55] indicate that a major drawback of the optimization approach is that it requires all the data related to the problem to be included in the definition of the problem, however, human actors have implicit knowledge and information that remains unknown to the model and in most cases is difficult to model. However, in a lot of use cases, not all aspects of the human actor's cognitive process need to be replicated in a model [170]. Thus, MAS-based simulations can be combined with optimization approaches to provide a solution that is representative of the real complex system as was presented by Denysiuk et al [175] and Karfopoulos et al [176].

5.2.2 Game Theory Applications for Modeling Local Energy Communities

Baaci et al describe a game as “a situation in which the benefit or cost reaped by each decision maker (called player) from an interactive situation does not only depend on its own decisions but also those taken by other players”. Building on this definition, Bacci further defines game theory as a “branch of mathematics that enables the modeling and analysis of the interactions between several players who can have conflicting or common objectives”. Game theory has been demonstrated to be effective at modeling the decision processes involved in peer-to-peer energy trading [177–179] (and by extension collective self-consumption). Two key categories of game theory algorithms exist, these are

1. **Non-cooperative game:** In such a game, each player is only concerned with their own personal benefit, and will consequently make a decision that maximizes their gain and is based on an assessment of the historical decisions of other players in the game [170], [55]
2. **Cooperative games:** In this type of game, each player takes the costs and benefits of other players into consideration when deciding. As such a player’s decision is made such that it maximizes the collective gain of all players and not just their gain [170].

Cooperative games capture and reflect the true spirit behind the concept of local energy communities, however, as pointed out in [171], approaches in literature that consider cooperative games tend to model the players as rational and always seeking the greater good, in reality however, this is usually far from the truth. This brings to bear the complexity involved in modeling the true behavior of a player, especially in the context of a cooperative game where the player is expected to be rational and put the greater good above their personal interests.

On the other hand, Simoiu et al [55] indicate that Multi-Agent System based simulations present an equally interesting alternative solution for modeling the interactions in an energy community. This solution models the trading (or energy-sharing) mechanisms within the community using several agent types and scenarios. Thus, a combination of game theory (both cooperative and non-cooperative) and MAS-based simulation present a useful solution for simulating human behavior in the context of a local energy community.

5.3 Multi-Agent System Based Approach for Simulating EV User Behavior

As already indicated in sub-chapter 5.2.1, MAS approaches can be combined with either an optimization or game theory-based approach. However, for our use case (assessing the impact of EV user behavior on the global energy system of a non-residential building) we consider a MAS approach in tandem with a MILP optimization. Game theory was not considered as the human actors are expected to make decisions without consideration of the decision of other participants. Additionally, we modeled the MAS using the MESA [180] library in Python.

Given that human behavior is a complex system and is difficult to accurately represent with a model [170], we focus on the aspects of an EV user's behavior that have direct consequences on a building's energy system, these are:

1. The decision to drive their EV to the building (in our case this is a drive to work).
2. The time an EV user decides to arrive at the building premises.
3. The decision to plug or unplug their EV from the charging infrastructure.
4. The decision to stay on-site or leave the premises.

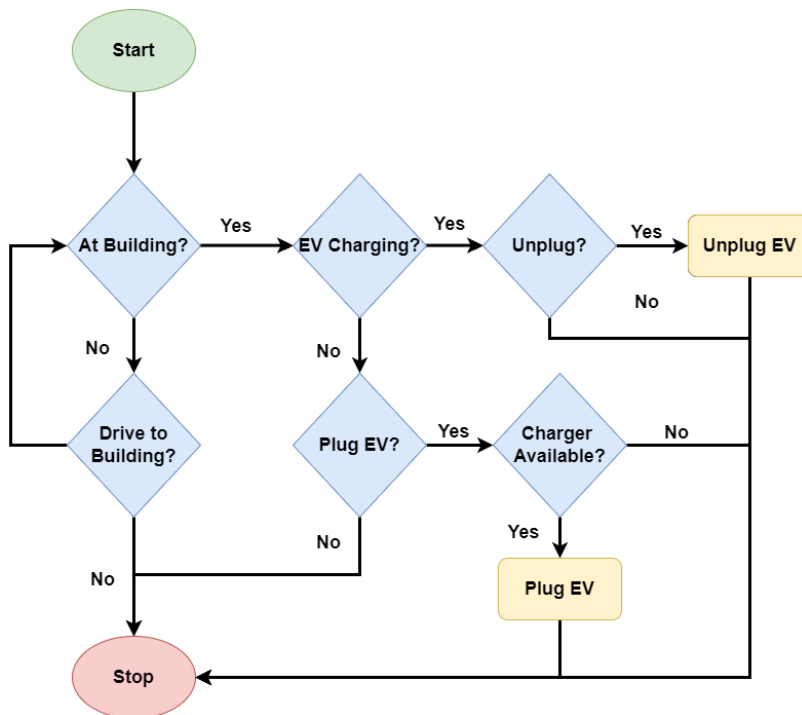


Figure 5.1: Flow chart representation of EV users' decisions for Multi-Agent System based simulation of members (EV users) in an energy community that offers demand-side energy flexibility (load shifting) at the building scale.

Thus, using these four decision variables (see Figure 5.1, we can simulate the behavior of EV users that would consequently impact

the energy performance of the building. Furthermore, since we consider the EV users as a community, we adopt the method proposed by Simoiu et al [54] and model the willingness of a community's members to participate. Thus, we categorize the members into three groups:

1. **Enthusiastic:** This group of participants is highly motivated to effect a change and is thus very willing to partake in community-related activities. If we consider the game theory perspective, these participants would be seen as being cooperative, thus, this group is considered to be the ideal human in the control system. For the purpose of simulation, the willingness to participate ($Will_{ha}$) of this category of human agents is denoted by a value of 1. This value represents the probability that the agent would respond positively⁵ to any signals they receive during the simulation. The ($Will_{ha}$) parameter is used as a part of the decision probability for the human agent expressed in eqn 5.1.
2. **Neutral:** This classification refers to participants who have some level of motivation and are willing to participate in the community, however, their level of interest is less than ideal. In the simulation, the willingness to participate in this category of agents is represented by a value of 0.5 (likelihood to participate value used in eqn 5.1).
3. **Apathetic:** This group has almost no motivation to participate, their participation in community-related activities is very limited and is usually to serve their own interest (non-cooperative). This group can be considered to be non-ideal. The willingness to participate in this group is denoted by a value of 0 (likelihood to participate value used in eqn 5.1).

5: Positively here implying the agent acts in an ideal manner and strictly respects the signals received

Using the defined criteria above, we conceptualized two approaches for simulating the impact of EV user behavior on the building's energy performance. These approaches are categorized based on the computation and dissemination of the optimal charging strategy to the human agents. To enhance comprehension and reduce the cognitive strain associated with processing complex information, we adopted a color-coded signaling strategy. Furthermore, we envision that the use of this color-coded signaling would also serve the purpose of simplifying the visualization of these social signals. The color-coded signals considered are detailed as follows:

1. **Red:** Charger is available however charging is discouraged at this time. If an EV is plugged in, red also indicates that the vehicle must be displaced.
2. **Green:** Charger is available and charging at this time is encouraged. i.e., it is a suitable time to charge

3. **Blue:** The charger is not available because another EV user is using the charging facility
4. **Black:** The charger is not available because the building is not accessible, or the charging facility has broken down. Thus, charging is not possible

Furthermore, for the simulation approaches devised, we defined four principal types of agents, these are:

1. **Human Agents:** This refers to the Human-in-the-control system which in this case refers primarily to the drivers/owners of EVs in the Predis-MHI building. The separation of the Human actors is necessary because it allows for the testing of concepts such as fleet sharing in such an energy community. Furthermore, this agent implies it is possible to test scenarios where cooperation between human agents allows for a human agent that is not available to designate another human agent (who is available) to plug or unplug the vehicle on behalf of the EV owner. This agent provides information related to their availability.

These agents decide when to plug in or unplug their vehicle, and this decision is modeled as a probability which is determined by the human agent's vehicle SOC and their willingness to participate. A key assumption we made concerning an EV users to charge was that the decision to charge is based on the state of charge of the EV, this is represented as $1 - SOC_{EV}$ in eqn 5.1. Additionally, we assumed that the influence of the EV's SOC had the same influence on the decision to charge as the $Will_{ha}$ parameter. Hence the final likelihood to charge was an average of these two probabilities. This probability of participation is expressed mathematically as:

$$\text{Prob}_{\text{participate}} = \begin{cases} \frac{(1-SOC_{EV})+Will_{ha}}{2}, & \text{if } signal > 0 \\ 1 - \frac{(1-SOC_{EV})+Will_{ha}}{2}, & \text{if } signal \leq 0 \end{cases} \quad (5.1)$$

Where $Prob_{\text{participate}}$ is the probability to participate, SOC_{EV} is the State of Charge of the EV, $signal$ is the social signals⁶ sent by the coordinator agent to the human agents (ha) and $Will_{ha}$ is the willingness to participate. The formulation in eqn 5.1 effectively captured the basic assumption of charging decisions being tied to Electric Vehicle's SOC, whilst allowing for the $will_{ha}$ parameter to be taken into account.

Additionally, the human agent must decide when to arrive at work, if they will stay the entire period on-site, and when to leave for their homes. These decisions are based on a probability which is derived from a sigmoid function expressed

6: For the simulation, we considered the signal to be green when $signal$ was greater than zero, and red when $signal$ was less or equal to zero.

mathematically as:

$$Prob_{move}(t) = \frac{1}{1 + e^{(-k \times (t - x_0))}} \quad (5.2)$$

Where t is the hour of the day, k represents the steepness of the curve and x_0 is the midpoint of the curve (i.e., the value of t for which $prob_{move}$ is equal to 0.5). This function was used such that:

- a) If the human agent's location is at home or another location (denoted "other") between the hours of 7:00 and 13:00 there is a high probability that the move to the office (0.65 to 0.85)
 - b) If the agent's location is not at work after 12:00, then there is a low likelihood that they decide to move to the office.
 - c) If the agent is at the office after 16:00, then there is a high likelihood that they will move out of the office.
2. **EV Agents:** his agent represents the EV. They are assigned an owner when initialized and are expected to provide information related to the specific vehicle such as the current battery State of Charge (SOC) and energy required (to charge to 100% SOC).
 3. **Charger Agents:** These are stationary agents that represent the charging stations, they provide data on their availability and if a human agent decides to charge, they provide the charging energy requested. The charging power per timestep is defined as:

$$P_{charge}(t) = \min \left(\frac{E_{bat}(t) - E_{bat}(t)}{timestep}, P_{charge_{nominal}} \right) \quad (5.3)$$

Where $P_{charge_{nominal}}$, $E_{bat_{cap}}$ and $E_{bat}(t)$ are the nominal power of the charger, the battery capacity and the energy remaining in the battery respectively, thus, $\frac{E_{bat_{cap}} - E_{bat_{cap}}}{timestep}$ is the maximum power that can be charged into the battery.

4. **Coordinator Agent:** This refers to the central computer, which is responsible for collecting all the data, devising an optimal strategy, and transmitting the strategy to the relevant agents (in this case the human agents). The coordinator proposes an optimal strategy to the human agents as calculated using a Mixed Integer Linear Programming approach (detailed in the subsequent sub-chapters).

Additionally, for each timestep, the agents (humans) are activated randomly and not sequentially or following a specified rule, this prevents some agents from having an advantage. To illustrate, if the

agents were activated sequentially, Human_Agent_1 would always be activated first and would always have access to the chargers before any other human agent.

Concisely, considering the three types of agents, the signaling, and the defined willingness to participate, we detail the two proposed approaches for simulating energy communities in the subsequent sub-chapters.

5.3.1 Generalized Approach for Electric Vehicle Energy Community Co-Simulation

For this approach, there are two components; the optimization component and the simulation component. The optimization component is realized using a MILP optimizer whilst the simulation component is achieved using MAS.

The optimization entails using the predicted PV production, demand, and the EV charger demand (this comes from the EV agents) to optimize the use of the 50-kwh stationary battery and the plugging and unplugging of EVs. Thus, for this approach, the availability of human agents is not required for determining the optimal scheduling of the battery (i.e., the direct flexibility) and the scheduling of EV charging. The optimal strategy is calculated at the start of each simulation day and the signaling is then subsequently sent to the human agents on an hourly basis.

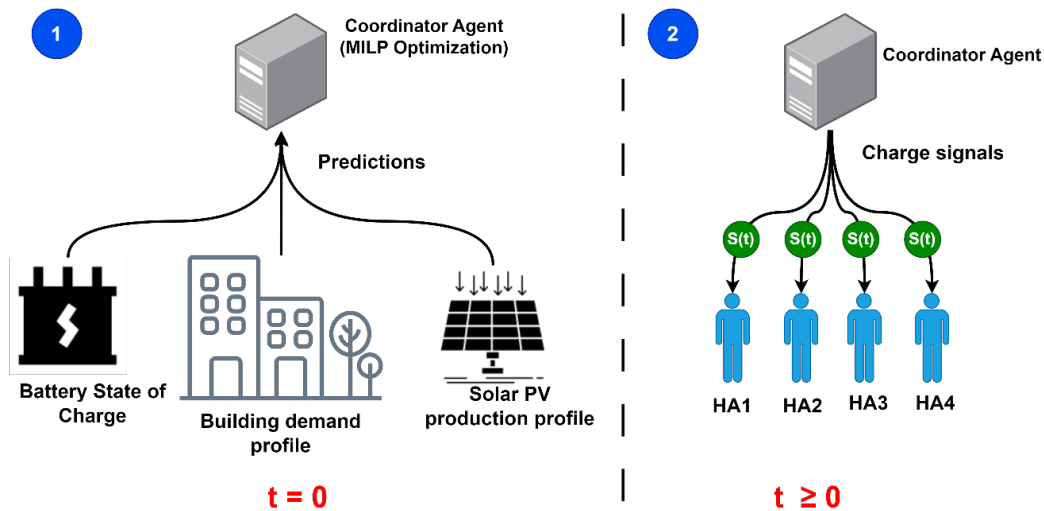


Figure 5.2: Generalized approach for simulating EV user behavior showing step 1: (left) the charging schedule estimation and step 2(right): the signaling of the EV users.

Based on the optimal schedule obtained from the MILP, the corresponding signals (one signal per timestep) are then sent to each human agent. Each human agent receives the same signal and decides to charge or not charge based on the received signal, the

SOC of their EV, and their willingness to participate (see Figure 5.2). If the decision is to charge, then the human agent checks for an available charging point and proceeds to use one if there are any such charging points unoccupied.

The optimization considered for this approach considered the problem definition in Chapter 3.2.2 (eqns 3.1 - 3.10). Subsequently, the signals were extracted from the optimal charging schedule and transmitted to the human agents in the MAS-based simulation.

5.3.2 Individualized approach for Electric Vehicle Energy Community Co-Simulation

Similar to the Generalized approach, this approach also considers two components, the optimization and simulation components. In this approach, however, the schedule of the human actor is a key component for the optimal scheduling of the battery and chargers. Thus, the day ahead schedule (i.e., the availability) of the human agent must be known and transmitted to the coordinator agent at the beginning of the day simulation.

Based on this schedule, the MILP optimizer proposes an optimal EV charging schedule that is adapted to the additional constraint induced by the availability of human agents. Thus, for this approach, each timestep has n number of signals, where n is the number of human agents (specifically EV owners).

The problem formulation for the individualized approach builds on the MILP formulation considered in the generalized approach. Thus, for this optimization, we still consider the problem formulation from chapter 3.2.2, specifically eqns 3.1 - 3.10. However, to consider the schedules of the human agents, the objective function as defined in eqn 3.1 was modified such that:

$$\text{objective} = \min \sum_t E_{\text{unmet}} + [P_{\text{import}}(t) - P_{\text{export}}(t)] \times \text{timestep} \quad (5.4)$$

Where $[P_{\text{import}}(t) - P_{\text{export}}(t)] \times \text{timestep}$ refers to the NEEG⁷ [54] and E_{unmet} is the total unsatisfied energy demand of the EV charging stations and is expressed mathematically as:

$$E_{\text{unmet}} = \sum_{x=1}^X E_{\text{demand EVs}}(x) - \sum_{t=0}^T \sum_{\text{ch}=1}^{\text{CH}} P_{\text{charger}}(\text{ch}, t) \times \text{timestep} \quad (5.5)$$

7: Net Energy Exchanged with the Grid and is the sum of import power and export power (Note: export power p_{export} is negative.

Where $\sum_{x=1}^X E_{\text{demand EVs}}(x)$ is the total demand of the EVs and x is a member of the set of EVs defined as $\{1, 2, \dots, X\}$ and $P_{\text{charger}}(\text{ch}, t) \times \text{timestep}$ is the energy consumed by the charger

denoted by ch (ch is a member of the set $\{1, 2, \dots, CH\}$) at timestep t .

To determine the time for each EV user to plug in and unplug their vehicle (i.e., the personalized optimal charging schedule), the constraints below were employed:

$$T_{\text{unplug}}(x, ch, t) = T_{\text{plug in}}(x, ch, t) = \begin{cases} 0, & \text{if } EV_{\text{avail}}(x, t) = 0 \\ 0, & \text{if } \text{hour} < T_{\text{open}} \text{ or } \text{hour} > T_{\text{close}} \end{cases} \quad (5.6)$$

Else,

$$\sum_{ch=1}^{CH} T_{\text{plug in}}(x, ch, t) \leq 1 \quad (5.7)$$

$$\sum_{ch=1}^{CH} T_{\text{unplug}}(x, ch, t) \leq 1 \quad (5.8)$$

Where $T_{\text{plug in}}(x, ch, t)$ and $T_{\text{unplug}}(x, ch, t)$ are binary values for determining the time to signal a plug in or unplug event for EV designated as x at the charger ch , and $EV_{\text{avail}}(x, t)$ refers to the schedule of EV x . Having defined a constraint that ensures that the EV owner plugs in and unplugs their EV, it is essential to ensure that a plug-in event is a precursor to an unplug event, thus, the following constraint was introduced into the problem definition:

$$\sum_{ch}^{CH} \sum_t^T T_{\text{unplug}}(x, ch, t) \times t - \sum_{ch}^{CH} \sum_t^T T_{\text{plug in}}(x, ch, t) \times t \begin{cases} = 0, & \text{if } \sum_t EV_{\text{avail}}(x, t) \leq 1 \\ \geq 1, & \text{if } \sum_t EV_{\text{avail}}(x, t) > 1 \end{cases} \quad (5.9)$$

This ensures that for an EV to be considered for charging there is more than 1 hour of availability and that T_{unplug} is always greater than $T_{\text{plug in}}$. Furthermore, to prevent an EV owner from being assigned a charge event multiple times during the optimization horizon (1 day) and also to ensure multiple EVs are not assigned to the same charger:

$$\sum_{ch}^{CH} \sum_t^T T_{\text{plug in}}(x, ch, t) \leq 1 \quad (5.10)$$

And to ensure that an EV owner receives the same number of plug-in requests as unplug requests:

$$\sum_t^T T_{\text{plug in}}(x, ch, t) = \sum_t^T T_{\text{unplug}}(x, ch, t) \quad (5.11)$$

Given that the availability of EV reduces the feasible region of our optimization, the hard constraint defined in eqn 3.8 had to be relaxed such that:

$$\sum_{t=0}^T \sum_{ch=1}^{CH} P_{\text{charger}}(ch,t) \times \text{timestep} \leq \sum_{x=1}^X E_{\text{demand EV}_s}(x). \quad (5.12)$$

Lastly, to prevent an EV user from being assigned to multiple chargers, we added the constraint:

$$\sum_o T_{\text{plug in}}(x, ch, t) \leq 1 \quad (5.13)$$

Using the problem formulation defined above, we can now compute an optimal strategy. Thus, following the optimization, each human agent receives their personalized signal and acts accordingly on the received signal, see Figure 5.3.

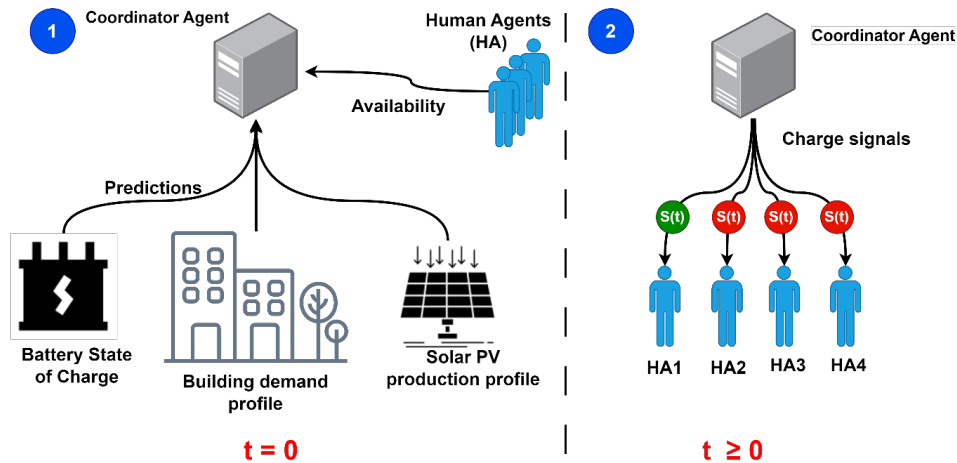


Figure 5.3: Individualized approach for simulating EV user behavior showing step 1: (left) the charging schedule estimation and step 2(right): the signaling of the EV users.

For this application, just as was the case in the generalized approach, the decision to charge is based on the human agent’s EV SOC, their willingness to participate and the signal received. Given the optimization aspects of the co-simulation have been defined, the next sub-chapter will detail the models for the various agents and the assumptions made in defining these agents.

 **Highlights:**

- ▶ The proposed approaches are mainly distinguishable by the approach to optimization. The individualized approach is a more constrained optimization and might not yield a global optimal result.
- ▶ Typically in the individualized approach, not all the demand will be met as the availability schedule reduces the feasible region of the solution. However, the problem formulation takes this into account and minimizes the unmet demand.

5.3.3 Use Case: Simulating EV User Behavior in the Predis-MHI Building

Given the two approaches described in the preceding sub-chapters, we considered the Predis-MHI as a use case with the parameters detailed in Table 5.1. The simulation was carried out considering the data from the Predis-MHI building for the year 2022 (1st January 31st December 2022) and was such that at the start of each day, each EV would have a randomly chosen SOC between 50% and 100%. Additionally, each human agent had a nominal distance (daily distance traveled from home to office) which was used to estimate the energy required to drive to and from the Predis-MHI building.

The devised co-simulation can be summarized in 3 steps as depicted in Figure 5.4:

1. **Initialization step:** in this step, the MAS is initialized and provides as an output the starting state of charge $SOC(0)$ for each EV in the simulation. Considering the starting SOC and the daily distance to be traveled, the projected demand for each EV (and by extension the accompanying human agent) is estimated. Furthermore, at this stage, each human agent generates their availability (1 for available and 0 for busy) for the simulation horizon (24 hours in our use case).
2. **Optimization Step:** In this step, the projected demand and the availability of the human agents (only for the individualized approach), the current state of the battery⁸ are provided as inputs to the MILP optimizer. At the output, the optimizer provides the optimal charging schedule for the EVs (personalized in the individualized approach) and the optimal battery schedule.
3. **Simulation Step:** This step is in two phases: the first step involves the simulation of the MAS to provide the charging

8: The battery state of charge at initialization is considered to be the last state of charge for the previous day ($SOC(23)$) and is an output from the battery's digital twin (described in chapter 4.4.3, except in the first run of the simulation where it is a user input)

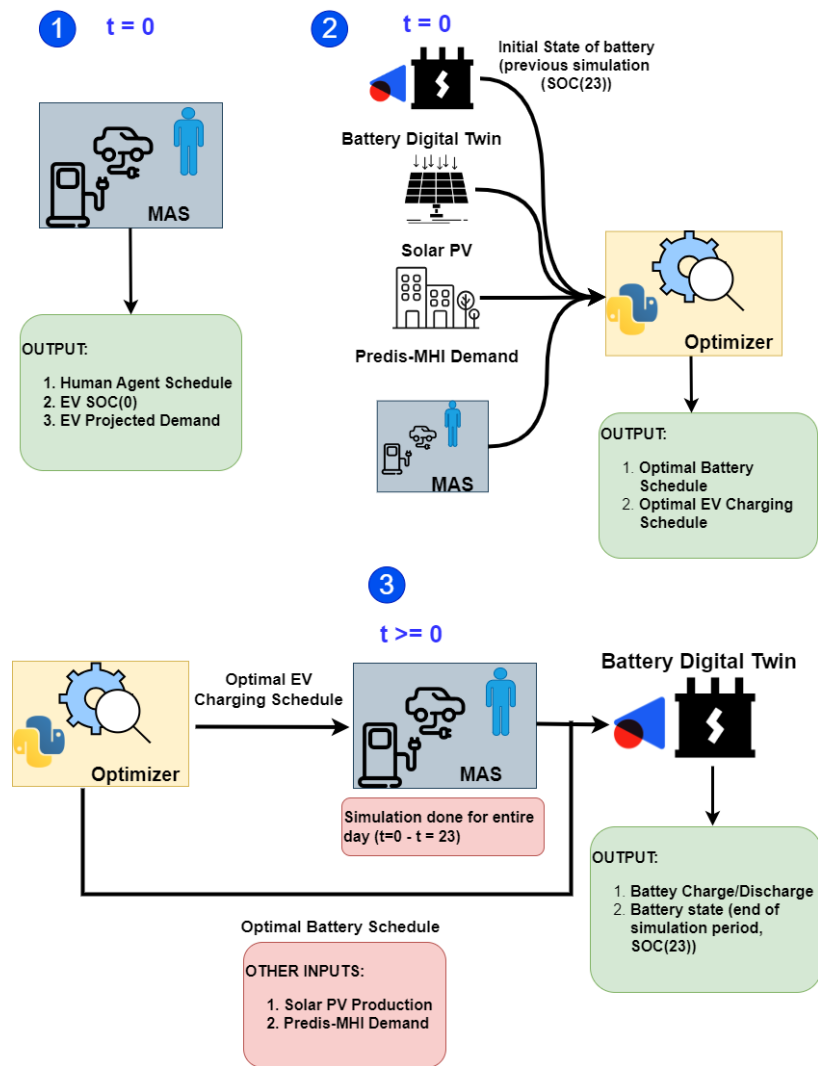


Figure 5.4: Graphical representation of the co-simulation tool for Local Energy Communities

profiles (from the Charger Agents) as depicted in Figure 5.5. In this phase, behavior associated with the use of charging infrastructure is simulated.

The second phase involves the simulation of the battery (using the digital twin as described in chapter 4.4.3, thus, the digital twin takes as input the EV demand (from MAS) the building demand, and the solar PV production. The outputs of the digital twin in this phase are the end-of-day SOC ($SOC(23)$) and the simulated battery schedule.

Self-consumption was used as the evaluation metric for assessing the impact of the interplay between direct and indirect flexibilities. For the period considered (July 2022), the self-consumption without EV charging demand was evaluated to be approximately 28%⁹. Considering the EV charging demand, the self-consumption was evaluated to be 32%, indicating a low utilization rate for the charging infrastructure.

9: In summer, self-consumption is typically low due to the high solar PV production and relatively low demand

Given the parameters above and the three (3) types of agents, we

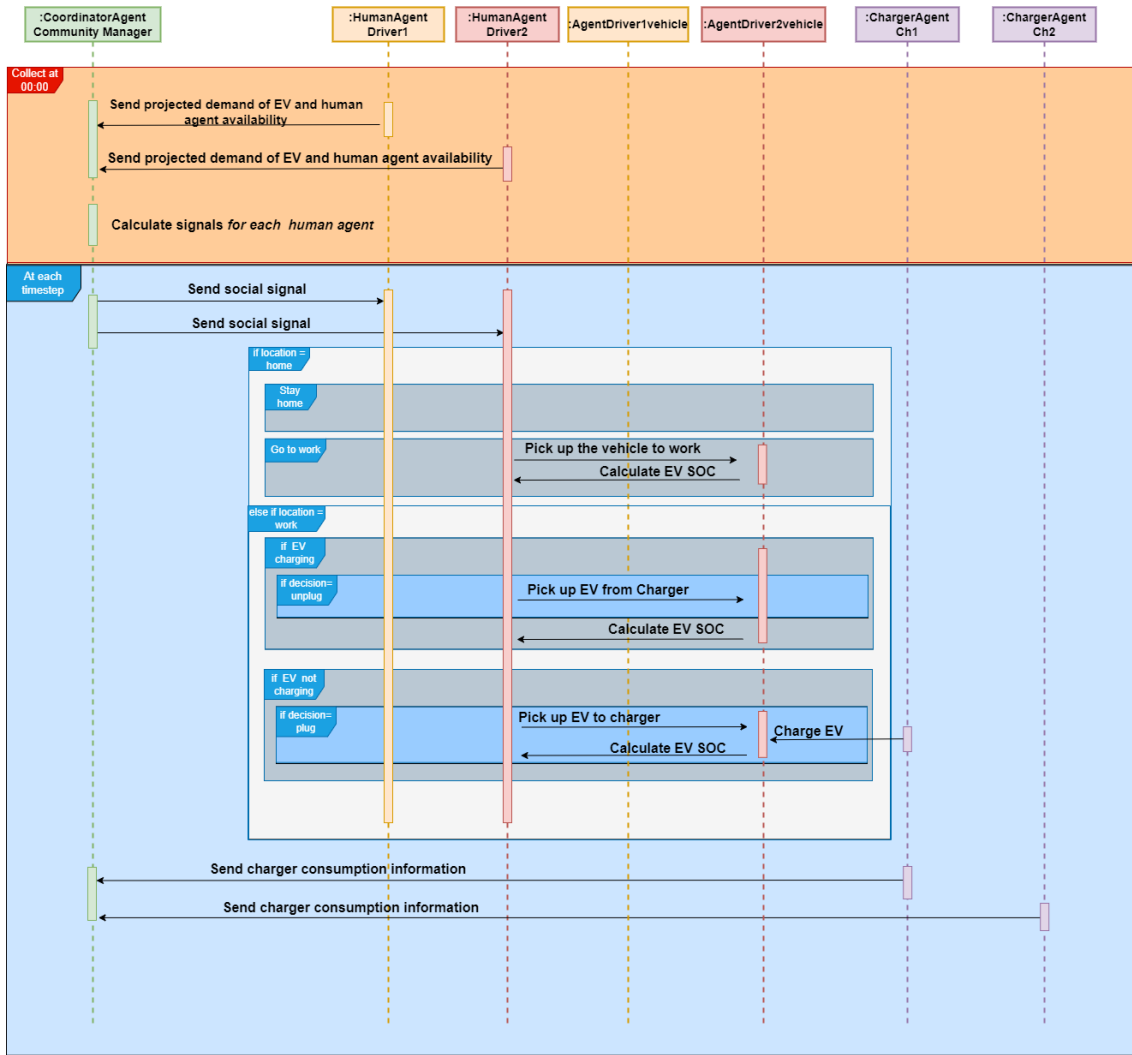


Figure 5.5: Unified Modeling Language (UML) Sequence diagram of the Multi-Agent System (MAS) component of the proposed co-simulation

simulated four (4) scenarios which are detailed below:

1. **Motivated Human Agents Scenario:** This scenario is highly optimistic and represents an ideal case in many regards. For this scenario, all six human agents were considered motivated (thus, their willingness parameter was set to 1). In order to study the impact of these human agents on the energy sub-system, we considered a Monte Carlo¹⁰ simulation approach (as was the case for all the considered scenarios). Thus, for both the generalized and individualized approaches, the simulation was run multiple times, and the distribution of the self-consumption obtained is illustrated in Figure 5.6. The results show that optimization strategies were able to achieve high self-consumption rates (greater than 100% because of the energy in the battery at initialization). However, in this scenario, the Generalized approach proved more effective, with the results showing a self-consumption rate of

10: Monte Carlo experiments are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The underlying concept is to use randomness to solve problems that might be deterministic in principle (source: [Wikipedia](https://en.wikipedia.org/wiki/Monte_Carlo_simulation))

Table 5.1: Summary of Predis-MHI local energy community (EV) co-simulation parameters

PARAMETER	UNIT	VALUE
CHARGER AGENTS		
Number of Chargers	-	4
Nominal Charger Power	kW	7
EV AGENTS		
Number of EVS	-	6
Nominal Battery Capacity	kWh	52
Daily Distance Considered	km	12 - 30
Average Energy Consumption	km/kWh	5.2
HUMAN AGENT		
Availability	-	1 / 0
Willingness to Participate	-	0 - 1 0, 0.5, 1
Battery		
Nominal Capacity	kWh	50
Charging Efficiency	%	98
Discharging Efficiency	%	98
Minimum SOC	%	20
Maximum SOC	%	100
Maximum Charge/Discharge Power	kW	40

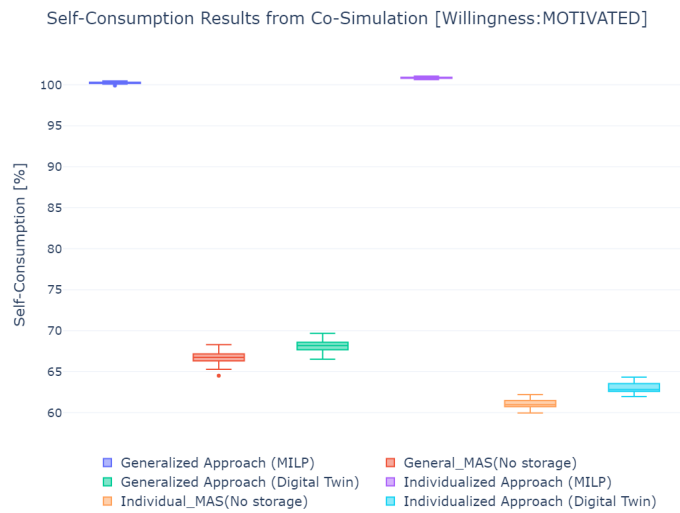


Figure 5.6: Box and whisker diagram representation for the results of the Motivated Human Agent only scenario (Jupyter Notebook online at [GitLab: Co-simulation](#))

70% for the lower bound and 67% (a 3% variation in results). The individualized approach on the other hand yielded a self-consumption rate of 62% (lower bound) and 64% (upper bound). Also of interest is the self-consumption rate only using the indirect flexibility ¹¹.

Given that this is an ideal (best) case, and the optimal cases did not vary significantly between the individualized and generalized approaches, one would expect the individualized

11: This parameter is denoted by General_MAS (no storage) for the generalized approach and Individual_MAS (no storage)

approach to have performed better.

However, since in this approach, each agent receives a maximum of one charge (green) signal per day, an agent that decides not to charge when they receive this signal is highly unlikely to charge since they are most likely to respect the do not charge/no action signals which they will receive for the rest of the simulation period. The Generalized approach remedies this situation as all agents will continue to receive signals to charge provided the conditions are favorable.

2. **Apathetic Human Agents Scenario:** In this scenario, all Human Agents were considered to be apathetic (not motivated to participate, and more likely to act on their own intuition). This scenario should represent the worst case; however, we still need to bear in mind that a Human Agent not being motivated to follow signals does not necessarily imply that their actions would impact the system's performance negatively.

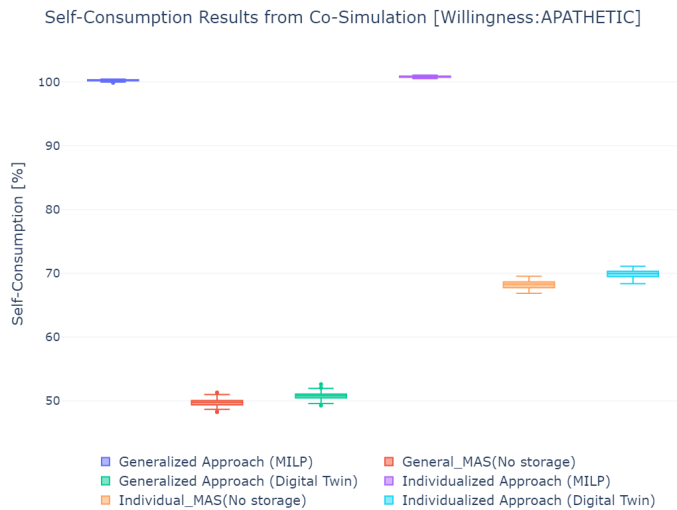


Figure 5.7: Box and whisker diagram representation for the results of the Apathetic only Human Agent scenario (Jupyter Notebook online at [GitLab: Co-simulation](#))

Figure 5.7 shows a similar trend to the result depicted in Figure 5.6, The MILP results are significantly higher. However, in this scenario, contrary to the results obtained for the Motivated Human Agents only scenario, the Generalized approach resulted in relatively lower self-consumption rates (48 - 51%) compared to the individualized approach (68 - 71%).

Since the human agents considered here are not the motivated kind, but rather the apathetic kind, their decision to charge depends less on the signal received (they still take it into account) and are less impacted by the continuous signal to not act. Thus, this type of agent is not inclined to respect the signalling (if anything they might be more inclined to do contrary) and as such in the individualized approach where they are receiving multiple do not charge signals, they have a tendency to decide to charge.

3. **Neutral Human Agents:** For this scenario, we considered all human agents to have a neutral willingness to participate (i.e., the willingness parameter was set to 0.5). The results obtained for this scenario are depicted in Figure 5.8. For this scenario also, the individualized approach performed better relative to the generalized approach with self-consumption rates between 60 to 63% compared to 65 to 68% in the case of the generalized approach.

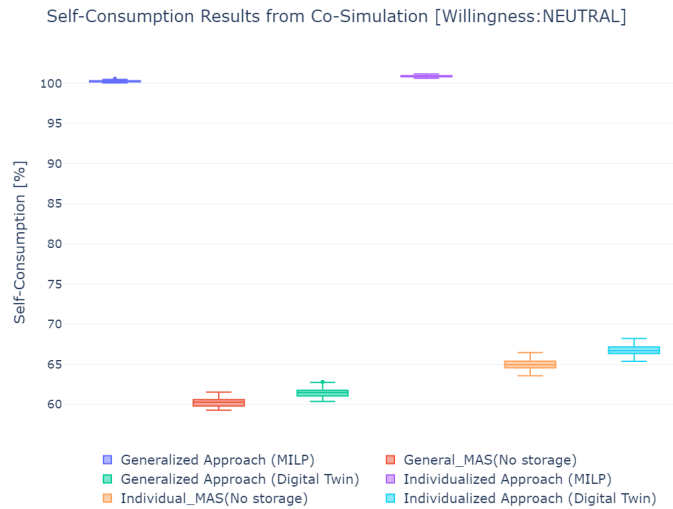


Figure 5.8: Box and whisker diagram representation for the results of the Neutral only Human Agent scenario (Jupyter Notebook online at [GitLab: Co-simulation](#))

4. **Hybrid Human Agents:** For this scenario, we considered a mix between the 3 defined willingness to participate, thus, two agents each were defined with a willingness to participate of 1 (motivated), 0.5 (neutral), and 0 (apathetic). This scenario will in many cases represent true-to-life systems, however, there are still many factors that could influence how this scenario impacts the energy sub-system. The results from this scenario are depicted in Figure 5.9 and reaffirm the overall better performance of the individualized approach. For this scenario, the generalized approach yielded a self-consumption rate between 60 to 62% whilst the individualized approach yielded a self-consumption rate between 65 to 68%. The explanation remains the same as was the case of the Apathetic Human Agents scenario.

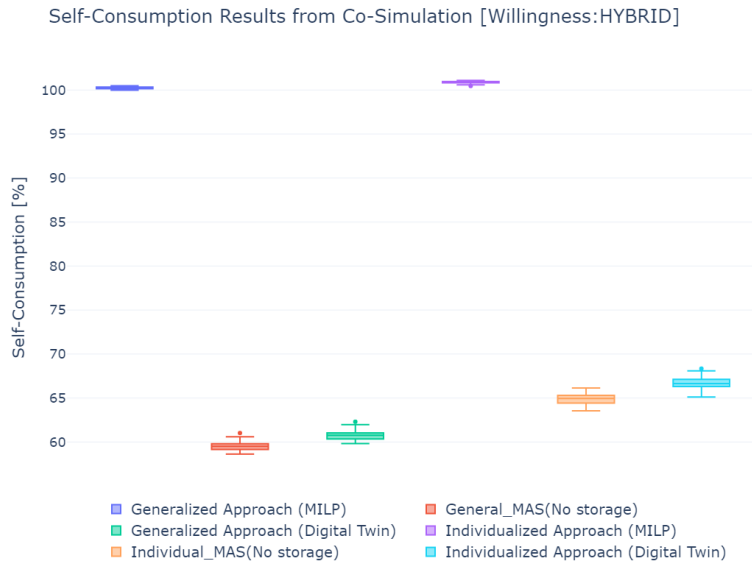


Figure 5.9: Box and whisker diagram representation for the results of the Hybrid Human Agents scenario (Jupyter Notebook online at [GitLab: Co-simulation](#))

Table 5.2 provides a summary of the results depicted above.

From Table 5.2 it can be deduced that the indirect flexibility is capable of increasing the self-consumption rate by up to approximately 20 - 35% (given the reference case was originally 32%), with the direct flexibility (i.e. the battery) accounting for a 2- 4% increase in the self-consumption rate. This lower participation can be attributed in part to the control of the battery using the output from the MILP optimizer. In all scenarios considered, the MILP results were significantly higher compared to the results obtained from the MAS simulation, accruing from the less-than-optimal behavior of the human agents and the control strategy imposed on the battery by the optimizer.

Also, considering the results from the individualized (see Table 5.2 the motivated agents only scenario yielded the lowest self-consumption rates. As these human agents were ideal, one would have anticipated the best results from the motivated human agents only scenario. The ideal nature of these agent however meant that they were more likely to follow the signals and if they missed a charge signal, were more likely to not charge during that day.

Table 5.3 shows the simulation time for different simulation periods (with 50 repetitions) on an Intel core I5¹² laptop with 16GB of RAM.

¹²: Intel 10310U with 4 cores and a base clock frequency of 17GHz

Table 5.2: Summary of Self-Consumption rates obtained from EV energy community co-simulation

	Upper Bound	Lower Bound	Median Value	Difference Between Upper and Lower Bound
Motivated Human Agents Only				
Generalized Approach (MILP)	100.47	99.91	100.31	0.56
Generalized_MAS (No Storage)	68.30	64.52	66.75	3.78
Generalized Approach (Digital Twin)	69.68	66.63	68.18	3.05
Individualized Approach (MILP)	101.07	100.64	100.87	0.43
Individualized_MAS (No Storage)	66.22	59.96	60.98	6.26
Individualized Approach (Digital Twin)	64.34	61.97	62.81	2.37
Apathetic Human Agents Only				
Generalized Approach (MILP)	100.46	99.88	100.26	0.58
Generalized_MAS (No Storage)	51.31	48.25	49.78	3.06
Generalized Approach (Digital Twin)	52.61	49.27	50.81	3.34
Individualized Approach (MILP)	101.18	100.52	100.82	0.66
Individualized_MAS (No Storage)	69.55	66.87	68.29	2.68
Individualized Approach (Digital Twin)	71.11	68.37	69.95	2.74
Neutral Agents Only				
Generalized Approach (MILP)	100.58	100.05	100.24	0.53
Generalized_MAS (No Storage)	61.53	59.29	60.28	2.24
Generalized Approach (Digital Twin)	62.81	60.38	61.58	2.43
Individualized Approach (MILP)	101.17	100.63	100.88	0.54
Individualized_MAS (No Storage)	66.47	63.58	64.96	2.89
Individualized Approach (Digital Twin)	68.22	65.37	66.72	2.85
Hybrid Human Agents				
Generalized Approach (MILP)	100.49	99.99	100.25	0.50
Generalized_MAS (No Storage)	61.02	58.63	59.52	2.39
Generalized Approach (Digital Twin)	62.31	59.83	60.77	2.48
Individualized Approach (MILP)	101.10	99.46	100.88	1.64
Individualized_MAS (No Storage)	66.15	63.55	64.95	2.60
Individualized Approach (Digital Twin)	68.34	65.12	66.64	3.22

Table 5.3: Summary of co-simulation computation time for different time horizons

Time Horizon	Total Number of Simulations	Total Simulation Time [seconds]
1 Day	100	489
1 Month	3000	7092
1 Year	36500	83269

5.4 Conclusion

In this chapter, we presented a co-simulation approach for simulating human behavior in an energy community. Our approach focused on an electric vehicle energy community providing load-shifting services to a building (in this case Predis-MHI). We devised two main approaches centered on how the optimal scheduling of the EV charging was computed and disseminated to the human agents; an Individualized approach that personalizes the signals sent to the human agents based on a schedule provided by them and a generalized approach that considered everyone to be available all day and sent the same signal to all human agents in the simulation.

Given the complex nature of human behavior and the added difficulty of taking into account all the factors that influence an individual's behavior. Our proposed framework focuses on the decision to charge or not which incorporates the choice to respond to a signal (we defined four). This decision to respond to signals was incorporated by associating a willingness to participate parameter to each human agent.

Our results show that for all the scenarios considered except the one in which all agents were considered to be highly motivated the individualized approach yielded better results as compared to the generalized approach. This better performance of the generalized approach compared to the individualized approach can be attributed to the ideal nature of the human agents which plays as a disadvantage particularly when an agent decides to not charge when they receive a charge (*green*) signal. Once a motivated human agent passes on the chance to charge all subsequent signals are do not charge (*red*) signals which this ideal human agent is more inclined to respect. However, in the generalized approach, because the human agents will receive multiple charge signals during the simulated day, this issue is mitigated.

With regards to the realism of the simulation, the simulation assumes most (if not all) EVs (we considered six) are present on-site, whilst this is not the case for Predis-MHI where there are eight (8) chargers with ten (10) EV users (the EVs are not always on-site). This accounts for the significant increase of the simulated indirect flexibility potential (approximately 30%) relative to the potential calculated in chapter 3 (approximately 2 - 8%). Consequently, the simulation and the results represent a future (at least in the case of Predis-MHI) where there is a higher penetration of EV users in the Predis-MHI building and consequently a higher charger utilization.

Gitlab Repository

The code and associated notebooks for the solutions proposed in this chapter can be found in the following repository: Comparison of rule-based and optimization-based control strategies: [GitLab: Co-simulation](#) Additionally, see Appendix B.1 for a list of all available notebooks

Additionally, the base assumptions on which the likelihood to charge is based may not be close to the ground truth, and as such a multi-disciplinary investigation into the charging behaviors (possibly using a real-life experiment of the simulated setup) is required to improve and validate the results from the co-simulation.

Further, the proposed co-simulation was conceptualized and implemented around the specificities of the Predis-MHI building. However, the Predis-MHI setup is not unique, in that it is reflective of many non-residential (office) buildings. Thus, the model can be applied to other similar setups albeit with some modifications.

Focusing on the interplay between the direct and indirect flexibilities, it can be seen from the results that the indirect flexibility if properly harnessed can be used as the primary source of energy flexibility with the battery (i.e., the direct flexibility) playing a secondary role. This potentially would also translate into less stress on the battery and ultimately a longer lifespan.

Lastly, the implementation of the signaling and human agents in the MAS showed that having only ideal community members (highly motivated actors) does not guarantee the best results. Our results show that for the motivated (ideal) agents, the generalized approach was a better form of signaling (in fact this yielded the best results for the generalized approach), whilst the individualized approach yielded the worst self-consumption rates for the same motivated human agents-only scenario.

General Conclusions and Perspectives

6

6.1 Connecting the Dots: A Summary of Key Points and Findings

Buildings (the end node in most energy networks) undoubtedly have a crucial role to play in the transition toward a sustainable and distributed energy landscape. The change in the role of buildings from consumer to prosumer and the introduction of the smart building (building with decision aided energy system) has opened a new paradigm of energy-related services that buildings can offer (from building scale to grid scale).

Like many systems, the building system (especially the energy sub-system) interfaces with humans (i.e., the occupants). Thus, in designing, modeling, and implementing building energy sub-systems, the human-in-the-control system (i.e., the building) cannot and should not be ignored (after all, buildings do not consume energy, humans do). Whilst human behavior cannot be directly controlled, it is possible to encourage and achieve a behavioral change in a desired direction (i.e., a positive behavioral change).

Building on this theme, the research work presented in this thesis has focused on mobilizing human behavior as an energy flexibility resource to offer load-shifting services to the building's energy subsystem. Our research focuses on the intricate interplay between direct and indirect flexibilities in smart¹ non-residential buildings but has similar implications for residential buildings.

In the subsequent sub-chapters, we present a summary and conclusion of each chapter of the thesis.

6.1.1 Chapter 1

In this chapter, we introduced the central theme of the thesis and presented an initial insight into our research question. The chapter sheds light on the role of energy flexibility in enabling and facilitating the transition toward a low-carbon, renewable, and sustainable energy landscape. We also presented fundamental but key concepts and definitions essential to this work's central theme, notably self-consumption (the evaluation metric for assessing the energy performance of our experimental setup), and direct and indirect flexibility.

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1: Reminder: Smart here refers to a building with a decision aided energy system.

In a nutshell, this chapter shows that the building is a socio-technical system, and the direct and indirect flexibilities represent the technical and social components, respectively. As such, it is important to consider the human-in-the-control system in all aspects of the operational phase of the building system to maintain a healthy balance between the needs of the human and the performance of the building system.

6.1.2 Chapter 2

In this chapter, we present the central theme of this thesis, our main research sub-question, to recap:

Main Research Question

“To what extent can human (occupant) behavior, which is the social component of the building system, be effectively mobilized and integrated with technical and highly controllable solutions to facilitate the delivery of energy flexibility services at the building and local energy community scale”.

Based on this main question, we derive four sub-questions that form the main basis of this research. Subsequently, we presented the Predis-MHI platform, a (smart) living lab that was used in this research as an experimental setup for testing and evaluating our proposed solutions.

6.1.3 Chapter 3

This chapter focuses on indirect flexibility and addresses 2 of our research questions, the first being:

SQ.1

“What methodologies can be employed to validate the potential and accurately quantify the impact of an identified indirect flexibility on the energy performance of a building?”

To this end, we proposed a framework for quantifying the available indirect flexibility potential. The proposed framework was applied to our experimental setup using self-consumption as an evaluation metric and showed that the indirect flexibility potential was approximately 2.81% (i.e. 563.94 kWh) in 2020 and approximately 8.65% in 2021 (i.e. 1,810.81 kWh) and 7.34% in 2022 (i.e. 1,687.56

kWh), with 2020 being significantly different as a result of the Covid-19 restrictions in France.

Following the results from the first part of this chapter, we addressed the second sub-question:

SQ.2

“How does one effectively account for indirect flexibility in the optimal dimensioning of direct flexibilities (battery storage)?”

To address this question, we proposed a MILP-based optimal battery-sizing methodology that mobilizes indirect flexibility to achieve a significantly reduced battery size compared to conventional sizing approaches. Testing on data from the experimental setup showed that to reach a target self-consumption rate of 70%, the proposed methodology resulted in a battery size 29.91% smaller relative to conventional sizing approaches.

In summary, in this chapter, we demonstrated that indirect flexibilities are significant, can be quantified, and have direct consequences on the energy performance of a building. Additionally, our proposed methodology for sizing batteries demonstrates how these indirect flexibilities can be considered in energy system models.

A key limitation to the proposed approach is that it assumes an ideal human, one that is rational and would always consider the greater good (i.e., the performance of the energy sub-system).

6.1.4 Chapter 4

This chapter focuses on direct flexibility, particularly battery energy storage systems, and is constituted of two key parts which address the sub-question:

SQ.3

“Given an energy system, what is the appropriate level of complexity and computational cost that ensures optimal and efficient use of a battery energy storage system?”

The first part focuses on control algorithm complexity and compares a rule-based approach to an optimization-based approach. The results show that for a simple application such as a system made up fixed demand profile, a fixed PV profile, and a battery, the rule-based approach has performance comparable to the optimization-based approach, however, increasing the complexity (for example adding a shiftable load as was the case in our setup)

would require more complex rule definitions and the performance of the rule-based approach would most likely deteriorate (it is more difficult to define rules that would be sufficient to capture all the system dynamics as complexity increases).

The second part of this chapter focused on a Machine Learning based Model Predictive Controller (ML-MPC) for the 50kWh battery installed in our experimental setup. This ML-MPC was constituted by a machine learning-based forecasting component and a MILP-based optimization component.

The machine learning models for the production and demand profiles resulted in 24-hour forecasts with low errors except for the Electric Vehicle demand forecast which owing to the data (highly sparse and random) had significantly high prediction error. This forecasting error consequently affected the performance of the ML-MPC.

The optimization component was defined such that the objective function was to reduce Net Energy Exchanged with the Grid, with the decision variables being the battery power and the power of the EV charges (i.e., the direct and indirect flexibilities respectively).

Due to the high prediction errors from the EV demand forecasts, there was a self-consumption shortfall of approximately 11.1% relative to the global optimal (optimal solution estimated with perfect prediction), however combining the ML-MPC with the reactive control (found in the BMS) of the battery, the shortfall was reduced from 11.11% to approximately 7.50%.

6.1.5 Chapter 5

In this chapter, we focused on the Sub-question:

SQ.4

“How do we evaluate and quantify the impact of the synergy between direct and indirect flexibilities on a building’s energy performance?”

In lieu of this question, we proposed a co-simulation framework for studying the interplay between direct and indirect flexibilities. The approach is based on a MILP optimization and a Multi-Agent System (MAS based simulation. Due to the complex nature of human behavior, only the decision to charge or not was modeled in the MAS. Furthermore, the human agents were categorized according to their willingness to participate (1: motivated, 0.5 neutral, and 0: apathetic). The MILP optimization component yielded a charging schedule (signals for human agents) and the

schedule of the battery, whilst the MAS simulated the response of EV owners to these signals.

Two approaches were conceived based on how the optimal charging schedule was calculated and disseminated to the human agents. The first, a generalized approach did not require the schedule of human agents and transmitted one signal to all agents per timestep. The second approach differed in that the optimization considered the availability of each human agent and then sent personalized signals to each agent.

We considered four scenarios; motivated human agents only, neutral human agents only, apathetic human agents only, and a mixed (hybrid) scenario. The generalized approach showed relatively better performance only in the motivated human agents scenario whilst the individualized approach was comparably better for the remaining scenarios.

The results also showed that the indirect flexibility (i.e., the charging of the EVs) was a valuable resource for improving the self-consumption and could potentially be used as the primary energy flexibility resource for building systems, with the battery energy storage system only providing supplementary energy flexibility in all the scenarios considered.

Lastly, the results from chapter 3, showed an indirect flexibility potential of 2 - 8% for the Predis-MHI, however, our simulation results indicate a potential of approximately 30%. This is largely due to the fact that in the simulation, it was assumed there EVs are present on-site daily, translating into a high charger utilization. Thus, this simulation represents a possible future where there is a high EV user penetration in the building and consequently a high charger utilization.

6.2 General Conclusion

Indirect flexibilities remain a generally untapped resource, however, in order to transition to a low-carbon energy system effectively and sustainably with high Renewable Energy Resources penetration, there must be a conscious and consistent effort from us the humans in the control system. This effort is typically reflected in human behavior, fortunately, human behavior is both adaptive and dynamic.

In this thesis, we have proposed a framework for quantifying the available potential of indirect flexibility. Our use case considered self-consumption as a metric for assessing the indirect flexibility potential, however, the framework is not restricted to self-consumption and can be applied to other metrics such as

financial cost and carbon emissions. This framework assumes ideal human behavior which is not the case, and the solution does not warrant the elimination of direct flexibility but establishes a need for both these flexibilities to complement each other.

We also examined the impact of indirect flexibilities on the dimensioning of direct flexibilities (specifically battery storage systems) and found that, by considering the indirect flexibility, it is possible to significantly reduce the required battery capacity compared to conventional battery sizing approaches (these only size the battery using demand and production data).

Additionally, we conceived and implemented a Machine Learning based Model Predictive Controller on a 50-kWh battery installed in our experimental setup. However, due to constraints related to the installation of the battery on-site, and subsequently restrictions regarding the export of energy from the off-site location onto the local distribution network, the ML-MPC had to be tested using a digital twin of the physical battery.

The results showed an 11% decrease in self-consumption which was reduced to 7% by the reactive control component of the physical battery. The significantly lower performance of the ML-MPC was a consequence of the low accuracy of EV demand predictions (that was largely due to the EV charger demand data being sparse and susceptible to the stochastic nature of human behavior).

Furthermore, by simulating the behavior of EV users in the energy sub-system, we found that indirect flexibility can be harnessed and utilized as the primary energy flexibility for improving a building's self-consumption. Additionally, our results show that there is a need to rethink our approach to energy flexibility as indirect flexibilities can and should be used as the primary energy flexibility with direct flexibilities being used to supplement the shortcomings related to human behavior and not the other way around.

6.3 Limitations

In this research work, we considered humans to be rational and have ideal behavior in the optimization aspects, this is however one of the key limitations of our work as human behavior might be far from this ideal. One might argue for automated systems to reduce the impact of human behavior. However, [42] point out that such a system is highly prone to be rejected or being *short-circuited* by the humans-in-the-control system.

We addressed this limitation in our optimization approaches partially by using Multi-Agent Systems which allowed us to simulate

an EV Local Energy Community in our experimental setup. However, as already indicated, human behavior is complex and difficult to model. As such, the behavior of EV users in one geographical location might not necessarily be indicative of the behavior of EV users in a different location.

Additionally, despite having an experimental test bed to implement a real-life Machine Learning based Model Predictive Controller, regulatory and technical constraints warranted that a digital twin of the battery is used instead.

6.4 Future Prospects

Based on the work presented in this thesis, there exist several prospects for future work. However, real-life implementation of the EV energy community with both the individualized and generalized approach is of particular interest. This experiment would essentially provide a much-needed insight into:

1. how effective the signaling is for users (interpretability).
2. how EV users respond to the proposed signaling (effectiveness).
3. how cooperative users are willing to be (game theory implications).

Thus, the experiments would provide feedback on the social acceptance of the proposed method as well, and possibly serve as a launch pad for trans-disciplinary solutions for achieving low-carbon and sustainable energy flexibility solutions for the future grid.

Additionally, given that the Machine Learning algorithms did not perform exceptionally well in the case of the EV demand profile, some more work has to be carried out to improve the predictability of the data.

A few methods exist such as data augmentation. Generally, work also needs to be done to improve the prediction accuracy for the demand and solar PV production profiles as well.

Furthermore, an assessment of the impact of prediction errors is also required to determine the level of tolerance the Machine Learning based Model Predictive Controller has for prediction errors.

6.5 Publications

1. **Twum-Duah, Nana Kofi**, Manar Amayri, Stéphane Ploix, and Frédéric Wurtz. 'A Comparison of Direct and Indirect Flexibilities on the Self-Consumption of an Office Building: The Case of Predis-MHI, a Smart Office Building'. In: *Frontiers in Energy Research* 10 (2022). (Visited on 06/15/2023)
2. **Twum-Duah, Nana Kofi**, Sacha Hodencq, Manar Amayri, Stéphane Ploix, and Frédéric Wurtz. 'Optimal Sizing of Stationary Battery Storage Taking into Account Indirect Flexibility in Tertiary Buildings : Use case of an Electric Vehicle Community'. In: (June 2022)
3. Muhammad Salman Shahid, Seun Osonuga, **Twum-Duah, Nana Kofi**, Sacha Hodencq, Benoit Delinchant, and Frédéric Wurtz. 'An Assessment of Energy Flexibility Solutions from the Perspective of Low-Tech'. In: *Energies* 16.7 (2023)
4. Jonathan Coignard, Sacha Hodencq, **Twum-Duah, Nana Kofi**, and Rémy Rigo-mariani. 'Solar panels – is more always better ?: Assessing the carbon footprint of communities'. In: *TATuP - Zeitschrift für Technikfolgenabschätzung in Theorie und Praxis* 31 (2022)
5. Sacha Hodencq, Jonathan Coignard, **Twum-Duah, Nana Kofi**, and Lucas Hajiro Neves Mosquini. 'Including greenhouse gas emissions and behavioural responses in the optimal design of PV self-sufficient energy communities'. In: *COMPEL - The international journal for computation and mathematics in electrical and electronic engineering ahead-of-print* (ahead-of-print Jan. 1, 2022). (Visited on 09/19/2022)

APPENDIX

A

Battery Documentation

A.1 50kWh Li-Ion Battery Technical Specifications

xStorage Compact

Single rack energy storage system







All in one

The Eaton xStorage Compact energy storage system enables buildings owners and facility managers to solve power management challenges for their small and medium commercial and industrial sites. Eaton xStorage Compact helps them increase local renewable energy consumption and integrate electric vehicles charging infrastructure on site. Eaton xStorage Compact is available in a single rack version which is easy to install, ready-to-use with symmetric charge and discharge and is backup ready. The system also includes a control platform with user interface and simple expansion options. This compact system is modular, scalable and well suited for a wide range of energy storage applications.

Key features

- Up to 50 kWh per string of 5 battery packs
- Bidirectional 3-phase converter up to 40 kW
- Symmetrical charge and discharge
- Battery pack with proprietary Battery Management System (BMS)
- Expandable with parallel connections from 42 kWh/rack to 100 kWh/rack
- Integrated user interface and application controller
- Battery backup

Benefits

-  Multi-usage system enabling PV self consumption, peak shaving, load shifting, back-up power, electric vehicle charging station integration
-  One single supplier providing you with one point of contact for certifications, warranty and services
-  Scalable, modular and quick to deploy
-  Highly efficient with minimum system losses
-  Safe and reliable with tested systems, controls and a proprietary Battery Management System (BMS)
-  Small system footprint – All included in less than 1 sqm/rack



This is a visual representation.
The final product may differ.

Eaton.com/xstorage

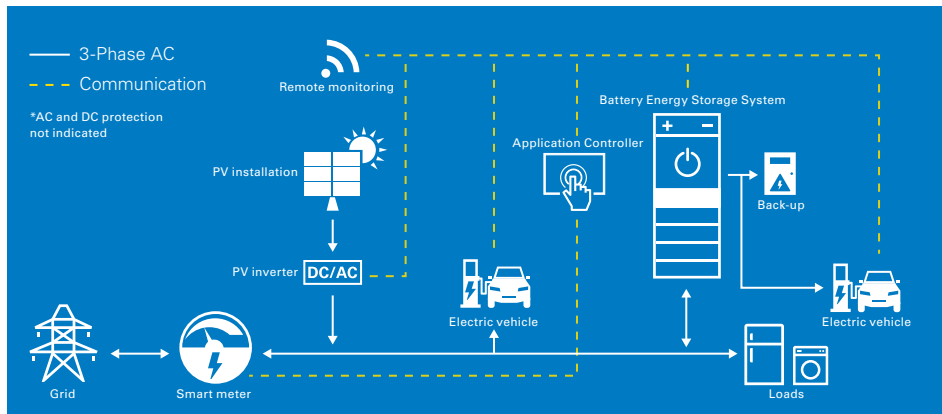
Technical disclaimer

In line with our goal to continuously improve the products and the customer service we provide, all specifications contained in this document are subject to change without notice. All drawings, descriptions or illustrations contained in this document serve to provide a clear overview and/or technical explanation of the present product and its various components and accessories.

Single rack energy storage system

A multifunctional system

xStorage Compact enables light commercial building facility managers and operators to store energy from renewable sources or the grid to improve the building resiliency and reduce its carbon footprint. The system can also provide use cases such as peak shaving, load shifting or maximize PV self consumption.



Technical specifications

Eaton.com/xstorage

Battery	Second-life	New
Nominal system capacity	21 kWh per string, up to 3 strings	50 kWh per string, up to 3 strings
Modularity	additional 42 kWh/rack	additional 100 kWh/rack
Cell Chemistry	LMO (Lithium Manganese Oxide)	NMC (Lithium Nickel Manganese Cobalt)
BMS	1 BMS per battery pack (5 BMS per battery string to ensure safety and monitoring performance)	
Battery warranty	Up to 5 years	Up to 10 years
Max. charge/discharge current DC	132 A	
Compliance and standards	IEC 62619, IEC 62040-1, IEC 62477-1, UN 38.3	
System		
Conversion power range	20 kW to 40 kW, parallel up to 5 units	
Nominal AC Grid Voltage	220 V/380 V; 230 V/400 V; 240 V/415 V; 3-phase (TN, TT, 4-wire)	
Rated output frequency	50 Hz/60 Hz; configurable	
Topology	Bidirectional rectifier/inverter - Backup	
Full system dimensions H x W x D	1987 mm x 600 mm x 1000 mm	
Full system weight	From 690 kg to 725 kg	
Degree of protection	IP20	
Topology / Grid integration	Transformerless / AC coupled grid tie / Grid forming	
Operating environment	From 0 °C to 35°C / From 5 % to 95% relative humidity (non-condensing) / Pollution degree 2	
Application controller capability	Back up, peak shaving, load shifting, PV self consumption and EV integration	
Minimum clearances	Front: 900 mm, Back: 200 mm, Top: 300 mm, side to side: 0 mm	
Round trip efficiency	> 85%	
THD	<1.5% at 100% linear load	
Communication protocol	Modbus TCP (Eaton XV303 interface capability)	
Compliance and standards	Safety: IEC 62040-1, IEC 62477-1 Grid connection: EN 50549-1, VDE-AR-N 4105:2018, CEI 0-21:2019, G99	



B

Open and Reproducible Science

B.1 Jupyter Notebooks for Open and Reproducible Research

Jupyter Notebooks are open-source and interactive computing applications that allow users to create and share documents that may contain live (executable) code, visualizations (these may be interactive), and explanatory text. Jupyter Notebooks offer a clear advantage over standard document formats as the application is still interactive. It utilizes a web-based interface that combines code, text, and media elements, thus making it a powerful tool for data analysis, open and reproducible scientific research, and collaborative work. Below are some reasons why Jupyter Notebooks are more interesting for our research compared to traditional document formats:

1. **Interactivity:** Live code elements (cells) can be added to the Notebook, thus, enabling interactive computing and open and reproducible research by allowing others to execute and modify the code used in achieving results. Additionally, plots and visualizations can be made interactive, thus allowing for analysis of results within the Notebook itself.
2. **Documentation:** notebooks offer what can be described as a seamless integration of code, images, visualizations, and text. The notebook can be segregated into sections and subsections, equations, and explanatory text can be added to any part of the Notebook. Thus making notebooks a more effective means of documentation.
3. **Reproducibility and transparency:** As already pointed out, Notebooks promote open and reproducible science, since the Notebooks come with live code. This feature in Notebooks also facilitates and encourages transparency in research. For this thesis, we subscribe to the principles of open science and as such, have chosen to provide the appendices related to the work carried out in this research as interactive notebooks which have been deposited online as summarized below:

Table B.1: Summary of Jupyter Notebooks related to this research



Chapter	Notebook Description	URL
Two	Analysis of the Predis-MHI dataset: Here you will find all the data used for this thesis 2020-2022	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_2_Predis_MHI_Data_Analysis.ipynb
Three	Assessment of energy flexibility potential of Predis-MHI: This Notebook presents the methodology proposed for assessing the flexibility potential, additionally, we used carbon emissions as a second metric to show that the method is not restricted to the self-Consumption metric. You can find an article published on the subject matter here: https://www.frontiersin.org/articles/10.3389/fenrg.2022.874041/full	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_3_indirect_flexibility_assessment.ipynb
Three	In this Notebook, we detail the approach for battery sizing which takes into account the available indirect flexibility. You can find the published article here: https://hal.science/hal-03696240v1	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_3_Battery_sizing.ipynb
Four	In this Notebook we detail the comparison of rule-based and optimization-based control of direct flexibilities (batteries)	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_4_Comparison_of_control.ipynb
Four	In this Notebook, we show the implementation of all the forecasting Models as used in this thesis.	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_4_Comparison_of_Forecasting_Models.ipynb
Four	In this Notebook, we have the implementation of the proposed Model Predictive Controller (MPC) for the control of the 50 kWh battery installed in the experimental setup	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_4_MPC_implementation.ipynb
Five	In this notebook, we have the implementation of the proposed co-simulation approach (optimization and Multi-Agent Systems) for an EV Local Energy Community.	https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/thesis_energy_flexibility/-/blob/main/notebooks/Chapter_5_Co-simulation.ipynb

B.2 Using the Jupyter Notebooks

To use the notebooks, there are a number of options, however, we will detail two of these options.



1. **mybinder:** Each of the notebooks provided in Table B.1 will have in its preamble (the very first cell at the top of the Notebook) a link to [mybinder](#), usually indicated using



. If this is the preferred method, then one must simply click the icon (you will be redirected to [mybinder](#)), all required libraries (you can check the requirements.txt file) will already be loaded in the environment and all you have to do is click on either the **Run** button  (executes only the currently selected cell) or the **Run all**(fast forward) button  (executes the entire notebook).

2. **Download:** It is possible to download the notebook from the GitLab repository. However, it is important to note that all the required dependencies (data sets, python files, etc.) required to make the notebook work will also have to be downloaded (we recommend downloading the entire project).

Once downloaded, the file can be opened using a local Jupyter server (For this we recommend installing [Anaconda](#). we recommend setting up a virtual environment (see [python virtual environments](#)) and installing the requirements (you can do this using "pip install -r requirements.txt" - Note you should use this from a command line interface opened in the project directory and running your virtual environment if you opted for this approach).

Once everything is fully installed, you just need to open the notebook (from the jupyter web application) and click on either the **Run** button  (executes only the currently selected cell) or the **Run all**(fast forward) button  (executes the entire notebook).

B.3 Sample Jupyter Notebook


Predis-MHI Data Analysis

July 14, 2023

1 Analysis of Predis-MHI Data:

1.1 *Notebook related to Chapter Two of the Thesis with title:

1.2 Direct and indirect energy flexibility interactions at the Building and community scale: From system to the Human-interfaced systems

First time using a Jupyter Notebook ? In order to use this notebook online through the Mybinder public service, click the following icon 

You can then easily use this Jupyter notebook by running each cell with the Run (“Exécuter” in French) icon in the toolbar on top of the page. When the orange notebook icon in the tab turns into an hourglass, this means the code is still running. Do not hesitate to modify and adapt the code, working with Mybinder creates an online copy of the repository ipynb original file.

1.3 Data sources

- GReEN-ER (Predis-MHI) energy data (EV charging data, building energy usage, PV production) available at <https://mhi-srv.g2elab.grenoble-inp.fr/grafana/d/Xl5OAbQGk/ve-borne-de-rechargement?orgId=3&from=now-1y&to=now>

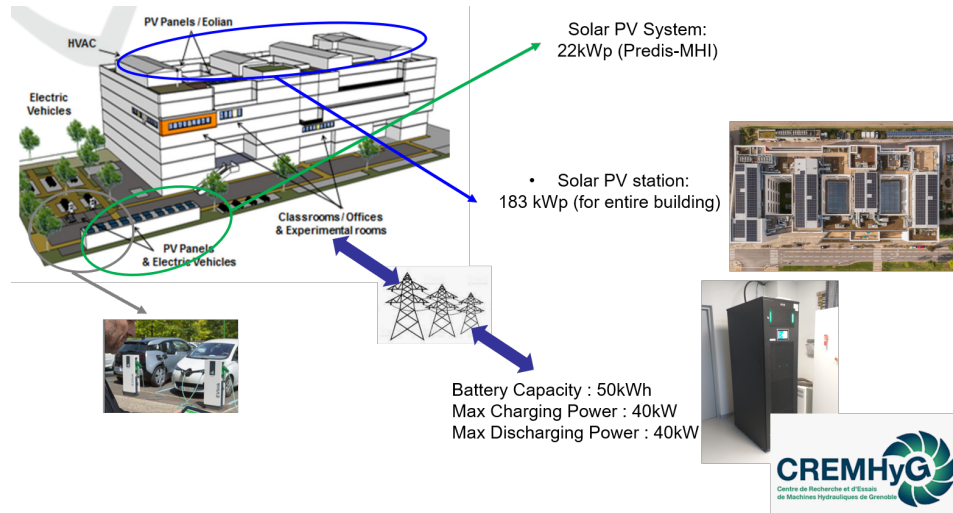
1.4 Objectives

In this notebook, we read and analyze the data related to Predis-MHI

1.5 Relevant imports

to run this notebook, the following libraries are required: * pandas Version => 1.2.4 * numpy Version => 1.19.5 * plotly Version => 4.14.1

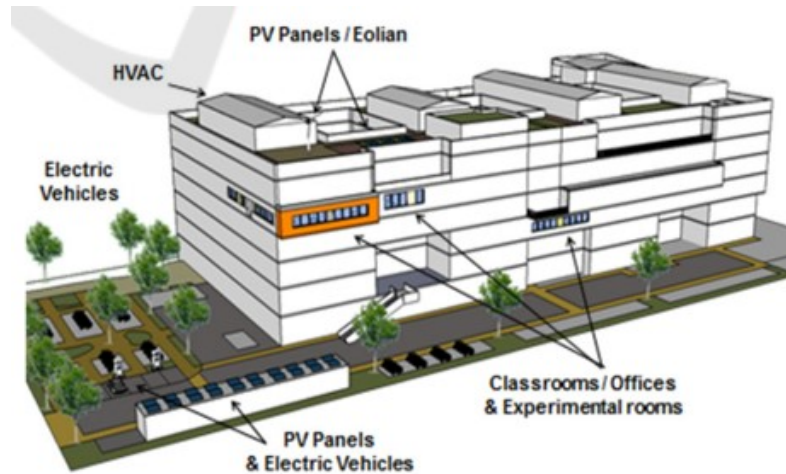
1.6 The GreEn-ER Building in a nutshell



The Predis – MHI (Monitoring and Habitat Intelligence) platform is a living lab that is housed in the GreEn-ER building. This is a smart building, commissioned in 2015, that is owned and operated by Grenoble Institute of Technology's school of Energy, water and environment (École Nationale Supérieure de l'Énergie, l'Eau et l'Environnement - ENSE3). It houses the Grenoble Electrical Engineering lab with a total floor area of approximately 27000m² (6 floors, each with 4500m²).

The platform which is the demonstration zone of the GreEn-ER building was conceived to achieve net-zero energy status. The platform is constituted of 600m² of floor space composed of offices, lecture rooms, and experimental rooms which make up the demand, a Heating Ventilation and Cooling (HVAC) system, 22kWp of solar PV, four EV charging stations (each with two charging leads) and a 50 kWh lithium-ion battery. Typically, the demand for the platform is comprised of lighting, HVAC, electrical outlets (typically computers), and EV charging stations. The platform not only allows for innovation and experimentation of technological solutions but also allows for the evaluation of the human element (i.e. the occupant). Thus allowing for the development and testing of solutions in real-life settings.

1.7 Zooming in on the predis-MHI platform



```
[1]: import pandas as pd
import plotly.express as px
import numpy as np
import plotly.subplots as sp
```

1.8 Load the data from CSV files

```
[2]: df = pd.read_csv("../Datasets/predis_mhi_2015.csv", index_col = "Datetime",
    ↪ parse_dates = True, sep = ",",
    ↪ decimal = ".")
df = df [df.index >= "2016-01-01"]
df["Total_consumption"] = df[["charger 1", "charger 2", "charger 3", "charger_
    ↪ 4"]].sum(axis=1) + df["Consumption"]

df = df[["production", "Consumption", "Total_consumption", "charger 1", "charger_
    ↪ 2", "charger 3", "charger 4" ]]

df["Self_cons"] = np.minimum(df["production"], df["Total_consumption"])
```

```
[3]: df.describe()
```

```
[3]:
```

	production	Consumption	Total_consumption	charger 1	\
count	61170.000000	61365.000000	61365.000000	35061.000000	
mean	2.477816	1.890524	2.169886	0.128378	
std	4.372846	1.500258	2.564261	1.204577	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	1.000000	1.000000	0.000000	
50%	0.000000	2.000000	2.000000	0.000000	
75%	3.000000	3.000000	3.000000	0.000000	
max	22.000000	35.000000	59.000000	32.995594	

	charger 2	charger 3	charger 4	Self_cons
count	35063.000000	61367.000000	61367.000000	61168.000000
mean	0.225081	0.045953	0.031450	0.864396
std	1.568359	0.650877	0.500419	1.541980
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	1.000000
max	36.000000	22.000200	27.999885	17.000000

2 Consumption

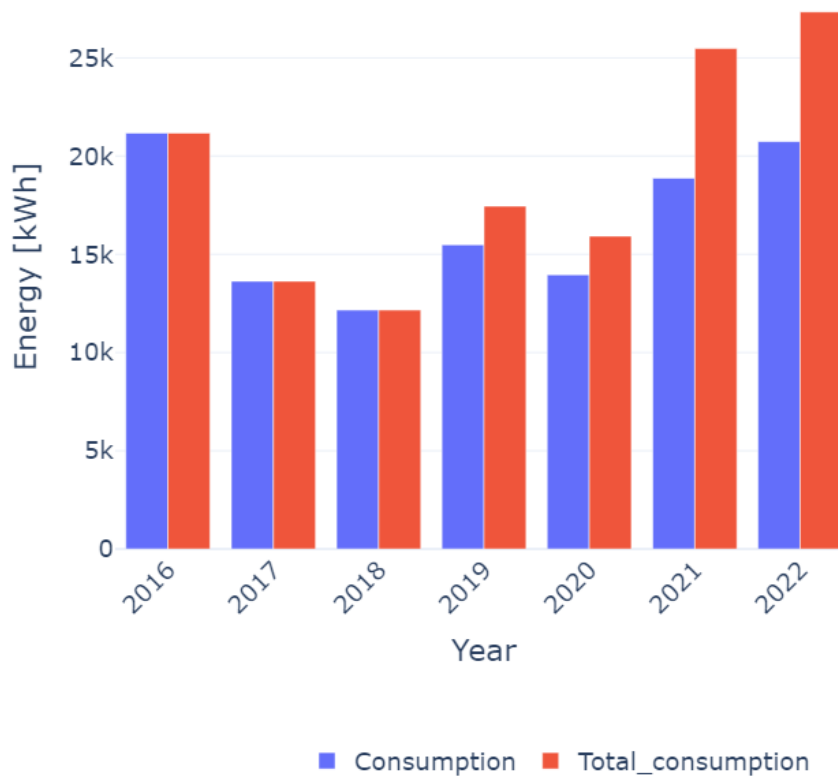
2.1 Annual Consumption

```
[4]: layout = {"template" : "plotly_white" ,
              "font":{"size" : 20},
              'xaxis': { "title_text" : "Year","tickangle" : -45},
              "yaxis": {"title_text" : 'Energy [kWh]'}}

fig = px.bar(df[["Consumption","Total_consumption"]].resample("1Y",
↳label="left").sum(),
            title = "Year on year energy consumption for Predis-MHI" , barmode=
↳="group")
fig.update_layout(layout)

fig.show()
```


Year on year energy consumption for Predis-MHI



```
[5]: ### Monthly Consumption
```

```
[6]: layout = {"template" : "plotly_white" ,
              "font":{"size" : 20},
              'xaxis': { "title_text" : "Year","tickangle" : -45},
              "yaxis": {"title_text" : 'Energy [kWh]'}}

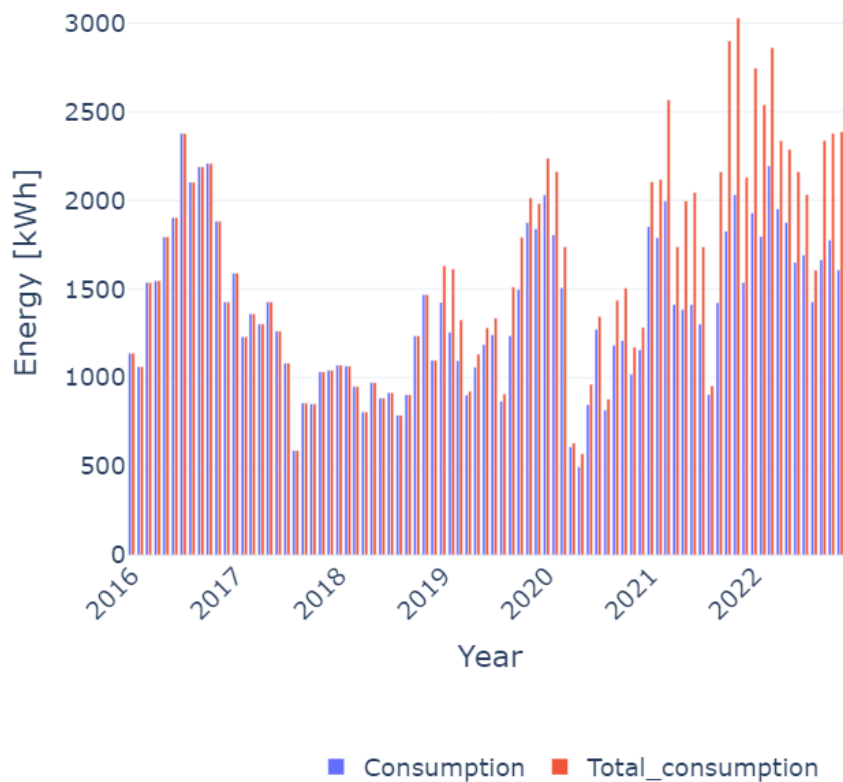
temp = df[["Consumption","Total_consumption"]].resample("1M", label="left").
↳sum()

fig = px.bar(temp,title = "Year on year energy energy consumptio for_
↳Predis-MHI" , barmode = "group")

fig.update_layout(layout)
```

```
fig.show()
```

Year on year energy energy consumptio for Predis-M



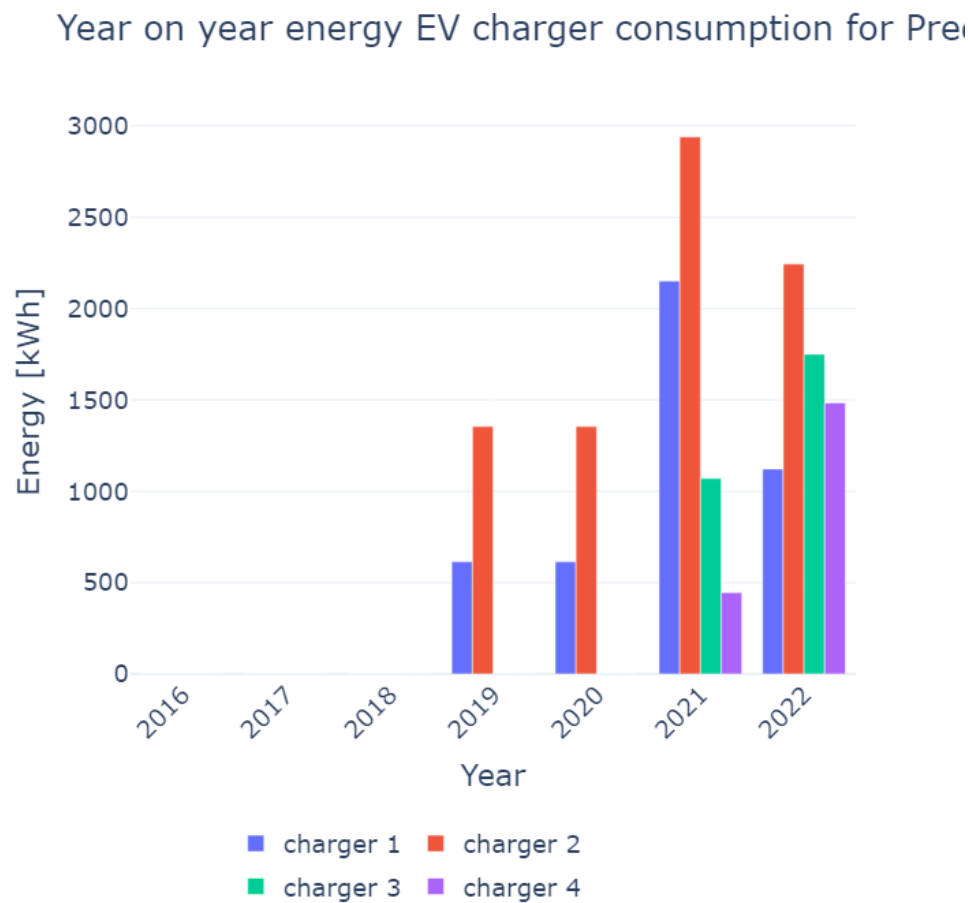
2.1.1 comments

The demand curve is typical for Europe, lowest in summer and highest in winter (when heating is required) There was annual growth in the demand except in 2020 which can be attributed to the covid-19 restrictions in France

2.1.2 Annual Charger demand

```
[7]: temp = df[["charger 1","charger 2","charger 3","charger 4"]].resample("1Y",
↳label="left").sum()

fig = px.bar(temp,title = "Year on year energy EV charger consumption for Pre
↳Predis-MHI" , barmode = "group")
fig.update_layout(layout)
fig.show()
```



2.1.3 comments

- EV demand is only present starting in 2019
- for 2020, the covid 19 restriction impacted the demand

- in 2021 there was an addition of 2 new chargers

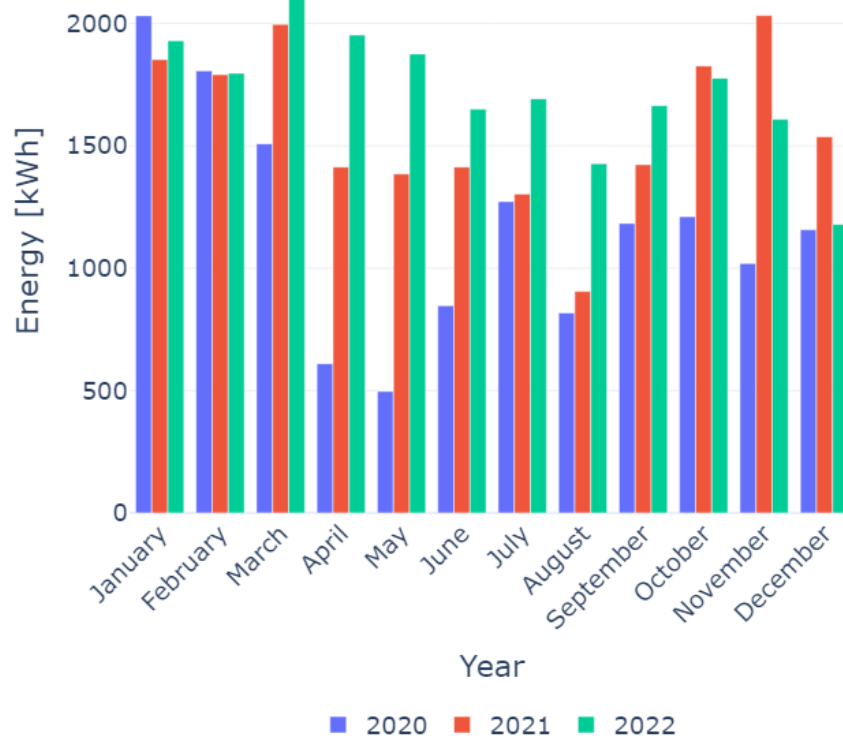
```
[8]: temp = pd.DataFrame()

df_monthly = df[['Consumption']].resample('1M', label = "right").sum()
for ind, frame in df_monthly.groupby(df_monthly.index.year):
    # print(frame)
    if ind >= 2020:
        temp[ind] = frame["Consumption"].tolist()

temp.index = ["January", "February", "March", "April", "May", "June", "July",
↳ "August", "September", "October",
    "November", "December"]

fig = px.bar(temp, barmode = "group", title = "Comparison of Monthly Energy
↳ consumption for Predis-MHI")
fig.update_layout(layout)
fig.show()
```

Comparison of Monthly Energy consumption for Pred



2.1.4 Comment

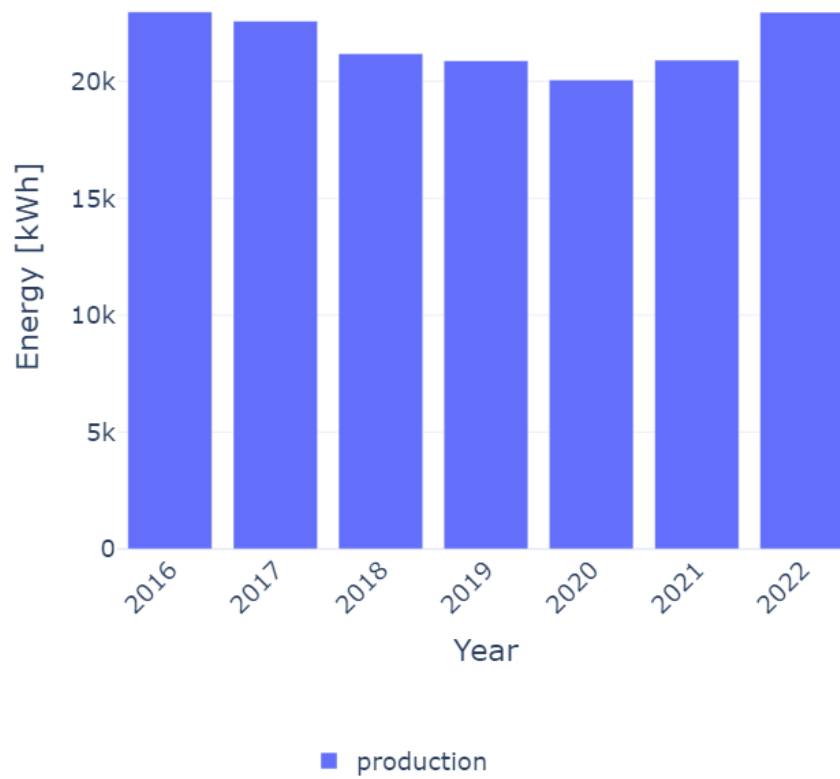
In 2020 for the confinement months, the consumption was significantly lower as the building was predominantly unoccupied

2.2 Annual PV Production

```
[9]: temp = df[["production"]].resample("1Y", label="left").sum()

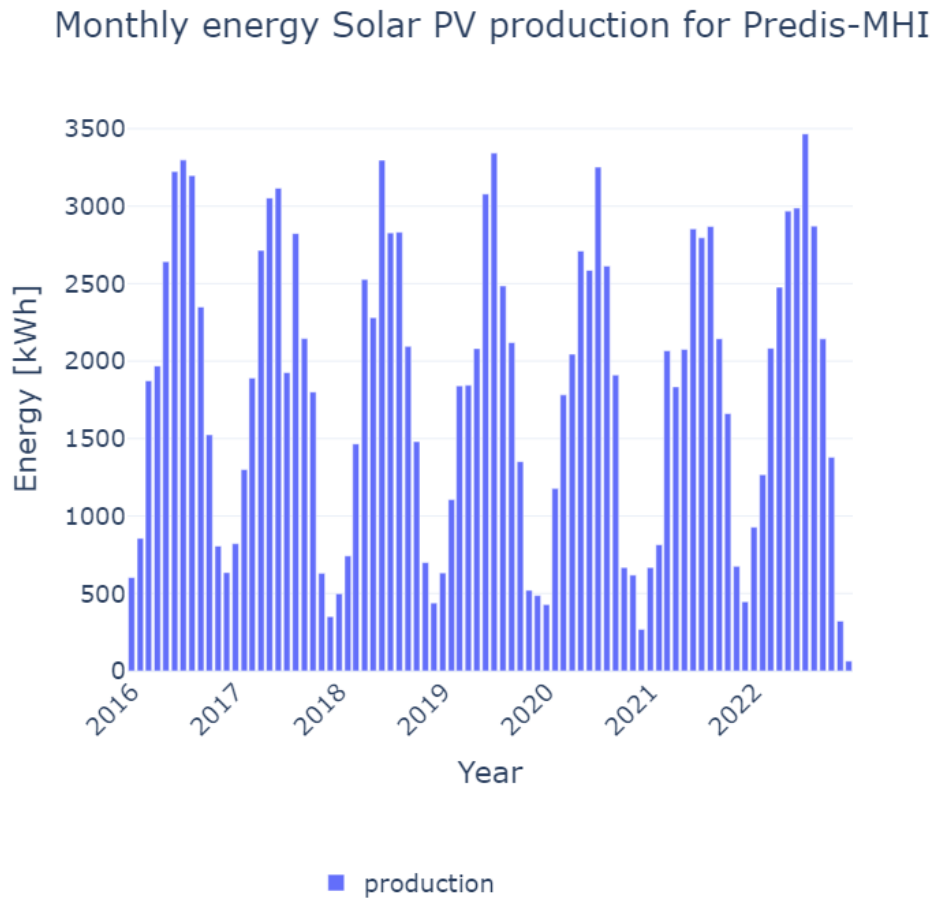
fig = px.bar(temp, title = "Year on year energy Solar PV production for_
↳Predis-MHI" , barmode = "group")
fig.update_layout(layout)
fig.show()
```

Year on year energy Solar PV production for Predis-M



```
[10]: temp = df[["production"]].resample("1M", label="left").sum()

fig = px.bar(temp, title = "Monthly energy Solar PV production for Predis-MHI",
             barmode = "group")
fig.update_layout(layout)
fig.show()
```



2.2.1 Comments

looking at the annual PV production of from the 22kWh installation shows that there was little variation in the annual PV production, with 2020 being the lowest production year.

From the monthly plot, we can see that the production follows the typical trend for Europe, highest in the summer months (April, May, June, July) and is lowest during the winter months (November, December and January)

2.3 Load Match Indicators

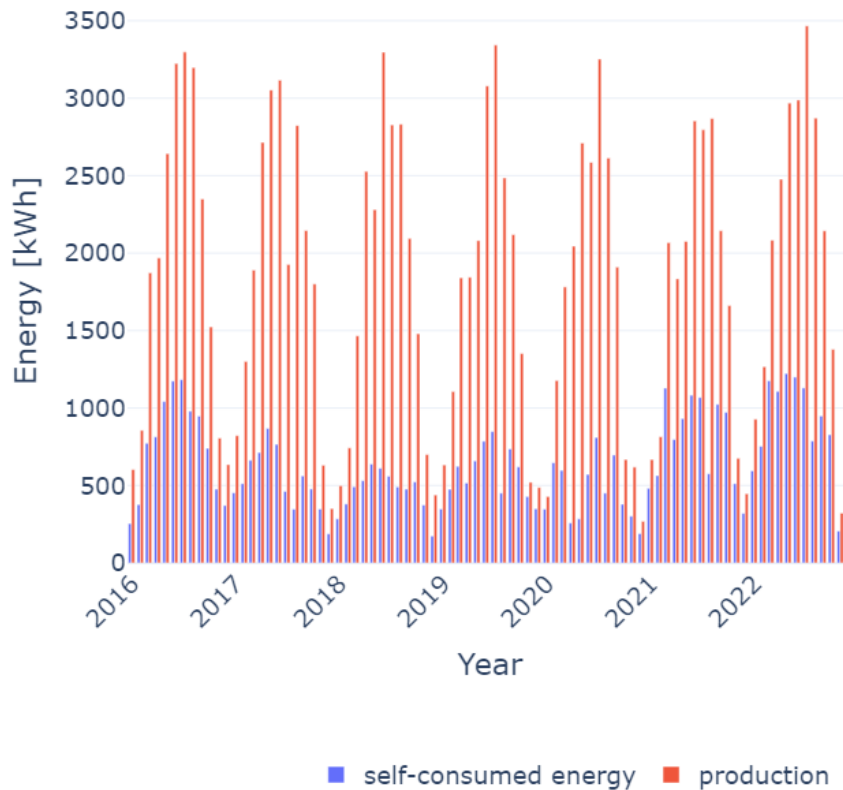
Self-Consumption This is the ratio of self-consumed energy to the production and provides an indication of how much of the local on-site production is being consumed locally.

Self-Production This is the ratio of self-consumed energy to the consumption. This indicator provides insight into how much of a building's demand is served by the local energy production resource.

```
[11]: temp = df.resample("1M", label="left").sum()

fig = px.bar(temp, y = ["Self_cons", "production"], title = "Monthly_
↪self-consumed energy vs Production for Predis-MHI" , barmode = "group")
fig.data[0].name = "self-consumed energy"
fig.update_layout(layout)
fig.show()
```

Monthly self-consumed energy vs Production for Prec




```
[12]: layout["yaxis"] = {"title_text" : "%"}

temp = df.resample("1Y", label="left").sum()

temp["Self-consumption"] =( temp["Self_cons"] / temp["production"]) * 100
temp["Self-Production"] =( temp["Self_cons"] / temp["Total_consumption"]) * 100

fig = px.bar(temp, y = ["Self-consumption","Self-Production"],title = "Year on_
-year load match indicators for Predis-MHI" , barmode = "group")
fig.update_layout(layout)
fig.show()
```

Year on year load match indicators for Predis-MHI



```
[13]: layout["yaxis"] = {"title_text" : "%"}

```

```

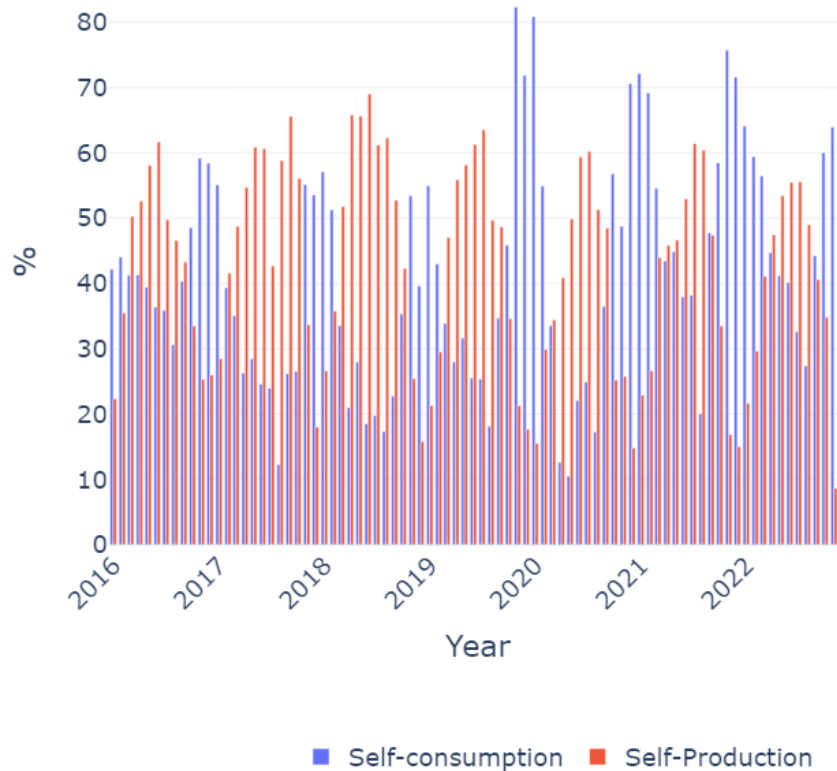
temp = df.resample("1M", label="left").sum()

temp["Self-consumption"] =( temp["Self_cons"] / temp["production"]) * 100
temp["Self-Production"] =( temp["Self_cons"] / temp["Total_consumption"]) * 100

fig = px.bar(temp, y = ["Self-consumption","Self-Production"],title = "Monthly_
↳load match indicators for Predis-MHI" , barmode = "group")
fig.update_layout(layout)
fig.show()

```

Monthly load match indicators for Predis-MHI



2.3.1 Comment

- Self-consumption and self-production rates here are calculated without battery storage as the storage had not been implemented in the system

2.4 Entire Data set

```
[14]: df_ = df.copy()
layout = {
    "font":{"size" : 15}, "template": "plotly_white", "height" : 600,
    'xaxis': {'zerolinecolor':'black',"title_text" : "Year" ,"tickangle" : -45},
    'xaxis2': { "title_text" : "Year","tickangle" : -45},
    "yaxis": {"showline": True,"linecolor": "black", "linewidth": 2,
↳'zerolinecolor':'black',
        "side": 'left', "title_text" : "Energy [kWh] " },
    "yaxis2": {"showline": True,"linecolor": "black", "linewidth": 2,
↳'zerolinecolor':'black',
        "side": 'left', "title_text" : "", "overlying": 'y' },
    "legend" : {"tracegroupgap":5 ,"font_size": 16, "orientation":"h",
↳"yanchor":"bottom",
    "y":-0.42,"x":0.05, "title" : ""}
    }

df_["Consumption(no chargers)"] = df_["Consumption"]
df_y = df_.copy().resample("1Y", label = "left").sum()
df_y['total'] = df_y[["charger 1","charger 2","charger 3","charger 4"]].
↳sum(axis=1)
df_y["Consumption(with chargers)"] =df_y["Consumption"] + df_y['total']

fig = px.bar(df_y, y = ["production","Consumption(with
↳chargers)","Consumption(no chargers)"],
    barmode =
↳"group",color_discrete_sequence=["#009ce9", "#ff3442", "#00e277"])
fig.data[0]["name"] = "Solar PV Production"

y = [f"charger {i}" for i in range (1,5,1)]

fig1 = px.bar(df_y,y = y, barmode = "group", color_discrete_sequence=
    ["#6ba3b9", "#678052", "#7b4039", "#b18d1c"])
figure = sp.make_subplots(rows=1, cols=2, subplot_titles=("Solar PV and Demand",
↳"Charger Demand"))

for trace in range(len(fig["data"])):
    figure.append_trace(fig["data"][trace], row=1, col=1)

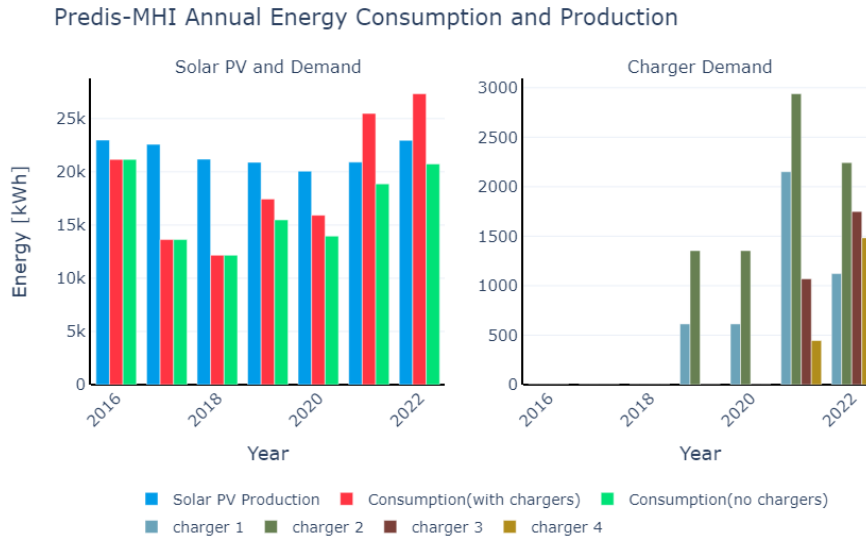
for trace in range(len(fig1["data"])):
#     figure.data[-1].showlegend = False
```

```

figure.append_trace(fig1["data"][trace], row=1, col=2)

figure.update_layout(layout, title = "Predis-MHI Annual Energy Consumption and
↵Production")
figure.show()

```



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Here are the references in citation order.

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