



Methods and tools for an online service infrastructure for energy communities in the context of collective self-consumption

Haicheng Ling

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Méthodes et outils pour une infrastructure de service en ligne pour les communautés énergétiques dans le cadre de l'autoconsommation collective

Methods and tools for an online service infrastructure for energy communities in the context of collective self-consumption

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ABSTRACT

Addressing climate change requires enhancing renewable and low-carbon energy use in residences, eco-districts, and regions. Our study examines a housing group sharing locally produced solar energy, an approach now recognized as Collective Self-Consumption (CSC), a French concept similar in spirit to those of the EU-regulated energy communities.

We first provide an overview of CSC focused on optimizing energy sharing. We review advanced techniques essential for supporting energy management, such as energy storage, demand response technologies, non-intrusive load monitoring, and other advanced energy system management tools. We develop two Information Communication Technology (ICT)-supported nudging pipelines: one using a non-intrusive AI-based model to disaggregate consumption curves, and an intrusive one relying on household consumption information collected via surveys. Both predict power output, assess flexibility, and send scheduling suggestions via email.

For the first nudging pipeline strategy, we identify limitations of NILM under ultra-low frequency (30 minutes) conditions, noting varying performance across different datasets. We then develop a classifier to determine household suitability for pretrained NILM models. While effective at 10-minute intervals, the classifier faces challenges at 30-minute intervals, leading to its abandonment due to inconsistent performance.

We assess our second nudging pipeline in simulations using synthetic and semi-real data. Simulations on individual self-consumption systems confirm that energy prediction outperforms weather prediction to identify consumption favourable periods. Introducing a coordinator module in CSC systems shows the importance of allocating surplus renewable production information differently depending on households, and the impact of survey-derived information. Further refining with an appliance-level coordinator enhances self-consumption rates but presents challenges like user complexity and notification fatigue. Finally, we outline plans to test our nudging pipeline in real-world settings and discuss future research perspectives.

Keywords: *Renewable Energy, Energy Self-Consumption, Information Communication Technologies, Nudges, Energy system optimization, System Control.*

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List of Abbreviations

Abbreviation	Definition
AB	AdaBoost
BESS	Battery Energy Storage Systems
CD	Clothes Dryer
CEC	Citizen Energy Communities
CSC	Collective Self-Consumption
CNNs	Convolutional Neural Networks
DEWH	Domestic Electric Water Heating Systems
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
DT	Decision Tree
DW	Dish Washer
ESS	Energy Storage Systems
FN	False Negative
FP	False Positive
GAN	Generative Adversarial Network
LR	Logistic Regression
ICT	Information Communication Technologies
KNN	K-Nearest Neighbors
MILP	Mixed Integer Linear Programming
NB	Naive Bayes
NILM	Non-Intrusive Load Monitoring
OMEGAAlpes	Optimisation ModEls Generation As Linear Programs for Energy System
PV	Photovoltaic
REC	Renewable Energy Communities
RES	Renewable Energy Sources
RF	Random Forest
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
V2G	Vehicle-to-Grid
WH	Water Heater
WM	Washing Machine

CHAPTER 1

Introduction: Designing Digital Solutions for Aligning Local Consumption with Renewable Energy Production in Collective Self-Consumption Systems

Abstract: In response to the urgent need for an energy transition to deal with climate challenges, increasing the share of renewable and decarbonized energies, such as solar energy, at the scale of condominiums, eco-districts, and territories has become crucial. In this context, the concept of local collective self-consumption systems has emerged in France and is rapidly developing, while also posing new challenges for grid management. This chapter offers a comprehensive overview of the definition and essential concepts of collective self-consumption. It also introduces a new energy management strategy designed to optimize self-consumption in collective self-consumption systems. This strategy integrates various energy management technologies, including energy forecasting, energy flexibility assessment, energy systems optimization and information and communication technologies, to enhance the effectiveness of collective self-consumption systems.

1.1 Forming Local Collectives: A Key Strategy for Efficient Renewable Energy Use and Sharing to Advance Energy Transition

Since the Industrial Revolution, the burning of fossil fuels like coal, oil, and natural gas, along with deforestation, has led to a significant increase in greenhouse gases (such as carbon dioxide and methane) in the atmosphere, causing global warming. This warming has resulted in more frequent extreme weather events (heatwaves, droughts, floods, typhoons), rising sea levels (due to melting polar ice caps and thermal expansion of seawater), ecosystem damage (threatening biodiversity), impacts on food security (potential decrease in crop yields and higher food prices), and increased health risks (spread of diseases like malaria and dengue). To combat global warming, the historic Paris Agreement was reached at the 21st Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change (UNFCCC) in 2015. Its primary goal is to limit the global average temperature increase to well below 2 degrees Celsius above

pre-industrial levels, while pursuing efforts to limit the temperature increase even further to 1.5 degrees Celsius. This agreement marks a global commitment to addressing climate change and its impacts (*The Paris Agreement* 2023).

In the context of the urgent need for an energy transition to address climate change, increasing the share of renewable and decarbonized energies to reduce the emission of CO₂ becomes an unavoidable necessity. Renewable energy refers to energy sourced from natural sources such as solar, wind, and hydroelectric power. These sources are considered “clean” because they produce little to no greenhouse gases or pollutants during energy generation. This contrasts sharply with fossil fuels, which significantly contribute to atmospheric CO₂ levels and other environmental issues. Increasing the share of renewable and decarbonized energies is crucial to mitigate these impacts, making it a critical component of global efforts to promote sustainability and reduce the environmental footprint of energy production. However, a significant challenge remains in the intermittency of these energy sources: solar and wind power are highly dependent on climatic conditions and are not always available (e.g., during cloudy days or calm weather). This variability can complicate energy planning and stability.

Due to the intermittency of renewable energy, its production often does not align with consumer demand, leading to surplus energy being fed into the electrical grid for use by other households. However, the distance between power production facilities, and points of consumption, entails inefficiencies, due to the dissipation of energy as it travels through the distribution network. To enhance the efficiency of renewable energy sharing, it is more effective to synchronize local consumption with local production, minimizing energy loss and maximizing the utilization of generated renewable energy. Therefore, forming local collectives to consume locally produced renewable energy emerges as an effective strategy to enhance energy efficiency.

The shift towards local collectives offers numerous advantages. It represents a cost-efficient model as sharing financial responsibility for the renewable energy system setup and maintenance makes it economically viable for individual members, allowing greater inclusiveness. It contributes to grid stability by alleviating peak demand pressures and promotes decentralized energy production. Furthermore, it fosters community engagement, strengthening the community spirit as members unite for sustainable energy utilization. Finally, it supports energy independence, enhancing resilience, and reducing dependence on external power sources, which gives individuals more control over their energy expenses and supply. The framework of local collectives, therefore, not only addresses environmental concerns by reducing carbon emissions through the use of renewable resources over fossil fuels but also yields significant socio-economic benefits, reinforcing the collective capability to navigate and shape future energy landscapes.

1.2 What is a Collective Self-Consumption System?

In the context of the energy transition, concepts such as Collective Self-Consumption (CSC) have emerged, particularly within a legislative framework established by France in 2017 (see *French Government - Code de l'énergie* (2020) for an updated version of the framework). This CSC model is in the overall spirit of the Renewable Energy Communities (REC) and Citizen Energy Communities (CEC). These CECs and RECs have been legally defined within the framework of new European directives adopted in 2018 and 2019 by the European Commission, and are initiatives that enable citizens, local authorities, and small businesses to participate directly in producing, consuming, and sharing renewable energy (European Commission 2019). These directives are set to govern energy markets in the coming years. To this end, they are currently being incorporated into the law and regulations of all European countries. The idea is to enable the emergence of collectives at the scale of condominiums, eco-districts, and territories. These collectives themselves must be able to invest in local renewable energy production means, and more importantly, be able to consume locally produced energies with a “short-circuit” approach, using public distribution networks, and trying to increase the rates of self-consumption and self-production.

A comprehensive exploration of REC, CEC, and CSC is provided in the subsequent sections. These discussions delve into the definitions of each concept (Section 1.2.1), assess the efficiency of energy consumption within collective self-consumption systems (Section 1.2.2), and examine how these systems distribute the production of renewable energy sources (Section 1.2.3).

1.2.1 Definition of Renewable Energy Community, Citizen Energy Community and Collective Self-Consumption

The definitions for Renewable Energy Communities (RECs) and Citizen Energy Communities (CECs) are not identical across all European countries. While there is an EU framework aimed at harmonizing the concept, individual member states have the discretion to adapt these definitions according to their national contexts and energy policies. This results in variations in the specifics of how RECs and CECs are implemented, managed, and regulated across different European nations.

A renewable energy community (REC) in France is a legally independent entity characterized by its open and voluntary membership, which includes individuals, Small and Medium-sized Enterprises, and local authorities. These communities are not primarily commercial; instead, they focus on providing environmental, economic, or social benefits to their members and the local area, rather than pursuing financial profit. They maintain effective control over the renewable projects they are part of and contribute to.

A citizen energy community (CEC) in France is a legally defined group that anyone can join voluntarily. It is managed by its members, who may be individuals, local governments, or small businesses and aims to provide benefits to the community and local area, rather than make profits. Such communities are involved in various aspects of electricity from renewable source, including production, efficiency services, and sales, while also sharing electricity among members and engaging in energy markets. They also hold financial responsibility for any imbalances their activities cause in the electricity system.

Collective self-consumption (CSC) is a concept that can be related to both Renewable Energy Communities (RECs) and Citizen Energy Communities (CECs), depending on the specific legal definitions and frameworks in place within a country. In general, CSC involves a group of consumers and producers sharing energy from renewable sources within a defined network or community, which aligns with the broader objectives of both RECs and CECs. However, whether CSC is categorized under RECs or CECs, or considered a separate entity, is determined by national legislation. The concept and implementation of collective self-consumption (CSC) varies significantly across European countries, reflecting diverse legal frameworks and national strategies for renewable energy and community engagement. The Italian legislative framework introduced with the *Decreto legislativo 8 novembre 2019* (2020) and further developed with Law N8/2020 (*Decreto Legislativo - Gazzetta Ufficiale* 2020), provides a comprehensive approach to collective self-consumption of renewable energy. This framework allows for the creation of energy communities and the collective use of energy produced from renewable sources by installations with a capacity of less than 200 kWh on an experimental basis. Spain promotes CSC by enabling groups to share energy from a single renewable source within specific proximity (500 meters) and voltage limits. Germany has a tradition of CSC, particularly in multi-family residential buildings, supported by the "Mieterstrommodell"¹ which integrates direct sale of locally produced electricity to tenants.

From the legislative framework in France we can give a brief definition of a collective self-consumption (CSC) in France. It refers to the practice where a group of consumers (shown in Figure 1.1) collectively use the electricity generated from a shared renewable energy source located in their vicinity (adhering to the French law that defines proximity as being not further away than 2 kilometers) with a cumulative power of the production facilities below 3 MW on the continental metropolitan territory and 0.5 MW in non-interconnected areas (*French Government - Code de l'énergie* 2020). This model is most common in settings such as apartment buildings, housing cooperatives, eco-districts, and small communities. In the collective self-consumption system

¹The "Mieterstrommodell" is a German initiative promoting on-site renewable energy production and direct consumption within residential buildings, mainly through photovoltaic systems.

consumers and producers are regrouped together in a legal entity whose main role is to facilitate the consumption of energy produced within the same site or nearby. The energy may come from solar panels, wind turbines, or other renewable technologies. This energy is then transmitted via the public distribution network. Within this system, the power produced is allocated among the members of the collective according to specific distribution rules. (more details in Section 1.2.3) predefined by the legal entity of the collective self-consumption or the Distribution System Operator (DSO, the principal French DSO is Enedis²).



Fig. 1.1 Collective Self-Consumption System

1.2.2 Assessing Energy Efficiency in Collective Self-Consumption Systems: Achieving Optimal Rates through 100% Self-Consumption and Production

In collective self-consumption systems, two critical metrics to evaluate energy consumption efficiency are the self-consumption rate and the self-sufficiency rate. The self-consumption rate is defined as the proportion of solar energy produced that is directly consumed on-site, whereas the self-sufficiency rate measures the extent to which the consumption is met by the solar production.

In Figure 1.2, the solar energy output of a CSC system, represented by the orange and yellow areas, is juxtaposed with the total energy consumption curve, comprised of the gray and yellow areas. The overlapping yellow area denotes the self-consumed solar energy. Accordingly, the self-consumption rate is calculated by the ratio of the

²Enedis, a public French company, manages most of France's electricity distribution network. It focuses on operating and maintaining the electricity grid, ensuring a stable power supply, and integrating renewable energy sources.

self-consumed portion (yellow) to the total photovoltaic production (orange plus yellow), and the self-sufficiency rate is determined by the ratio of the self-consumed portion (yellow) to the total consumption (gray plus yellow). These rates are pivotal for assessing the performance and efficiency of CSC systems. The efficiency of a collective self-consumption (CSC) system improves as the self-consumption and self-sufficiency rates approach 100%. Higher rates indicate that a greater proportion of the solar energy produced is directly utilized on-site, and a larger share of the total energy consumption is covered by solar production. Therefore, optimizing a CSC system means trying to maximize these rates to approach as close to 100% as possible, thereby enhancing the system's overall energy efficiency and reducing reliance on external energy sources.

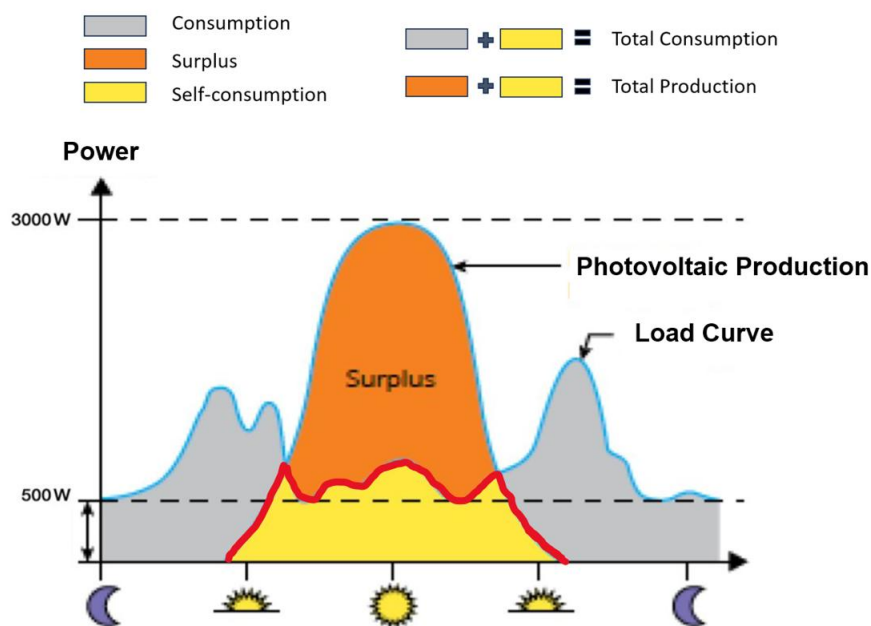


Fig. 1.2 Consumption and Production Profile of a Self-Consumption System

1.2.3 Sharing Mechanisms in Collective Self-Consumption System: How Key Rules Allocate Renewable Energy Production

Regardless of the type of source renewable installation (whether solar panels, wind turbines, or other technologies) — whether for individual self-consumption, total sale, with or without collective self-consumption — the electrons move in the same way within the electrical grid, that is, from the production site to the nearest point of consumption. Collective self-consumption is therefore not a physical method of distributing electricity production, but rather a means of economic valuation, similar to individual self-consumption or total sale, to which it can be associated.

In this context we need to determine how the collectively generated electricity is shared and accounted for financially among the households or units that are part of the

collective. So we introduce a method or rules named “distribution key” and used to contractually distribute the electricity produced by a common renewable energy source among the different participants in the system. The distribution key is critical because, in physical reality, electricity follows the path of least resistance and cannot be “directed” towards a specific consumer. Therefore, even though the electricity produced is consumed by the group as a whole, there needs to be a method to attribute how much electricity each participant has “effectively” used or is entitled to claim. We show some available sharing keys in Figure 1.3:

Type of Key	Description	Use Cases	Advantages	Disadvantages
STATIC	Constant distribution coefficients at each 30-minute time step predefined by the organizing legal entity	Example: coefficients assigned by the organizing legal entity based on the amount of financing provided by each participant to the PV plant	Ease of use for the organizing legal entity	- Non-optimal distribution of production - High risk of having a surplus of production (not self-consumed by the participants)
DEFAULT DYNAMIC	Variable distribution coefficients at each 30-minute time step, automatically calculated by the Distribution System Operator (DSO) in proportion to each participant's consumption	If user n°1 use for 10% of the collective's total consumption on a 30-minute window, then he/she is entitled to 10% of the total production during that time window	- Automatic optimization with maximum allocation of production - No values to communicate to DSO	- Favors large consumers and disadvantages small consumers - Not customizable
CUSTOM DYNAMIC	Variable distribution coefficients at each 30-minute time step, defined by the organizing legal entity a posteriori and transmitted to the DSO each month.	- Search for optimization - Need for prioritization among participants	- Optimization possible with maximum allocation of production - Possibility of prioritizing the allocation of production	Every month, it is necessary to communicate to the DSO the value of the distribution coefficients to be applied every 30 minutes.

Fig. 1.3 Distribution Keys

Thanks to the distribution key and an advanced metering system, the Linky³ meter, developed by Enedis in France, we can easily track each user's energy consumption and figure out their rate of self-consumption and production.

1.3 Research Background: Enhancing Enogrid's Online Services to Optimize Self-Consumption Systems for Clients

My thesis is conducted within the context of a collaboration between Enogrid and the G2ELAB laboratory, focusing specifically on collective self-consumption systems in France. We begin by introducing Enogrid (Section 1.3.1), and we continue with an exploration of the context, the objectives and the problem statement of my thesis (Section 1.3.2).

³The Linky smart meter is an advanced digital electricity meter developed by Enedis. This meter allows for remote reading of electricity consumption, providing real-time data and eliminating the need for manual meter readings. It enables more efficient energy management by allowing consumers to monitor their energy usage more closely. Additionally, the Linky meter facilitates the integration of renewable energy sources into the grid and supports dynamic pricing schemes.

1.3.1 Enogrid: A French Company Specialized in Collective Self-Consumption

Enogrid, a collaborative partner in my PhD research, is a French company specialized in collective self-consumption, which plays a pivotal role in the energy transition. Figure 1.4 illustrates the comprehensive suite of online services and digital tools provided by Enogrid, designed to support and facilitate projects in the realm of collective self-consumption.

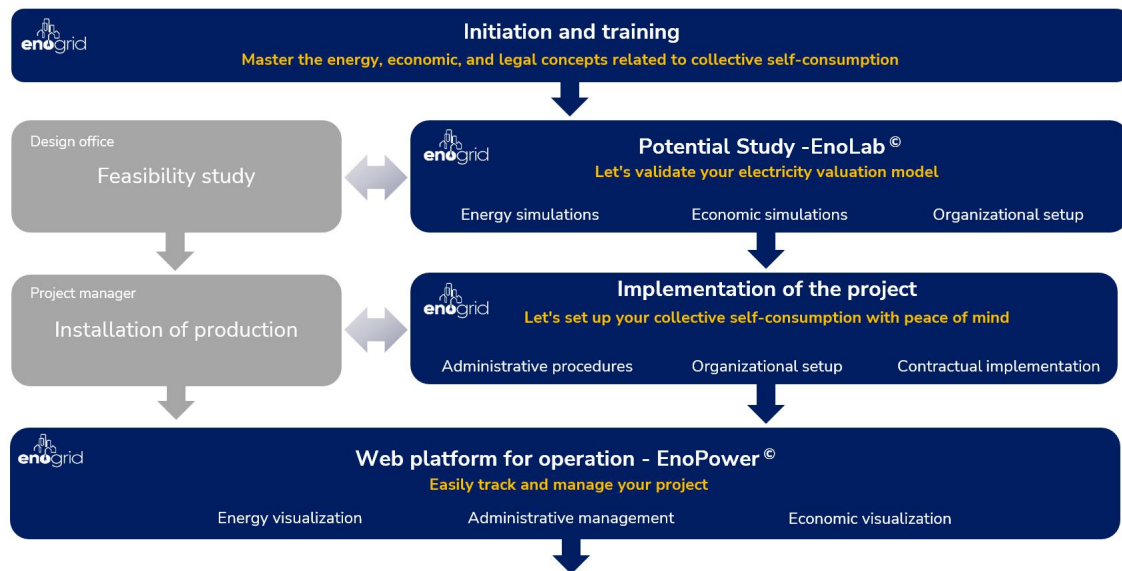


Fig. 1.4 Enogrid's Online and Consultancy Services

In the Figure 1.4, the grid blocks represent not the services of Enogrid, but rather those of Enogrid's partners. The main services of Enogrid are as follows:

- **Training:** Enogrid provides training on collective self-consumption, teaching participants how to create and manage such operations. The training covers the essentials of collective self-consumption, and presents practical examples and case studies from their own experiences. They partner with certified training centers to ensure optimal quality. The training aims to save time in learning about collective self-consumption and to assist participants in making informed decisions for their projects.
- **Project Analysis:** Enogrid helps validate the coherence of projects using their experience and a specialized simulation tool, EnoLab. It is a simulation tool designed for energy professionals involved in collective self-consumption projects. It caters to various professionals, including engineering offices, installers, developers, energy unions, and renewable energy project managers. EnoLab enables these professionals to autonomously generate energy and financial models for their projects, while also anticipating organizational needs. The tool facilitates

easy data input and offers detailed project reports, ensuring energy coherence and economic performance.

- **Expert Support:** Enogrid offers expert guidance for the realization of collective self-consumption projects. Their team assists in various stages of project development, including identifying participants, studying multiple scenarios, analyzing organizational structures, and finding business models. They also support the creation of legal entities, participant recruitment, contract setup, and administrative procedures. Enogrid's expertise and experience help save time and ensure efficient project execution.
- **Operation Management:** Enogrid also provides a tool, EnoPower, for management of collective self-consumption operations. It allows Organizing Legal Entities ("Personne Morale Organisatrice", PMO⁴ in French). to easily pilot their operations. Key features include visualizing energy flows, tracking individual and collective self-consumption, customizing distribution keys, simplifying administrative management, editing local electricity bills, and centralizing operations documents. It provides insights for better energy consumption, communication among participants, and financial monitoring. EnoPower is designed to be intuitive and adaptable, requiring no hardware installation by participants and is connected with Enedis for automatic data exchange.

Overall, Enogrid is dedicated to supporting clients throughout their collective self-consumption projects, continuously enhancing their online services to improve user experience.

1.3.2 Towards Optimal Integration of Local Renewable Energy Production Using Digital Tools

The development of collective self-consumption in France has gradually accelerated over the past 5 years. From only 6 in 2018, it has since been growing at an almost doubling rate each year, to reach 454 in Jun 2024 (as depicted in Figure 1.5), with more than 5731 participants for a total power of more than 38 MW, predominantly from photovoltaic panels.

The emergence and rapid development of collective self-consumption implies a transformation in the power system from centralization to decentralization. This shift is not only a result of advances in renewable energy technologies but also of the development of an infrastructure that supports such changes, such as smart grids and energy

⁴A "Personne Morale Organisatrice" (PMO) in French refers to a legal entity that organizes and manages collective activities or operations within specific frameworks, such as collective self-consumption energy systems.

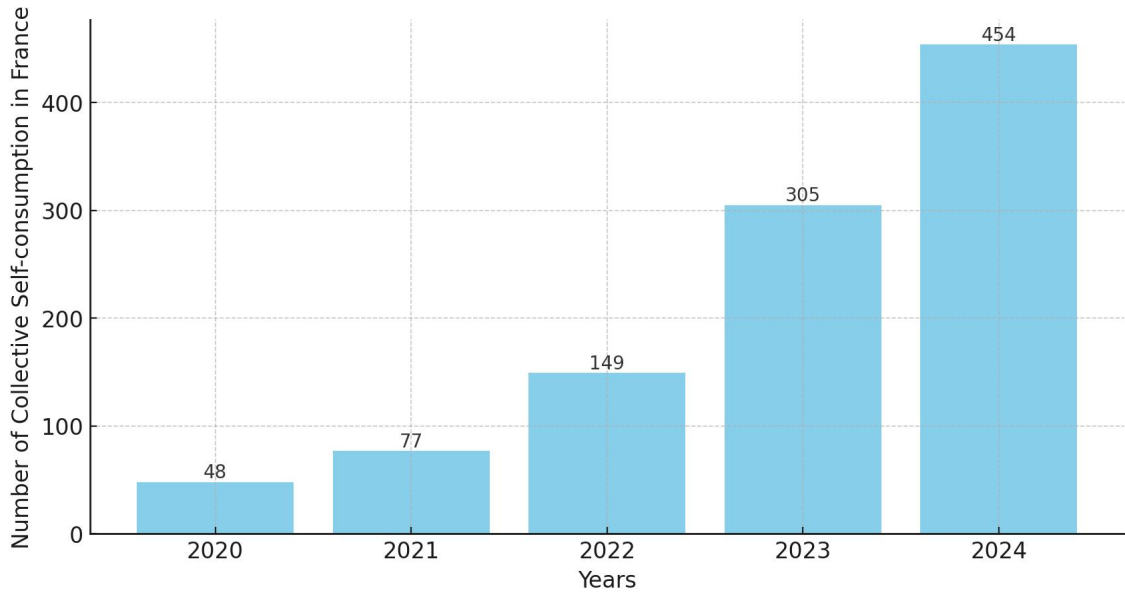


Fig. 1.5 Number of Collective Self-Consumption Operations in France from 2020 to Jun 2024

storage technologies. Particularly, online service platforms and digital tools become crucial in this context, offering communities the means to efficiently manage and monitor their energy consumption and production.

In our research, we aim to develop and implement effective strategies for optimal energy management within collective self-consumption systems. Our focus is on improving the self-consumption rate in these frameworks. Additionally, we intend to integrate these strategies into the online services provided by Enogrid to optimize the energy consumption behavior of Enogrid’s customers, who are either currently utilizing or in the process of establishing collective self-consumption systems.

The central question of our research is: **How can local energy production be effectively aligned with local consumption patterns to maximize self-consumption and enhance energy efficiency within collective self-consumption systems through the use of online service platforms and digital tools?**

1.4 Research and Development Strategy for Achieving Optimal Self Consumption and Production in Collective Self Consumption Systems through Energy Flexibility

To achieve the goal of optimizing self-consumption and production rates in collective self-consumption systems, energy flexibility is crucial. This endeavor requires a comprehensive understanding of the concept of energy system flexibility and the relevant methodologies, as elaborated in Section 1.4.1. We then present our strategy to leverage energy flexibility to ultimately maximize the self-consumption rate in the collective

self-consumption systems of Enogrid’s customers (Section 1.4.2).

1.4.1 Exploring Energy Flexibility: Definitions and Methodological Approaches for Aligning Consumption with Production

Today’s power systems are going through a major change. This change involves adding more renewable energy sources (RES) because of their benefits to the environment and economy. The main challenge with this change is dealing with increased variability and uncertainty in keeping the power supply stable. To address this challenge, (Nosair and Bouffard 2015) underscored the significance of assessing the potential for operational flexibility of individual power system assets, as well as their collective integration at the system level. However, they refrained from offering a universal definition of energy system flexibility, citing the variability in interpretations as various groups and authors have independently formulated their own definitions. (Nosair and Bouffard 2015) and Li et al. (2021) both agree that the definition of energy system flexibility highly depends on the characteristics of the systems. Recently, Kaushik et al. (2022) provide a comprehensive overview of power system flexibility. They elaborate on the definition of energy system flexibility as the capability to modulate supply and demand in order to maintain energy equilibrium. This encompasses a detailed examination of how various components of the power system, including energy storage, grid infrastructure, and demand-side management, can be optimized to achieve a balance between energy production and consumption.

Energy flexibility can be categorized into direct and indirect energy flexibility. Direct energy flexibility refers to the ability of an energy system to respond to changes through real-time adjustments of energy supply and demand. This typically involves direct control of energy production and distribution, such as rapid adjustments in generation, charging and discharging of storage systems, and real-time management of renewable energy generation. Achieving direct flexibility requires advanced technical components and infrastructure. Indirect energy flexibility, on the other hand, is the ability to optimize energy use and achieve system stability by managing demand-side resources and external factors. This includes demand-side management, energy efficiency improvements, smart grid technology, policies and market mechanisms that indirectly influence energy demand and usage. Crucially, indirect flexibility operates through the transmission of signals to consumers and other stakeholders, encouraging adaptive behavior without necessitating the costly deployment of physical infrastructure. This form of flexibility presents a socio-technical challenge that fundamentally requires a human-in-the-loop approach to effectively engage participants and optimize the overall energy system. Twum-Duah (2023) provides a detailed introduction to direct and indirect flexibility and explores how the integration of technical (direct) and

social (indirect) components can optimize the flexibility of building energy systems, ultimately enhancing overall system performance.

Within the context of our research on self-consumption systems, energy flexibility in both individual and collective self-consumption systems aims not only at maintaining power balance but also at prioritizing the utilization of renewable energy sources. It focuses on locally consuming energy generated from renewable sources, thereby optimizing the use of sustainable energy systems. To achieve this level of energy flexibility in self-consumption systems, two primary methods are employed and shown in Figure 1.6: (a). store the surplus energy generated using Energy Storage Systems (ESS), allowing for later use when production is lower, (b) align consumption times with those of renewable energy production, utilizing Demand Response (DR) strategies or other Demand Side Management (DSM) strategies to effectively shift energy usage of potential loads to periods of high renewable generation. Both methods (a) and (b) can be achieved through direct or indirect approaches.

ADEME⁵ (“Agence de l’Environnement et de la Maîtrise de l’Energie” in French) identifies four potential loads that can actively contribute to the challenge of energy flexibility: water heating, white goods (such as washing machines, clothes dryers, and dishwashers), electric vehicles, and space heating. Among these, white goods, along with space cooling and heating, can be considered as shiftable loads. We can utilize method (b) to optimize the cooling, space heating, and coupling energy system. For instance, users may choose to use clean electricity from PV (photovoltaic) production during periods of high surplus instead of consuming expensive electricity during peak evening hours, thereby saving on electricity bills. Meanwhile, water heaters and electric vehicles function as Energy Storage Systems (ESS), utilizing method (a) to store surplus renewable energy for later use. These systems, however, also need to synchronize their operation with periods of high renewable production by using method (b), for example, shifting electric vehicle charging to daytime when PV output peaks, thus integrating energy storage and consumption strategies effectively.

1.4.2 Research and Development Strategy: Why Focus on the Residential Sector, Exclude Battery Storage, Employ Indirect Energy Flexibility, and Start with Simulations Before Real-World Testing?

My research aims at ultimately contributing to the online services of Enogrid by proposing a demand-side management solution to estimate the energy flexibility of Enogrid’s clients and maximize their self-consumption rate using energy flexibility. Initially, our

⁵In France ADEME is a public agency under the joint authority of the Ministry for the Ecological Transition and the Ministry of Higher Education, Research, and Innovation. Its primary mission is to participate in the implementation of public policies in the areas of the environment, energy, and sustainable development.

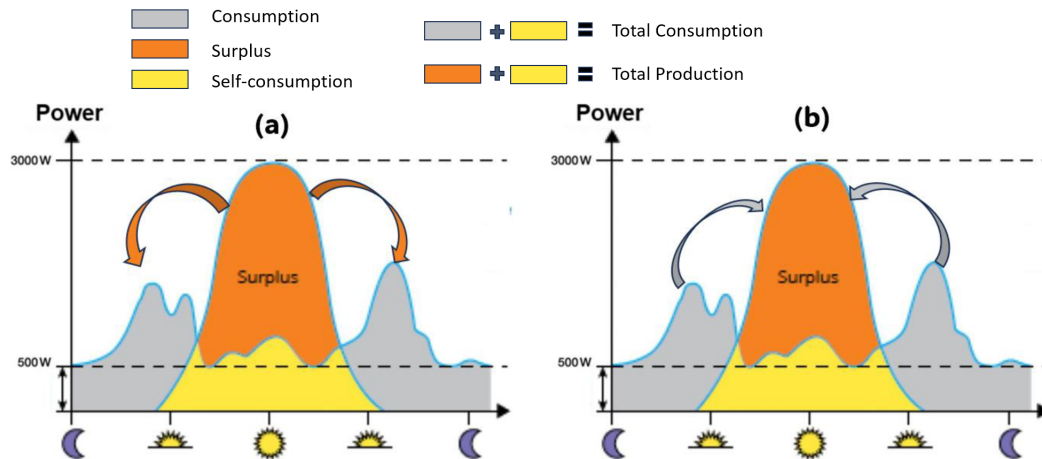


Fig. 1.6 Two Main Methods to Align Production and Consumption: (a) Storing Surplus Energy for Use During Consumption Peaks, (b) Rescheduling Energy Use to Match Renewable Production Peaks

research will concentrate on the residential sector without the use of battery storage systems. We will adopt an indirect energy flexibility approach, aiming to align consumption with production to enhance energy efficiency. Prior to real-world testing, we will focus on simulations to validate our strategies and ensure their effectiveness in practical scenarios.

Why Does Our Research Focus on the Residential Sector? Enogrid has a total of 98 collective self-consumption operations, which include various types such as Tertiary, Agriculture, Residential for instance. Our study focuses mainly on the residential sector in France. This is because the residential sector constitutes a significant portion of the overall energy demand and CO2 emissions globally. The 2022 energy report from RTE⁶ (French : Réseau de transport d'électricité) indicates that in total, France consumed 459.3 TWh of electricity. Of this, 46.3% was consumed by businesses and professionals (Transport, Tertiary, Agriculture, etc.), 37.6% by residential customers, and 16.1% by large industries. Figure 1.7 shows the development of energy consumption by sector in France in TWh, highlighting that the residential sector remains the largest consumer of energy, followed by the tertiary sector and the industrial sector. Additionally, 34 of Enogrid's 98 operations are categorized within the residential sector, accounting for almost 35% of the total. Therefore, we have chosen to commence our research with a focus on the residential sector.

Why Does Our Research Exclude the Use of Battery Storage Systems? Enogrid's objective is to enable everyone to contribute to the energy transition with a focus on so-

⁶Réseau de Transport d'Électricité (RTE) is the French public electricity transmission network operator responsible for the high and very high voltage electricity transmission network in mainland France.

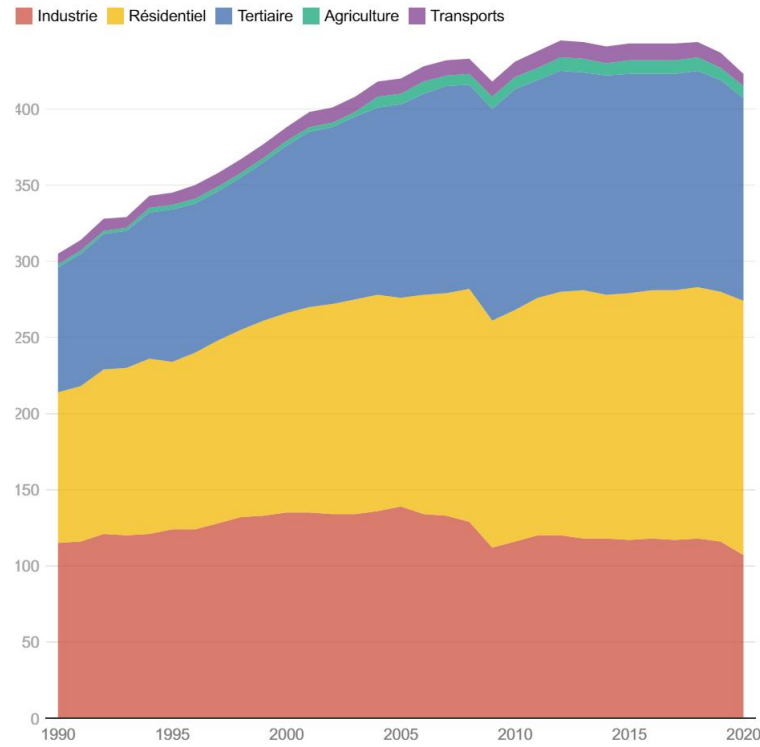


Fig. 1.7 The Development of Energy Consumption by Sector in France in TWh (Ouest-France 2022)

cial justice, striving to make energy transition solutions accessible to all. Therefore, the aim is to explore models of collective self-consumption (CSC) that are inclusive and ecological, ensuring widespread applicability. For instance, storage systems, which are limited by strong geographical constraints are not considered in this study due to their limited generalizability across all CSC systems. Furthermore, Energy Storage Systems (ESS) are deemed economically impractical for single application services due to their high costs (Zhao et al. 2015). Recent research indicates that traditional residential battery energy storage systems are not economically viable for the majority of households (Tang et al. 2019, Barcellona et al. 2018), with only a few of Enogrid’s current CSC clients in the residential sector equipped with such systems. Thus, CSCs with traditional battery storage will not be the focus of our research.

However, electric vehicles, whose popularity has been rapidly increasing in recent years, are a good solution to store intermittent renewable energy and then use it later, or use Vehicle-to-grid (V2G⁷) technology to supply power to the grid during peak power consumption periods. In addition, electric water heaters are very commonly used in French residential buildings. So in the end, the system we studied could take these two energy storage systems and treat them as flexible loads to participate in the process of improving the self-consumption rate.

⁷V2G technology allows electric vehicles to communicate with the power grid to sell demand response services by either returning electricity to the grid or by throttling their charging rate.

Why Does Our Research Focus on Indirect Energy Flexibility? For the same reason of inclusiveness, we focus on indirect flexibility because direct flexibility, such as direct load control, may infringe on customer privacy, lack necessary scalability, and potentially causes a loss of human comfort. It also requires technological components that increase the initial investment costs. Consequently, we chose a non-mandatory indirect flexibility mechanism—sending nudges (for a detailed definition and introduction of nudge, please see Definition 2.4.1), incentivizing signals to change consumer behavior to optimize the self-consumption of the collective self-consumption system (Section 1.4.3).

Why Does Our Research Begin with Simulations Before Real-World Testing? Given the outlined objectives and their inherent complexities, it is evident that practical applications of our online service within real-world settings present significant challenges:

- **Time and duration :** Experiments in the real world are time-intensive to establish.
- **Uncontrollable variables:** Numerous factors can influence outcomes, making it difficult to isolate the variables under test.

In this context, we would like to simulate our nudging system before the real-world testing, because simulations offer a controlled environment where variables can be isolated and manipulated individually to observe their effects without the interference of external factors. They allow for the rapid iteration of scenarios, save time and resources, and can highlight potential issues before implementing costly real-world solutions. Therefore, simulations are a vital step in developing and refining hypotheses, optimizing system performance, and ensuring reliability before proceeding to real-world deployment.

In light of these considerations, we introduce a new email nudge (a non-monetary incentive signal, see details in Section 2.4) system to integrate the two key solutions delineated in Section 1.4.3.

1.4.3 Nudging Pipeline Strategies

The core mechanism of our nudge system involves gathering consumption data from participating individuals and weather forecasts to accurately predict optimal consumption periods. Through weekly email alerts, participants receive guidance to fine-tune their solar energy usage. For instance, an alert may suggest, “Use energy on Wednesday afternoon due to clear skies, but reduce usage on Friday morning due to forecasted rain.” This approach is designed to be inclusive, requiring no significant financial investment from users, and ecological, as it does not necessitate additional equipment. This mechanism focuses primarily on employing (b) Demand Response (DR) strategies

to align consumption patterns with the production of renewable energy. The system utilizes electric vehicles and electric water heaters, treating them as flexibility loads. However, both present energy storage capabilities, which suggests that they could indirectly support (a) energy storage methods. This is not our current focus, but it could be an interesting direction for future research.

Given these challenges, the scientific and technical objectives of my thesis are outlined as follows:

- The development of methods and tools for forecasting individual and collective consumption and production
- The identification of flexibility potentials, through two models:
 - **Non-Intrusive Energy System Model:** This model employs AI-based methodologies coupled with physical modelling to analyze consumer usage patterns without requiring detailed knowledge of their equipment. By obtaining consent from users to access and use their energy data, the system disaggregates consumption curves to pinpoint flexibility sources and potential load shifts. The goal is to enhance both individual and collective self-consumption rates by identifying key areas where energy usage can be optimized.
 - **Intrusive Energy System Model:** In contrast, this model involves direct engagement with households within a collective self-consumption (CSC) system through surveys. It gathers detailed information about household equipment to assess energy flexibility. The model combines user-provided data to estimate the potential for energy management and optimization within the CSC framework.
- The development of methods and tools for optimizing flexibility potentials involves rescheduling the flexibility load to enhance overall system performance and achieve optimized energy solutions.
- The design of signals (nudges) to be sent to self-consumers once the flexibility potentials are identified, with a proposal for evaluating their impact.

Combining all the energy management techniques mentioned above, we proposed two distinct nudging pipeline strategies (a non-intrusive approach and an intrusive approach, based on the two models introduced above) to optimize the self-consumption rate of the CSC. Both strategies are supported by Information and Communication Technologies (ICT⁸).

⁸Information and Communication Technologies (ICT) refer to a diverse set of technological tools and resources used to communicate, create, disseminate, store, and manage information.

1.4.3.1 Definition of the Pipeline Concept: Application in Energy Consumption Recommendation Systems

In a general context, a “pipeline” refers to a series of processes or steps that systematically move data, products, or materials from one stage to the next in order to achieve a specific outcome. In various industries, the concept of a pipeline is used metaphorically to describe workflows, information processing, or supply chains where inputs are transformed through a sequence of operations to produce a desired output. This term is widely used across fields such as computing, manufacturing, data analysis, and project management to denote the streamlined flow of operations or data that are executed in a prescribed order to ensure efficiency and effectiveness in producing end results.

We utilize the concept of a pipeline to construct our nudging pipeline, a data-driven framework illustrated in Figure 1.8. This framework processes and analyzes consumption and production data to influence human consumption behavior through communication mechanisms. As mentioned before, the core mechanism involves gathering consumption data from participants and weather forecasts to accurately predict optimal consumption periods (collection, ingestion, preparation, computation) and then communicating this information to participants to optimize their solar energy usage (presentation).

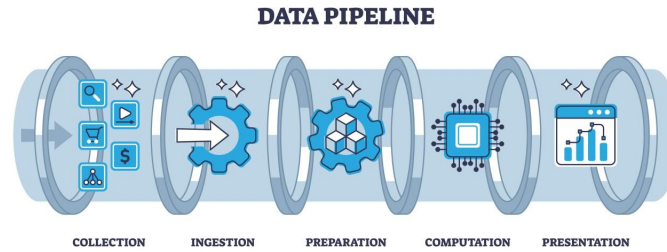


Fig. 1.8 Example of a Data Pipeline Framework

1.4.3.2 Nudging Strategy by Quantifying Energy Flexibility via Non-Intrusive Load Monitoring.

Strategy 1 is illustrated in Figure 1.9. We start by forecasting the PV production and individual household loads within the CSC (more energy forecasting details in Appendix H) for the ensuing week utilizing predictive analytics. Subsequently, Non-Intrusive Load Monitoring (NILM, a technique that deduces individual appliance energy usage from aggregate consumption data, is detailed in Chapter 3) algorithms disaggregate each household’s load into distinct appliance usage profiles, identifying flexible loads as shiftable. Leveraging optimization tools, these shiftable loads are rescheduled to coincide with the PV production peaks, thereby augmenting the CSC’s self-

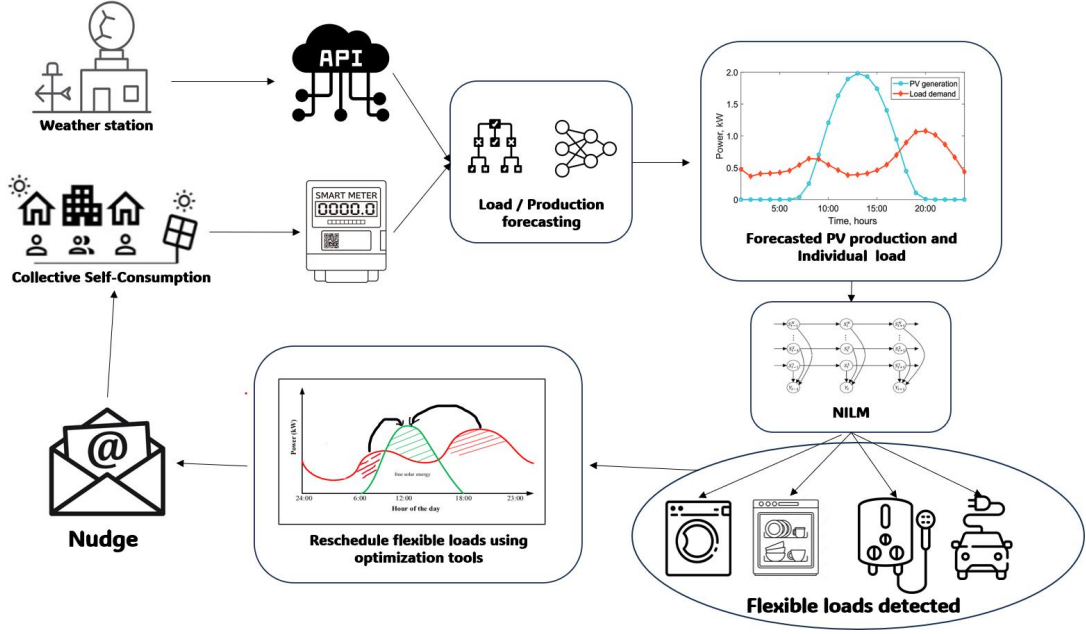


Fig. 1.9 Strategies for Nudging Pipeline: Quantifying Energy Flexibility via Non-Intrusive Load Monitoring

consumption rate (The optimization tools for energy rescheduling are detailed in Appendix I for individual self-consumption and Appendix L for collective self-consumption). Ultimately, the rescheduled plan is formulated into a nudge and disseminated to consumers, encouraging modifications in energy consumption behaviours. However, we were unable to successfully implement this nudging pipeline due to the complexity of applying NILM techniques in real-world settings; more details are provided in Chapter 3 and Chapter 5.

1.4.3.3 Nudging Strategy by Quantifying Energy Flexibility via Online Survey.

Strategy 2 is illustrated in Figure 1.10. This strategy retains a core similarity to Strategy 1, except for the methodology utilized to assess energy flexibility within the CSC system. Accompanying this methodological difference, necessary changes are made to fit with the specifics of energy flexibility assessment. In this strategy, forecasting focuses on the PV production and the collective load of the CSC, since individual load profiles are not required for breaking down appliance usage to gauge energy flexibility. Instead, flexibility is estimated from additional information obtained through online surveys. This indirect estimation does not produce precise profiles for each shiftable appliance but rather specifies a volume of energy susceptible to temporal reallocation. The variation in methods for estimating energy flexibility consequently influences the choice of optimization tools used to devise rescheduling solutions, further discussed in Chapter 6.

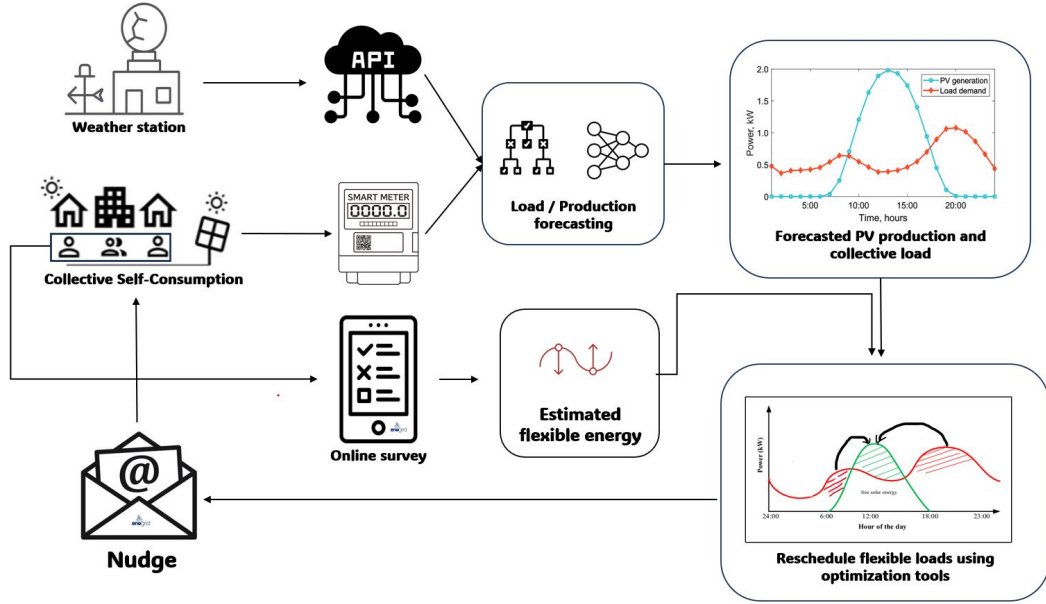


Fig. 1.10 Strategies for Nudging Pipeline: Quantifying Energy Flexibility Through Available Information

1.5 A Concise Overview of our Thesis Outline for Optimizing Energy Efficiency in Collective Self-Consumption Systems

In our thesis, we clearly define “collective self-consumption”, underscoring the peculiar challenges of this mode of energy consumption. we also detail our research methodology, clearly articulating our strategy for selecting the appropriate technologies. We propose two types of Information and Communication Technology (ICT) pipelines, each with different technologies designed to optimize energy efficiency within collective self-consumption systems (Chapter 1).

Then, we review the state of the art in optimizing energy use and energy flexibility within buildings and energy communities (Chapter 2), highlighting the technological advancements necessary for efficient energy system management. This examination encompasses the integration of renewable resources, energy storage, demand response, and other smart management technologies, offering insights into improving energy sustainability and energy efficiency.

Following this, our research project is presented in two main phases corresponding to our two nudging pipeline strategies (Figure 1.11). Initially, for the first nudging pipeline strategy, which involves quantifying energy flexibility via non-intrusive load monitoring (NILM), we explore NILM technologies (see Chapter 3) to identify energy flexibility non-intrusively. We assess the performance of existing high-performance algorithms and discuss their transferability limitations, concluding that disaggregation results vary widely between datasets and settings. In practical environments, ensuring

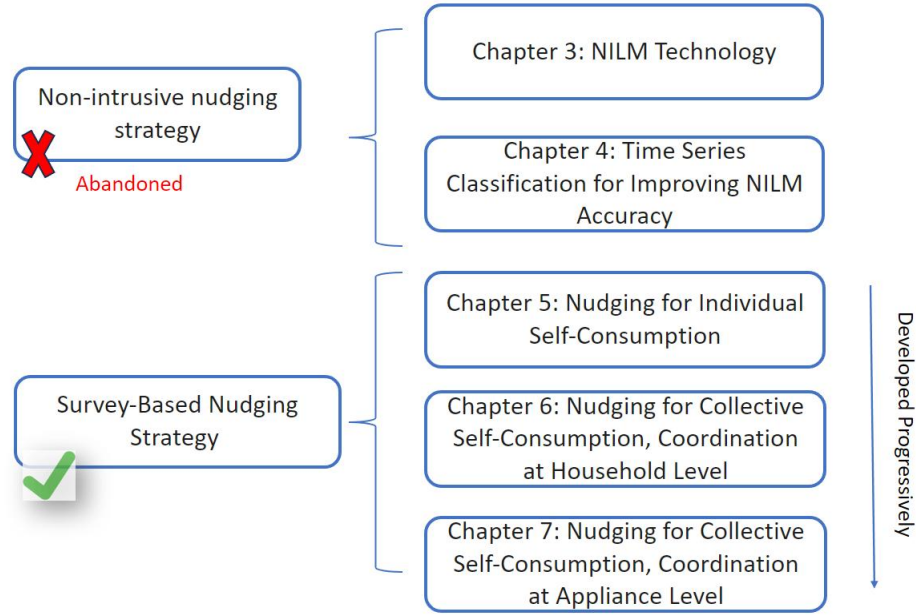


Fig. 1.11 Outline and Strategy Overview of My Thesis

successful disaggregation is essential. However, due to the lack of detailed appliance data for verification, we could not confirm the accuracy of disaggregation. Consequently, we decided to identify datasets on which we could conduct disaggregation accurately. We introduced a classifier (see Chapter 4) to determine whether the data from a household could be disaggregated by a specific pre-trained disaggregation model. We demonstrate the efficiency of our classifier but also highlight its limitations in real-world applications, such as the need for more detailed data and high computational costs. Ultimately, we abandoned this nudging strategy.

Subsequently, for the second nudging pipeline strategy, which quantifies energy flexibility via an online survey, we developed our nudging pipeline progressively. Initially, we focused on individual self-consumption systems (see Chapter 5), as they present fewer complexities compared to collective systems. We then extended our research to collective self-consumption scenarios (see Chapter 6), introducing a coordination module at the household level. This module estimates the flexible load of each household as a whole unit and sends personalized notifications to shift this aggregated load to optimal times to maximize the self-consumption rate. However, we found this household-level coordination to be insufficiently precise. Consequently, we further refined our nudging pipeline by introducing a new coordination module at the appliance level (see Chapter 7). This module estimates the flexibility of each appliance individually, allowing for more granular optimization by shifting each appliance independently to achieve better system efficiency.

In Chapter 5, we developed two types of notifications to inform users of optimal consumption periods, encouraging the use of solar PV production during peak times.

The first type is based on weather forecasts, for example, indicating that there will be ample solar energy production at noon the next day, prompting users to shift their consumption to that time to benefit from solar energy. The second type is based on energy forecasts, which predict favourable consumption periods due to predicted surpluses. Users are encouraged to shift their consumption to these times to utilize the available surplus energy. We compared the effectiveness of these two types of notifications and concluded that notifications based on energy forecasts were more effective than those based on weather forecasts. This is particularly the case when favourable weather leads to high energy production, but simultaneous high consumption results in minimal surplus energy available.

In Chapter 6, we extended our research to collective self-consumption scenarios by introducing a coordination module at household level that determines which households receive personalized notifications and establishes an optimal choice to maximize the self-consumption rate. We compared this with a no-coordination case where the same information is sent to all households within the collective self-consumption system. Our findings indicate that the coordination case outperforms the no-coordination case. Additionally, depending on the different information available from the online survey, such as the types of appliances in the household, the appliance usage frequencies, the nominal power of appliances, and even the forecasted activation schedule of appliances, the coordination can become increasingly refined, and the improvement in the self-consumption rate can become progressively better.

In Chapter 7, we introduced a new coordination module at appliance level. It notifies households about which shiftable appliances to use during optimal consumption favourable periods. This finer coordination enables more precise allocation of solar power. Our findings demonstrate that the appliance-level coordinator surpasses the household-level coordinator in efficiency when there are no limits on the number of notifications. However, this approach diminishes human comfort, as receiving too many notifications may cause user fatigue. To address this issue, we propose equipping appliances with automated devices that can activate upon receiving a signal. This would enable the appliance-level coordinator to maintain high efficiency without compromising user comfort. However, it would also increase costs, potentially making our nudging pipeline less inclusive. Therefore, we decided not to implement this approach in the future real-world application phase.

Chapter 8 presents a comprehensive summary of our findings, discussing the overall conclusions of the study. It also addresses the limitations encountered during the research and provides insights into perspectives for further research.

CHAPTER 2

Maximizing the Self-Consumption Rate in a Collective Self-Consumption System via Energy Flexibility: A State of the Art review of key Pillars

Abstract: Renewable energy encounters challenges related to intermittency and the synchronization of supply with real-time demand; thus, energy flexibility is essential for overcoming these obstacles. To explore the nudging pipeline introduced in Section 1.4.3, various advanced technologies may be used, including energy storage systems, demand response, nudging techniques, and digital tools such as energy forecasting, power disaggregation (NILM), and energy system optimization. This chapter provides an overview of these advanced technologies designed to improve energy efficiency by leveraging energy flexibility.

2.1 Enhancing Energy Flexibility in Renewable Systems: An Introduction to Technologies and Strategies

Renewable energy production is inherently intermittent, which may lead to a significant decoupling of energy generation and consumption. This decoupling results in inefficiencies and challenges in matching supply with demand in real-time. In the context of collective self-consumption systems, it is crucial to account for this intermittency to optimize self-consumption rates. To address this issue, the application of energy flexibility to align intermittent energy production with consumption presents a promising approach. By doing so, we aim to enhance the efficiency and reliability of energy systems, making the best use of greener, more localized energy sources. However, fully harnessing this potential is not without complexities. Significant efforts have been expended in exploring and enhancing this potential across various energy systems, including smart grids, renewable energy communities, and collective self-consumption models. Within the scope of these energy management initiatives, a suite of advanced technologies spanning various disciplines has been employed to render flexibility attainable.

These technologies aim to implement two primary methods to access energy flexi-

bility, as illustrated in Figure 1.6. Method (a) involves storing surplus energy generated using Energy Storage Systems (ESS) for later use when production is lower. Method (b) involves aligning consumption times with renewable energy production, utilizing Demand Response (DR) strategies or other Demand Side Management (DSM) strategies to effectively shift energy usage of potential loads to periods of high renewable generation. For a better understanding and overview of these technologies, this chapter provides a brief review of the state of the art, including energy storage systems (Section 2.2), DR algorithms (Section 2.3), nudging strategies (Section 2.4), and other advanced algorithms such as non-intrusive load monitoring solutions and energy system optimization platforms, which can be considered foundational components that support ESS, DR, and other DSM systems (Section 2.5).

2.2 Enhancing Energy Flexibility through Energy Storage Systems

For effective implementation of energy flexibility using the method (a)-store the surplus energy generated using Energy Storage Systems (ESS) outlined in Figure 1.6, the adoption of advanced energy storage technology is essential. This technology supports the dynamic storage and retrieval of energy, catering to fluctuations in energy production and consumption, thus facilitating a more resilient and sustainable energy system.

Energy storage technology is a rapidly evolving field, currently divided into five main categories based on the form of stored energy: mechanical, electrochemical, chemical, thermal, and electrical (As illustrated in Figure 2.1). Among these, Pumped Hydro Storage (PHS) is the largest and most mature, especially in power systems. However, the installation of PHS depends on geographical conditions and impacts the natural environment, limiting its application flexibility (Zhao et al. 2015). With the development of renewable energies like solar and wind, their intermittency and unpredictability necessitate more efficient and flexible energy storage technologies to ensure continuous and reliable power supply.

Weitzel and Glock (2018) emphasized that publications in the field of Battery Energy Storage Systems (BESS) have significantly surpassed those of any other electrical energy storage technology. This trend is primarily due to the distinct advantages of BESS, such as their rapid response time, high efficiency, minimal self-discharge, and the scalability afforded by their modular design. These advantages underscore the potential for batteries to emerge as the dominant form of energy storage in renewable energy sector. Diouf and Pode (2015) presented the advantages of Li-ion batteries than other batteries technologies : longer lifespan, higher energy and power densities and presented the potential for a wide use of li-ion batteries as primary storage in the renewable energies. The authors also presented the main limitation of large-scale application of Li-ion batteries in the renewable energy sector, which is that the cost is too high.

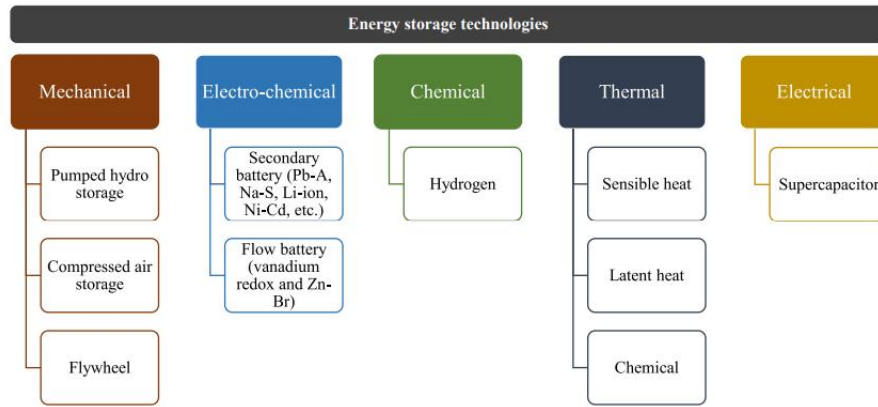


Fig. 2.1 Classification of Energy Storage Systems Based on the Form of Energy Stored (Rahman et al. 2020, Zhao et al. 2015)

and pointed out that the development of the electric vehicle industry could be the driving force for the renewable sector making Li-ion batteries more affordable as a benefit of mass production. This is indeed the case. With the popularity of electric vehicles in recent years, the demand for efficient and high-capacity batteries has continued to grow (International Energy Agency (IEA) 2023). This not only promotes the development of battery technology and reduces battery costs, but also promotes the innovation and application of energy storage systems, such as vehicle to grid (V2G), is an advanced energy technology that allows electric vehicles (EVs) to not only draw power from the electrical grid for charging but also to send power back to the grid when needed (Ustun et al. 2013). V2G technology can charge EV batteries during off-peak times (like overnight) and feed electricity back to the grid during peak periods or when electricity prices are high. This helps in balancing the load on the grid, reducing strain. Similarly, in the collective self consumption system, we can also charge electric vehicles to store surplus and maximize self consumption rate when renewable energy production is greater than consumption. In addition to battery energy storage systems, thermal energy storage is also widely used in energy systems. Water heating is one of the most energy intensive applications, hot water systems are recognized for their role as a form of thermal energy storage, offering substantial flexibility within buildings. This flexibility contributes to grid-supportive actions (Balint and Kazmi 2019), as evidenced by the utility of domestic electric water heating systems (DEWH) storage tanks, which are acknowledged as a key element of flexible energy utilization in the built environment (Sørensen, Åse Lekang et al. 2021) and offer large thermal storage for moving electrical load across the day.

The application studies of battery energy storage systems (BESS) display a variety of focus areas within the domain of energy management. For instance, Kermani et al. (2021) optimize the energy savings of a smart building linked to a battery, and connected to a microgrid, by acting on the controllable loads of the building. Barone et al.

(2020) leverage high frequency consumption data obtained by smart meters, to regulate the charging of electric vehicles, and maximise the self-consumption of a 4 users community. Aslam et al. (2020a) developed an effective energy management strategy using Mixed Integer Linear Programming (MILP¹). This strategy is designed to optimally schedule smart appliances and the charging/discharging of electric vehicles (EVs) to reduce energy costs. It also incorporates an energy storage system (ESS) to enhance energy utilization efficiency. Transitioning from electrical to thermal energy storage, similar innovative approaches have been explored. For instance, Yildiz et al. (2021) examines the integration of domestic electric water heating systems with photovoltaic (PV) energy production to enhance the utilization of excess PV output. The findings indicate that a household with a standard working family profile can achieve 48% of their daily DEWH energy needs—equivalent to 6 kWh of energy and 142 liters of hot water—using a 4.5 kW PV system. This represents a significant improvement in PV self-consumption, amounting to a 28% increase.

2.3 Enhancing Energy Flexibility through Demand Response

Demand response (DR), is the program for modification of consumer demand for energy through various methods such as financial incentives, price signal, a financial, grid reliability trigger and behavioral change through education. Usually, the goal of demand response is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak times such as nighttime and weekends (Qdr 2006, Zhang and Li 2012). The potential of energy flexibility, accessible through Demand Response (DR) programs, is substantial. A study by Gils (2014) conducted a comprehensive analysis of the theoretical demand response potential among consumers across various sectors in European countries. This analysis highlighted significant hourly demand response potential throughout the year in the steel, cement, pulp and paper industries, as well as in commercial and residential sectors. On an hourly average, the minimum achievable load reduction is estimated at 61 gigawatts (GW), with the potential to increase load by at least 68 GW. Such reductions can be realized by deferring demand to later times or through active load shedding, whereas increases typically involve advancing the operation of processes or equipment.

Demand Response (DR) strategies are becoming increasingly essential in the contemporary energy sector, ensuring the reliable operation of power systems amid the growing complexities introduced by the integration of variable renewable energy sources. Nevertheless, with the increase in distributed resources, the variability of power gen-

¹MILP is a mathematical optimization or decision-making method used in operations research. It involves finding the best solution from a set of possible solutions, based on given constraints. In MILP, the mix of integer and continuous variables allows for complex modeling in areas like logistics and scheduling, accommodating both discrete and continuous decisions.

eration, and the growing prevalence of intelligent devices such as smart thermostats, existing electrical systems and demand response (DR) programs must adapt to a new environment (Chen and Liu 2017). In the context of the emerging energy community models of this year, along with the imperative to maximize collective self-consumption to enhance the utilization of clean energy, traditional DR programs have become inadequate. This necessitates the introduction of new DR programs or other demand-side management initiatives to align consumer energy consumption with periods of peak renewable energy production, this strategy, referred to as method (b) in Figure 1.6. In the following paragraph, we will review traditional DR programs, highlight their limitations, and explore new possibilities for DR strategies adapted to the renewable energy context.

Generally, Demand response can be classified as two categories: Incentive-Based DR and Price-Based DR, a hierarchy of demand response schéma is briefly given in Figure 2.2.

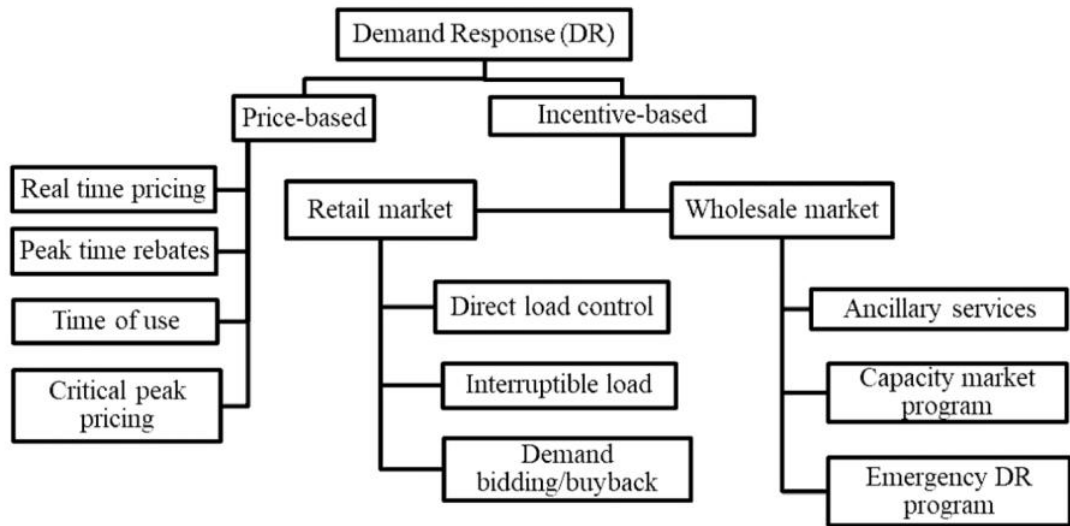


Fig. 2.2 Hierarchy of Demand Response (Alasser et al. 2021)

Incentive-based Demand Response (DR) encompasses a variety of programs where consumers are encouraged to reduce or shift their electricity usage during peak demand periods, emergencies, or when electricity prices spike. The incentives can take several forms:

- **Direct Load Control (DLC):** This program allows the utility to remotely control certain appliances, like air conditioners (Chu et al. 2005) or water heaters (Ericson 2009), during peak demand to reduce load on the grid.
- **Interruptible/Curtailable Service (I/C):** Large consumers agree to reduce their energy consumption on request and receive a financial incentive for doing so (Gedra and Varaiya 1993, Majumdar et al. 1996).

- **Demand Bidding/Buyback (DB):** Customers bid to reduce their load in exchange for payment, essentially selling back excess energy to the utility.
- **Emergency Demand Response Program (EDRP):** Offers incentives to customers to reduce their load during emergency situations to help prevent blackouts or brownouts.
- **Capacity Market Programs (CMP):** Participants commit to reduce electricity usage during peak times and are compensated based on their ability to provide this “megawatt” capacity.
- **Ancillary Services Market Programs (ASMP):** Customers can be paid for providing services that support the reliability of the grid, such as frequency regulation or reactive power.

Customers participating in these programs may receive discounted rates or separate incentive payments for reducing their energy usage. Contractual arrangements usually outline how baseline energy consumption is established and how much the customer is expected to reduce during DR events. If customers don’t meet their reduction commitments when a DR event is called, they may face financial penalties. These programs are designed to enhance grid reliability and lower costs by reducing the need for additional power generation during peak periods.

Price-based Demand Response (DR) is a type of DR program that involves varying electricity prices to influence consumer behavior regarding electricity usage. This approach includes several pricing schemes, such as Time-of-Use (TOU) rates, Real-Time Pricing (RTP), and Critical Peak Pricing (CPP). Here’s a brief explanation of each:

- **Time-of-Use (TOU) Rates:** These rates vary depending on the time of day. Electricity costs more during high-demand periods (peak hours) and is cheaper during low-demand times (off-peak hours). Consumers can lower their electricity bills by shifting their usage to off-peak times.
- **Real-Time Pricing (RTP):** Prices fluctuate in real-time based on market conditions and the balance of supply and demand. Consumers can respond to these price signals by reducing or shifting their usage when prices are high.
 - **Sioshansi (2010)** indicate that introducing RTP can reduce the rescheduling costs caused by day-ahead wind resource forecast errors and eliminate loss of load events.
- **Critical Peak Pricing (CPP):** This pricing scheme is similar to TOU but has an added component where prices can increase significantly during times of ex-

ceptionally high demand (critical peak periods). Consumers are encouraged to reduce their demand during these periods to avoid high charges.

- **TEMPO** is a specific tariff option from EDF, the French electric utility company. TEMPO categorizes days into three colors based on the electricity demand and price - blue, white, and red, with blue being the cheapest and red being the most expensive (Albadi and El-Saadany 2007).

In price-based DR programs, customers are usually required to sign contracts with DR sponsors (like utility companies) and agree to the terms of the pricing scheme. All load modifications under these programs are voluntary, meaning that customers choose how and when to adjust their usage in response to price signals, without direct control from the utility. The aim is to provide economic incentives for consumers to reduce or shift their demand, thereby lowering their electricity costs and helping to balance the grid during times of high demand.

Both incentive-based and price-based Demand Response (DR) programs have proven effective in the energy sector by encouraging users to adjust their energy consumption patterns. However, each approach also presents specific limitations that need consideration. Direct Load Control (DLC) and other incentive-based programs frequently infringe on customer privacy and lack the necessary scalability (Parrish et al. 2020). Furthermore, uniform pricing strategies applied across varied consumer consumption patterns, as seen in price-based programs, is unfair to those who already have a normal or low level of consumption. Additionally, the fluctuating price rates across different times may result in customer confusion (Haider et al. 2016a). To address these challenges, a reformed DR program is proposed. This program should be non-intrusive, ensuring no additional hardware installation is required, thereby being more environmentally friendly. It should also be inclusive, accommodating diverse customer needs and consumption levels. Importantly, the program must offer clear and easily comprehensible information to customers to facilitate informed decision-making. Collectively, these attributes will make the reformed DR program accessible to everyone, significantly enhancing its scalability. Finally, by influencing consumption behaviors subtly, the new DR program aims to align with the overarching goal of maximizing self-consumption and, consequently, bolstering the use of clean energy. This vision is made possible by the application of a behavioral economics concept, nudge, as a generalized form of demand response.

Advanced technologies in Information and Communications Technology (ICT) further enable the effective implementation of such DR programs, enhancing their reach and impact. As noted by Haider et al. (2016b), ICT advancements present significant opportunities to develop residential demand response relevant in smart grid applications. Furthermore, Laicane et al. (2015) assess the potential of demand side manage-

ment to reduce consumption in households, indicating that ICT can be instrumental during unexpected and disruptive events (Strielkowski et al. 2021). More broadly, the integration of ICT has been recognized as essential for leveraging the full potential of smart grids equipped with renewable energies (Abrahamsen et al. 2021, Veichtlbauer et al. 2021).

2.4 Enhancing Energy Flexibility through Nudge

A nudge is a non-monetary signal. It's an intervention aimed at making people adopt a behaviour, which they would not adopt spontaneously. Moreover, the intervention must be as light as possible, so as not to become a constraint. They can take many forms (like mails, or advertisement campaigns), and also differ in contents (these can be feedback, or “explicit injunctions”, for instance). Thaler and Sunstein (2008) define nudge as follows:

Definition 2.4.1. *[Nudge] “[A nudge] is any aspect of the choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid.”*

A common, everyday example of a nudge is the placement of warning slogans like “Smoking Kills” on cigarette packages. This strategy aims to reduce tobacco consumption and promote self-care in health management. Such nudges do not interfere with the individual’s freedom to purchase tobacco products, but they do influence behavioral patterns to some extent. This approach is subtle yet effective in nudging individuals towards making healthier choices without restricting their autonomy. According to Thaler and Sunstein (2008), nudges can primarily be categorized into two types:

- **Type 1 Nudges:** These nudges are based on the human decision-making process that is automatic and instinctual, also known as “System 1” thinking. Such nudges are often subconscious, involving simple, fast decision-making—for instance, placing healthier food at eye level at the supermarket checkout to encourage better eating habits, or designing stairs to be more prominent than elevators to promote walking.
- **Type 2 Nudges:** These nudges are based on the human decision-making process that involves reflection and logical reasoning, also referred to as “System 2” thinking. These nudges are more conscious and involve a more complex and deliberative decision process. An example would be encouraging households to install more efficient heating systems by providing detailed information on energy conservation and potential long-term savings.

Today, nudge theory is widely applied across various sectors. Below, we present brief studies and use cases that illustrate its applications.

- **Government:** The Malaysian government applied nudge theory, as described by Minoi et al. (2020), to influence public behavior during the COVID-19 pandemic. By promoting nationalistic nudges, the government successfully encouraged compliance with the Movement Control Order (MCO), which included school closures, mandatory mask-wearing, social distancing, and frequent handwashing. Specific nudges included adjustments and priming through messages from health authorities, empathetic arousal via feedback from the community, and improvements in processes leading to the development of new health-focused products. Faced with escalating socio-economic crises, these nudges also prompted the government to implement swift policy responses, including significant public health and economic stimulus measures to aid recovery from the pandemic's impacts.
- **Healthcare:** Misawa et al. (2020) studied a novel integration of machine learning and nudge theory that substantially enhanced colorectal cancer (CRC) screening rates in Hachioji, Tokyo. This method utilized historical health data to identify individuals recommended for screening. The nudges applied followed the "EAST" framework for making behavior change easier, more attractive, socially normative, and timely. For instance, it emphasized that CRC screening could be completed at home (easy), mentioned a significant subsidy reducing the cost by JPY 3800 (84.5%, attractive), was clearly communicated as a public health initiative by the city (socially normative), and set a fixed deadline for screening (timely). Of the 12,162 targeted, 3,264 (26.8%) underwent screening, thereby exceeding the initial expectation of 19.0%. Furthermore, Kwan et al. (2020) discusses the potential of nudging as a mechanism to enhance diabetes management. This study summarizes findings from various research efforts assessing the efficacy of different nudge strategies—including framing, reminders, social modeling, and social influence—in improving outcomes for diabetes patients.
- **Environmental conservation :** Kappel and Grechenig (2009) proposes promoting sustainable behavior through feedback in the form of a shower water meter (referred to as "show-me") that displays water usage during a shower with LEDs assembled on a stick, visualizing an increasing water level. An evaluation of Show-Me was carried out in four households over a three-week period. The results showed an average decrease in water consumption per shower from 10 liters.

In addition, nudge is also widely used in finance market, education, business management and also in energy consumption management. The most intuitive application of nudge theory in energy consumption management is the promotion of the dangers of the greenhouse effect (Type 2 nudges). “*According to the results of the quantitative study, awareness, beliefs, and concerns toward climate change appeared as necessary conditions to drive pro-sustainable behaviors. (Olya et al. 2023)*” Still, climate change awareness isn’t enough to change everyone’s behavior (McKercher et al. 2010, Lorenzoni and Pidgeon 2006, Howarth 2008), which means the behavior of those least willing to change may need more of a push (Type 1 nudges). So more nudging strategies are interesting for energy consumption management aiming at helping people improve the way they consume energy: see for instance the review Karlin et al. (2015). Experiments have been conducted as well on private households (Salman Shadid et al. 2020, Ruokamo et al. 2022) as on working premises (Charlier et al. 2021). Analysis the results of the large scale OPOWER study showed nudging to be efficient in helping reduce consumption (Allcott 2011). In this study, the company sent letters to customers, contrasting their consumption with that of their neighbours. Nudging is especially interesting as it represents a non-monetary, and cost-effective, way to help improve energy consumption (Allcott 2011). In that regard, emails and internet platforms possess a huge scalability potential.

2.5 Achieving Energy System Flexibility Using Interdisciplinary Advanced Technologies

In practical applications of ESS (Energy Storage Systems) and DR (Demand Response), interdisciplinary technologies are applied to overall energy management to support ESS or DR functionalities. Building on the synergy between interdisciplinary technologies and energy management practices, We will further explore the state of the art of these advancements.

2.5.1 Energy Forecasting Technologies

Load forecasting (Hong et al. (2020) or Eliana Vivas and Salas (2020)) is an important feature of many energy management tools. It enables utilities to predict demand over varying timeframes, thereby optimizing resource allocation and energy distribution. Depending on the temporal scope, load forecasting can be divided into several classifications : Very Short-Term LF (VSTLF), Short-Term LF (STLF), Medium-Term LF (MTLF) and Long-Term LF (LTLF)(Azeem et al. 2021). Methods available range from statistical methods (Weron 2006), to probabilistic ones (Wang et al. 2019), or machine learning ones (Zhang et al. 2021), for instance. The statistical-probabilistic

family of methods includes linear models (Goia et al. 2010), autoregressive moving average (ARMA) models (Pappas et al. 2008), or the ARIMA model of Box and Jenkins (Stellwagen and Tashman 2013). The methods of this family use linear processes. They are simple to implement and well adapted for the short term, but unable to handle the non-linearity existing in the load series (Eliana Vivas and Salas 2020, A.Lahouarab 2015). Machine Learning approaches include notably random forests (A.Lahouarab 2015), K-Nearest Neighbors (KNN) (Fan et al. 2019), or Fuzzy Neural Network-Based Forecasting Methods (Yang et al. 2016). Hybrid methods that combine artificial intelligence and metaheuristic optimization have proved highly effective (A.Lahouarab 2015).

These forecasts are used as input in tools that perform various functions, such as scheduling, reserves estimation, and trading in electricity markets (Carriere and Kariniotakis 2019). For instance, Martin Nascimento et al. (2021) help assess the forecast errors of short-term forecasting models of building consumption, used in consumption planning. Reducing the error helps improve the efficiency of these tools. Ozturk et al. (2013) demonstrates an integrated demand response system that employs an Adaptive Neuro-Fuzzy Inference System (ANFIS²-based) model to forecast residential energy demand and to optimize the scheduling of appliances according to time-of-use pricing, thus improving home energy management. Zuazo et al. (2021) emphasize the need for quality load forecasting of building consumption, in order to enable load management, with the eventual aim of maximising collective self-consumption. Carriere and Kariniotakis (2019) proposes a unified model integrating forecasting and decision-making into a single optimized process to improve photovoltaic and wind power trading. It uses an analog ensemble model and support vector regression for accurate market forecasts and employs a meta-optimization strategy, including particle swarm optimization, focusing on maximizing electricity market revenue. Coignard et al. (2021) examines how local energy communities can use load forecasts for better energy scheduling to enhance self-sufficiency, assessing forecast value in terms of community benefits like cost and fairness. Conte et al. (2022) presents a hybrid AI method combining a Time Delay Neural Network with a stochastic Model Predictive Control to efficiently manage energy in renewable communities, handling uncertainties in demand and solar generation, tested on a public dataset, improved the community's income by up to 18.72% by optimizing battery energy storage system operations. Grève et al. (2020) presents a novel data analytics method to enhance neural network forecasts for Renewable Energy Communities to optimize scheduling and improve forecast accuracy by 10%, despite economic disruptions from the COVID-19 crisis, proven in a Belgian pilot project.

²An ANFIS-based model, is a kind of artificial intelligence that combines neural networks and fuzzy logic principles to model complex systems.

2.5.2 Non intrusive load monitoring (NILM) for Quantifying Energy Flexibility

Non-Intrusive Load Monitoring (NILM), also known as load disaggregation, was first introduced by Hart (Hart 1992). It is a technique used in energy management systems to determine which appliances are being used in a building and how much power each consumes. This process involves the application of the “Blind Source Separation problem” to energy consumption and production data. By analyzing changes in voltage and current entering the building from a single point of measurement—typically the main electrical panel—NILM leverages advanced algorithms to identify unique electrical signatures (as illustrated in Figure 2.3). This method does not require individual sensors on each appliance, making it a streamlined and efficient approach to monitoring energy usage.

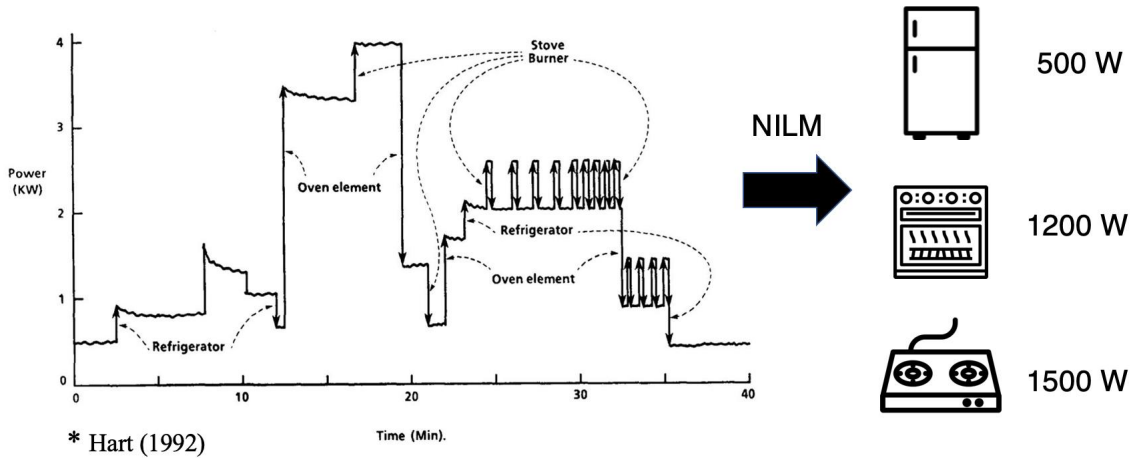


Fig. 2.3 Identification of Electrical Signatures Using NILM

Based on its characteristics, NILM can be applied in the estimation of energy flexibility, which is critical for enhancing Demand Response services. For example, Lucas et al. (2019a) introduces a methodology using Non-Intrusive Load Monitoring to estimate a household’s load flexibility for Demand Response services for optimizing appliance operation in the UK energy market. Azizi et al. (2021) proposed a novel unsupervised NILM method to characterization the energy flexibility of a single building by extracting the consumption pattern of shiftable appliances via analyzing the active and reactive power.

Since the introduction of NILM, it has evolved with advancements in signal processing, machine learning, and data analytics. NILM techniques have ranged from simple on-off event detection to complex disaggregation algorithms using statistical and Artificial Intelligence (AI) methods. In recently review, Schirmer and Mporas (2023) categorizes NILM technologies into three types:

- **Source separation:** Source separation is the process of isolating individual com-

ponents or signals from a mixture, commonly used in audio processing to extract voices or instruments from recorded music. The most popular algorithms used for NILM are Independent Component Analysis (ICA)(Kim et al. 2023), Non-Negative Matrix Factorization (NMF), Non-Negative Tensor Factorization (NTF)(Durand et al. 2021), and Sparse Component Analysis (SCA).

- **Pattern matching:** Pattern matching is a technique used to identify recurring sequences, structures, or regularities within data sets or complex objects, facilitating tasks such as searching, recognition, and classification. It is also based on the 3 main architectures: Dynamic Time Warping (DTW) (Liu et al. 2017), Multi-Variance-Matching (MVM) (Schirmer et al. 2020), and Graph Signal Processing (GSP) (Zhao et al. 2023).
- **Machine learning:** Machine learning is a field of artificial intelligence that enables computers to learn from and make decisions based on data without being explicitly programmed. Machine learning based NILM algorithms are mainly based on Hidden Markov Models(HMM) (Raiker et al. 2018, Kumar and Abhyankar 2023), Long Short Time Memory (LSTM) (Le et al. 2021, Andrean et al. 2022) and Convolutional Neural Network (CNN) (Pan et al. 2020b) architecture.

In the face of numerous NILM (Non-Intrusive Load Monitoring) algorithms, the challenge of comparing them effectively arises. To address this issue, Batra et al. (2014) introduced the Non-Intrusive Load Monitoring Toolkit (NILMTK), which is an open-source toolkit explicitly designed for facilitating the reproducible comparison of energy disaggregation algorithms. Subsequently, Batra et al. (2019) further supplemented this toolkit with additional deep learning algorithms in their subsequent research. However, in NILMTK, only machine learning-based algorithms were compared, and there is a lack of comparison for pattern matching-based and source separation-based algorithms. In a recent review conducted by Schirmer and Mporas (2023), the comparison of these two categories of algorithms was addressed, and a comprehensive summary of their performance in terms of accuracy, computational time, and transfer learning³ capability was provided for these three types of NILM techniques. Transfer learning is a significant capacity of comparison in this context. Transfer learning in NILM offers the advantages of reducing the necessity to install sensors for each appliance and conserving computational resources by reusing pre-trained models across different datasets (D’Incecco et al. 2020). Within this comparative framework, it has been observed that machine learning-based NILM algorithms generally outperform other types in terms of both accuracy and transfer learning potential. Notably, the CNN⁴ (Zhang et al. 2018)

³Transfer learning in NILM refers to the practice of using knowledge or models acquired from one dataset or domain to improve the performance of NILM algorithms on a different dataset or domain.

⁴It’s implemented at NILMTK

and Generative adversarial network (GAN) (Pan et al. 2020a) algorithms stand out for their exceptional accuracy and transferability. Among these, the GAN algorithm exhibits the best transferability.

Currently, NILM technology is divided into high-frequency NILM and low-frequency NILM. The latter typically uses a sampling frequency ranging from 1 Hz (once per second) to once per minute. This low sampling rate is sufficient to capture overall energy consumption changes but may not be detailed enough to distinguish between all individual appliances. On the other hand, high-frequency NILM employs significantly higher sampling frequencies, typically ranging from hundreds to thousands of samples per second. Such elevated sampling rates yield more granular electricity usage data, thereby enhancing the accuracy in differentiating and pinpointing the energy consumption patterns of individual devices. Notably, utilizing raw data sampled at 1 MHz can even enable the distinction between appliances of identical types (Huber et al. 2021). Additionally, this increased precision in data acquisition is confirmed by other studies that underscore the superiority of high-frequency NILM in detailed appliance-level monitoring (Liaqat and Sajjad 2022, Gupta et al. 2010). However, the Imbalance Settlement Period (ISP⁵) in Europe will standardize to 15 minutes by 2025 (European Union 2017), though France has an extension until then to transition from the current 30-minute period. This is much lower than even the sampling rate used for low-frequency NILM. To date, no algorithms have been tested under these ultra-low frequency conditions (15-30 minutes), posing a substantial challenge for real-world applications in Europe.

2.5.3 Optimizing Energy Flexibility Rescheduling

The optimization of energy systems is a crucial question, made all the more acute by the introduction of renewable energies, while systems were not originally designed for such sources (Hall and Buckley 2016). However, renewable energies introduce new constraints, like the intermittence of production, which must be taken into account, in order to make for reliable systems. That is why their use requires complex design, planning and control optimization methods (Baños et al. 2011). In renewable energy communities, various optimization algorithms, are utilized to enhance energy efficiency and system performance. Mathematical techniques, like mixed-integer linear programming, or genetic algorithms, are used to optimize challenging models (Morvaj et al. 2016). In addition, meta-heuristic algorithms, including Simulated Annealing (SA) and Particle Swarm Optimization (PSO), are adopted for addressing optimization challenges. Dynamic Programming (DP) and Multi-Objective Optimization (MOO) provide robust solutions for multi-stage decision-making processes and achieving multiple goals, re-

⁵ISP refers to the time interval over which the net difference between actual electricity consumption and scheduled generation or consumption is calculated and settled financially.

spectively. Mixed-Integer Nonlinear Programming (MINLP) serves as a comprehensive optimization framework for tackling intricate issues that involve both linear and nonlinear constraints, as well as mixed (continuous and discrete) decision variables (Lu et al. 2015). Within the domain of system control, Model Predictive Control (MPC) is implemented as a sophisticated technique for enhancing the dynamics and responsiveness of energy systems (Valverde et al. 2012). This approach ensures the reliability and economic efficiency of the energy supply. However, the diversity of the models used (Hall and Buckley 2016) make difficult the construction of an all-encompassing approach. Hodencq et al. (2021) constructed the OMEGAlpes model in such a way that it can be most easily used, and open-sourced the code.

For instance, Aslam et al. (2020b) introduces an advanced energy management strategy that utilizes mixed integer linear programming (MILP) for the optimal scheduling of household appliances and electric vehicle charging, aiming to reduce peak to average ratio and energy costs in residential settings. The effectiveness of this optimization is validated through comprehensive simulations, demonstrating significant cost savings and efficiency enhancements in home energy usage. Cosic et al. (2021) study on the application of advanced mixed-integer linear programming to optimize renewable energy community operations within microgrids, referencing a case study in Austria. The optimization resulted in a 15% cost reduction and a 34% decrease in carbon emissions for the community, showcasing both economic and ecological benefits. Lazzari et al. (2023) study on optimizing Renewable Energy Communities (RECs) using combinatorial and multi-objective genetic algorithms to enhance participant selection and solar energy distribution. The results indicate enhanced energy sharing, consumption, CO2 emission reduction, and economic benefits within a REC in Northeastern Spain. Ye et al. (2017) propose an online algorithm for cost-effective energy sharing in communities with renewable energy sources, aimed at minimizing total energy costs and ensuring fair revenue distribution. It employs Lyapunov optimization theory for efficient management of energy storage systems, achieving up to 12% cost savings while maintaining fairness among users. Yi et al. (2018) presents a control strategy for islanded hybrid AC/DC microgrids using Finite-Control-Set Model Predictive Control (FCS-MPC), improving the efficiency of distributed energy resources like solar PV systems.

2.6 Conclusion

In this chapter, we explore advanced technologies that enhance energy flexibility to address the intermittency issues inherent in renewable energy systems, thereby improving energy efficiency. We discuss two primary methods: (a) storing energy for later use, and (b) aligning consumption with periods of high renewable energy production.

For method (a), we offer a detailed presentation on energy storage systems, briefly

introducing their types and highlighting the advantages of battery storage systems among all storage options. These advantages include lack of geographical constraints, longer lifespans, higher energy and power densities, and cost reductions driven by economies of scale from the widespread adoption of electric vehicles. This scale has also advanced Vehicle-to-Grid (V2G) technologies, making battery storage systems more flexible and efficient compared to other energy storage technologies. On the other hand, we also explore how residential electric water heating systems can serve as thermal storage. These systems are widely used in energy systems to store renewable energy, leveraging their capacity to act as effective thermal storage solutions.

For Method (b), we provide a comprehensive review of Demand Response (DR), including its definitions and classifications into price-based and incentive-based strategies. Under these categories, we explore both traditional DR algorithms and practical case studies. Furthermore, we present their limitations, notably the lack of privacy in incentive-based strategies, the potential for unfairness and confusion in price-based strategies, and the limited scalability common to both approaches. Emphasizing the need for traditional DR programs to adapt to the decentralized nature of modern energy systems, we argue for a reformed DR program to enhance scalability. This new program should be non-intrusive, requiring no additional hardware installation, inclusive, and provide clear, easily understandable information to ensure accessibility for all users. Building on this foundation, we propose the use of “nudge”, a behavioral economics concept, to fulfill these criteria. Moreover, we discuss the potential of Information and Communications Technology (ICT) as a medium for disseminating nudges, thereby enhancing the reach and effectiveness of these interventions in energy systems. Subsequently, we provide an overview of nudge techniques, detailing their definition and use cases across various domains. We place particular emphasis on specific projects that demonstrate the application of nudge strategies in the energy field.

In this section, we also present an overview of advanced digital tools frequently utilized in energy projects, supporting both method (a) and method (b) for energy system management. We begin with a comprehensive review of energy forecasting, highlighting various algorithms employed in this field. Notably, hybrid methods that integrate artificial intelligence with metaheuristic optimization have demonstrated high effectiveness. Additionally, we discuss technologies for power disaggregation, noting that among the categories of machine learning pattern matching and source separation, machine learning exhibits superior performance and transfer learning capabilities. Specifically, algorithms based on Convolutional Neural Networks (CNNs) are most effective. However, we identify a gap in testing under ultra-low frequency conditions, which raises questions about the algorithms’ applicability in real-world scenarios where data frequency is extremely low. Finally, we explore various methods and practical ex-

amples of energy optimization tools, emphasizing their critical role in energy system management by rescheduling appliance usage to achieve optimal energy efficiency.

CHAPTER 3

Non Intrusive Nudging Strategy part 1: Trying to Disaggregate Real Data

Abstract: How to identify energy flexibilities is a crucial question that this chapter addresses while exploring our nudging pipeline strategy I (as presented in Section 1.4.3.2). It introduces Non-Intrusive Load Monitoring (NILM) technology to tackle this challenge. The focus of this chapter is on NILM; it evaluates the performance and transferability of an open-source NILM algorithm under ultra-low frequency conditions in practical settings and highlights the complexities of deploying NILM in real-world scenarios. The conclusion underscores the need for further efforts to optimize NILM for practical applications.

3.1 NILM: Challenges in Real-World Applications

To explore our nudging strategy, as introduced in Section 1.4.3, which aims to influence consumer behavior towards more efficient energy usage in a non-intrusive manner, we initiate with energy forecasting to anticipate future consumption patterns. After the forecasting phase, our objective is to identify which components of the predicted future consumption are flexible and can be shifted to align with the schedules of renewable energy production. Once these flexible components are identified, we recommend that consumers adjust their consumption accordingly to synchronize better with energy production schedules. In this chapter, we do not delve into the prediction of future consumption because, in real-world applications, load forecasting already has numerous mature use cases (As illustrated in the state-of-the-art review of load forecasting in Section 2.5.1); instead, we address how to identify flexibilities within aggregated consumption curves. Given that in France we only have access to aggregated consumption data from Linky meters, which is sampled every 30 minutes, identifying flexible components presents a significant challenge. This challenge is a classic example of Blind Source Separation, and when applied to load curves, it is referred to as “Non-Intrusive Load Monitoring” (NILM) (Hart 1992).

As discussed in Section 2.5.2 (the state of the art of NILM), NILM technology

facilitates the accurate assessment of energy flexibility and enhances the management of electricity use in energy systems. However, the practical implementation of NILM faces significant obstacles:

- **Is there a high-performance algorithm that has been evaluated under ultra-low frequency conditions (30 minutes)?** Despite the availability of high performance algorithms, none have been tested under conditions where data is recorded at ultra low frequencies, such as every 30 minutes. This raises concerns about the ability of these models to maintain robust performance in such scenarios, highlighting a critical area of ongoing research.
- **Is there a high-transferability algorithm that can be effectively applied in real-world households without appliance-specific power meters?** NILM algorithms perform well when trained and tested using detailed data from environments where each appliance’s power usage is monitored. However, NILM technologies are designed to function in environments without appliance-specific power meters. This implies a lack of detailed appliance power consumption data in real-world applications. To overcome this, a NILM model must be pretrained using an alternative data source (potentially a public dataset) and then applied to real-world households, necessitating high model transferability.

To address these challenges, this study explore the GAN-Seq2subseq (Pan et al. 2020a) algorithms to evaluate the accuracy and transferability under varying frequency conditions, utilizing datasets with detailed data at both aggregated and appliance levels.

In the following section, we first outline the essential materials required for evaluating the performance of NILM models in Section 3.2. Subsequently, we present the performance evaluation of NILM models in Section 3.3 and assess their transferability in Section 3.4. Finally, we discuss our findings and their practical implications for the implementation of NILM technologies in ultra-low frequency conditions in Section 3.5.

3.2 Assessment of NILM Algorithms: Overview, Key Data, and Evaluation Metrics

To evaluate the performance of NILM algorithms, researchers rely on detailed, real-world energy consumption datasets. These datasets provide the granular data necessary for developing, testing, and refining algorithms that disaggregate total energy consumption into appliance-level usage. Complementing this, evaluation metrics offer a comprehensive assessment of algorithmic performance, focusing on accuracy, robustness, scalability, and generalizability. These metrics enable researchers to quantitatively assess how effectively NILM techniques can disaggregate total energy consumption, adapt

to varying household behaviors, and maintain consistent performance across diverse environments. This systematic approach to evaluation is crucial for refining NILM technologies, ultimately leading to more effective and efficient energy management solutions.

We start by presenting the algorithm employed for the subsequent evaluations, detailed in Section 3.2.1. Next, we introduce the dataset used for these evaluations, as outlined in Section 3.2.2. This is followed by an explanation of the metrics utilized for assessment, discussed in Section 3.2.3.

3.2.1 NILM Algorithm Used for Further Evaluation: Generative Adversarial Networks Based Sequence to Subsequence Learning

We use GAN-Seq2Subseq (Pan et al. 2020a) for our subsequent research because this algorithm has demonstrated the best performance and transferability in a systematic comparison presented in Schirmer and Mporas (2023). However, their experiments were conducted under conditions with data sampling at a few seconds or higher frequency. Therefore, we need to test whether this algorithm can maintain its high performance and transferability under ultra-low frequency conditions with 30-minute intervals.

3.2.1.1 Principle of GAN-Seq2Subseq Model

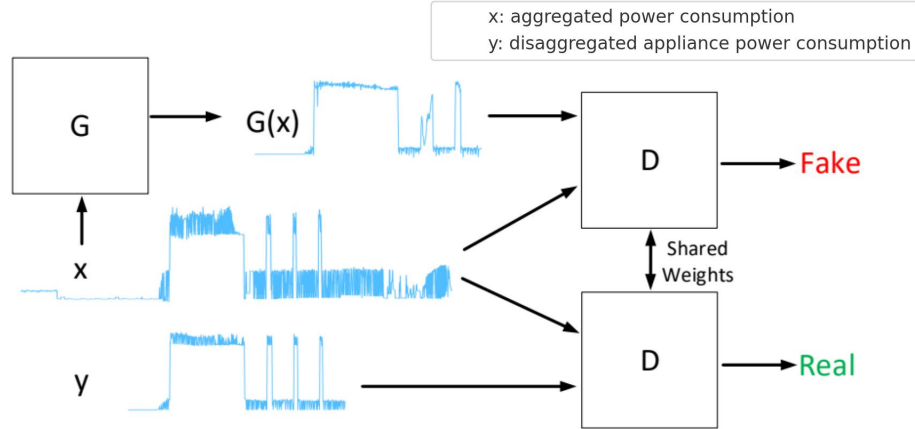


Fig. 3.1 GAN Seq2Subseq Model for Power Consumption Disaggregation (Pan et al. 2020a)

GAN-Seq2Subseq combines the principles of Generative Adversarial Networks (introduced by Goodfellow et al. (2020)) with Sequence to Subsequence¹ learning to

¹Seq2Subseq is a neural network architecture designed for transforming an input sequence into a shorter, relevant subsequence for tasks such as text summarization, anomaly detection, signal processing, and extracting key events from time series data.

create a powerful model. Figure 3.1 illustrates the GAN-Seq2Subseq model for power consumption disaggregation. Here, the generator (G) takes aggregated power consumption patterns (x) and produces synthetic disaggregated patterns (G(x)). The discriminator (D) evaluates these synthetic patterns against real disaggregated patterns (y), using shared weights for consistency. The discriminator then labels the outputs as "Fake" or "Real," aiming to distinguish between synthetic and actual disaggregated power consumption. This adversarial process helps improve the model's ability to accurately disaggregate appliance power consumption from aggregated data.

3.2.1.2 Computational Resources and Training Time for GAN-Seq2Subseq Model

The training process is a computationally intensive task. We utilize the computational server of G2ELAB, which features 48 cores at 2.4GHz / 96 logical processors (threads), 256 GB of memory, and an Nvidia RTX6000 GPU with 24 GB of memory, to handle this workload. The training time significantly depends on several factors, including the data frequency and the quantity of training data. Higher frequency data results in more data points and therefore longer training times, which can vary across different datasets. Additionally, the training duration is affected by the server's current state, specifically the availability of the GPU and memory resources. Typically, if the GPU is unavailable, training a model takes about one to two days. However, with 100% GPU utilization, the training time can be reduced to a few hours to around ten hours.

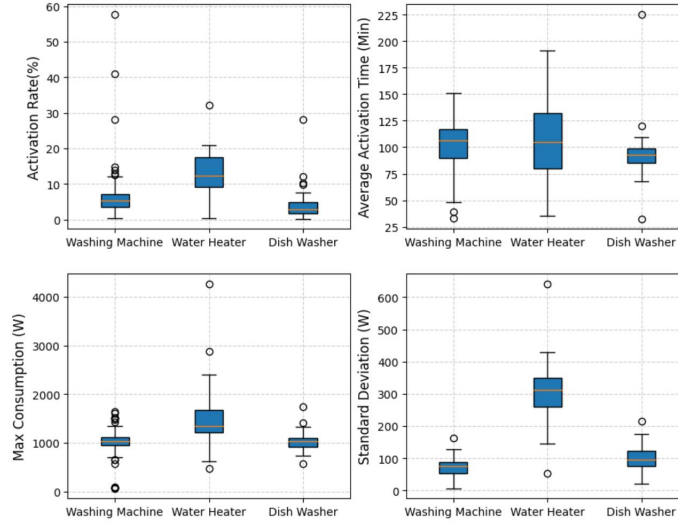
3.2.2 Public Data Set Used for NILM Performance Evaluation

In our study, we utilized four pivotal datasets: UKDALE, AMPds, REFIT, and IRIS and only focus on the task of flexible load disaggregation, encompassing white appliances, domestic electric water heaters, electric vehicles, and similar devices, due to their significant potential for energy efficiency improvements.

Iris : The Iris dataset is a subset from a European database of residential consumption collected as part of the REMODECE² (Residential Monitoring to Decrease Energy Consumption) project (*Mesure de la consommation des usages domestiques de l'audiovisuel et de l'informatique* 2008). The Iris dataset contains the energy consumption data of 98 houses for a span of one year. The data sampling step is 10 minutes. We make the appliance names homogeneous between the houses, as there are sometimes small variations in the terminology. Figure 3.2 shows the range of some statistical characteristics of flexible appliances contained in each household of IRIS dataset. For more detailed features, please see Appendix A

²The REMODECE project is an initiative focused on monitoring and reducing energy consumption in residential buildings. It aims to develop innovative solutions and technologies to promote energy efficiency and sustainability in the residential sector.

Fig. 3.2 Statistical Distribution (Activation Rate¹, Average Activation Time², Max Consumption and Standard Deviation³) of Appliance Consumption Characteristics in the IRIS Dataset.



¹ Activation Rate is calculated as the ratio of activation time to the total time; ² Average Activation Time is calculated as the sum of the activation times of an appliance divided by the total number of activations; ³ The standard deviation is a statistical measure that quantifies the amount of variation or dispersion in a set of data values around the mean.

UKDALE: UK-DALE, an open-access dataset from the UK, captures Domestic Appliance-Level Electricity for the purpose of supporting research on disaggregation algorithms (Kelly and Knottenbelt 2015). This dataset is characterized by its collection of data at a high sample rate of 16 kHz for whole-house measurements and at a lower rate of 1/6 Hz for individual appliances. Data were gathered from five different households, with one particular household being monitored continuously for a period of 655 days. For our research purposes, we specifically utilize data from houses 1, 2, and 5 within the UKDALE dataset. This selection is based on the availability of flexible load profiles, such as washing machines and dishwashers, in these buildings. More details on the statistical attributes of the UKDALE dataset can be found in Appendix B.

AMPds: The AMPds (Almanac of Minutely Power dataset)(Makonin et al. 2016) is a publicly available dataset created by Simon Fraser University’s (SFU) Electricity and Power Research Centre in Canada. It offers high-resolution energy consumption data collected from residential households. The dataset covers the period from 2012 to 2014 and includes measurements of electricity, water, and natural gas usage at one-minute intervals for an individual building in Canada. It can be found on the project’s official website³ or through various data repositories and academic platforms. More details on the statistical attributes of the AMPds dataset can be found in Appendix C.

REFITE: The REFITE Electrical Load Measurements dataset, hosted by the Uni-

³It is available at <http://ampds.org/>

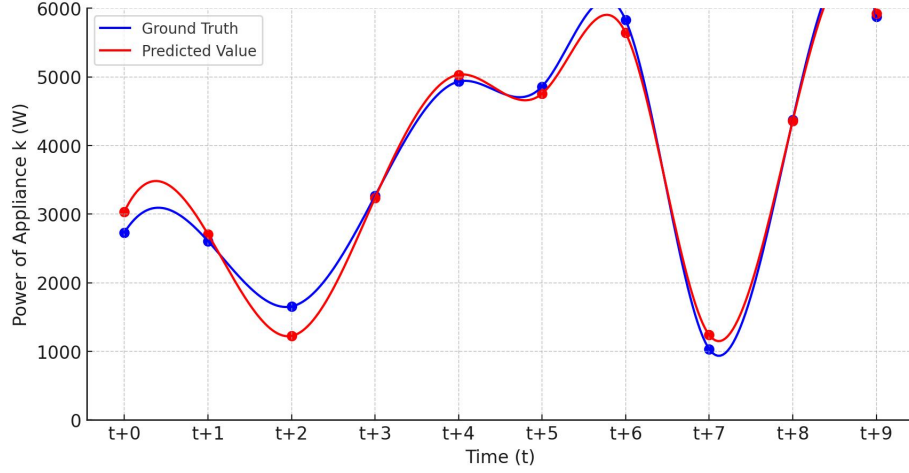


Fig. 3.3 Comparison of Ground Truth and Predicted Power Consumption for Appliance k

versity of Strathclyde (Murray and Stankovic 2016), spans from October 2013 to June 2015, provides cleaned electricity consumption data for 20 UK households, detailed at both aggregate and appliance levels, with 8-second interval timestamps. More details on the statistical attributes of the REFIT dataset can be found in Appendix D.

3.2.3 Metrics Used for NILM Performance Evaluation

For NILM algorithms, accuracy hinges on their ability to predict the power consumption of each appliance, termed as “predicted values”, against the “ground truth”. The ground truth represents the actual power drawn by each appliance, measured directly via individual meters. Predicted values, generated by NILM algorithms, estimate these measurements. By comparing predicted values to the ground truth, we assess the effectiveness and accuracy of NILM algorithms. Evaluation metrics, which quantify the magnitude of errors in predictions over a specified time period, are essential for determining the performance of these systems. In the following discussion, we will explore some of the commonly used metrics for evaluating NILM algorithms.

First, to evaluate the performance of NILM on appliance k , we define the time interval (t_{begin}, t_{end}) as the specified period for assessment. Let P_t represent the ground truth of power consumption in watts at time t and $\hat{P}_t$ denote the predicted value of power consumption in watts, as generated by the NILM algorithm. As illustrated in Figure 3.3, red points represent $\hat{P}_t$ and blue points denote P_t . The commonly used metrics that quantify the comparison between P_t and $\hat{P}_t$ are defined as follows:

- **Mean Absolute Error (MAE):** The average of the absolute differences between the predicted values $\hat{P}_t$ at time t and ground truth values P_t at time t . A lower MAE indicates more accurate model predictions and better performance (0 indicates perfect performance), while a higher MAE suggests larger prediction errors

and poorer performance.

$$\text{MAE} = \frac{1}{t_{\text{end}} - t_{\text{begin}}} \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} |P_t - \hat{P}_t|$$

- **Signal Aggregate Error (SAE):** It indicates the relative error of the total energy. E ($E = \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} P_t * \delta t$) denotes the total consumption of the appliance and $\hat{E}$ ($\hat{E} = \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} \hat{P}_t * \delta t$) the predicted total energy. A lower SAE value indicates a more accurate model with predictions closer to actual energy consumption (0 indicates perfect performance), while a higher SAE signifies larger discrepancies and less accuracy.

$$\text{SAE} = \frac{|\hat{E} - E|}{E}$$

- **R^2 Score:** The R-squared score is a statistical measure of how well the predictions approximate the real data points. R^2 score of 1 indicates that the predictions perfectly fit the data. In contrast, an R^2 score of 0 would indicate that the model does not explain any of the variability of the response data around its mean. Negative R^2 values can occur when the chosen model does not follow the trend of the data. Note that $\bar{P} = \frac{1}{t_{\text{end}} - t_{\text{begin}}} \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} P_t$ represents the average value of the ground truth at the specified period.

$$R^2 = 1 - \frac{\sum_{t=t_{\text{begin}}}^{t_{\text{end}}} (P_t - \hat{P}_t)^2}{\sum_{t=t_{\text{begin}}}^{t_{\text{end}}} (P_t - \bar{P})^2}$$

- **Estimation Accuracy:** The accuracy metric is defined in a customized manner and is employed to assess the performance of NILM algorithms as documented in (Pan et al. 2020a, Schirmer and Mporas 2023). Superior performance of the algorithms is indicated by this metric approaching one hundred percent. The metric may also assume negative values, indicating poor performance (<50%)

$$\text{Accuracy} = \left(1 - \frac{\sum_{t=t_{\text{begin}}}^{t_{\text{end}}} |P_t - \hat{P}_t|}{2 \times \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} P_t} \right) \times 100$$

3.3 Evaluating NILM Performance: Intra-Building Model Training and Testing Across 1 and 30 Minutes Frequency Conditions

To evaluate the performance of NILM algorithms under low-frequency and ultra-low-frequency conditions, we have trained and tested models within the same buildings. These models are assessed using various public datasets that have been specifically

resampled at 1-minute and 30-minute intervals. We first present our experimental setup in Section 3.3.1, and then discuss the results in Section 3.3.2.

3.3.1 Experimental Setup for Intra-Building Model Training and Testing

Data Utilization and Model Training: In our study, we utilized the UK-DALE and AMPds datasets to train models for appliance energy disaggregation. Specifically, we focused on the following disaggregation models:

- A washing machine disaggregation model trained using data from House 1 of the UK-DALE dataset.
- A dishwasher disaggregation model trained with data from House 5 of the UK-DALE dataset.
- Models for washing machines, clothes washers, and dishwashers trained using the AMPds dataset.

Training and Validation Setup: We allocated 75% of the data from each building in the different datasets for training and reserved 25% for validation purposes. The sizes of the training and validation subsets of the datasets used in this study after resampling at 1-minute and 30-minute intervals, are shown in Table 3.1

Table 3.1 Subset Sizes of Flexible Load for Training, Validation, and Testing of Models Using the UKDALE Dataset under 30-Minute Sampling Conditions

Data	Target	1min Training Subset Size	1min Validation Subset Size	30min Training Subset Size	30min Validation Subset Size
UKALE House1	WM ¹	849k	283k	28k	9.4k
UKALE House5	DW ²	148k	49k	5k	1.6k
AMPds	WM	788k	262k	26k	8.73k
	DW	788k	262k	26k	8.73k
	CD ³	788k	262k	26k	8.73k

¹ Washing Machine ² Dish Washer ³ Clothes Dryer

Evaluation Metrics Utilized: In our subsequent analysis, we will primarily utilize R2-Score and Accuracy to validate model performance. Meanwhile, MAE and SAE will serve as supplementary metrics to corroborate the appropriateness of the R2 and Accuracy measurements. Table 3.2 displays the parameter ranges for R2 and Accuracy in the context of model performance validation.

Evaluation Workflow: Figure 3.4 illustrates an example evaluation workflow for the Ukdale washing machine disaggregation model.

In **Stage 1**, we train the disaggregation model using GAN-seq2subseq learning algorithms with 75% of the data from Ukdale House 1 (indicated by the red circle). This includes both the aggregated consumption data and the washing machine consumption data (the blue line represents total power consumption, and the green line represents washing machine consumption).

In **Stage 2**, we test the model with the remaining 25% of the aggregated consumption data from the same household (indicated by the blue circle). The model disaggregates the test data to predict the washing machine consumption (red line), which is then compared to the actual washing machine consumption data (in the green circle) using evaluation metrics. This comparison allows us to assess the performance of the disaggregation model and the efficacy of the learning algorithms.

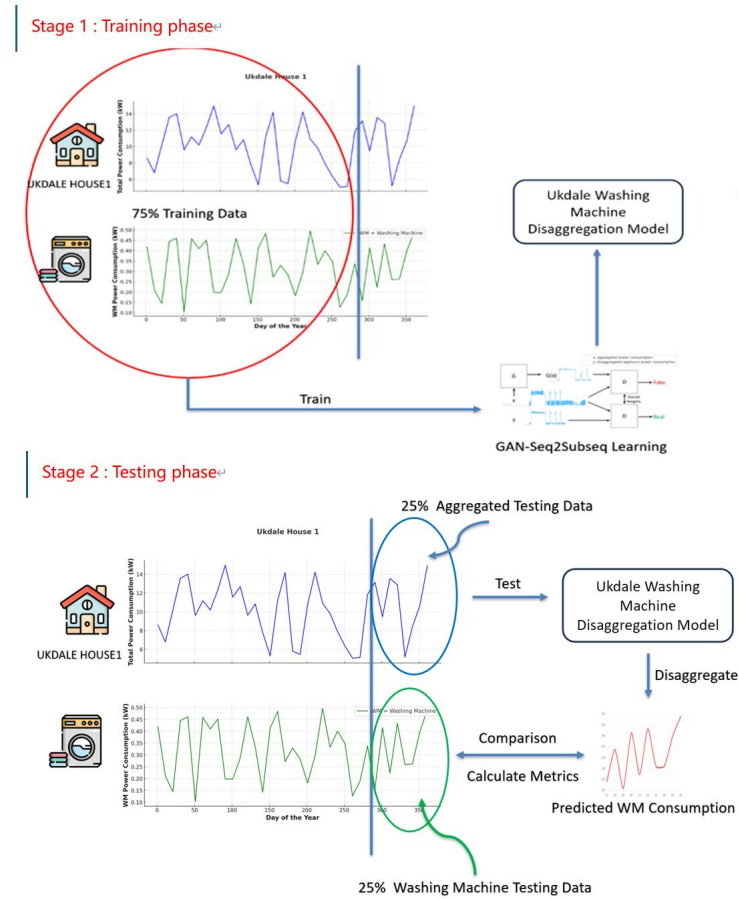


Fig. 3.4 Evaluation Workflow for the Ukdale Washing Machine Disaggregation Model

Table 3.2 Performance Categorization Based on R2 Score and Accuracy

Performance Level	R2 Score Range	Accuracy Range
High Performance	> 0.9	> 90%
Reasonable Performance	0.7 to 0.9	70% to 90%
Low Performance	0.5 to 0.7	50% to 70%
Inadequate Performance	< 0.5	< 50%

3.3.2 Results: Detailed Outcomes from Intra-Building Model Training and Testing Across 1 and 30 Minutes Frequency Conditions

Table 3.3 illustrate the accuracy of the models and their capability in power disaggregation tasks, specifically how well the predictions approximate the real data points. For 1-minute interval datasets, half the models demonstrated high accuracy and excellent model fit, with accuracy values approaching 100% and R2 values nearing 1, while the other half showed reasonable performance. Conversely, with 30-minute sampling, both accuracy and R2 values declined, exemplified by AMPds's accuracy dropping from 71.29% to 54.3% and by UK-DALE's accuracy dropping from 95.46% to 86.78%. (For detailed results concerning the MAE and SAE metrics, as well as visualizations of the disaggregation results, refer to Appendix E.)

Table 3.3 Accuracy of NILM Algorithm Performance Across Various Datasets and Sampling Frequencies in Intra-Building Train-Test Scenarios (High Predictive Performance Metrics Highlighted in Green.)

Metric	Appliance	Dataset	Frequency	
			1 min	30 min
ACC ⁴	WM ¹	UK-DALE	95.46	86.78
		AMPds	71.29	54.3
	DW ²	UK-DALE	95.53	71.11
		AMPds	85.14	68.43
	CD ³	AMPds	93.6	65.75
R2	WM	UK-DALE	0.96	0.83
		AMPds	0.67	0.21
	DW	UK-DALE	0.96	0.50
		AMPds	0.77	0.35
	CD	AMPds	0.94	0.489

¹ Washing Machine ² Dish Washer ³ Clothes Dryer ⁴ Accuracy

From a theoretical perspective, data sampled at a frequency of 1/60Hz (once per minute) are likely to capture more intricate details of appliance consumption than data sampled at 1/1800Hz (once every 30 minutes). This is due to the higher sampling rates' ability to detect subtle variations in appliance on/off states and transient power consumption fluctuations that may be overlooked at lower frequencies. Such granular data are critical for the performance of disaggregation models, and a reduction in sampling frequency can consequently lead to a significant decline in performance. Additionally, performance degradation in disaggregation models may be attributed to fewer data points being available for model training—for instance, reducing from 849,000 at a 1-minute interval to 28,000 at a 30-minute interval in the case of UK-DALE House 1. This substantial decrease in data volume restricts the learning capabilities of the models, impairing their ability to generalize across varied appliance usage patterns, thus

adversely affecting their performance.

In this study, the NILM models exhibit limited performance, with notable degradation observed at the 30-minute sampling intervals. Despite this, certain models still maintain reasonable performance under these conditions. For instance, the washing machine disaggregation model from UK-DALE House 1 achieves an R^2 score of 0.83 (reasonable performance). However, other models demonstrate poor performance, with R^2 scores below 0.50 (inadequate performance) under the same conditions.

3.4 Assessing the Adaptability of NILM Models for Cross-Dataset Application Under 10 and 30 Minute Sampling Intervals

Despite the limited performance of the non-intrusive load monitoring (NILM) model under a 30-minute sampling interval, some models still maintain reasonable performance, for example, the UK-DALE model achieves an accuracy of 86.78%. This suggests that NILM has potential for real-world applications, provided that superior models are selected. However, the question of whether these models possess transferability remains unresolved.

As mentioned above, the lack of detailed appliance-level data in practical environments necessitates pretraining a disaggregation model on a dataset containing these details, potentially a public dataset, and then applying this model to practical scenarios. However, it is uncertain whether the model can be effectively transferred from one dataset to another without significant loss of accuracy or performance.

In Section 3.2.2, significant variations in energy consumption patterns across different dataset are observed. These variations manifest through diverse statistical characteristics, including average running time, activation rate, maximum power consumption, and standard deviation. Notably, even among identical appliance types such as washing machines , there is a wide range of disparities. For example, average running times span from 50 to 500 minutes, and maximum power consumption fluctuates between 600 watts to approximately 3000 watts. Such differences in statistical characteristics can lead to substantial variations in consumption patterns for the same type of appliance, thereby severely impacting the transfer learning capabilities of power disaggregation models.

To assess the transferability of the NILM technique, we have designed various across-building and dataset tests, which are detailed in Section 3.4.1 regarding their setup. Subsequently, the outcomes of these tests are presented in Section 3.4.2.

3.4.1 Experimental Setup for Evaluating NILM Model Adaptability for Cross-Dataset Application

In this study, we adopted the same training, validation setup, and evaluation metrics as described in the previous experiment (Section 3.3.1); however, the data utilization and the model training and testing scenarios differ.

Data Utilization, Model Training, and Testing: In this study, we utilized the UK-DALE, Iris, AMPds, and REFIT datasets to train models for appliance energy disaggregation. Subsequently, we tested all these models across all buildings in the Iris dataset, which offers sufficient buildings to serve as representative samples. Specifically, we focused on developing disaggregation models tailored to these datasets:

- The same models for washing machines and dishwashers from the UK-DALE dataset, as well as the models for washing machines, dishwashers, and clothes washers from the AMPds dataset described in the previous section (Section 3.3.1), were employed for intra-building training and testing experiments.
- Disaggregation models for washing machines, dishwashers, and water heaters are trained using data from multiple houses within the Iris dataset: washing machines with data from houses 991, 944, and 928; dishwashers from houses 981, 936, and 953; and water heaters from houses 991, 953, and 944.
- A washing machine disaggregation model trained using data from House 5 of the REFIT dataset.

Evaluation Workflow: Figure 3.5 illustrates an example of transferability evaluation workflow for the Ukdale and Iris washing machine disaggregation models.

In **Stage 1**, we train a Ukdale washing machine disaggregation model using data from Ukdale House 1, and an Iris washing machine disaggregation model using data from Iris houses 928, 944, and 991.

In **Stage 2**, we test these disaggregation models on all households within the Iris dataset that contain washing machine data. For each household, we obtain an accuracy metric for the Ukdale model (represented by red points in the plot) and an accuracy metric for the Iris disaggregation model (represented by blue points in the plot). By grouping the accuracy metrics of a disaggregation model across the entire Iris dataset, we can create a boxplot that presents the range and diversity of the performance results of this disaggregation model on the Iris dataset (the performance boxplot of the Iris washing machine disaggregation model on other buildings of the Iris dataset is highlighted in a red circle). If the range of this boxplot is consistently above 70% accuracy, it demonstrates that the model has high transferability, as it shows reasonable performance across all tested households.

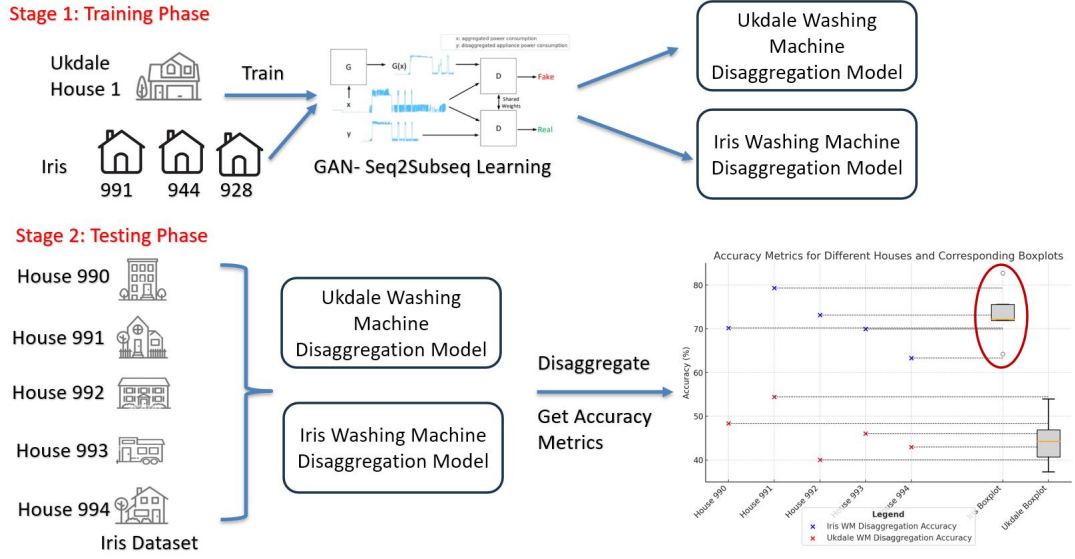


Fig. 3.5 Transferability Evaluation Workflow for the Disaggregation Model

3.4.2 Results: Detailed Outcomes from Cross-Building Model Training and Testing Under 10 and 30 Minute Sampling Intervals

We first present the results of the Iris model, followed by models from other datasets, emphasizing that the Iris disaggregation model was trained and tested across different buildings within the same dataset. This methodology may yield results that differ from those obtained when models are trained and tested across various datasets.

We specifically focus on the Accuracy and R2 Score to analyze the outcomes. The categorization of performance based on these metrics is detailed in Table 3.2. For this study, we consider models with an Accuracy greater than 70% and an R2 Score above 0.7 to demonstrate reasonable transferability. Additionally, we employ the SAE, which ranges from 0 (indicating perfect performance) to 1 (indicating the poorest performance), to aid in the evaluation.

Cross-Building Evaluation within the Same Dataset: Figure 3.6 presents a series of boxplots that illustrate the performance metrics of the IRIS disaggregation model during cross-building tests with sampling intervals of 10 and 30 minutes. For the 10-minute intervals, both the dishwasher (DW) and water heater (WH) models show robust transfer learning performance. The water heater model averages an accuracy of approximately 80% and an R2 score of 0.75, while the dishwasher model averages around 70% accuracy. However, there is a noticeable decline in performance at the 30-minute intervals, evidenced by reduced accuracy and R2 scores, and an increase in the SAE, with the dishwasher model's average SAE approaching 1 and its average R2 score turning negative. Despite this, the water heater model sustains some transfer learning capability, with tests on several households surpassing 70% accuracy, nearing 80%, and maintain-

ing a comparatively low SAE. The washing machine model, conversely, underperforms in both the 10-minute and 30-minute tests, with high SAE values ranging between 0.6 to 0.7 and a below-zero average R2 score in both scenarios.

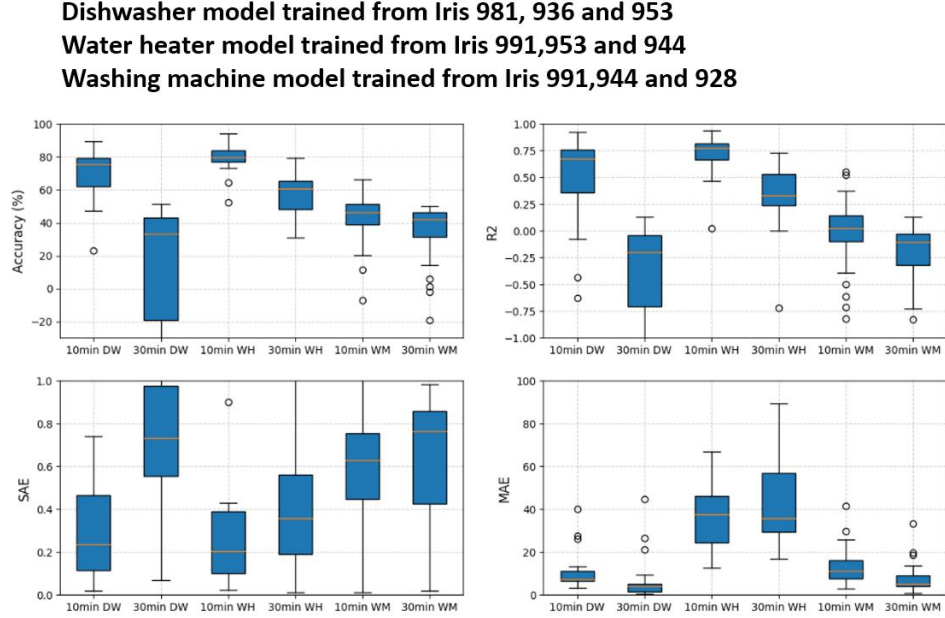


Fig. 3.6 Evaluation Metrics for IRIS Disaggregation Model Cross-Building Transfer Learning: 10 and 30-Minute Interval Tests (Performance Criteria Detailed in Table 3.2)

Figure 3.7 presents the accuracy metrics for the IRIS Water Heater Disaggregation Model, offering a clear visualization of performance metrics across different test intervals. Notably, the bars representing the 30-minute test intervals (in red) are consistently lower than those for the 10-minute intervals (in blue), indicating a significant drop in performance when sampling the data from 10-minute to 30-minute intervals. Furthermore, while the water heater disaggregation model maintains high accuracy in some household tests at the 30-minute intervals, its performance does not reach an optimal level in others. This inconsistency raises concerns about the model's ability to generalize effectively in real-world applications, highlighting potential limitations in its transfer learning capabilities.

Cross-Dataset Evaluation: Figure 3.8 illustrates the results of evaluation metrics for cross-dataset transfer learning. The blue boxes denote metrics evaluated over a 10-minute duration, while the red boxes represent a 30-minute evaluation. Focusing with accuracy, the AMPds disaggregation model demonstrates better performance at both 10-minute (dish washer and washing machine model) and 30-minute (washing machine model) intervals compared to other models, with most values falling between 25% and 50%. This level of accuracy, while better than that of other models, is still below 50%, categorizing it as very low. In contrast, the UK-DALE model for washing machines and dishwashers reaches nearly 70% accuracy in some houses, indicating reasonable trans-

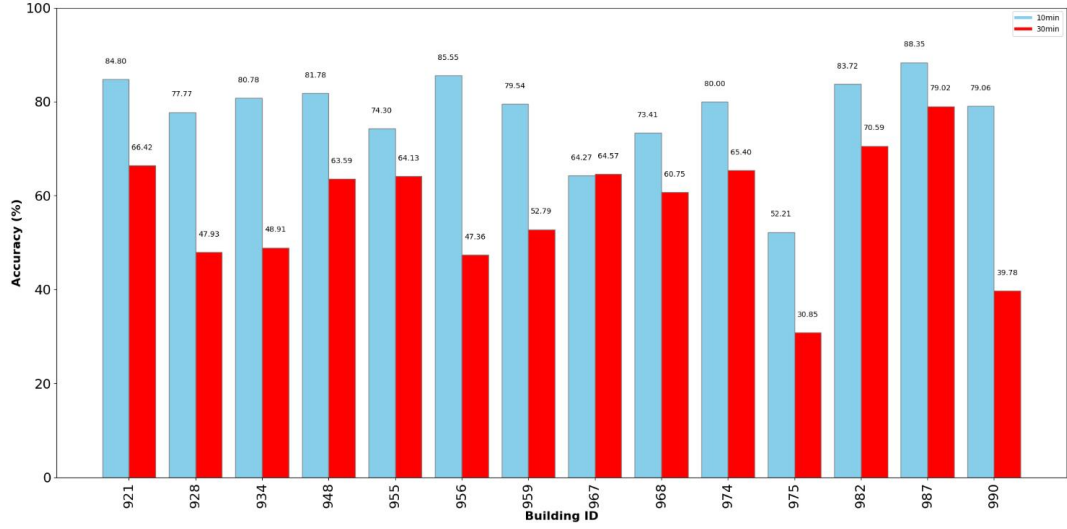


Fig. 3.7 Accuracy of Cross-Building 10 and 30-Minute Interval Tests for IRIS Water Heater Disaggregation Model (Performance Criteria Detailed in Table 3.2)

ferability. However, in other houses, accuracy often falls below 0, suggesting significant variability in performance across different testing environments.

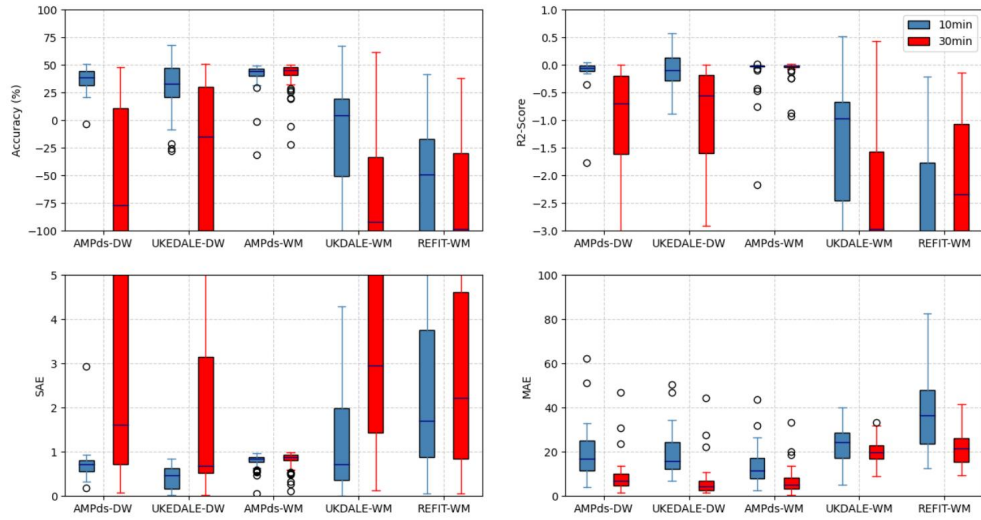


Fig. 3.8 Evaluation Metrics for Cross-Dataset Transfer Learning: 10 and 30-Minute Interval Tests (Performance Criteria Detailed in Table 3.2)

The results from testing models from other datasets on the Iris dataset generally performed worse compared to models from the Iris dataset tested across different buildings within the same dataset. This underscores the complexity of transferability across datasets. In summary, the results indicate that the seq2subseq model lacks adequate transfer learning capabilities under ultra-low frequency conditions. We are unable to extensively apply a model pre-trained on one dataset for power disaggregation on other datasets, particularly under ultra-low frequency conditions. This limitation significantly impacts real-world applications, especially since our energy management strategies rely

crucially on accurate power disaggregation.

3.5 Conclusion and Discussion

We underscore the crucial role of Non-Intrusive Load Monitoring (NILM) in our nudging strategy 1 to identify the energy flexibility within collective self-consumption systems. To identify reliable NILM algorithms suitable for our practical environment, where data is sampled at 30-minute intervals, we evaluated the open-source GAN-Seq2Subseq algorithm (Pan et al. 2020a). This algorithm have demonstrated good performance and transferability in scenarios involving much higher frequency conditions, suggesting potential applicability in our targeted settings.

We conducted performance and transferability tests on this NILM algorithm using multiple well-known public datasets under various frequency conditions. Testing revealed that some models exhibited superior performance under 1-minute frequency conditions, achieving accuracy levels above 90%. However, a significant decline in performance was observed as the frequency increased to 30 minutes, although some models still maintained reasonable performance (accuracy $>70\%$), others exhibited low performance. In testing the model’s capability for transfer learning across different households and datasets for appliance power disaggregation, we observed that the model’s transferability was quite limited. Specifically, with 30-minute sampling datasets, various models only showed satisfactory energy disaggregation performance in a few households when tested on nearly 100 dataset samples from the Iris dataset. In the 10-minute sampling scenario, while some models exhibited strong transfer learning capabilities, they still failed to successfully disaggregate in all data tests, showing poor performance in certain household tests. This underscores the limitations of the model’s effectiveness in practical applications, particularly under less frequent data sampling conditions.

The performance of existing NILM algorithms in practical environments is currently insufficient for establishing a reliable nudging strategy. Further efforts are necessary to enhance the real-world application of NILM technologies. Our findings indicate that the same model performs differently across various houses and datasets. Although tests in most houses under 30-minute frequency conditions showed poor transferability, some houses still demonstrated reasonable performance (accuracy $>70\%$). We believe that specific conditions determine whether a model from one dataset can be successfully transferred to another. Identifying these conditions is crucial for successfully integrating NILM algorithms into our nudging strategy and will be a key focus of Chapter 4.

CHAPTER 4

Non-Intrusive Strategy Part 2: Identifying Data Suitable for Accurate Disaggregation

Abstract: As discussed in Chapter 3, the results of disaggregation varied significantly across different datasets and settings. Consequently, we sought to identify which model for which dataset could be efficiently used so that disaggregation could be accurately conducted. We framed this challenge as a classification problem: given a household within a collective self-consumption scheme and its consumption data, can we predict if a specialized pretrained disaggregation model will successfully disaggregate the data? This chapter outlines our methodology for developing this classifier, demonstrates its effectiveness, and highlights the limitations in real-world applications that ultimately led us to abandon our non-intrusive nudging strategy.

4.1 Evaluating the Applicability of Pretrained Disaggregation Models through Binary Time Series Classification

Despite generally poor results, disaggregation models had notable successes in specific tests. For instance, the water heater model from the Iris dataset excelled in 10-minute intervals, showing strong transfer learning capabilities compared to other models, although its performance dipped in 30-minute intervals tests (Figure 3.6). Likewise, in cross-dataset tests, the washing machine and dishwasher models from UK-DALE performed well (accuracy near 70%) in some Iris households but poorly in others (Figure 3.8). These results pose a significant query: Although we have pretrained disaggregation models, their applicability in real-world scenarios remains uncertain. Each new test household presents a recurring challenge regarding whether our models can successfully disaggregate household energy consumption profiles. However, due to the availability of only total household energy consumption data and the lack of detailed appliance-level energy usage information, we are unable to verify the accuracy of the models.

To address this issue, we propose training a classifier that can automatically determine whether a pre-trained disaggregation model is capable of successfully disaggre-

gating the energy consumption of a household requiring power disaggregation. Households where disaggregation is feasible are labeled as class 1, and those where it is not, as class 0. Given the time-series nature of household energy consumption data, we frame this issue as a binary time series classification task.

To train a program that can make decisions automatically (which we call a classifier), we use a method known as supervised learning that involve training a model on a labeled dataset. Each instance within this dataset is characterized by a set of features and a corresponding label that categorizes it into one of several classes. The goal is for the model to discern the relationship between the features and the labels, enabling it to predict the labels of new, unseen instances based on their features. As illustrated in Figure 4.1, we assessed the performance of a disaggregation model across various test buildings. Some tests demonstrated the model’s efficacy; these successful cases are labeled as class 1, while unsuccessful cases are labeled as class 0, forming our labeled dataset. We aim to develop a classifier that can learn why this model can successfully identify power usage in some buildings but not in others. We believe that the energy consumption characteristics of the buildings, such as maximum and average power consumption, might affect the suitability of the model. Identify these influential features and to establishing the relationship between the features and the labels will enable us to determine if a new building’s consumption can be disaggregated by a specific disaggregation model.

To achieve this, considerable effort has been invested in data preparation, particularly in feature selection, the choice of machine learning algorithms, and the evaluation of classifiers. We will detail the experimental setup for our classifier’s training process in Section 4.1.1, the results of these experiments will be discussed in Section 4.1.2.

4.1.1 Setting Up the Experimental Framework for Evaluating Disaggregation Models Applicability

Training Data Preparation. In this study, we employ the Iris dataset as training data because various disaggregation models have been tested on this dataset, and we have already evaluated the performance of each model on the different buildings included in the Iris dataset. This facilitates the formation of our labeled dataset. Models achieving an accuracy exceeding 70% are considered reasonably performing and are labeled as 1, while those yielding lower accuracies are categorized separately and labeled as 0. Consequently, we selected 10-minute intervals for further research, **as under the 30-minute condition, nearly none of the models achieved an accuracy exceeding 70%.** This results in the absence of the class 1 label, making it impossible to conduct machine learning without both classes present.

However, the number of buildings in the Iris dataset may not be sufficient for an ef-

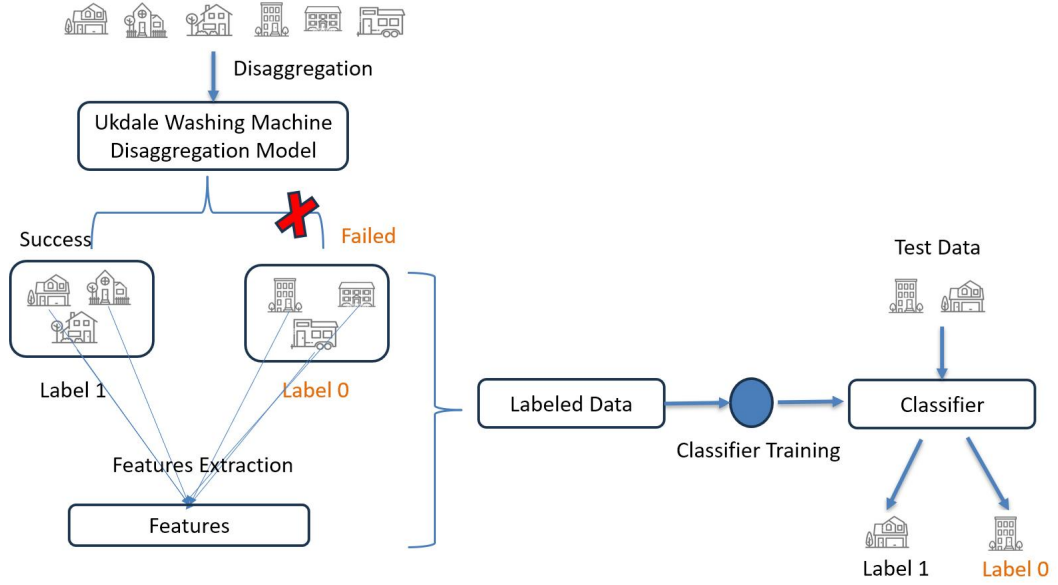


Fig. 4.1 raining and Testing a Classifier: Determining Household Suitability for Energy Disaggregation by a Pre-Trained Disaggregation Model

fective training process. It is well-known that when a machine learning algorithm lacks sufficient training samples, it may lead to overfitting¹, poor generalization², and difficulties in accurately assessing and selecting models. To address this issue, we enriched the training dataset by separating the data of each household that has both washing machine and dishwasher data into four subsets (since not all Iris buildings have washing machines or dishwashers). We achieved this by randomly extracting data for an identical number of days from each household within the Iris dataset, thereby forming the four subsets. While these subsets are equal in length, they contain data from non-overlapping time periods. This process resulted in a new dataset with 128 data profiles. We reassessed the performance of various disaggregation models on these newly constituted subsets. The primary objective of this approach was to augment the training data, thereby improving the models' accuracy and generalization capabilities while reducing the risk of overfitting.

Features Extractions and Selection. Feature selection is crucial for building effective machine learning models. Too many features can cause the “curse of dimensionality”, leading to overfitting, data sparsity, and reduced model interpretability, while also increasing computational costs. Conversely, too few features can result in underfitting, where the model cannot capture the data’s complexity, performs poorly on training data, and generalizes poorly on new data. This balance is essential to optimize model performance and interpretability.

¹Overfitting occurs when a model learns the detail and noise in the training data to an extent that it negatively impacts the performance of the model on new data.

²Poor generalization happens when a machine learning model performs well on its training data but fails to perform similarly on new, unseen data.

To effectively address the challenges of feature set construction, our methodology integrates both time series data analysis and heuristic insights. This dual approach aims to capture a comprehensive view of household energy consumption patterns, thereby enhancing the NILM model’s accuracy and generalizability. Below, we detail the specific strategies employed in constructing our feature sets, each designed to leverage different aspects of the available data:

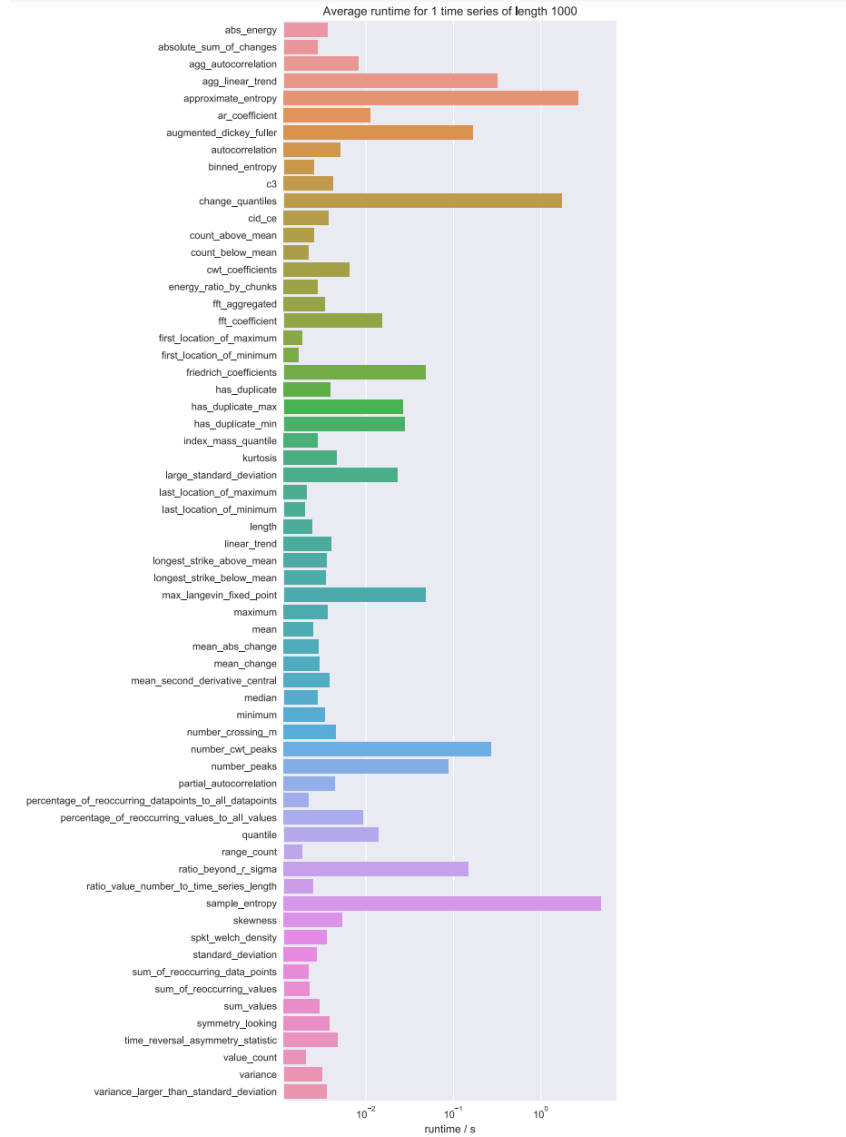


Fig. 4.2 Features Extracted From Tsfresh and The Compute Time For Each Feature Extraction (Christ et al. 2018)

- **Simple Statistical Features Set:** As shown in Section 3.2.2, we observed significant variations in statistical features like maximum power, mean power, median power, and standard deviation across different households. We hypothesize that similar statistical features might facilitate NILM model transferability between households. Thus, our initial feature set includes these basic statistical features.

- **Automatic Feature Extraction and Selection (TsFresh Feature Set):** Using the TSFresh Python package³ (Christ et al. 2018), we compute a vast array of time series characteristics and utilize its feature selection capabilities to choose relevant features for our problem. Figure 4.2 showcases all the features automatically computed and extracted by the tsfresh feature engineering framework, along with their computational times for a time series of length 1000. This includes categories such as Time-Based Features, Statistical Features, FFT Features, and coefficients of natural regression, among others. For a detailed description of the features, refer to <https://tsfresh.readthedocs.io/en/latest>.
- **Heuristic Feature Set:** Some heuristic features, such as the types of appliances in a household, can be obtained through surveys. We include these to enrich our feature set. Our set captures data on all 35 appliances in the Iris dataset, providing appliance-specific insights. Figure 4.3 displays all the types of appliances included in the dishwasher test subset of the Iris Dataset, along with the quantity of each appliance type contained within this subset.
- **Combined Feature Set:** We integrated heuristic features with two other feature sets from the same data source to create two combined sets: **Simple Statistics and Heuristic Set** and **Tsfresh Heuristic Set**.

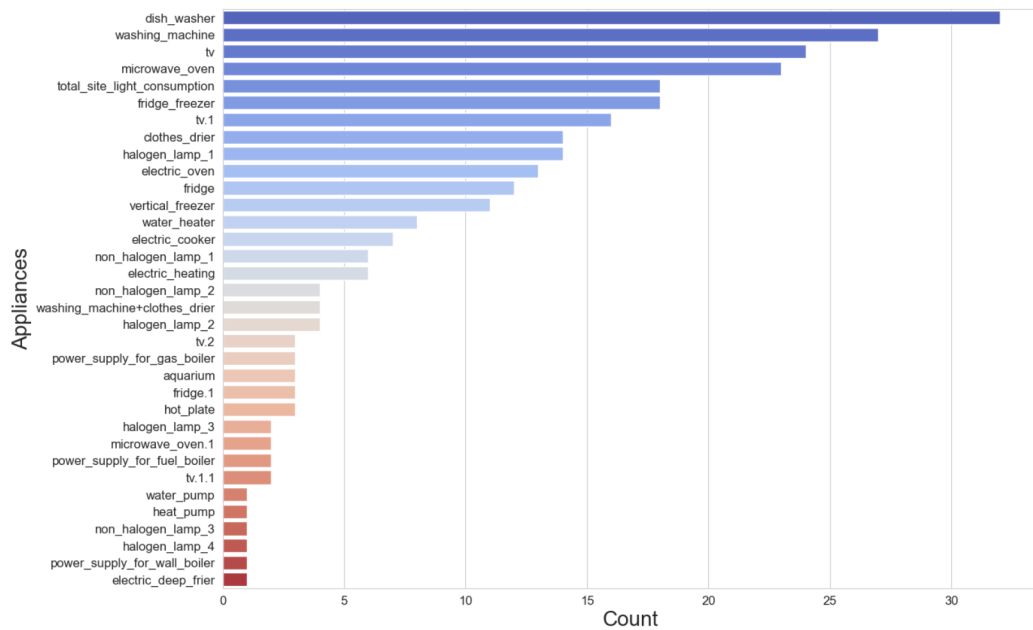


Fig. 4.3 Heuristic Feature Set for the Iris Dataset Dishwasher Test Subset and Feature Counts

³TSFresh (Time Series Feature extraction based on scalable hypothesis tests) is a Python library for extracting relevant features from time series data.

Within the complex features, we aim to identify specific features that can accurately determine whether the total energy consumption of a house can be disaggregated by a specific energy disaggregation model. Further calculations and tests are required to validate this, with Shapley Additive Explanations (SHAP) serving as a valuable tool. SHAP (Shapley Additive Explanations) is a method in machine learning that quantifies the contribution of each feature to the prediction of any model, using principles from cooperative game theory⁴. This method enables us to interpret the impact of individual features on specific predictions and evaluate the global significance of features. These insights are instrumental in selecting the optimal sequence of features for our classification tasks. The computational results of these analyses will be presented in Section 4.1.2.

Machine Learning Algorithms and Performance Enhancement Techniques. We utilized several classical supervised machine learning algorithms widely applied in various domains. These include: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), K-nearest Neighbors (KNN), Naive Bayes (NB), AdaBoost (AB) and Support Vector Machine (SVM) (for more detail about these algorithms, refer to (Hastie et al. 2009), or (Zhou 2021)). To further enhance our models' performance and address we applied various techniques. Specifically:

- **Data Normalisation:** Data normalization is the process of scaling individual features to a common range or standard, ensuring that each feature contributes equally to the model and improving the convergence of optimization algorithms.
- **Cross-validation:** We use cross-validation for parameter tuning by dividing the data into multiple subsets, training the model on some subsets, and testing it on the remaining subsets to identify the best model parameters.
- **Synthetic Minority Over-sampling Technique (SMOTE):** A method used in machine learning to address class imbalance, a situation where one class significantly outnumbers others (as observed in the UKDALE washing machine disaggregation model test in the Iris dataset, where only a few tests' accuracy exceeds 70% and are labeled 1, while almost all tests are labeled 0). This imbalance can lead to biased model performance favoring the majority class. SMOTE generates synthetic examples for the minority class, thereby improving overall model performance. (for more comprehensive details on this technique, refer to Elreedy and Atiya (2019))

⁴In the context of SHAP (Shapley Additive Explanations), cooperative game theory is used to determine the contribution of each feature in a model by treating features as players in a coalition game, where the payoff is the predictive accuracy of the model, and each feature's contribution is quantified by its impact on the model's performance.

- **L1 Regularization:** Also known as Lasso (Least Absolute Shrinkage and Selection Operator), L1 regularization is a technique in machine learning that adds a penalty equal to the absolute value of the magnitude of the coefficients to the loss function. This approach encourages sparsity and feature selection in the model, making it particularly useful for handling high-dimensional data, such as the feature set generated by TsFresh. By mitigating the curse of dimensionality, L1 regularization helps improve model performance and interpretability. For more detailed information on this technique, refer to Schmidt (2005) (Schmidt 2005).

Classification Evaluation Metrics. In the context of binary classification tasks, understanding prediction outcomes is essential for evaluating model performance. The terms True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are central to describing these outcomes. In our research, we define household consumption data that can be disaggregated by a pretrained model as class 1, and data that cannot be disaggregated as class 0. A True Positive occurs when disaggregable data is correctly classified as class 1. Conversely, a False Negative arises when disaggregable data is incorrectly classified as class 0. A True Negative is when non-disaggregable data is accurately classified as class 0, and a False Positive occurs when non-disaggregable data is mistakenly classified as class 1. Based on these foundational notions, a more comprehensive suite of metrics designed to evaluate classification models is subsequently presented.

- **Confusion Matrix:** that visually assesses a model’s performance by comparing actual versus predicted classifications. In a confusion matrix, the absence of false positives and false negatives indicates perfect performance. The confusion matrix for a binary classifier is structured in Table 4.1:

Table 4.1 Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

- TP: Instances correctly predicted as positive. - TN: Instances correctly predicted as negative.

- FP: Instances incorrectly predicted as positive. - FN: Instances incorrectly predicted as negative.

- **Precision:** Precision measures the proportion of correctly predicted positive observations (True Positives, TP) to the total predicted positive observations (the sum of True Positives and False Positives, FP). High precision indicates a low rate of false positives. A precision score of 1 means all predicted positives are correct, while a score of 0 indicates none are correct.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall:** Recall measures the proportion of actual positives that are correctly identified (True Positives, TP) out of the total actual positives (the sum of True Positives and False Negatives, FN). High recall indicates a low rate of false negatives. A recall score of 1 indicates perfect identification of all actual positives, while a score of 0 means no actual positives are identified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1:** The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances both the precision (the accuracy of positive predictions) and recall (the coverage of actual positive cases) of a model, which is particularly useful when you want to strike a balance between these two metrics. It's especially handy when dealing with imbalanced classes. An F1 score of 1 indicates perfect precision and recall, while a score of 0 suggests the worst possible performance in both metrics.

$$F1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Accuracy:** Accuracy measures the proportion of all instances (both positive and negative) that are correctly identified, combining True Positives (TP) and True Negatives (TN) over the total number of cases (including True Positives, True Negatives, False Positives, and False Negatives). An accuracy score of 1 signifies perfect accuracy, where every classification is correct, while a score of 0 denotes that all classifications are incorrect. Although accuracy is an intuitive measure, it may be misleading in cases of imbalanced classes, as the majority class might disproportionately influence the metric.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Evaluation Workflow: Figure 4.4 outlines our evaluation workflow. We start with a labeled dataset (for example, a binary classification dataset indicating whether the Ukdale DW disaggregation model can effectively disaggregate data for certain households, with label 1 for successfully disaggregated households and label 0 for others) and various feature sets. Our goal is to find the feature set that best facilitates the learning of this classification problem, thereby creating an optimal classifier that can accurately determine whether a household can be successfully disaggregated using the Ukdale DW disaggregation model. To achieve this, we divide our labeled data into two sets: 75% for training and 25% for testing.

In the training phase, we train different classifiers by applying various algorithms

and feature sets. For example, we may train a classifier with a linear regression algorithm and statistical feature set, or a classifier with decision tree algorithms and heuristic feature set.

In the testing phase, we evaluate each classifier's performance using the testing set to assess its success in learning the classification problem (as shown by the F1 metric in Figure 4.4). The feature set that enables the classifier to achieve the best performance is identified as the optimal feature set. A high performance metric (e.g., F1 score) demonstrates the effectiveness of our classifier, indicating that it can accurately identify which households can be used with which disaggregation model.

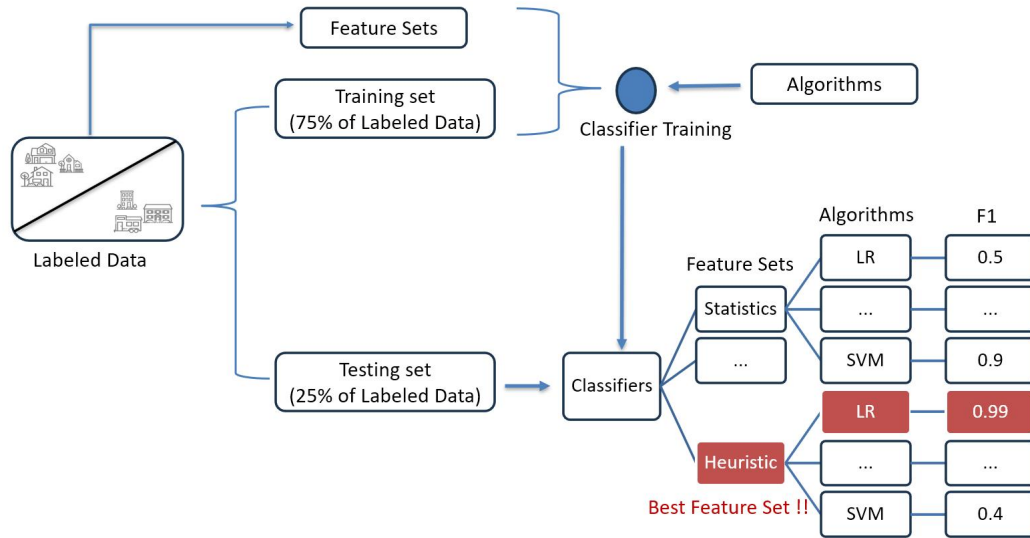


Fig. 4.4 Evaluative Framework for Optimizing Feature Sets in Machine Learning

4.1.2 Analysis and Exploration of Experimental Results

In this study, we train classifiers for two disaggregation models: the Iris Dishwasher Disaggregation Model and the UK-DALE Dishwasher Disaggregation Model, both of which operate over 10-minute intervals. This binary classification task distinguishes between two scenarios: one involving balanced data classification, where the number of samples for the two labeled classes is nearly equal, as demonstrated by the Iris model, and another featuring highly imbalanced data, as observed with the UK-DALE model. The aim is to validate whether the classifiers can effectively handle these distinct data scenarios to facilitate further real-world applications.

Balanced data classification (Iris model). Table 4.2 displays the optimal classification evaluation metrics obtained from various classification algorithms, each trained with distinct feature sets. The test dataset exhibits a perfectly balanced distribution, with each class consisting of 16 instances, totaling 32 instances which represents 25% of the overall sample size (Recall that we train and evaluate our classifier on a newly

enriched dataset based on the Iris dataset that contains 128 data profiles, as presented in Data Preparation in Section 4.1.1). The results indicate that models trained using the heuristic feature set, specifically the linear regression model and the Decision Tree model trained with a combined set of simple statistical and heuristic features, demonstrate superior classification performance, with accuracy and F1 scores approaching 1. Notably, there was only one false negative reported among the 32 tests, as depicted in the confusion matrix (refer to Figure 4.5). This highlights the effectiveness of the heuristic features in addressing the binary classification problem of determining households suitable for the Iris Dishwasher Power Disaggregation Model.

Table 4.2 Evaluation Metrics for Determining Household Suitability for the Iris Dishwasher Power Disaggregation Model

Feature Set	Model	Class	Count	Precision	Recall	F1	Accuracy
Statistic	RF ¹	0	16	0.81	0.81	0.81	0.81
		1	16	0.81	0.81	0.81	
Statistic-Heuristic	LR ²	0	16	0.94	1	0.97	0.97
		1	16	1	0.94	0.97	
Tsfresh	RF	0	16	0.84	1	0.91	0.91
		1	16	1	0.81	0.9	
Tsfresh-Heuristic	LR	0	16	0.84	1	0.91	0.91
		1	16	1.00	0.81	0.9	
Heuristic	DT ³	0	16	0.94	1	0.97	0.97
		1	16	1	0.94	0.97	

¹ Random Forest ² Logistic Regression ³ Decision Tree

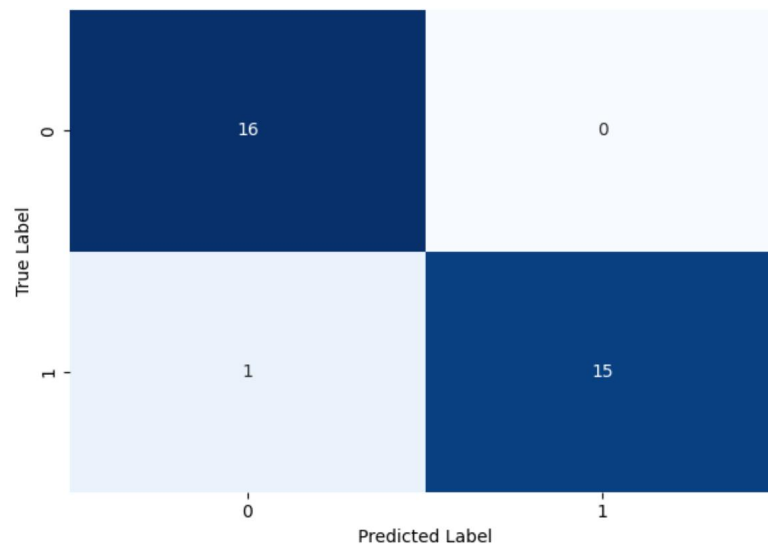


Fig. 4.5 Assessing the Efficacy of the Heuristic Feature Set and the Statistic-Heuristic Feature set in Balanced Data Classification: A Confusion Matrix Approach

An analysis of SHapley Additive exPlanations (SHAP) values also confirms that heuristic features (information about the types of appliances) significantly influence

classification performance. SHAP values provide insight into the contribution of each feature to the predictive accuracy of the model. The results, which are detailed further in Appendix F, demonstrate that heuristic features have a more substantial impact on model outcomes compared to other feature types.

Unbalanced data classification (Ukdale model). The study presented in Table 4.3 focuses on the results of the UK-DALE disaggregation model in scenarios of unbalanced data. In such cases, we cannot rely solely on accuracy to evaluate the model's performance, as it can be misleading. For instance, models using a simple statistic feature set might achieve high accuracy (94%), but their results tend to be biased towards the majority class (0), with almost no recognition ability for class 1 (F1=0). Therefore, in situations of imbalance, our attention shifts towards the model's detection performance for the minority class, namely the F1 score. The results also indicate that the model trained with the heuristic feature set is optimal, achieving the best classification performance with the fewest input features. This is further corroborated by the confusion matrix (Figure 4.6), where the Naive Bayes model successfully classified two minority class instances correctly and misclassified only one sample from the 30 majority class instances as a minority class. This demonstrates that in unbalanced scenarios, it is still possible to train effective classifiers to address binary classification problems for specific contexts. This is particularly meaningful for power disaggregation over 30-minute intervals, where our model for disaggregating power in 30-minute sampled data faces an imbalance of very few houses being available versus the majority being unavailable.

Table 4.3 Evaluation Metrics for Determining Household Suitability for the Ukdale Dishwasher Power Disaggregation Model

Feature Set	Model	Class	Count	Precision	Recall	F1	Accuracy
Statistic	AB ¹	0	30	0.94	1	0.97	0.94
		1	2	0	0	0	
Statistic-Heuristic	NB ²	0	30	1	0.97	0.98	0.97
		1	2	0.67	1	0.80	
Tsfresh	DT ³	0	30	0.97	1	0.98	0.97
		1	2	1	0.50	0.67	
Tsfresh-Heuristic	DT	0	30	0.97	1	0.98	0.97
		1	2	1	0.50	0.67	
Heuristic	NB	0	30	1	0.97	0.98	0.97
		1	2	0.67	1	0.80	

¹ AdaBoost ² Naive Bayes ³ Decision Tree

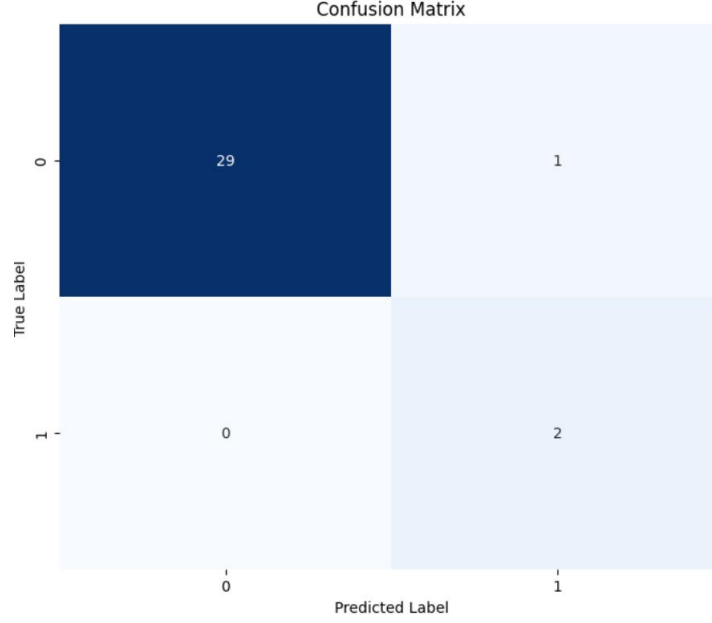


Fig. 4.6 Assessing the Efficacy of Heuristic Feature Set and Statistic Heuristic Feature Set in Unbalanced Data Classification: A Confusion Matrix Approach

4.2 Conclusion

We believe that the model demonstrates potential for transfer learning; however, defining the specific conditions under which this potential can be realized is crucial. To this end, we conducted supervised learning classification experiments on previously evaluated disaggregation models, focusing on whether household energy consumption data can be successfully disaggregated by a specific disaggregation model. By extracting and analyzing diverse features from household energy consumption data and learning the relationship between these features and the effectiveness of disaggregation models in disaggregating appliance energy consumption, we successfully developed a classifier that can accurately determine whether a specific pretrained model can be applied to new household data. **We discovered that heuristic information related to appliance types plays a pivotal role in solving this binary classification problem. The results show that information on the types of appliances present in households is a critical determinant in assessing the feasibility of cross-household application of the disaggregation model.**

However, despite identifying a set of characteristics that could potentially dictate the applicability of disaggregation models across various datasets, we contend that these models still encounter formidable obstacles when subjected to real-world evaluation. A primary concern remains the disaggregation of data sampled over 30-minute intervals. In this study, we evaluated the classifier using only 10-minute intervals and did not extend the evaluation to 30-minute intervals. The primary reason for this decision

is that the 10-minute interval data provides sufficient labeled data for both class 1 (successfully disaggregated) and class 0 (failed disaggregation). In contrast, the 30-minute interval data generally showed very poor performance in disaggregation models when applying transfer learning, as illustrated in Figure 3.8, none of the models achieved 70% accuracy. While our classification approach has demonstrated efficacy in identifying minority classes, the 30-minute interval data often lacked labels for class 1, which prevented the classifier from learning effectively. Consequently, future research may need to incorporate additional datasets to increase the likelihood of achieving effective disaggregation and to enhance the labeling of class 1 under 30-minute conditions. Moreover, the necessity for labels in supervised learning models poses another significant challenge. The prospect of building and then validating models for each household in every dataset suggests a level of computational expense that may be considered excessive for practical applications. A more viable solution in real-world applications might involve deploying robust unsupervised learning algorithms capable of clustering to identify households within our datasets that resemble those in a specific real-world context. The purpose of this clustering is to categorize households into similar groups, enabling a NILM model to be trained on the data from one household in a particular category and then successfully applied to other households within the same category. By training NILM models on these specifically identified households, we could substantially mitigate computational requirements.

However, within the sphere of energy management composite algorithms, we encounter a scenario wherein errors from one algorithm propagate through to all succeeding algorithms. This chain reaction fosters a cumulative error effect, potentially precipitating outcomes of considerable inaccuracy. Should NILM algorithms be integrated into the services provided by Enogrid, we anticipate facing cumulative errors originating not only from weather forecasting and energy prediction algorithms but also from the NILM algorithms themselves. Addressing this concatenation of errors to ensure the effective performance of NILM algorithms constitutes a significant hurdle. In light of these challenges, we have opted to temporarily suspend research into the practical applications of NILM, choosing instead to pivot our focus towards employing Strategy 2 in subsequent studies, as depicted in Figure 1.10.

CHAPTER 5

Enhancing Energy Self-Consumption in Individual Residential Buildings through Information and Communication Technology Nudging Pipelines

Abstract: In response to the challenges identified with Non-Intrusive Load Monitoring (NILM) in real-world applications (Chapter 3 and Chapter 4), we have revised our initial strategy (Strategy 1 discussed in Section 1.4.3.2) and transitioned to Strategy 2 (Section 1.4.3.3). In the first stage, rather than attempting to disaggregate and optimize energy consumption, we now focus solely on using our prediction module to inform residents about optimal consumption times through nudging. This approach allows for individual decision-making regarding consumption adjustments to align with local energy production. In this chapter, we evaluate two simplified nudging pipelines using semi-real data within a simulation environment. We focus on enhancing self-consumption for individual households, which presents fewer complexities compared to collective systems. The results and limitations of these pipelines are discussed, setting the stage for future research on collective self-consumption (Chapter 6).

This chapter is mainly copied from our previous publication, as cited in Ling et al. (2023). We have removed the related works section in this chapter, as it is comprehensively covered in the general related works presented Chapter 2.

5.1 Introduction: Proposing Two Nudging Pipelines to Enhance Self-Consumption Building Energy Efficiency: Load Forecasting vs. Meteorological Forecasting

Our work here addresses challenges at the intersection of two important tropes. One is the increasing attention given to the optimisation of the energy consumption of buildings, both for economical, and ecological, reasons. For instance, the residential sector is known to represent about 25% of European energy consumption (Laicane et al. 2015). One way to lower this consumption is to improve the thermal isolation of buildings. Another way is linked with the second trope, which is the increasing usage of renewable energies in energy systems (Veichtlbauer et al. 2021) Among the main renewable

sources are wind, and solar, energy. While they may help lower global consumption, reduce carbon emissions, and create local generation-consumption loops, they come with specificities, with respect to traditional systems, which make taking full advantage of their potentialities a challenge. Chief among these specificities is the intermittent nature of the resulting production. This is the point we focus on in our study.

One ever more common situation, nowadays, is that of an household with photovoltaic panels on its rooftop. Consumption which is not covered by the panels is provided by the regular distribution network. It is more interesting for the household to use the solar production, rather than that brought by the energy provider. Therefore, there is much value in aligning consumption with solar production as best as possible (Lund et al. 2015). However, alignment is not straightforward to reach.

There are two ways to improve consumption-production alignment in a building: direct, and indirect, flexibilities (Twum-Duah et al. 2022). The first one refers to automated activation or deactivation of electrical appliances through addition of hardware, and software, in the consumption loop. The second refers to changes in consumption behaviour done by the users of the building. Arguably, the latter is more cost-friendly, and energy friendly, as it does not require the addition of equipment in the building. Moreover, it is efficient: Twum-Duah et al. (2022) estimate that self-consumption could be improved by as much as 9% in the case of a smart building, where users can reload their electrical vehicles. And SHAHID (2022) estimate that the intervention of nudge signal results in approximately 18% energy conservation during the orange periods when people are nudged not to consume. Additionally, during the green periods, there is an increase of over 11% in the energy self-consumption. However, while it is possible for households to try and align their consumption with solar production on their own, this often represents time-consuming work. Indeed, studies have shown that retired households more actively reduce their consumption upon receiving feedback, likely because they have more time available than working households (Aydin et al. 2018). Moreover, households may improperly assess their own consumption (Byrne et al. n.d.).

Therefore, there is a case for recommendation services discharging the user of most of this work, and presenting them with ready-made, and sharp, consumption advice, as for instance “consume on Wednesday afternoon, but not on Friday evening”. Indeed, mere feedbacks about consumption have already shown some efficiency in helping users reduce their energy consumption (*Residential Electricity Use Feedback: A Research Synthesis and Economic Framework* 2009). More generally, nudges (Thaler and Sunstein 2008) can be used to entice users to adopt renewable friendly consumption patterns.

The recommendations could be either provided by humans, or automated. Automation, through the use of Information Communication Technologies (ICT), is scalable,

contrary to human-provided services. Indeed, it allows fast processing of the large amounts of data needed, and concurrent generation of recommendations for all households using the service. Therefore, we use ICT nudging pipelines to construct our service. ICT pipelines designate the chain of technologies, be it hardware or software, which collect information, process it, and produce an output. In our case, they collect consumption, and weather, data, they make algorithmic computations on those, and output advice, in the form of nudges suggesting to users when to use energy-consuming appliances.

To design the recommendations, we would ideally like to know in advance which part of their consumption the households would be willing to shift. However, this knowledge is practically impossible to obtain in real-world settings, if only because household people may not know it themselves, in advance. We therefore introduce two nudging pipelines using only information accessible in real life: aggregate past consumption of the household, and weather forecasts for the future. One pipeline merely signals sunny periods, while the other predicts available production (that is, excess production with respect to the predicted consumption), thanks to load forecasting techniques.

We show our pipelines are efficient, even with them using real, and therefore incomplete, information, by validating them on semi-real data, coming from several publicly available datasets, coupled with a simulation environment. We intend to validate them on a real world setting in the future but, due to the many constraints in setting-up a real-world experiment, we wanted to first test our pipeline in a simulated setting. Under reasonable user behaviour assumption, the simulator provides a first validation of our pipeline.

Our work takes place in ongoing efforts to help energy communities, using renewable energies, reach their full potential. This requires shifts in consumption patterns, with respect to usages linked with traditional energy sources. These changes of habits will only be possible if efforts are made to increase general consciousness about the culture changes implied, and providing accurate information to the users. We elaborate on these goals in the discussion section.

We start by presenting the problem statement, and starting our contributions, in Section 5.2. Next, we introduce our model in Section 5.3. We then present our numerical simulations results in Section 5.4. Finally, we discuss our results, and their practical implications for the real-world deployment of our pipelines, in Section 5.5. The code for the numerical simulations is available on the following URL:

<https://gitlab.com/enogrid/open-source/realistic-nudging-pipelines-for-energy-consumption>.

5.2 Problem Statement and Our Contributions

We first present our problem statement (Section 5.2.1), and then stating our contributions (Section 5.2.2).

5.2.1 Problem Statement: How can efficiently align individual household energy consumption with solar production while limiting the information delivered to users?

The problem we study runs as follows. On the one hand, we have an household endowed with private solar panels, which provides part of the household consumption, while the remaining part comes from the network provider. In order to better align their consumption to solar production, the people in the household are willing to shift the consumption of some of their appliances, known only to them, upon reception of a signal from an external service. The signal consists in the labelling of consumption favourable moments. However, the household people are only willing to entertain signals with few labelled periods, as having too many of them leads to user fatigue.

On the other hand, the nudging service has only access to real, therefore incomplete, information: weather forecast, and aggregated past household consumption. Crucially, the service does not know the shiftable part of the household consumption. It strives at indicating to the household the best moments to consume.

Our problem is therefore: **how best to identify consumption favourable periods, so as to help the household align their consumption to solar production, while keeping the number of labelled periods low?**

5.2.2 Contribution: Demonstrating Effective ICT Nudging in Self-Consumption Systems and Highlighting Load Forecasting Outperforms Meteorological Forecasting

We conduct numerical simulations on a full simulator, taking into account the response of an household to nudges. The data we feed our simulator with are semi-real. We use in particular the well-known Iris (*Mesure de la consommation des usages domestiques de l'audiovisuel et de l'informatique* 2008) and AMPds (Makonin et al. 2016) energy datasets. Our contributions are threefold.

1. First, we show numerically that, even with scarce information, and even when sending nudges with few labelled periods, we manage to achieve significant consumption improvements.
2. Second, we show numerically that, in some situations which we characterise, a load-forecasting based nudging pipeline outperforms the mere “weather based” one, which targets periods with high sunshine.

3. Third, we identify two important aspects concerning the efficiency of our procedure:

- (a) there is a sweet spot in production, at which nudging is most efficient;
- (b) increasing the number of labelled periods in the nudges increases performance, but this increase levels off, and huge improvements already occur for few periods.

Compared to previous work like Pajot, Morriet, Hodencq, Delinchant, Maréchal, Wurtz and Reinbold (2019), we consider the realistic setting where we do not know which devices are shiftable or not for the household. We validate our nudging pipeline on simulated data, which allows us to evaluate it much quicker than would be possible on a real-world experiment. Moreover, in one of our pipelines, we offer personalised advice, using analysis of the household consumption, and production, to construct our nudge, rather than merely telling the user when the sun will shine. Though simulation is a well-established tool to assess consumption flexibilities (Pajot, Artiges, Delinchant, Rouchier, Wurtz and Maréchal 2019), it had not yet been branched on a human behaviour model, so as to experiment with a full nudging situation, at least up to our best knowledge. For the forecasting part, we use a simple predictor detailed in the appendices, which offers a good trade-off between accuracy of predictions, and computational time required.

5.3 Model Overview: Detailed Examination of Each Component in Our ICT Nudging Pipeline

We start by presenting our household model (Section 5.3.1). Next, we define the self-consumption, and self-sufficiency, rates (Section 5.3.2). We then define the format of the nudges we use (Section 5.3.3), before introducing the controllers which compute the nudges (Section 5.3.4). Finally, we can describe the entire nudging pipeline (Section 5.3.5). All main notations are gathered in Table 5.1.

Table 5.1 Main Notations

Notation	Definition	Meaning
$\mathbb{T}$	sequence $0 \leq t_0 < t_1 < \dots$	time scale at which power is sampled
l_t	$l_t \in \mathbb{R}_+$	load of an appliance at time t
L_t	$L_t \in \mathbb{R}_+$	aggregate load at time t
$\mathcal{P}_t$	$\mathcal{P}_t \in \mathbb{R}_+$	solar production at time t
$\Lambda_{t_{\text{begin}}, t_{\text{end}}}$	$0 \leq \Lambda_{t_{\text{begin}}, t_{\text{end}}} \leq 1$	self-consumption rate
$\Pi_{t_{\text{begin}}, t_{\text{end}}}$	$0 \leq \Pi_{t_{\text{begin}}, t_{\text{end}}} \leq 1$	self-sufficiency rate
$\mathcal{N}$	—	nudge set
$\mathcal{W}_{t_{\text{begin}}, t_{\text{end}}}$	—	weather forecast set
$\mathcal{H}_t$	—	past data at time t

5.3.1 General Residential Household Model

Let $\mathbb{T} = (t_k)_{k \geq 0}$ be the time scale at which the load is sampled, that is a sequence $0 \leq t_0 < t_1 < \dots$ of positive real numbers representing moments in time (or timestamps).

Household consumption. We consider an household which possesses several electrical appliances. Each appliance consumes energy as it is used. The consumption of an appliance is a positive sequence $\mathbf{l}_{\text{app}} = (l_t)_{t \in \mathbb{T}}$, together with a finite family of non overlapping intervals $(t_{\text{begin}}^k, t_{\text{end}}^k)_k$, with bounds in $\mathbb{T}$. The t_{begin}^k 's are the times of beginning of the appliance usages, and the t_{end}^k are the ends of usages. The load l_t is nonzero if, and only if, there is a k (uniquely defined) such that $t_{\text{begin}}^k < t < t_{\text{end}}^k$. All residual consumption of all appliances is gathered in the “mains” appliance. The household consumption $\mathcal{L} = \{\mathbf{l}^{\text{app}}\}_{\text{app} \in \text{appliances}}$ is the family of appliance consumption. The aggregate load at time t , L_t , is the sum over all appliances of the load at time t of each appliance, $L_t = \sum_t l_t^{\text{app}}$.

Shiftable appliances. An appliance may be:

1. shiftable, meaning the household may be willing to shift its usage intervals, provided these periods are not too far away from the base use time, which depends on the appliance; the length of usage intervals, that is the values $t_{\text{end}}^k - t_{\text{begin}}^k$, remain fixed;
2. not shiftable, meaning the times at which the appliance are used are fixed.

For instance, the household people may be willing to shift their use of the washing machine by two to three days at most, while the time at which they use heating is fixed (when there is no demand restraint, the study of which is beyond the scope of this paper). For every shiftable appliance, there is a maximum time delay the household

people are willing to shift this appliance consumption by. The length by which appliance usages may be deferred has been estimated for instance by Kwon and Østergaard (2014) or Lucas et al. (2019b). The Table 5.2 shows the time delays we assumed for every shiftable appliance. The fact the lengths of usage intervals are fixed means for instance that the washing machine takes 2.5 hours per usage, irrespective of when it is used.

Table 5.2 Maximum Shift Delays for Shiftable Appliances in the Iris and AMPds Datasets

Shiftable appliance	Maximum shift delay
Washing machine and clothes dryer	540 min
Dish washer	540 min
Water heater for domestic hot water	600 min *

* In France, it is commonly observed that water heaters for domestic hot water run during designated off-peak hours, namely between 12 p.m. to 5 p.m. and between 8 p.m. to 8 a.m. Hence, it is hypothesized that the time of use of the water heater may be shifted by rescheduling the operation of the water heater from one off-peak period to another. So here we choose 10 hours for the maximum shift delay.

Solar energy production. Photovoltaic panels provide the building with the energy $\mathcal{P}_t$ at time t . If it is not enough to cover L_t , the building feeds itself on the regular network to cover $L_t - \mathcal{P}_t$. If $\mathcal{P}_t > L_t$, excess production is “lost”. No storage capacity is used. At each time $t \in \mathbb{T}$, a smart meter measures the aggregate load L_t , as well as the solar production.

5.3.2 Self-Consumption and Self-Sufficiency Rates: Definitions and Mathematical Modeling

We assess the energy consumption efficiency with the two following metrics. For each $t \in \mathbb{T}$, the self-consumption at time t equals $\min(L_t, \mathcal{P}_t)$: if the household consumes more ($L_t > \mathcal{P}_t$) than it produces, then it self-consumes only what it has produced, that is $\mathcal{P}_t$, while if it consumes less, then it has self-consumed the amount L_t . Let us now recall the standard definitions of the self-consumption, and the self-sufficiency, rates (Ciocia et al. 2021, Luthander et al. 2015).

Definition 5.3.2 (Self-consumption rate, self-sufficiency rate). *For a household consumption $\mathcal{L}$, and two dates $t_{\text{begin}} < t_{\text{end}}$, we call the self-consumption rate between t_{begin} and t_{end} the ratio of self-consumption to the total production:*

$$\Lambda_{t_{\text{begin}}, t_{\text{end}}}(\mathcal{L}) = \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} \min(L_t, \mathcal{P}_t) \bigg/ \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} \mathcal{P}_t.$$

We call the self-sufficiency rate between t_{begin} and t_{end} the ratio of self-consumption to the total consumption

$$\Pi_{t_{\text{begin}}, t_{\text{end}}}(\mathcal{L}) = \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} \min(L_t, \mathcal{P}_t) \bigg/ \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} L_t.$$

The self-consumption rate measures the ratio of the solar production which has been consumed, and the self-sufficiency rate measures the ratio of consumption which has used solar production.

5.3.3 Nudges used in Our ICT Pipeline and Human Behavior Models: Nudges on Consumption-Favourable Periods and Ideal Human Behavior Model with 100% Response

We first define the notion of nudge we use, before explicating the model of human behaviour we assume, upon reception of a nudge. The concept of green period is inspired from Salman Shadid et al. (2020).

Definition 5.3.3 (Green period, nudge). *We call green period a tuple $(t_{\text{begin}}, t_{\text{end}}, E)$, where $t_{\text{begin}}, t_{\text{end}} \in \mathbb{T}$ are the beginning, and end, points of the period, $t_{\text{end}} = t_{\text{begin}} + 2H$ and $E \geq 0$ is the strength of the period. A nudge is a set of green periods. We write $\mathcal{N}$ the set of nudges.*

The number of green periods in a nudge is decided by the recommendation service. The strength of green periods is used to rank them. The user tries to shift their consumption first to periods with high strength, as we explain below.

Model of human behaviour upon nudge reception. We use an ideal model, to evaluate the maximum ideal potential of our ICT pipelines. Upon reception of a nudge, the household people try to shift their consumption as follows. For every shiftable appliance,

1. they look if there are use intervals outside of the green periods;
2. if so, for every green period, ranked according to their strength, they look if shifting the use of the appliance to the green period is admissible (if the new use interval would not be too far away from the old use interval);
3. if so, the consumption is shifted; else, nothing is done.

This behaviour upon nudge reception is ideal, in the sense that the user makes full use of the information provided. Indeed, our study aims at evaluating the potential of ICT pipelines to help improve consumption. Explicitly modelling realistic behaviour upon nudge reception, and assessing its impact, represents a following step for our research.

5.3.4 Overview of Controllers in Our Nudging Pipeline: Weather vs. Combined Controller

We define a controller as a function which computes nudges as follows, each Sunday, just before midnight. Assume we are Sunday, in the evening. Let t_{begin} be midnight, on the incoming Monday. Let t_{end} be 23:30, the following Sunday. Let $\mathcal{W}_{t_{\text{begin}}, t_{\text{end}}}$ be the set of weather forecasts for the incoming week: this is a set with weather forecast data for the sunshine coefficient, the temperature, and other likewise data which the controller might use to compute the nudge. Let $\mathcal{H}_{\rightsquigarrow t_{\text{begin}}}$ be the set of past household data available upon nudge computation: these are the past aggregate load, and the past production.

Definition 5.3.4 (Controller). *A controller is a function taking as arguments weather forecasts, and past household aggregate consumption data, and outputting a nudge, that is a function*

$$F : \mathcal{W}_{t_{\text{begin}}, t_{\text{end}}} \times \mathcal{H}_{\rightsquigarrow t_{\text{begin}}} \rightarrow \mathcal{N}.$$

On Monday, the household receives the nudge, and the user adapts or not their consumption for the week.

Designing good controllers is not straightforward. Indeed, write $n \cdot \mathcal{L}$ the household consumption once modified from $\mathcal{L}$ according to the nudge. Then, finding the best possible nudge amounts to solving either of the optimisation problems (which are equivalent when production is fixed):

$$\max_n \Lambda_{t_{\text{begin}}, t_{\text{end}}}(n \cdot \mathcal{L}) \quad \text{or} \quad \max_n \Pi_{t_{\text{begin}}, t_{\text{end}}}(n \cdot \mathcal{L}),$$

which means maximising either the self-consumption rate, or the self-sufficiency rate, of the household, over the coming week, for the nudged consumption $n \cdot \mathcal{L}$. What complicates matters is that the effect the nudge has on the consumption is unknown to the controller. Therefore, they have to make guesses as to what would lend itself to efficient nudges. Conversely, the household people know the effect a nudge has on them, however, the optimisation problem they would have to solve would be too burdensome for us to expect most households to solve it every week. Therefore, to compute nudges, we do not solve these optimisation problems, but introduce the following two heuristic controllers. We validate their efficiency in our numerical simulations.

Weather Controller. The first one is called “Weather Controller”. It takes as input the sunshine coefficient forecast for the coming week. It averages the predicted sunshine coefficient over 2 hours periods. The strength parameter is set to these values. Namely, if $\hat{s}_t$ is the forecast of the sunshine coefficient at time $t \in \mathbb{T}$, then the strength parameter

at time t_{begin} equals

$$E_{t_{\text{begin}}} = \frac{1}{4} \sum_{t \in \mathbb{T}, t=t_{\text{begin}}}^{t_{\text{end}}=t_{\text{begin}}+2\text{H}} \hat{s}_t.$$

(There are four half-hours in two hours, and we use a time scale $\mathbb{T}$ of 30 minutes steps.) Then, it ranks the periods according to their strength, and outputs the three (say) best periods. The Weather Controller therefore signals the periods when it is most sunny, as they are those with the most solar production.

Combined Controller. The second controller is called “Combined Controller”. It takes as inputs the sunshine coefficient forecast for the coming week, together with past aggregate consumption data, and past production data. It then uses load forecasting techniques to forecast excess production, that is the difference between forecast production and forecast consumption (see Appendix H for details). It averages the predicted excess over 2 hours periods, and sets the strength parameter to these averages. Finally, it outputs the three (say) best periods. Precisely, writing $\hat{l}_t$ the forecast load at time t , and $\hat{\mathcal{P}}_t$ the forecast production at the same time, the predicted excess is

$$\hat{\Delta}_t = \max \left(\hat{\mathcal{P}}_t - \hat{l}_t, 0 \right).$$

Then, the strength parameter at time t_{begin} equals:

$$E_{t_{\text{begin}}} = \frac{1}{4} \sum_{t \in \mathbb{T}, t=t_{\text{begin}}}^{t_{\text{end}}=t_{\text{begin}}+2\text{H}} \hat{\Delta}_t.$$

The Combined Controller therefore signals periods when there will be (if the forecast is accurate) the most excess. The idea is that there may be sunny periods where consumption will be high. In these periods, spare solar production will be low. As a result, shifting more consumption to these periods will not help. Therefore, by forecasting excess production, the Combined Controller manages to identify periods, shifting consumption to which is profitable.

5.3.5 Nudging Pipeline: Data-Driven Workflow for Optimal Consumption Using Weather and Energy Forecasting

Therefore, the system “household + controller” is a controlled system, illustrated on Figure 5.1. The nudging pipeline, which represents the system, save for the human behaviour part, consists in the following several components. Production and consumption data are monitored by a smart sensor located on the household premises. Weather APIs provide us with accurate forecasts for the upcoming days, in particular concerning solar irradiance. All information is gathered by the Controllers, which use it to compute

solar consumption friendly periods. These periods are gathered into nudges, which are sent to the household people through emails, for instance. Finally, upon receiving the nudge, the household people update their consumption accordingly.

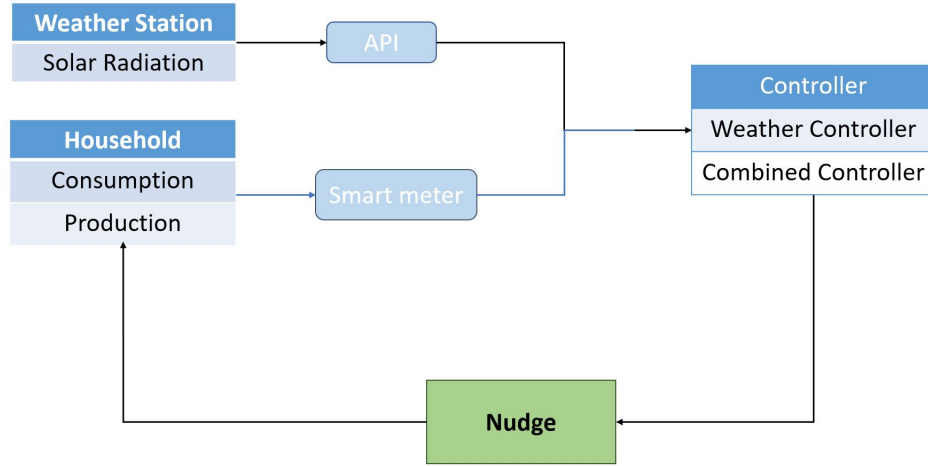


Fig. 5.1 Nudging Pipeline

5.4 Numerical Simulation: Building and Validating the ICT Nudging Pipeline in an Open Source Simulation Environment

We first describe our numerical simulations set-up (Section 5.4.1). Then, we show the results of simulations on synthetic data (Section 5.4.2 and Section 5.4.3) and the results of simulations on semi-real data (Section 5.4.4 and Section 5.4.5). Finally, we study the influence of the capacity of production installed (Section 5.4.6), and of the number of green periods in the nudges (Section 5.4.7), on the nudging pipeline efficiency.

5.4.1 Numerical Simulations Set-Up and Configuration

Synthetic data preparation. We generated two synthetic datasets, representing two use cases: a commuting household¹, and a non-commuting household². The commuting household represents for instance the household of people going to work away from home, but who have equipped their domestic electrical appliances with sensors, allowing them to launch, or stop, these appliances, remotely. The non-commuting household represents for instance the household of people remote working.

For each household, we use as fixed consumption (that is, not shiftable), the not shiftable part of the consumption of a real energy profile (which is part of the Iris

¹A commuting household refers to a group of individuals who live together in the same residence but travel to different locations for work or school, typically on a regular basis.

²A non-commuting household refers to a group of individuals who live and work in the same place, without the need for regular travel to a workplace or school.

dataset (*Mesure de la consommation des usages domestiques de l'audiovisuel et de l'informatique* 2008)). To create a shiftable consumption,

we add a real dishwasher consumption to the data every day in the morning, a real washing machine consumption every three days in the evening, and a real water heater for domestic hot water consumption every day in the evening. Therefore, the shiftable part of the consumption occurs in the morning or in the evening, and is thus representative of that of a commuting household.

For the “non-commuting household”, we added an additional electric cooker every day between 12 PM and 1:30 PM, and an additional air conditioner between 12 PM to 4 PM. As the people of the household are present during the day, they must cook their lunch, and they may use air conditioning, to maintain agreeable temperatures within the house in the afternoon. This may be the case for instance for a French household, endowed with air conditioning. While it is common in France to cook at lunch, air conditioning is not as widespread as in the United States of America, for instance, but its usage is nonetheless increasing. We classify air conditioning as non shiftable in this context of someone working from home during the afternoon, from a potentially badly isolated building. In such conditions, in order to maintain cool temperatures, the air conditioning system may need to run continuously.

Real datasets preparation. For the simulations using real datasets, we select a subset of appliances, which we define to be “shiftable”, and we fix their maximum shifting delay (see Table 5.2 for details). We divide each dataset into past data, on which we train our model, and future data, on which we conduct the simulation. Finally, we renormalise the data sampling steps to 30min steps.

The AMPds (Almanac of Minutely Power dataset)(Makonin et al. 2016) is a publicly available dataset created by Simon Fraser University’s (SFU) Electricity and Power Research Centre in Canada. It offers high-resolution energy consumption data collected from residential households. The dataset covers the period from 2012 to 2014 and includes measurements of electricity, water, and natural gas usage at one-minute intervals for an individual building in Canada. It can be found on the project’s official website or through various data repositories and academic platforms.

The Iris dataset is a subset from a European database of residential consumption collected as part of the REMODECE (Residential Monitoring to Decrease Energy Consumption) project (*Mesure de la consommation des usages domestiques de l'audiovisuel et de l'informatique* 2008). The REMODECE project is an initiative focused on monitoring and reducing energy consumption in residential buildings. It aims to develop innovative solutions and technologies to promote energy efficiency and sustainability in the residential sector. The Iris dataset contains the energy consumption data of 98 houses for a span of one year. The data sampling step is 10 minutes. We make the appli-

ance names homogeneous between the houses, as there are sometimes small variations in the terminology.

Solar energy production. As part of our simulator, we generate an artificial solar production as follows. We first simulate a sunshine coefficient as the product between

1. a value taking into account the time of day (representing the fact there is no sun at night);
2. a value taking into account the month of year (representing the fact the sun shines brighter during summer than winter);
3. a value taking into account the amount of clouds (representing the fact more clouds implies less light for photovoltaic panels).

The process giving the amounts of clouds is simulated by a Markov Chain transitioning between five levels of clouds, from “sunny” to “awful weather”. The chain is designed so that periods of sunshine alternate with cloudy periods. Precisely, write P the stochastic matrix, such that each coordinate $0 \leq P_{i,j} \leq 1$ is the probability of the chain going to state j , given it is currently in i . Therefore, each line $P_{i,\cdot}$ is a probability distribution. The chain is a discrete time chain, and for each $n \geq 1$, X_n represents the weather between the times $t_{\text{begin}} = 4(n - 1)$ hours and $t_{\text{end}} = 4n$ hours. As a result, to simulate trajectories of the chain, we start at $X_0 = \text{sunny}$ and, for $n \geq 1$, we simulate X_n according to:

$$X_n \sim P_{X_{n-1}, \cdot}$$

Finally, the solar production generated by the panels from this synthetic sunshine coefficient is simulated as a linear function of the sunshine coefficient, renormalised before to the segment $(0, 1)$. The maximum power possible, that is the capacity of the solar panels.

Controllers. We use three controllers, and an upper-bounding optimiser:

1. the Weather Controller and Combined controller, defined in Section 5.3.4, which performances we want to assess;
2. the “No Control” controller, and the “OMEGAlpes” optimiser, described below, which we use as references.

The “No Control” controller represents the worst case, when there are no nudges. We call it “reference” in the plots. OMEGalpes (Hodencq et al. 2021) provides an upper-bound for the best possible case. It is a linear optimisation energy systems modelling tool (see Appendix I for details). It computes the best possible shifting of the consumption. However, it uses data like detailed knowledge of the shiftable consumption of the household, and therefore cannot be used in real life. Moreover, OMEGalpes

has no restrictions on the number of the formal equivalent of green periods it uses. Therefore, OMEGalpes is not a controller in the sense of Definition 5.3.4, but provides an upper-bound on the possible performance of controllers. We provide some context about the way OMEGalpes computes its solution in Appendix I. The nudges sent by our controllers each contain 4 green periods.

Simulation. The simulations run over one month. For each setting, we run 20 simulations to account for the stochasticity of the production generation.

Metrics displayed. We display the self-consumption rates of the household, for the different controllers and OMEGalpes. We also display the improvement of our controllers (self-consumption rate with the controller minus self-consumption rate with no controller), as a percentage of the improvement of OMEGalpes (self-consumption rate with OMEGalpes minus self-consumption rate with no controller). For each statistic, we show its mean, as well as the 10% – 90% interval of values. The results for the self-production rates are similar to those with the self-consumption rate. We present them in Appendix J.

5.4.2 Simulating a Commuting Household Scenario Using Synthetic Data

We first present the results for the synthetic, commuting, household. We show in Table 5.3 the self-consumption rate of the household, under the different controllers, and OMEGalpes. We see both the Weather and Combined controllers improve the self-consumption rate, with respect to the “No Control” reference. In average, with “No Control”, the rate is 67.4%, while it is 77.35% for the Weather Controller and 77.63% for the Combined Controller. We also show the performances of our controllers as percentages of that of OMEGalpes. They range between 45.9% and 47.25%. Clearly, we cannot obtain the full improvements of OMEGalpes with our nudges, but we can still obtain a significant part of it.

Table 5.3 Commuting Household: Mean Self-Consumption Rate and Mean Improvement Ratio with Various Controllers

	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)	67.4	77.35	77.63	89.12
Mean of improvement ratio (%)	0	45.9	47.25	100

5.4.3 Simulations for Non-Commuting Households Using Synthetic Data

In the non-commuting scenario, a large, not-shiftable consumption (due to the electric cooker and the air conditioner) takes place in the afternoons, when solar production

is potentially at its maximum. Therefore, even if there is a lot of production in the afternoons, there is not a lot of excess production. As a consequence, looking at the sunshine coefficient to identify green periods will be misleading, as we now see. In Table 5.4, we see that the self-consumption rate with the intervention of the Combined Controller (93.82% on average) is significantly higher than that with the Weather Controller (90.9% on average). Indeed, the percentage of improvement, with respect to the OMEGalpes reference, of the Combined Controller, is more than 29% that of the Weather Controller (average of 47.94% against 18.53%). This happens because the Weather Controller only considers periods when the weather is favourable for production, but does not take into account the household's consumption patterns. As a result, it may identify a green period when there is a high production, without noticing there is also a high consumption taking place. It may therefore encourage people to shift consumption to a moment where production is already saturated. On the other hand, by forecasting consumption as well as production, the Combined Controller is able to identify moments where there is likely to be excess production. Shifting consumption to these moments therefore helps improve the self-consumption rate.

Table 5.4 Non-Commuting Household: Mean Self-Consumption Rate and Mean Improvement Ratio with Various Controllers

	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)	89.01	90.9	93.82	99.08
Mean of improvement ratio (%)	0	18.53	47.94	100

5.4.4 Simulations for Individual Building Scenarios Using the Iris and AMPds Datasets

Table 5.5 Mean Self-Consumption Rate and Mean Improvement Ratio with Various Controllers: Iris and AMPds Datasets

Dataset	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)				
Iris	63.13	66.77	67.9	80.89
AMPds	70.06	70.86	70.92	72.9
Mean of improvement ratio (%)				
Iris	0	21.37	27.99	100
AMPds	0	27.73	29.72	100

We first run a simulation for an individual building of Iris and the AMPds building. We show on Table 5.5 the results of the simulation for Iris and AMPds. We see that both the Weather and the Combined Controllers manage to improve the self-consumption rate of the building, taking it from 63.13% to more than 66.77% (Weather) and 67.9% (Combined). Results are comparable for AMPds: we see that both the controllers improve the self-consumption rates from 70.86% to more than 70.92%. The fact the performances of the two controllers are close is probably due to the fact that excess production occurs mainly when absolute production is high (contrary to the use case of Section 5.4.3). We note that even the worse results of the controllers are better than all but the very best results of the reference situation in which there is no control, which shows the value of our procedure.

5.4.5 Collective Simulations Using the Iris Dataset

Then, we conduct simulations for all the buildings of the Iris dataset, and show the results on Table 5.6. The mean, and mean of the percentage of improvement, are averaged on all the buildings. We see that on average, the Weather and Combined controllers improve the self-consumption rate by about 2%. This corresponds to roughly 17%–22% of the OMEGalpes performance. While the results of OMEGalpes are much higher than that of the controllers, we believe it is mainly due to the limitless number of shifts in consumption it can perform, and to the fact it uses per-appliance knowledge of the true consumption. Therefore, given these advantages, we believe reaching 22% of its performance, in the case of the Combined Controller, still shows a reasonable efficiency of our nudging pipelines.

Table 5.6 Mean Self-Consumption Rate and Mean Improvement Ratio with Various Controllers: Collective Simulation on the Iris Dataset

	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)	62.21	63.78	64.23	72.25
Mean of improvement ratio (%)	0	17.22	21.59	100

To look at the influence of energy flexibility on the enhancements in the self-consumption rate, we conducted simulations on three distinct subsets of the Iris dataset, based on the numbers of shiftable appliances in each house: 1, 2, or 3. We show on Table 5.7 the results of the simulations. Unsurprisingly, the greater the number of shiftable appliances within the houses is, the greater the self-consumption rate increases when nudges are sent (going from 1% for the first dataset, to 4% for the third one), under similar

conditions such as weather and house type.

Table 5.7 Mean Self-Consumption Rate and Mean Improvement Ratio with Various Controllers: Collective Simulation on the Iris Subsets

Dataset	shiftable appliances number	Reference	Weather Controller	Combined Controller	OmegAlpes
Mean (%)					
Iris_1	1	54.4	54.97	55.18	58.45
Iris_2	2	66.77	68.64	69.1	78.51
Iris_3	3 or more	60.91	64.16	65.31	81.32
Mean of improvement ratio (%)					
Iris_1	1	0	16.32	20.86	100
Iris_2	2	0	18.43	22.86	100
Iris_3	3 or more	0	15.40	19.37	100

5.4.6 Investigating the Impact of Varying Production Amounts on Self-Consumption

We show on Figure 5.2 the increase of the self-consumption rate, for the Iris household, as a function of the amount of maximum possible production (this amounts increases when more solar panels are installed). We see that the increase of the self-consumption rate is maximum for a production between 2000-3000 W for both cases of controllers, and that it decreases for lower, and larger, values of production. Indeed, when there is very few production, there are not much gains to target by shifting consumption, therefore nudging does not help a lot. Likewise, when there is a lot of production, all consumption already takes place when solar production is high, therefore there is no need to shift consumption. On the contrary, for intermediate values of production, shifting may help improve self-consumption, and therefore nudging proves valuable. Finally, we see the superiority of the Combined Controller over the Weather Controller is highest in the production range where nudges are most efficient. This strengthens the case for using the Combined Controller.

5.4.7 Analyzing How the Number of “Green” Periods Affects Self-Consumption

We show on Figure 5.3 the efficiency of nudges as a function of the number of green periods in each nudge. This matters, as realistically, users will tire if presented with too much information. Therefore, we should strive to send nudges with as less as possible green periods. However, we must make sure the efficiency of the nudge remains satisfying. The augmentation of the self-consumption rate increases with the number of green periods of a week, which was expected. However, the slope of the curve decreases as the number of green periods increases. This means that every supplementary green

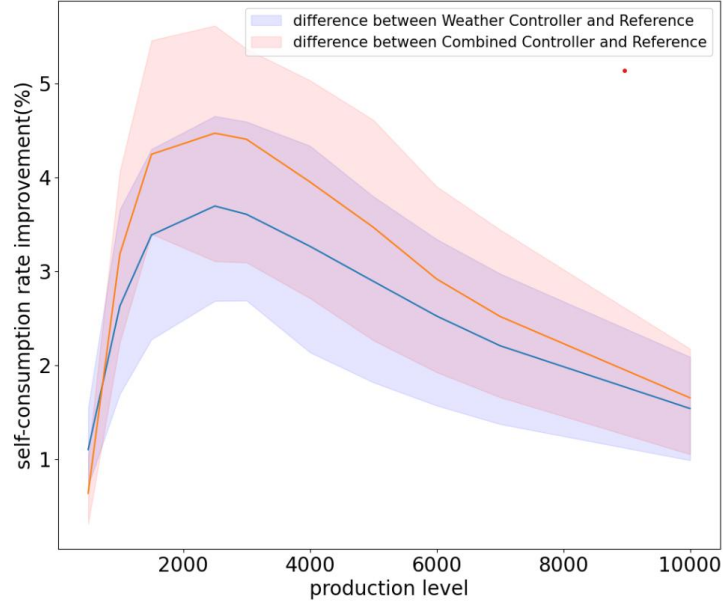


Fig. 5.2 Augmentation of the Self-Consumption Rate Due to the Combined Controller/Weather Adviser with Respect to a Reference with No Controller, as a Function of the Production

period helps increase the self-consumption rate less than the previous. As a result, we see that most gains are concentrated on the left of the plot, from 0 to 4 green periods by nudge, and that gains realised by adding more green periods are lower and lower. This is probably due to the fact most easily shiftable consumption is already shifted with fewer numbers of nudges. We therefore recommend that each weekly nudge contains 3 or 4 green periods, as it strikes a good compromise between having an efficient procedure, and avoiding user fatigue.

5.5 Conclusion

We have shown on semi-real data, in a simulated environment, that our ICT nudging pipelines using real-world accessible information were efficient in helping households improve their self-consumption. We have shown that forecasting excess production, and constructing nudges based on this, beats merely providing weather forecasts, when maximum solar production and excess production do not take place at the same time. We have observed that the more flexibility there is in an household, the more profitable sending nudges is. Moreover, we have seen that there was a sweet spot in production for which nudging was most efficient. Indeed, when production is too small, or too large, there are few improvements to obtain by shifting consumption. Finally, we have seen that most gains in self-consumption took place with few “green periods” by nudge, which is encouraging, as limiting their number helps prevent user fatigue.

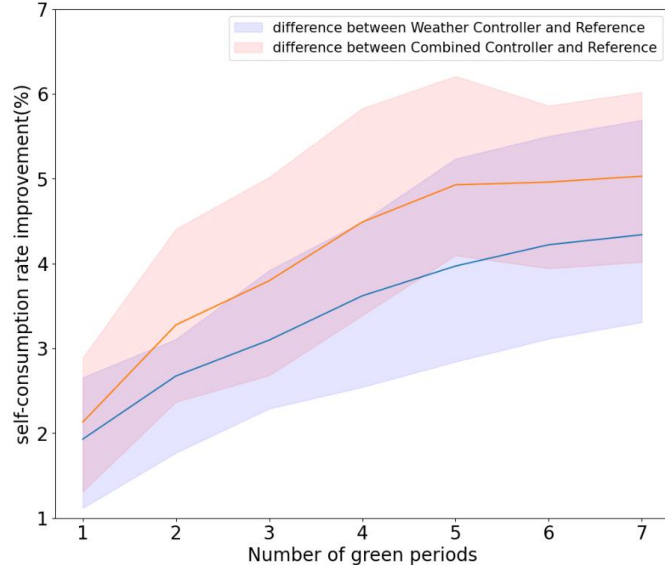


Fig. 5.3 Augmentation of the Self-Consumption Rate Due to the Combined Controller/ WeatherAdviser with Respect to a Reference With no Controller, as a Function of the Number of Green Periods by Nudge

While our results show we can obtain reasonable performances, with respect to the OMEGAAlpes reference, we also see that absolute improvements in the self-consumption, and self-sufficiency, rates, by merely shifting some part of the consumption upon nudge reception, are not enough to reach close to one (100%) rates. This probably entails that selectively reducing usage may be somewhat necessary, for households willing to reach much better rates. Note that this may not necessarily mean a reduction in the “comfort” provided by appliances usage, as “unnecessary” usages, like appliances let in sleep mode instead of turned-off, may be removed, without diminishing the benefits one gets from the appliance.

One takeaway of our study is the importance of assessing both the hardware, and the “human”, so to speak, components of the household, to identify settings where nudging will be efficient. Indeed, on the one hand photovoltaic capacity must be in the “sweet spot” we have identified. On the other hand, the household people must be willing to shift enough of their consumption, for these shifts to truly weigh on the part of solar energy used, with respect to standard energy. In turns, making these assessments requires patient ground-work, collecting individual information about photovoltaic capacity, and consumption usages. This may seem like time-consuming effort, while nudge pipelines are supposed to be easy to set-up, but they can be viewed as a “one-off”, initial investment, before letting the nudging pipeline run automatically.

We intend to pursue our work by testing our nudge scheme in real-world situations. Thanks to our simulations, we can have some confidence that it will be efficient, without overburdening users with information. Indeed, one important take of our simulations is

the fact we can restrict our weekly nudges to 3 or 4 green periods, while still getting satisfying results. It seems reasonable to imagine users mentally flagging these 3 to 4 periods during the week, and attempt to shift some consumption to these. Of course, we will have to test this assumption, first by directly asking the users, and second, by monitoring the key consumption metrics, to quantify the effect our pipelines have on users consumption. As far as the controller choice is concerned, we will deploy the Weather Adviser for households where solar production and excess production tend to be correlated, and the Combined Controller for the others. Of course, we might also attempt to shift controllers as time goes on. Finally, before deploying a nudging scheme, we will assess whether the solar panels capacity is indeed in the range where nudging might be profitable, as our simulations have shown there would be no interest in doing so, should it be insufficient, or too large.

However, two main limitations of our work will need to be addressed for our pipelines to prove efficient in real-world settings. The first limitation stems from the complexity of human behaviour in real-life situations, as individuals vary in their reception and response to information. In our simulations, we assumed an idealized human behaviour, whereby the household people would try their utmost to comply with the suggestions in the nudge. This may not be the case in real life, not for all individuals in any case. Thus, future research directions should focus on estimating the “compliance” rate of users receiving nudge, and devising ways to make this rate improve. The second limitation pertains to the energy, and weather, forecasting modules. We used a simple energy forecasting module, which will probably require enhancing to remain relevant in real-world situations. Fortunately, there are many possible models available in the literature, which we may use. However, even state of the art weather forecast may prove inaccurate, especially a few days down the line. The prediction errors, about energy usage, and weather, can potentially result in incorrect information about green periods. This may lead to bad consumption shifts from the users, and potentially discourage them from further using the scheme. One way to make the forecast more robust would be to use ensemble models, which gather forecast from several models, and construct an aggregated forecast from these, which often proves more reliable than any one taken separately.

In our work, we have considered the case of an individual building. Now, thanks to recent legislation (see Commission de Régulation de l’énergie (2018) for the case of France, Di Silvestre et al. (2021) for that of Italy, and Solar Power Europe (2023) for a broader view of the European Union), it is possible for building owners to create an association, and share their production with the members: this is called collective self-consumption. Now, alignment of consumption with production is made more complex by the fact there are several consumers. Designing efficient nudging strategies also gets

more complex. For instance, telling everyone that there will be a sunny afternoon may result in excess consumption, due to all members shifting their production at the same time. We intend to further our work in this interesting, and challenging, direction, in order to try and contribute to realising the potential these communities have to get close to zero net energy consumption. This means that all energy used within the community is also produced within the community (the equivalent, in the case of the community, of “zero consumption on the meter” for an individual household) and is one of the very important potential benefits of these communities.

We believe there are two main difficulties in deploying solar energy, related to user adoption. The first is the cultural shift required to fully exploit it. Indeed, people are not used to looking at the weather before using their washing-machine, for instance. Adapting behaviours accordingly will require time. This will only be possible through adoption of this energy. However, this runs into the second difficulty: user experience is, at least in the beginning, downgraded when one gives up using “standard” energy sources, and starts to use solar energy. Indeed, consuming whenever one sees fit is more convenient than taking into account the new constraint that one must pay attention to the sun. Of course, there are advantages in doing this, of economical and environmental kinds, but these are not immediately apparent, contrary to the inconvenience of having to take into account the sun. Widespread adoption of solar energy will therefore require efforts in order to make the transition as seamless as possible. We believe deploying recommendation services, providing just enough information to help users take advantage of the solar energy, in as non-intrusive a way as possible, will play a huge part in reaching this aim.

CHAPTER 6

Improving Energy Consumption Coordination in Renewable Energy Communities through Nudging

Abstract: In this chapter, we extend the nudging pipeline developed in the previous chapter (Chapter 5) from individual self-consumption to the more complex system of collective self-consumption. We identify periods of excess production through load forecasting and subsequently notify community members. However, disseminating the same consumption favourable period information to all residents could result in over-consumption and inefficient flexibility allocation. Therefore, we still need to identify and better coordinate flexibility. However, since NILM remains challenging to implement in real-world applications, we explore an alternative approach to identify flexibility through online surveys, estimating it from the survey data, as illustrated in Nudging Strategy 2 (Section 1.4.3.3).

This chapter is mainly copied from Ling, Massé, Rihet and Wurtz (2024). We have removed the related works section in this chapter, as it is comprehensively covered in the general related works presented Chapter 2.

6.1 Introduction: Extending Nudging Pipelines to Collective Self Consumption Systems with the Addition of a New Module Named “Coordinator”

Among growing calls within many countries to make human activities more environmentally friendly, special attention has been given to the production of energy. Indeed, fossil fuels driven production generates a lot of greenhouse gases (Agency (n.d.), accessed on 27 October 2023). Hopes have been placed into renewable energy sources which, albeit still not perfect from an ecological standpoint, offer greener energy, at least in the exploitation phase. Chief among these sources are solar and wind production. On the other hand, the distance between power production facilities, and points of consumption, entails inefficiencies due to the dissipation of energy as it travels through the distribution network (Beza et al. 2020). Moreover, energy distribution infrastructure is very costly (Rauschkolb et al. 2021).

The concept of “renewable energy community”, introduced by the European Union in 2018 (*Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources* 2018), offers some answers to these issues: these communities should use (as much as possible) energy produced locally, and from renewable sources. A typical instance is a group of households using shared solar panels facilities. The transposition into French law of this directive gave rise to the concept of “autoconsommation collective”, which translates as “collective self-consumption” (Légifrance (n.d.), accessed on 22 January 2024). A group of households localised into some circle of prescribed radius (most often 2 kilometers), can associate to share the power generated by some renewable energy source (most often solar, though operations using hydraulic energy also exist) situated within the circle. At each 30 minutes time step, energy produced by the panels is contractually shared between the participants of the operation. The amount of production given to each participant is computed through an algorithm, agreed upon by the members. Finally, energy demand not covered by the panels, is provided by the standard distribution network. The number of such active operations has grown steadily since the first ones came to life in 2018, reaching 259 operations in September 2023 (Enedis (n.d.), accessed on 27 October 2023), gathering 3357 households, for a total power available of nearly 18 MW.

Key metrics measuring the extent to which members of self-consumption operations are taking advantage of the solar energy, are the self-consumption and self-production rates. The former tells which amount of solar energy is used by members, while the latter quantifies the proportion of their energy consumption which is drawn from the solar panels (by opposition to the regular network provided energy). To maximise both, two cultural shifts are necessary, with respect to habits linked with regular network provided energy. The first one is taking into account the intermittence of production. The second one is taking into account the consumption of the other members of the operation. For instance, if everybody is using high consumption appliances at the same time, solar panels capacity may be outgrown, meaning regular energy will have to be used as a fallback. Now, shifting one’s habits may not be straightforward. Recommendation systems, advising the members of these operations accordingly, may help in that regard. In Chapter 5, we introduced such a system for the case of a single household endowed with solar panels. Here, we extend this work to the (much) more involved case of renewable energy communities.

For a single household, what mattered was identifying consumption favourable periods, so called “green periods”, and notifying the household of these. In the case of an energy community, a new module must be added, which computes the information sent to each different household. Indeed, sending the same information to all households

may result in outgrowing solar capacity, as discussed previously. We indeed show in our numerical simulations that this strategy is far from optimal. We therefore first construct these new modules required by the context of the energy community, which we call “coordinators”. Then, we show their worth in numerical simulations, using semi-real data, based on well-known consumption datasets. This validation is seen as a first sanity check, before deploying our pipelines in real-world self-consumption operations.

We start by presenting problem statement, and stating our contributions, in Section 6.2. Next, we introduce our model in Section 6.3, before introducing the coordinators in Section 6.4. We then present our numerical simulations results in Section 6.5. Finally, we discuss our results, and their practical implications for the real-world deployment of our pipelines, in Section 6.6.

6.2 Problem Statement and Our Contributions

We first presenting our problem statement (Section 6.2.1), and then stating our contributions (Section 6.2.2).

6.2.1 Problem Statement: How cCan We Efficiently Communicate Favourable Consumption Periods to Households within a Collective Self-Consumption Operation?

We study a collective self-consumption operation, getting energy from solar panels, and composed of residential households. The members of the operation may shift the consumption of some of their appliances, if they think it may improve their usage of solar energy. By collecting consumption and weather data, we can forecast, with some relative precision, consumption favourable periods, called “green periods”. These are the periods when the members of the operation should consume energy. The issue we address is: **how can we efficiently distribute information about these favourable consumption periods to the households within the operation, in order to help them optimise their usage of solar energy?**

6.2.2 Contribution: Personalized Recommendations by the Coordinator Improve Self-Consumption Rates Compared to Uniform Recommendations

We conduct numerical simulations on a full simulator, taking into account the response of households within the collective self-consumption operation to nudges. The data we feed our simulator with are semi-real data. We use the well-known Iris (*Mesure de la consommation des usages domestiques de l’audiovisuel et de l’informatique* 2008) and IDEAL (Pullinger et al. 2021) energy datasets. Our contributions are threefold.

1. First, we show numerically that sending individual information to the members of the operation proves superior to sending the same information to every household.
2. Second, we show numerically that our pipeline proves efficient, with respect to some ideal benchmark, computed with the OMEGAAlpes model Hodencq et al. (2021)(see Appendix L for an overview of the model)..
3. Third, we assess numerically the efficiency of our pipeline as a function of the information that members of the operation are willing to share about their energy usage.

We focus our study on the human in the loop component of consumption optimization, by opposition to automated load control systems. We present a realistic and simple to follow nudging framework, rather than some more involved, but also more complex, optimization scheme, like demand-response ones. Our work differs from that of Chapter 5, upon which we build, by extending it from the case of an individual household, to that of a collective self-consumption operation. In particular, we show that individually tailored nudges prove superior to the straightforward extension of the single household nudges used in Chapter 5, which consists in sending the same nudge to everybody (point 1. above). Finally, our work takes place in the French setting, but could easily be applied to other countries by taking into account the specifics of the realization of the Renewable Energies Communities concept into those. Indeed, the fundamentals of our work, sharing information about expected excess production periods between the members of the operation, will remain the same.

6.3 Model Overview: Detailed Examination of Each Component in Our Nudging Pipeline

We first describe globally our nudging pipeline in Section 6.3.1, before describing precisely each component in Section 6.3.2. For convenience, Table 6.1 compiles all the key notations we use.

Table 6.1 Main Notations

Notation	Definition	Meaning
$\mathcal{L}_t$	$\mathcal{L}_t \in \mathbb{R}_+$	collective self-consumption
$\mathcal{P}_t$	$\mathcal{P}_t \in \mathbb{R}_+$	aggregate load at time t
$l_t^{h,k}$	$l_t \in \mathbb{R}_+$	solar production at time t
$\Lambda_{t_{\text{begin}}, t_{\text{end}}}$	$0 \leq \Lambda_{t_{\text{begin}}, t_{\text{end}}} \leq 1$	load of appliance k of household h at time t
$\Pi_{t_{\text{begin}}, t_{\text{end}}}$	$0 \leq \Pi_{t_{\text{begin}}, t_{\text{end}}} \leq 1$	self-consumption rate
$x_{h,p}$	$x_{h,p} \in \{0, 1\}$	self-sufficiency rate
e_p	$e_p \geq 0$	allocation variable, between period p and household h
m_d^h	$m_h \geq 0$	excess production in green period p
$\hat{m}_d^h$	$m_h \geq 0$	available shiftable power of household h for day d
$\alpha^{h,k}$	$\alpha_{h,k} \geq 0$	estimation of the available shiftable power of household h for day d
$a_d^{h,k}$	$a_d^{h,k} \in \{0, 1\}$	maximum power of appliance k of household h
$f^{h,k}$	$0 \leq f^{h,k} \leq 1$	activation status of appliance k of household h for day d
		frequency of usage of appliance k of household h

6.3.1 Nudging Pipeline: Workflow of Our Recommendation Service with a Coordinator Module, Using Favourable Periods Information and Design rules

On Figure 6.1, we give an overview of our nudging pipeline. The related notions are defined precisely below, so we just give a brief description here. A collective self-consumption operation gathers several houses. Each house possesses a smart meter, and likewise for the solar panels, from which we can collect consumption, and production, data. Weather APIs provide us with accurate forecasts for the upcoming days. The control part of the system has two modules. The “green period finder” module (see Section 6.3.2) uses the mentioned data to identify green periods, when households are encouraged to use their electrical appliances. The coordinator module, which we introduce in this chapter, dispatches these green periods to the different households, according to specific rules aiming at maximising impact (Section 6.4). Finally, upon

receiving the nudge, the household people update their consumption accordingly.

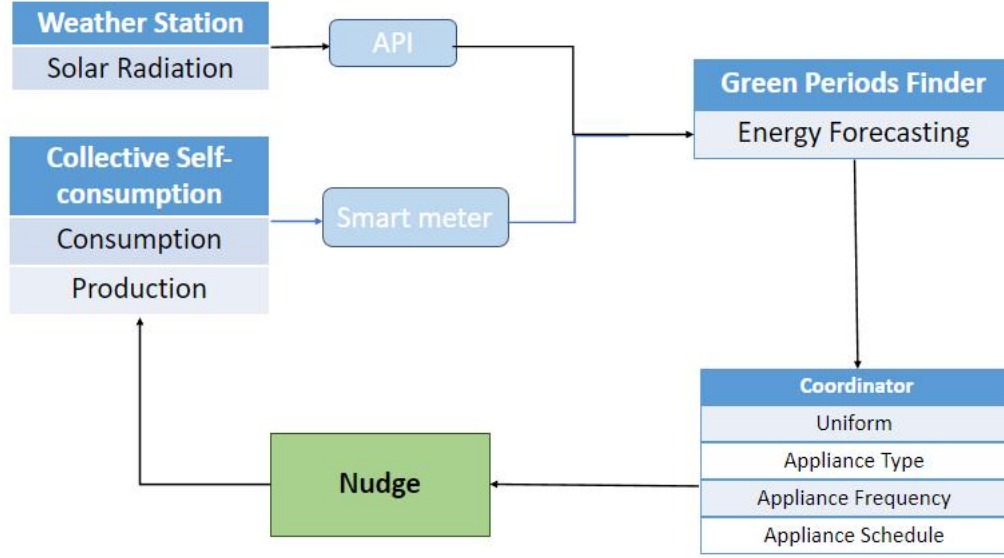


Fig. 6.1 Nudging Pipeline

6.3.2 Elements Necessary to Simulate the Nudging Pipeline in a Collective Self-Consumption Context

We introduce the main notions we use. Several, like that of shiftable appliance, described in Chapter 5, are the same, or straightforward extensions, of the similar notion used in the case of an individual household. In that case, we only give some brief explanations here. We point the reader to Chapter 5 for further details.

Collective Self-Consumption Operation. We consider a collective self-consumption operation which gathers several households, and solar panels. There is no battery, meaning energy cannot be stored, and used at a later time. There is no direct energy consumption, either (sometimes, a panel can feed in priority an household, and only send excess production to the other households; this is not the case here).

Household appliances. Each household possesses several electrical appliances. Each appliance may be shiftable, meaning that the household owners may shift usage during the day, upon reception of some advice to do so, or not shiftable, meaning the time of the usage is fixed, irrespective of any advice received by the household. Every shiftable appliance has a maximum shiftable delay: for instance, a washing-machine usage cannot be shifted to a time slot more than 9 hours (Table 6.2) from the original desired time slot. Let h be an household, and k be one of its appliances. We assume, to simplify things, that the load curve of k during usage is always the same (for a washing machine, it means that only one program is available, and that its length is not dependant on the amount of clothes to wash, for instance). We call profile of the appliance this load curve during usage, and write it $\ell^{h,k}$. It is therefore a non-negative function with

compact support. Therefore, the load curve, for some week, of the k^{th} appliance of the household h writes, for $t \geq 0$,

$$l_t^{h,k} = \sum_{u=1}^{u_{\max}(h,k)} \ell^{h,k}(t - T_{h,k}(u)),$$

were the u 's count the usages of the appliance during the week (for instance, if the washing-machine is used three times, we have $u_{\max}(h, \text{washing-machine}) = 3$), and $T_{h,k}(u)$ is the time at which the appliance started to be used the u^{th} time.

Table 6.2 Shiftable appliances maximum shift delays for the Iris and IDEAL Datasets

Shiftable appliance	Maximum shift delay
Washing machine and clothes dryer	540 min
Dish washer	540 min
Water heater for domestic hot water	600 min
Electric vehicle	336 min

Solar production sharing between members. The production of the solar panels is contractually¹ shared between the members, at each 30min time step, according to French law. The scheme we use in our work is the commonly used following one. Assume the solar panels produce 200 Wh between 2pm and 2:30pm. Assume there are 3 households within the operation, which consumed 100 Wh, 200 Wh and 0 Wh, respectively. Then, the first household receives $200 \text{ Wh} \times 100 / (100 + 200 + 0) = 66.67 \text{ Wh}$, while the second receives $200 \text{ Wh} \times 200 / (100 + 200 + 0) = 133.33 \text{ Wh}$, and the third receives $200 \text{ Wh} \times 0 / (100 + 200 + 0) = 0 \text{ Wh}$. If the amount of production is higher than the total demand during the time-step, excess production is fed back to the regular network. Note there is no battery in the operation, therefore it cannot be stored, and crucially consumed later. Therefore, the members of the operation have interest in first, consuming energy when solar production is important, and second, synchronising somewhat so as not to outgrow solar production by consuming all at the same time.

Operation self-consumption rate. As in Chapter 5, we measure the efficiency of solar energy usage with the self-consumption rate (Ciocia et al. 2021, Luthander et al. 2015), of the operation (all our conclusions also apply to the self-sufficiency rate, but we do not speak about it to simplify the presentation). Compared to the same notion for individual households, it is computed by summing the consumption of every household, and the production of all the solar panels. For $t \geq 0$, write $\mathcal{L}_t$ the total consumption of the operation at time t , that is $\mathcal{L}_t = \sum_{h=1}^{h_{\max}} \sum_k l_t^{h,k}$ where, for every household h , the

¹We say ‘‘contractually’’ by opposition to ‘‘physically’’: the energy of the panels is physically sent to the regular network, from which members draw the energy they need. The self-consumption operation operates at the legal level.

summation on k runs over all appliances of household h . Write also $\mathcal{P}_t$ the total solar production of the panels of the operation.

Definition 6.3.5 (Operation self-consumption rate). *The self-consumption rate of the operation between the dates t_{begin} and t_{end} is the ratio of self-consumption to the total production:*

$$\Lambda_{t_{\text{begin}}, t_{\text{end}}}(\mathcal{L}) = \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} \min(\mathcal{L}_t, \mathcal{P}_t) \bigg/ \sum_{t=t_{\text{begin}}}^{t_{\text{end}}} \mathcal{P}_t.$$

Green periods, nudges. We use the same notions of green periods, and nudges, as in Chapter 5, and we recall them here.

Definition 6.3.6 (Green period, nudge). *A green period g is a 2 hours period. We write $t_{\text{begin}} = t_{\text{begin}}(g)$ the beginning of the period, and $E = E(g)$ the amount of excess production in the period. A nudge is a set of green periods.*

The green periods are ranked according to the excess production available: the higher it is, the better the period.

Identification of green periods through load forecasting. We use the “combined controller” introduced in Chapter 5. It is a statistical algorithm, used to forecast excess production. It averages the predicted excess (if any) over 2 hours periods, and uses it as estimate of the excess available during the green periods. We write e the forecast excess. The forecast is performed at the operation level, meaning the excess predicted is that of the operation as a whole. The algorithm outputs green periods g_p , for $1 \leq p \leq p_{\text{max}}$. In all what follows, we assume green periods are ranked by descending order, according to their amount of excess production.

Model of human behaviour upon nudge reception. In all the equations below, we only show the shiftable appliances, to simplify the exposition (this does not change the overall reasoning). We use the same idealised model of human behaviour as in Chapter 5: when receiving a nudge, for every shiftable consumption outside the periods, the household people try to shift it to the first admissible green period. Namely, they discard all periods which are further away from the original consumption time than the maximum shiftable delay. Then, they rank the green periods according to their predicted excess, and to the closeness to the original consumption time. Then, they move the consumption to the first green period in that ranking. Write $\Delta_{h,k}$ the maximum shiftable delay for appliance k of household h . The load curve of an appliance shifted upon reception of the green periods depends on the green periods $g_1, \dots, g_{p_{\text{max}}}$. Therefore, making this dependency explicit, it writes, for $t \geq 0$,

$$l_t^{h,k}(g_1, \dots, g_{p_{\text{max}}}) = \sum_{u=1}^{u_{\text{max}}(h,k)} \ell^{h,k}(t - T_{h,k}^*(u)),$$

where the (potentially) shifted time $T_{h,k}^*(u)$ is the begin time of the green period solution of

$$\begin{cases} \arg \max_{1 \leq p \leq p_{\max}} E(g_p) \\ |T_{h,k}(u) - t_{\text{begin}}(g_p)| \leq \Delta_{h,k}, \quad 1 \leq p \leq p_{\max}, \end{cases}$$

if this period exists, and $T_{h,k}(u)$ else (in this case, the appliance is not shifted).

6.4 Coordinator: Definition and Mathematical Modeling of the Coordination Problem in a Collective Self-Consumption Context

We first define coordinators (Section 6.4.1), then present the optimization problem computing the best coordination (Section 6.4.2). Then, we introduce the available shiftable power matching coordinator (Section 6.4.3), and its three practical proxies (Section 6.4.4).

6.4.1 Definition of a Coordinator: a Module that Decides Which Household to Notify About Which Consumption-Favourable Period

Once we have identified green periods, we need to notify them to the households of the collective self-consumption operation. We call coordinator the module responsible for constructing the notifications: it decides which household it notifies about which green periods.

Definition 6.4.7 (Coordinator). *A coordinator computes allocation variables $x_{h,p}$, for every household h , and every green period p , where $x_{h,p} = 1$ if green period p is sent to household h , and 0 otherwise.*

The simplest coordinator is the one which sends the best green periods to all the households. We call it “uniform coordinator”. Let us write $\tau \geq 0$ the maximum number of green periods to send to each household.

Uniform coordinator. The uniform coordinator implements the naive strategy, whereby every household is notified of the same green periods. Therefore, we have

$$x_{h,p} = \begin{cases} 1, & 1 \leq h \leq h_{\max}, 1 \leq p \leq \tau, \\ 0, & \text{otherwise.} \end{cases}$$

6.4.2 Optimal Green Periods Allocation Problem: A Theoretical Problem That is Numerically and Algorithmically Too Complex to Solve

However, the uniform strategy may be sub-optimal. Indeed, notifying all households of the same green periods may result in all households consuming energy at the same time, and outgrowing available solar production. Therefore, we need to optimize the way we

allocate the green periods to the households. Let us write $\mathbf{x} = \{x_{h,p}\}_{1 \leq h \leq h_{\max}, 1 \leq p \leq p_{\max}}$. When sending green periods computed through a coordinator to a household, the shifted times now depend on $\mathbf{x}$, so we write them $T_{h,k}^*(u, \mathbf{x})$. Likewise, the shifted load curve of the k^{th} appliance of house h also depends on $\mathbf{x}$, so we write it $l^{h,k}(\mathbf{x})$. As a result, the shifted load of appliance k of household h writes, for $t \geq 0$,

$$l_t^{h,k}(\mathbf{x}) = \sum_{u=1}^{u_{\max}(h,k)} \ell^{h,k}(t - T_{h,k}^*(u, \mathbf{x})).$$

We want to find the set of $x_{h,p}$'s maximising the self-consumption rate of the operation. It amounts to solving the optimisation problem:

$$\begin{cases} \arg \max_{\mathbf{x}} \sum_{t=W_0}^{W_1} \min \left(\sum_{h=1}^{h_{\max}} \sum_k l_t^{h,k}(\mathbf{x}), \mathcal{P}_t \right), \\ x_{h,p} \in \{0, 1\}, \quad 1 \leq h \leq h_{\max}, \quad 1 \leq p \leq p_{\max}, \\ \sum_{p=1}^{p_{\max}} x_{h,p} \leq \tau, \quad 1 \leq h \leq h_{\max}, \end{cases}$$

where W_0 is the beginning of the week, and W_1 is the time slot 11:30 pm on the last day of the week. The denominator in Definition 6.3.5 do not appear above, as the total production is fixed (modifying consumption times does not change production), and the total consumption of the operation is also fixed, as shifting consumption times does not change the total consumption. The last constraint enforces the fact the number of green periods is not too large. Of course, one may add additional constraints to the optimisation problem, if needed.

Now, even for an omniscient oracle, knowing in advance the consumption of every household, and knowing in advance, and with perfect precision, the solar production, this optimisation problem would be difficult. Indeed, it is non linear in $\mathbf{x}$ (through the computation of the $T_{h,k}^*(u, \mathbf{x})$'s, and through the dependency of the shifted load curves to these shifted times), and there are $2^{h_{\max} p_{\max}}$ possible $\mathbf{x}$. Moreover, to have an omniscient oracle would imply that someone in the operation would know in advance all consumption of the members of the operation, as well as have access to perfect weather forecast. Therefore, such an assumption is highly unrealistic. As a result of these issues, we do not try to solve the optimisation problem directly, but propose an heuristic to compute the allocation variables $x_{h,p}$, which leads to two different coordinators, parameterised by the level of information they need. We evaluate the effectiveness of these coordinators in numerical simulations (see Section 6.5).

6.4.3 Available Shiftable Power Matching Coordinator: Optimizing Household Combinations to Balance Flexible Load and Production Surplus

Each green period is expected to have a certain amount of excess production available for additional consumption. Assume for instance a green period has 2000 Watts of excess production. Ideally, we would like to notify either a household which can shift 2000 Watts of consumption to this period, or two households, each in capacity to shift 1000 Watts. For each household, we call “available shiftable power” the power which the people of the household are willing to shift. The idea is then to match the green periods with a set of households, the sum of the available shiftable power of which matches as closely as possible the excess production in the period.

Definition 6.4.8 (Available shiftable power matching coordinator). *For each household h , for each day d , write m_d^h its available shiftable power. For each day d , let $e_1, \dots, e_{p_d, \max}$ be the forecast excess for the green periods of that day.*

The available shiftable power coordinator takes as inputs the m_d^h 's and the e_p 's, and computes the allocation variables $x_{h,p}$'s solving the minimization problem:

$$\left\{ \begin{array}{l} \arg \min_{\mathbf{x}=\{x_{h,p_d}\}_{h,p_d}} \sum_{p_d=1}^{p_d, \max} \left| \sum_{h=1}^{h_{\max}} m_d^h x_{h,p_d} - e_{p_d} \right|, \\ d = 1, \dots, 7, \\ \sum_{p_d=1}^{p_d, \max} x_{h,p_d} \leq 1, \quad 1 \leq h \leq h_{\max}, \quad d = 1, \dots, 7, \\ \sum_{d=1}^7 \sum_{p_d=1}^{p_d, \max} x_{h,p_d} \leq 4. \end{array} \right.$$

For every detected green period, the coordinator determines the combination of households, the sum of the available shiftable power of which is closest to the excess production of that specific green period. Then, this green period is allocated to the households in the optimal combination. Two constraints are enforced to prevent user fatigue or confusion. Firstly, each household can receive notification of just one green period per day (first set of inequalities). Secondly, each household can be notified of a maximum of four green periods per week (second set of inequalities). As a result, the same green period may be allocated to multiple participants. Nevertheless, an individual participant can only receive one green period per day and a maximum of four green periods per week. Finally, the solutions of the problem may not be unique. In case of equality, we proceed sequentially, and for each day, we select the solution for the day which increases the number of different households to have been allocated green periods. If this is not enough to obtain one unique choice, we select at random among the remaining choices.

Now, the available shiftable power is not known: indeed, we do not know, for each green period, which consumption which household would be willing to shift. As a result, we introduce two proxies with which we estimate this available shiftable power. Each way of estimating it depends on some additional information which we need to collect from the members of the operation. Obtaining finer information is more difficult than obtaining simple information, but we can hope (and we show in the numerical simulations) that it leads to better results. The supplementary information could be acquired thanks to a survey, for instance.

6.4.4 Available Shiftable Power Estimating Coordinators: Three Methods Using Supplementary Household Information

Appliance Type Coordinator. The Appliance type coordinator uses as proxy for the shiftable power of an household, its maximum shiftable power, that is the sum of the maximum power of all shiftable appliances in the household. For example, if a household possesses both a washing machine and a dishwasher, and household people are willing to potentially shift their usage of these devices, the maximum shiftable power would be the sum of the maximum power ratings of the washing machine and the dishwasher. Formally, let $\alpha^{h,k}$ be the maximum power of appliance k of house h . Then, we estimate the available shiftable power of house h by (the “ d ” dependency drops, as the right-hand side is independent of d),

$$\hat{m}_d^h = \hat{m}^h = \sum_{k=1}^{k_{\max}^h} \alpha^{h,k}.$$

Appliance Frequency Coordinator. One drawback of the appliance type coordinator is that the maximum shiftable power of the house may not be a good proxy for the available shiftable power. Assume you only use your washing machine on Mondays. Assume also that a green period is computed on Saturday. Then, the appliance type coordinator uses the power of your washing machine to compute the maximum shiftable power of the household. However, you may not be willing to shift your washing machine consumption by as much as 5 days, leading to suboptimal green periods allocation.

The appliance frequency coordinator attempts to remedy this by taking into account the frequency of usage of shiftable appliances, in its evaluation of the available shiftable power. It estimates the available shiftable power of a house by summing the maximum power of each shiftable appliance, weighted by the frequency at which the appliance is used during the week. Write $f^{h,k}$ the weekly usage frequency of appliance k in household h . If appliance k is activated every day of the week, then $f^{h,k} = 7/7 = 1$, and if it is not used at all during the week, then $f^{h,k} = 0/7 = 0$. As before, $\alpha^{h,k}$ is the

maximum power consumption of appliance k in household h . Define

$$\hat{m}_d^h = \hat{m}^h = \sum_{k=1}^{k_{\max}^h} \alpha^{h,k} f^{h,k}.$$

Note that $\hat{m}_d^h$ equals the value in the appliance type coordinator when all $f^{h,k}$'s equal 1, that is when all appliances are used every day.

Appliance Schedule Coordinator. Despite the Appliance Frequency Coordinator improving the accuracy of maximum power estimations by considering the frequency of usage of shiftable appliances, the specific days on which each shiftable appliance will be activated remain unknown. This leads to potential discrepancies between the estimated and actual maximum power. To address this, a coordinator that takes into account the day of usage could further enhance the accuracy of maximum power estimations.

The Appliance Schedule Coordinator aims to address this by factoring in the day of usage in its estimations of available shiftable power. For each day, it calculates the sum of the shiftable powers of appliances that household members are willing to use on that day. This approach necessitates additional information, which, for example, could be input into the automated system by members of the collective self-consumption operation every Sunday evening. Let $A_d^{h,k}$ denote the coefficient of activation of appliance k in household h for a specific day d . If appliance k is activated on that day, then $A_d^{h,k} = 1$; otherwise, $A_d^{h,k} = 0$. Define

$$\hat{m}_d^h = \hat{m}^h = \sum_{k=1}^{k_{\max}^h} \alpha^{h,k} A_d^{h,k}.$$

Note that $\hat{m}_d^h$ equals the value in the appliance type coordinator when all $A_d^{h,k}$'s equal 1, that is when all appliances are used every day.

6.5 Numerical Simulations: Building and Validating Our Nudging Pipeline in a Simulation Environment

We first describe the set-up of our numerical simulations (Section 6.5.1). Then, we show coordinators are better than a naive strategy (Section 6.5.2), and are efficient with respect to the OMEGAAlpes reference (Section 6.5.3). Finally, we compare their performance based on the information available about the consumption habits of the members of the operation (Section 6.5.4).

6.5.1 Numerical Simulations Set-Up and Configurations

We start by describing the datasets, real and synthetic, we use. Each dataset is used to model one collective self-consumption operation.

Real consumption datasets used. We use two real datasets. The Iris dataset was collected as part of the REMODECE (Residential Monitoring to Decrease Energy Consumption) project (*Mesure de la consommation des usages domestiques de l’audiovisuel et de l’informatique* 2008). The REMODECE project aims at reducing energy consumption in residential buildings, in order to improve energy sustainability. The Iris dataset contains the energy consumption data of 98 European houses, during one year, sampled at a 10 minutes rate.

The IDEAL household energy dataset (Pullinger et al. 2021) covers 255 UK homes, for a duration of 23 months running up to June 2018. It includes detailed electricity, gas, and sensor data. Sensor readings encompass room conditions, boiler temperatures, and detailed appliance usage for some homes. Survey data adds occupant demographics, energy awareness, and building characteristics. This dataset serves applications like energy analysis, building modeling, and load monitoring research. It can be found on the project data-share website, at the url <https://datashare.ed.ac.uk/handle/10283/3647?show=full>.

Real consumption datasets preparation. We do the following preprocessing on both datasets.

1. **Appliance Selection.** We classify as "shiftable" a subset of the electrical appliances present in the dataset. We fix the maximum shifting delay for these appliances to the same values as Ling et al. (2023) (see Table 6.2).
2. **Household Selection.** We construct a collective self-consumption operation by selecting a subset of the houses available in the dataset, containing houses with the most shiftable appliances. We detail in Appendix K the houses selected, as well as the shiftable appliances in them.
3. **"Shiftable" appliances addition.** In our analysis, we observed that the buildings in the Iris and IDEAL datasets exhibit limited energy flexibility, as indicated by the ratio of total shiftable energy outside of solar hours to total energy, detailed in Appendix K. To enhance the flexibility potential, we augmented each building in the IDEAL dataset with a water heater profile that activates in the evening at random frequencies. Similarly, for each building in the Iris dataset, we introduced an electric vehicle charging profile with random activation frequencies during the evening hours.

Synthetic consumption data preparation. We construct synthetic operations Syn

as follows. Again, choices like the types of shiftable appliances in each house are described in Appendix K.

1. **Base, not shiftable, consumption pattern.** We use as base, not shiftable, consumption pattern, the fixed consumption part of one house of the Iris dataset.
2. **Number of households.** We duplicate this profile a fixed number of times, to obtain several houses.
3. **Shiftable parts.** We add different shiftable appliances to each house. We then add different appliance usages, randomly, to model in a realist way the different consumption habits of the different households. For instance, one household may use the washing machine 3 times in a week, and 0 time in another week.

Information needed by the coordinators. We extract the additional information (maximum power, number of weekly usages of appliances) required by the coordinators from the datasets. In real-life, they could be obtained through surveys of the members, for instance.

Solar energy production. To simulate solar energy production, we use the same model that was used in Chapter 5. This model first computes a sunshine coefficient taking into account the time of day, the month of year, and the amount of clouds. A Markov Chain simulates the changes in cloud coverage. Then, the solar production of the panels is estimated by multiplying this coefficient, renormalised to $(0, 1)$, by the maximum capacity of the panels. The maximum capacity has been manually set for each operation as follows: 130 kW for Iris, 50 kW for IDEAL, and 26,6 kW for Syn.

Lower-bound benchmark. We use as lower-bound benchmark the case where there are no nudges, therefore no shift in consumption. We call it “reference” in the plots.

Using OMEGAlpes as an upper-bound benchmark. To get an upper-bound benchmark, we use the OMEGAlpes modelling tool (Hodencq et al. 2021). It is a linear optimisation energy systems modelling tool, which computes the best possible shifting of the consumption. Therefore, it computes ideal scenarios. We describe the way OMEGAlpes computes its solution in Appendix L. However, it is not usable in real world situations, as it uses complete knowledge of the consumption, and production, of the households, to compute its solution. Moreover, OMEGAlpes performs arbitrarily many and complex consumption shifts. For instance, it can move several appliance usages of an household to different periods, and perform many such moves. That, together with the perfect knowledge of the situation it has, makes its performances much better than those of our algorithms.

We still use it as a benchmark, as it represents a sound, well-defined, ideal solution. In what follows, we refer to this version as Optimistic OMEGAlpes. However, we also

use a tweaked version, to provide a more realistic ideal case. We call this version Realistic OMEGAlpes. To compute the Realistic OMEGAlpes solution, for each household, we apply the four best shifts performed by Optimistic OMEGAlpes. Therefore, this tweaked version respects the bound in the number of green periods by household our algorithms also respect, and is more realistic in that regard.

Simulation. The simulations run over one month. Since the production generation is stochastic, we perform 50 runs for each setting. The simulations are executed in the computation server of G2ELAB (48 cores at 2.4GHz / 96 logical processors – threads, 256 Go of memory, NVIDIA RTX6000 GPU with 24 GB of memory). The OMEGAlpes optimization is the computation-intensive part of the process, involving 243 variables and 516 constraints for a single day’s optimization for the CSC from Iris, sampled at 2-hour intervals. The complexity arises because the number of possible shifts OMEGAlpes considers grows exponentially with the number of households and the data length (day, frequency). This exponential growth occurs because each candidate shift for each household must be evaluated in relation to all other candidate shifts of the other households.

Metrics displayed. We display the self-consumption rate of the collective self-consumption operations, under the different configurations, averaged over all the runs done for these simulations. In each table, for each column, we display in bold the best metric.

6.5.2 The Appliance Frequency Coordinator Outperforms the Naive Strategy

Table 6.3 Mean Self-Consumption Rate, Efficiency of Coordinators

Green Periods Finder	Coordinator	Syn Mean(%)	Iris Mean(%)	IDEAL Mean(%)
No	No	64.19	67.05	73.3
Load Forecasting	Uniform	72.65	73.88	74.5
	App Frequency	75.82	84.78	87.17

In Table 6.3, we compare the mean self-consumption rates in the reference case (no coordination), in the case with the Uniform coordinator, and in the case with the appliance frequency coordinator, for the Syn, Iris and IDEAL datasets. Both algorithms (uniform and appliance frequency) enhance the self-consumption rate with respect to the reference case, increasing it from 64.19%, to 72.65% (uniform coordinator), or to 75.82% (appliance frequency coordinator), in the case of Syn for instance. We see that the appliance frequency coordinator leads to better improvements in the self-consumption rate,

when compared to the uniform coordinator. This enhanced performance is consistent across all the datasets, underscoring the value and efficiency of utilizing the appliance frequency coordinator to optimize self-consumption rates, compared to the “naive” uniform strategy.

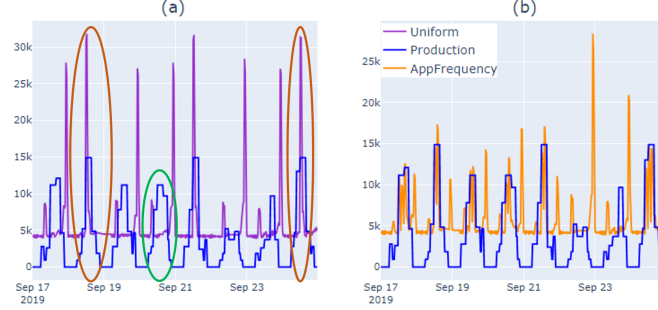


Fig. 6.2 Self-Consumption Rates Obtained in the Reference Case, and When Forecasting Green Periods Using the Uniform (a) and Frequency (b) Coordinators. Production Curves Are in Blue, While Consumption Curves Are in Dark Orchid (Uniform Coordinator) and Dark Orange (Appliance Frequency Coordinator).

In Figure 6.2, in scenario (a), we show that the uniform coordinator, which sends identical nudges to all households within the collective self-consumption operation, leads to issues where consumption outgrows excess production (as indicated by the red circles in the figure for scenario (a).). This happens due to all households shifting their shiftable appliances usages to the same green periods. Moreover, excess production remains (as indicated by the black circle in the figure for scenario (a).). However, using the appliance frequency coordinator (scenario (b)) successfully addresses these issues: consumption outgrows excess production much less than in scenario (a), and all the excess production available is effectively used. This further emphasizes the efficiency of the appliance frequency coordinator, with respect to the naive strategy.

6.5.3 Efficiency of Coordinators: the Performance of the Appliance Frequency Coordinator is Close to the Realistic Optimal Reference

In Table 6.4, we compare the appliance frequency coordinator performance to those of Optimistic, and Realistic, OMEGAlpes. The simulations are conducted for the Syn, IDEAL and Iris datasets. The appliance frequency coordinator achieves a 75.82% self-consumption rate for Syn, 87.17% for IDEAL, and about 84.78% for Iris. While our coordinator has lesser performances than Optimistic OMEGAlpes, it still realizes a significant portion of its performance. Moreover, our coordinator performs comparably to the Realistic OMEGAlpes version, which is much more realistic than the Optimistic one. Specifically, for Syn, our coordinator performance is very close to the 77.23% performance of Realistic OMEGAlpes, and likewise for IDEAL. In the case of Iris, the performance of our coordinator is only 3 percentage points less than the 87.22% of Re-

alistic OMEGAlpes. Therefore, the appliance frequency coordinator proves efficient, with respect to the OMEGAlpes upper-bounds.

Table 6.4 Mean Self-Consumption Rate with Various Datasets for OMEGAlpes and the Appliance Frequency Coordinator

Green Periods Finder	Coordinator	Syn Mean(%)	IDEAL : Mean(%)	Iris Mean(%)
No	No	64.19	69.4	67.05
Load Forecasting	App Frequency	75.82	87.17	84.78
	Realistic OMEGAlpes	77.23	87.94	87.22
	Optimistic OMEGAlpes	91.18	96.83	96.89

6.5.4 The Impact of Available Information on Coordinator Performance

Table 6.5 Mean Self-Consumption Rate with Various Coordinators

Green Periods Finder	Coordinator	Syn : Mean(%)	IDEAL : Mean(%)	Iris : Mean(%)
	Uniform	72.65	77.84	73.88
Load Forecasting	App Type	74.64	83.3	80.58
	App	75.82	87.17	84.78
	Frequency			
	App Schedule	76.26	88.24	85.4

In Table 6.5, we compare the performances of the tree available power matching coordinators, in order to evaluate the impact the information has on their performances. Recall that the Appliance Schedule Coordinator utilizes more detailed information compared to the Appliance Frequency Coordinator, and the Appliance Frequency Coordinator employs more detailed information than the Appliance Type Coordinator. The appliance type coordinator outperforms the uniform coordinator, which operates without any additional information. The improvement in performance ranges from 2% (as observed in simulations on Syn) to approximately 6% (as observed in simulations on Iris). Moreover, the Appliance Frequency Coordinator achieves an additional performance gain over the Appliance Type Coordinator, ranging from 1% (in Syn simulations) to 4% (in simulations on Iris and IDEAL). Additionally, the Appliance Schedule Coordinator exhibits further performance enhancements over the Appliance Frequency Coordinator, ranging from 0.44% (in Syn) to 1.07% (in IDEAL simulations). This shows the value of precise information in enhancing the efficacy of power matching coordinators.

However, compared to the improvements made by the appliance frequency coordinator over the appliance type coordinator, the enhancement provided by the appliance schedule coordinator over the appliance frequency coordinator appears to be minimal, with a maximum increase of only 1%. We believe this is because the coordination by the appliance frequency is already sufficiently effective. The results in Section 6.5.3, Table 6.4, demonstrate that the appliance frequency is already closely aligned with the Realistic OMEGAAlpes reference, indicating that there is limited scope for further increasing the self-consumption rate. Therefore, it is reasonable that the appliance schedule has not achieved a significant improvement. Additionally, acquiring the supplementary information required for the appliance schedule presents a considerable challenge; recall that the appliance frequency only requires the weekly operating frequency of the appliances, whereas the appliance schedule necessitates a precise operation plan for each shiftable appliance for the upcoming week. If we were to gather this information through user surveys, the complexity of the data needed for the appliance schedule would be several times greater than that for the appliance frequency, yet without a corresponding increase in performance.

6.6 Conclusion, Discussion

In a simulated environment using semi-real data, we have demonstrated the efficiency of our ICT nudging pipelines, using available real-world information, in enhancing collective self-consumption rates in a collective self-consumption operation. Our research has underscored the importance of using coordinators to manage the notification of consumption favourable periods to the members of the operation. Using coordinators not only leads to greater improvements in self-consumption when compared to scenarios without coordinators, but also effectively addresses the excess consumption issue that may arise when an uniform notification strategy is applied. We have shown the performance of coordinators increase with the amount of information they have about user consumption habits. Overall, our study has shown the efficiency of the coordinators, based on matching an estimation of the available shiftable power, with the forecasted excess, in improving the self-consumption rate of a collective self-consumption operation.

We identify two key limitations of our results, inherited from the previous work Chapter 5. The first limitation comes from the fact the model of human behaviour we use is idealised: each member does all they can to respond to green periods. However, in real-world situations, individuals may exhibit varying behaviors when receiving nudges. Therefore, future research endeavors should focus on estimating user compliance rates when receiving nudges and devising strategies to enhance this compliance rate. The second limitation relates to our load forecasting model, specifically concern-

ing the energy and weather forecasting modules. We employed a simple energy forecasting module, which may need enhancements to be used in real-world simulations. Fortunately, the literature offers numerous advanced models that we can be considered for this purpose, especially ensemble models. These models aggregate forecasts from multiple sources, constructing a more reliable prediction than relying on single models on their own. However, even state-of-the-art weather forecasts can exhibit inaccuracies, especially when predicting several days ahead. Prediction errors in energy usage and weather conditions can potentially result in incorrect information regarding green periods. Such inaccuracies may lead to suboptimal consumption shifts by users and could discourage their continued engagement with the project.

We would also like to note that the coordinator that yields the highest improvement in self-consumption rates may not always be the optimal choice. Indeed, we should take into account user comfort, which may be at odds with providing all the information our more involved coordinators require. Collecting the information about the maximal power of the shiftable appliances of users may require a yearly survey (provided they do not change appliances more often), and likewise for collecting information about the frequency at which they use their shiftable appliances. In addition, if the information submitted by the user does not match their actual behavior, it will reduce the performance of the coordinator. For example, a customer may say they use their washing machine twice a week, but in fact, use it a different number of times every week. As a result, the appliances frequency coordinator will use wrong inputs for its computations, resulting in a drop in advice quality. Efforts should be paid to making the sending of information from users as seamless as possible. Moreover, users will be all the more likely to actively participate in the project and provide the information required for its optimal functioning, if they see clear benefits in doing so.

We also tried a coordinator which used information about the exact days of the week the households intended to use their appliances on, but performance did not increase significantly with respect to the appliance frequency coordinator. On the other hand, collecting such detailed information represents a very high cost for the users. This shows that usage frequency data is already very informative, as far as making efficient coordinators is concerned.

In addition, notifying users of too many green periods may give them the feeling of being overwhelmed, making it challenging for them to respond effectively to the nudges. This is why we considered notifying users of a most 4 green periods per week. Overall, a well-balanced approach that considers both energy efficiency and user comfort is crucial when selecting the most suitable coordinator for a collective self-consumption system.

We plan to advance our research by implementing and testing our nudging pipelines

in real-world scenarios. However, evaluating their impact in real-life testing poses a significant challenge, as we lack reference data for comparison. Therefore, determining how to effectively assess the impact of our nudges will require specific work. We think of two possible approaches. One approach is to identify a similar collective self-consumption group that does not receive nudges, serving as a control group. By comparing the consumption patterns and outcomes of the group receiving nudges with those of the control group, we can assess the impact of the nudges program. Another method involves comparing the consumption data of individual households before and after they start receiving nudges. This allows us to evaluate whether there are notable changes in consumption behavior when households are exposed to the nudge program. Additionally, gathering feedback and conducting surveys with users who have experienced the nudge program can offer qualitative insights into its perceived effectiveness and any behavioral changes they may have noticed. Incorporating these evaluation methods can help us establish a robust framework for assessing the real-world impact of our nudging system, despite the absence of reference data.

CHAPTER 7

Appliance Level Coordination through Nudges to Improve Self-Consumption in an Energy Community

Abstract: We try to maximise the self-consumption of an energy community endowed with solar panels. We extend the nudging pipeline introduced in Chapter 6. The pipeline first forecasts periods of available excess production, then selectively notifies the households of the community about these periods, to encourage them to consume energy during these periods. The notification logic is performed by a coordinator module. In Chapter 6, the coordinator estimates flexibility at household level. In our work, we do it at appliance level, which offers a finer level of control. The efficiency of our approach is assessed through numerical simulations using semi-real data derived from public consumption datasets. Results show that the appliance-level coordinator outperforms household-level coordinator when notification numbers are unrestricted but loses human comfort. Our results suggest that, to take advantage of the coordinator working at appliance level, appliances should be endowed with automated devices able to activate them upon reception of a signal.

This chapter is mainly copied from (Ling, Massé, Rhiet and Frederic 2024). We have removed the related works section in this chapter, as it is comprehensively covered in the general related works presented Chapter 2. Additionally, we have excluded the experiment setup, as it remains consistent with that described in Chapter 6.

7.1 Introduction: Refined Appliance-Level Nudging Pipeline to Enhance Solar Power Efficiency in Energy Communities

Improving the energy consumption of buildings is important, both from an economical standpoint, and from an ecological one. Indeed, buildings are estimated to represent as much as 38% of green house gases emissions United Nations Environment Programme (2020). One possibility in this regard is endowing the building with solar panels, using for instance available space on the roof. This way, some part of the energy consumption may be drawn from the panels, rather than from the regular network, which energy may derive from less ecologically friendly sources.

In addition to individual buildings having solar panels for their own consumption, and ever increasing trope is now for several buildings to gather into an energy community, and share the energy produced by the panels. This is made possible by legislation European Commission (2019). In France, this type of energy communities is called an “autoconsommation collective” (collective self-consumption) Légifrance (2023).

Now, to truly benefit from the panels, one may overcome two issues. The first is the intermittence of production (as the panels will only produce under daylight). The second is the necessity to coordinate with other members of the community. Indeed, if everybody consumes energy at the same time, the capacity of the panels may be outgrown, and the excess demand will be atoned for by the regular network.

In Chapter 6, we introduced a nudging system which aimed at helping members of a collective self-consumption operation consume energy at appropriate moments. The system first predicted periods where users should be encouraged to consume (so called “green periods”). These periods were then selectively notified to the users in the form of nudges, through a coordinator module, which in particular aimed at avoiding having everybody consume during the same periods.

This coordinator module was based on a household level estimation of the flexibility available, that is the sum of the power of the appliances the members of the household are willing to use at different times than they first intended. However, this estimation of the flexibility was quite coarse. Here, we present a finer coordinator, which works at appliance level, and estimates flexibility on an appliance basis. It notifies households about which shiftable appliance it suggests to use during which green period. Through the finer coordination it offers, it enables a more precise allocation of solar power and enhances further the efficiency of energy consumption across the network.

We first present our model (Section 7.2). Then we present our experimental results (Section 7.3). Finally, we conclude, and discuss our results (Section 7.4).

7.2 Model Overview

We use the same framework introduced in Chapter 6, in which we introduce a new coordinator. The framework introduced in Chapter 6 uses a coordinator that operates at the household level. This coordinator sends nudges with information about consumption favourable periods, referred to as “green periods”, encouraging households to shift all their flexible loads to these times. This approach is somewhat coarse.

In the revised framework, a new coordinator is introduced that operates at the appliance level. This coordinator offers specific recommendations for each shiftable appliance across all households, identifying the optimal green period for their operation.

We start by briefly presenting our model in Section 7.2.1. For more detailed and comprehensive insights, we refer readers to Chapter 6. Then, we introduce the appliance

level coordinator in Section 7.2.2.

7.2.1 Review of the Nudging Pipeline from Chapter 6

On Figure 7.1, we give an overview of our nudging pipeline. Our collective self-consumption framework integrates multiple households, several of which may possess solar panels. Each household has a smart meter, allowing for the collection of energy consumption and production data. There is no battery, thus making it impossible to store electricity for later use. Each household possesses several electrical appliances, which are categorized into shiftable and non-shiftable categories. Shiftable appliances refer to those which usage times the users are willing to adjust upon receiving a recommendations. Every shiftable appliance has a maximum shiftable delay: for instance, a washing-machine usage cannot be shifted to a time slot more than 9 hours (For more details, see Table 6.2 in Section 6.3.2 of Chapter 6) from the original desired time slot.

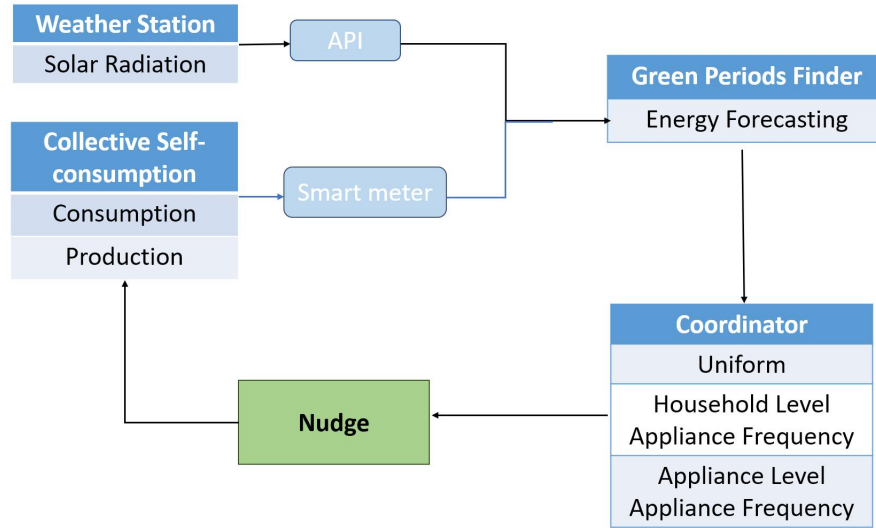


Fig. 7.1 Nudging Pipeline: Introduction of a Coordinator at the Appliance Level

This system obtains accurate weather forecasts via APIs, which inform the operation of two key control modules. The “Green Period Finder” module utilizes a statistical energy forecasting algorithm, as introduced in Chapter 5, to identify optimal usage times, called “green periods”, for electrical appliances, based on available data. The coordinator module then distributes these green periods among households according to rules aimed at maximizing environmental and efficiency benefits (maximizing the operation self-consumption rate). Finally, households adjust their shiftable energy usage in response to these nudges, optimizing consumption and contributing to the collective goal of sustainable energy use.

7.2.2 Coordinator: Definition and Mathematical Modeling of the Appliance-Level Coordination Problem

Once we have identified green periods, we need to notify them to the households of the collective self-consumption operation. We call coordinator the module responsible for constructing the notifications: it decides which household it notifies about which green periods. The easiest type of coordinator is one that shares the best green periods with every household the same way. We call this the "uniform coordinator," as in Chapter 6.

For each household h and for each appliance k , write $\alpha^{h,k}$ the maximum power of appliance k within household h . Write $f^{h,k}$ the weekly usage frequency of appliance k in household h . If appliance k is activated every day of the week, then $f^{h,k} = 7/7 = 1$, and if it is not used at all during the week, then $f^{h,k} = 0/7 = 0$. We evaluate the maximum shiftable available power of appliance k of household h , $\hat{m}^{h,k}$, by weighting the maximum power by the frequency at which the appliance is used during the week. Therefore, we have

$$\hat{m}^{h,k} = \alpha^{h,k} f^{h,k}.$$

Estimating $\hat{m}^{h,k}$ relies on gathering data which is acquired through engaging with the members of the operation by conducting surveys, for instance. While collecting detailed information presents more challenges than acquiring basic data, our numerical simulations demonstrate that this approach can significantly enhance the coordination outcomes.

Then, in each green period, we match the forecast excess of the period with a combination of appliances which total shiftable power is as close as possible to this excess, in order to fully use the excess power available during it. The goal is to match the power of shiftable appliances as closely as possible to the excess power available. For instance, assume a green period is predicted to have 2000 Watts available during it. We could suggest to shift a single appliance requiring the full 2000 Watts or two appliances from the same or different households shifting 1000 Watts each, aiming for the most efficient use of flexibility across all households. The allocation of periods to the households, with information about the appliances concerned, is computed by the appliance frequency coordinator at appliance level, which we now define.

Definition 7.2.9 (Appliance Frequency Coordinator at Appliance Level). *For each day d , let $e_1, \dots, e_{p_{d,\max}}$ be the forecast excess for the green periods of that day. For each day, let $x_{h,k,p}$ equal 1 if green period e_p is sent to household h for shifting appliance k ,*

and 0 otherwise. The $x_{h,k,p}$'s solve the minimization problem:

$$\left\{ \begin{array}{l} \arg \min_{\mathbf{x}=\{x_{h,k,p_d}\}_{h,k,p_d}} \sum_{p_d=1}^{p_{d,\max}} \left| \sum_{h=1}^{h_{\max}} \sum_{k=1}^{k_{\max}} \hat{m}^{h,k} x_{h,k,p_d} - e_{p_d} \right|, \\ d = 1, \dots, 7, \\ \sum_{p_d=1}^{p_{d,\max}} x_{h,k,p_d} \leq 1, 1 \leq h \leq h_{\max}, 1 \leq k \leq k_{\max}, d = 1, \dots, 7, \\ \sum_{d=1}^7 \sum_{p_d=1}^{p_{d,\max}} \sum_{k=1}^{k_{\max}} x_{h,k,p_d} \leq 4. \end{array} \right.$$

This differs from the appliance frequency coordinator in Chapter 6 in that the allocation variables also depend on the appliances (through the k index), while in Chapter 6, the allocation variables only depended on the households (and the green periods), leading to coarser information sent to the members of the operation. The shiftable power was estimated globally for each house, while we estimate it appliance by appliance.

A household may receive multiple green periods in one day, and several households can share the same green period. However, an appliance within a household is limited to one green period per day (first set of inequalities), and households are restricted to a maximum of four green period notifications each week to prevent user fatigue (second set of inequalities). If multiple appliances in a household are assigned the same green period, it counts as a single allocation. Solutions to assigning green periods may vary; in cases of identical outcomes, priority is given to solutions that spread green periods across a wider range of households. If a single solution still isn't achieved, a random selection is made from the remaining options.

7.3 Numerical Experiments

In this chapter, we use the exact same experimental setup as presented in Chapter 6, including the dataset, metrics, simulation environment, and reference benchmark. For more details, we refer the reader to Section 6.5.1 of Chapter 6; here, we will only present the results.

7.3.1 The Appliance Level Coordinator is Better than the Naive Household-Level Uniform Coordinator

We start by conducting a basic sanity-check. We compare the performance of the appliance-level coordinator against both the reference case (no nudges) and the naive household-level coordinator, which sends the same best green periods to all households. We show the results in Table 7.1.

Our results show the following.

Table 7.1 Average Self-Consumption Rate, Efficiency of Coordinators

Coordinator	Level	Syn Mean(%)	Iris Mean(%)	IDEAL Mean(%)
No	No	64.19	67.05	69.41
Uniform	Household	72.65	73.88	77.84
App Frequency	Appliance	74.5	82.9	86.83

- Both the household level uniform coordinator and the appliance-level coordinator improve the self-consumption rate compared to the reference case. Specifically, for the IDEAL dataset, the self-consumption rate increases from 69.41% to 77.84% with the Uniform Coordinator, and further to 86.83% with the Appliance Frequency Coordinator.
- The appliance-level coordinator consistently achieves superior enhancements in self-consumption rates across all datasets. Notably, there is an approximate 9% improvement in self-consumption when using the Appliance Frequency Coordinator at the appliance level compared to the Uniform Coordinator case for the IDEAL dataset. Across all datasets, the average self-consumption rate achieved by the Appliance Frequency Coordinator surpasses that of the Uniform Coordinator. The Appliance Frequency Coordinator utilizes more detailed information, while the Uniform Coordinator operates without any supplementary information. This indicates that the inclusion of precise, additional information significantly enhances the effectiveness of coordinators.

7.3.2 Optimal Performance of the Appliance-Level Coordinator Compared to the Household-Level One when Ignoring Human Comfort

We now compare the appliance frequency coordinator at appliance level to the appliance frequency coordinator at household level introduced in Ling, Massé, Rihet and Wurtz (2024). Moreover, we eliminate the constraints on the number of the weekly notifications of green periods (see next section for results when the constraints are on). Note that sending too many notifications may lead to user fatigue. Table 7.2 presents the self-consumption rates achieved under this scenario. We see that, on both the Syn and the IDEAL datasets, the coordinator at the appliance level outperforms its analogue at the household level. However, this is not the case on the Iris dataset. Theoretically, we expect coordinators functioning at the appliance level to provide finer control than those at the household level, leading to improved self-consumption rates compared to household-level coordinators. However, this should be qualified by the uncertainty about appliance usages (we only have imperfect information about those). Coordinating at the appliance level amplifies regulation complexity, and when combined with uncertainty, it may reduce the accuracy of adjustments. However, considering the overall

simulation results, the performance of appliance-level coordinators, without restrictions on the number of notifications, exceeds that of household-level coordinators, showing the interest of the approach.

Table 7.2 Average self consumption rate, Appliance-Level Coordinators vs Household-Level Coordinators When Ignoring Human Comfort

Coordinator	Level	Syn Mean(%)	Iris Mean(%)	IDEAL Mean(%)
App Frequency	Appliance	78.85	84.62	89.46
	Household	77.74	84.93	88.1

7.3.3 Suboptimal Performance of the Appliance-Level Coordinator Compared to the Household-Level One when Considering Human Comfort

We now turn back on the constraint limiting the number of notifications an household can receive each week, so as to prevent user fatigue. We show the results in Table 7.3. We see that the coordinator operating at the household level outperforms the one operating at the appliance level. At the household level, when a household receives a nudge, it will shift all shiftable appliances to the green periods indicated in the nudge. However, for the appliance-level coordinator, a green period notification may be sent for only one appliance. Therefore, finer coordination at the appliance level may require a greater number of green period notifications within a single nudge to achieve the same quantity of shiftable power as household-level coordination. This suggests that the effectiveness of appliance-level coordination is inherently limited by the restriction on the number of green period notifications that can be issued, hindering its potential to enhance self-consumption rates effectively. On the other hand, one could resort to automated piloting of their appliances, so as to fully benefit from the finer control of the appliance level coordinator, while avoiding the user fatigue issue. We expand on this in the discussion.

Table 7.3 Average self consumption rate, Appliance-Level Coordinators vs Household-Level Coordinators when Taking into Account Human Comfort

Coordinator	Level	Syn Mean(%)	Iris Mean(%)	IDEAL Mean(%)
App Frequency	Appliance	74.5	82.9	86.83
	Household	75.73	84.78	87.17

7.4 Conclusion, Discussion

In this study, we assessed the efficiency of our appliance-level coordinator, and in particular compared it to the analogue household-level coordinator from Ling, Massé, Ri-het and Wurtz (2024). We considered situations with constrained or not number of

notifications sent to the user. We used semi-real data supplemented by available real-world information. Our results show the appliance level coordinator is superior to the household level naive strategy. They also show that, in scenarios where any number of notifications may be sent, the appliance level coordinator is in general better than the household-level one. However, in scenarios where human comfort is taken in to account through a limitation of the number of notifications that can be sent to households, the appliance level coordination strategy proves inferior to the household level one.

Therefore, our results suggest that, to fully benefit from the finer control allowed by the appliance level coordinator, one should equip their shiftable appliances with suitable devices, such as home automation technologies like domotics, able to activate the appliances upon reception of notifications from our pipeline. This automated approach, however, necessitates additional installations, like smart plugs or meters. While offering improved energy efficiency and convenience, this shift to automation involves higher initial costs for purchasing and installing these devices. Moreover, not every consumer might welcome the need for such technological upgrades, due to concerns over costs, complexity, ecology and privacy. To show the worth of the upfront investment required, and overcome additional consumer reluctance, a detailed cost-benefits analysis should be conducted, which is an interesting direction of future research.

Our goal is to implement our solution in real-world environments. We face similar limitations as those discussed in Chapter 5 and Chapter 6. The first limitation relates to actual customer behavior, and the second concerns the accuracy of load forecasting. For more detailed information, we refer the reader to the conclusion of Chapter 6.

In our study, we have only focused on the self-consumption rate. However, several other aspects of the collective self-consumption system, including its economic, environmental, and integration (into existing power networks) challenges, should be assessed to get a full picture of the advantages, and drawbacks, entailed. While studying these aspects is beyond the scope of our work, let us point the interested reader to relevant literature. First, let us start with economic and environmental questions. Canova et al. (2022) discuss the evaluation of energy, economic, and environmental impacts of a renewable energy-based collective self-consumption model for multi-family residential buildings in Italy, revealing cost savings of up to 32%, and potential carbon emissions reduction of 60%. Reis et al. (2022) detail how collective self-consumption initiatives, utilizing metering systems and optimization strategies, can be implemented in multi-family buildings to improve energy management. Their study, based on a case in Coimbra, Portugal, using fixed-size photovoltaic and storage units, shows that even without integrating heat pumps, energy costs could be reduced by approximately 17%. As far as integration within the existing power networks is concerned, Brouwer et al. (2014) outline the anticipated shift in the Organisation for Economic Co-operation and

Development(OECD)*About the OECD* (n.d.) countries towards low-carbon electricity systems, focusing on the integration of Intermittent Renewable Energy Sources (IRES) such as wind and solar, along with thermal generators; it discusses the need for increased flexibility in power systems to accommodate this shift, the impact of IRES on system stability and thermal generator efficiency, and the direct costs associated with reserve increases due to IRES integration. It highlights the need for a comprehensive power system model that includes novel flexibility technologies. Kaushik et al. (2022) discuss the challenges that variable renewable energy (VRE) presents to power system operations, particularly as VRE penetration exceeds 80%. The authors highlight the need for long-term energy storage and flexibility, and conduct a detailed uncertainty analysis to ensure the stable functioning of power system networks with a high share of VRE. Finally, Erdiwansyah et al. (2021) give a critical review about the challenges and potential solutions related to the IRES into power systems, emphasizing the importance of developing a matrix to categorize technological solutions, which could facilitate the reduction of challenges and enhance cost-effective energy integration.

CHAPTER 8

General Conclusions and Perspectives

Collective self-consumption is a crucial element of the energy transition, significantly improving energy utilization and sharing. The intermittent nature of renewable energy sources, however, results in misalignments between consumption and production. This misalignment can result in surplus energy being fed into the grid, where a portion is inevitably lost, thus reducing the efficiency of renewable energy use. An effective approach is required to share the energy produced more efficiently and increase the rate of self-consumption within collective self-consumption systems, ultimately optimizing the utilization of renewable energy.

Energy flexibility is a key solution to address these challenges. In this thesis, we have made several efforts to assess energy flexibility and to use this knowledge to optimize collective self-consumption systems. We will present a summary and a conclusion for each chapter of the thesis in Section 8.1, followed by a review of the limitations of our research in Section 8.2, and conclude with perspectives for future research in Section 8.3.

8.1 Research Findings on Optimizing Collective Self-Consumption Systems

8.1.1 Chapter 1: Introduction - Designing Digital Solutions for Aligning Local Consumption with Renewable Energy Production in Collective Self-Consumption Systems

In this introductory chapter, we have outlined the primary theme of the dissertation, delved into our central research question, and provided a comprehensive overview of collective self-consumption as a pivotal element in the energy transition. We have identified the self-consumption rate as a key metric for assessing these systems. We have discussed how achieving high self-consumption rates is a significant challenge, due to the intermittent nature of renewable energy sources.

We have also articulated the main research problem:

How can the self-consumption rate be maximized within a self-consumption system?

In response, we have proposed energy flexibility as a primary solution, emphasizing a human-in-the-loop approach to enhance indirect energy flexibility. This approach integrates inclusiveness and environmental sustainability concerns, essential for optimizing self-consumption.

As we transition into the main body of the dissertation, we explore these strategies in depth. The subsequent chapters delve into our nudging pipeline strategy, which begins by forecasting energy consumption and production. We then employ both non-intrusive (Strategy 1) and intrusive (Strategy 2) techniques to identify flexible portions of the forecasted consumption. Subsequently, through a recommendation service, users receive suggestions to shift their flexible energy consumption to times of surplus production, optimizing both energy use and cost-efficiency. Employing these methodologies, this research aims to provide actionable insights and develop robust strategies that effectively address the challenges of maximizing self-consumption within the context of the energy transition.

8.1.2 Chapter 2: Maximizing the Self-Consumption Rate in a Collective Self-Consumption System via Energy Flexibility - A State of the Art review of key Pillars

This chapter has provided a comprehensive overview of advanced techniques for enhancing energy flexibility, crucial for integrating renewable energy sources into modern energy systems. We explored energy storage systems, highlighting their utility in mitigating the intermittent nature of renewable energy production by storing surplus energy for later use. In our discussion of demand response (DR) technologies, we elaborated on their role in directly controlling the usage times of flexible appliances, or signaling to adjust them, which helps align energy consumption with production. Despite their benefits, we recognized the limitations of traditional DR algorithms, leading us to turn to the nudge approach. This behavioral economics approach is proposed as a more effective alternative, designed to subtly influence consumer behavior to achieve better synchronization between demand and supply.

Furthermore, we reviewed essential supporting technologies such as load forecasting and energy systems optimization, which are extensively used in energy management. We also examined non-intrusive load monitoring (NILM) and identified its limitations in the context of our research. The current NILM outcomes do not sufficiently support our research due to a lack of performance tests under ultra-low frequency conditions, specifically 30-minute intervals. This underscores the need for further rigorous testing of NILM performance within our specific research context.

8.1.3 Chapter 3: Non Intrusive Nudging Strategy part 1 - Trying to Disaggregate Real Data

This chapter underscores the crucial role of Non-Intrusive Load Monitoring (NILM) in our approach to identify energy flexibility through a non intrusive approach. Given the inherent limitations of real-world environments, NILM technologies must operate under challenging conditions such as ultra-low frequency intervals (30 minutes). The frequent absence of detailed, appliance-specific data necessary for model training in practical settings necessitates pretraining NILM models on comprehensive datasets before applying them in real-world scenarios. These constraints frame the central question of this chapter:

How do NILM technologies perform under ultra-low frequency conditions, and how well can they be transferred across different environments?

Our experiments with the open-sourced Seq2subseq algorithms indicate limited overall performance, with accuracy notably declining at 30-minute intervals. While some models demonstrate adaptability to different datasets, the majority face significant challenges in transferability under these conditions, presenting substantial hurdles for real-world implementation.

8.1.4 Chapter 4: Non-Intrusive Strategy Part 2 - Identifying Data Suitable for Accurate Disaggregation

Despite generally poor results, disaggregation models showed notable successes in specific tests, highlighting a critical issue: the real-world applicability of pretrained disaggregation models remains uncertain. These constraints frame the central question of this chapter:

Can pretrained models be effectively applied in real-world scenarios given the lack of detailed appliance-level data for verification?

To address this, we propose training a classifier to automatically determine whether a pretrained model can successfully disaggregate a given household's energy consumption. Households where disaggregation is feasible are labeled as class 1, and those where it is not, as class 0.

Our results indicate that the classifier performs effectively across scenarios at a 10-minute frequency. This means that, given a new household, we can determine whether a pretrained disaggregation model can be effectively applied to that household under the 10-minute frequency condition. Furthermore, we identified that classifiers trained with heuristic features, which include appliance type information, perform better than those trained with other feature sets, such as statistical features.

However, under the 30-minute frequency condition, many models only perform poorly, leading to all buildings being labeled as class 0. This results in the classifier being unable to learn from these cases effectively. To address this, we need to increase our dataset to identify more instances of the other class. Due to the lack of additional data for such research and concerns about the cumulative errors propagated through multiple algorithms, we ultimately decided to abandon the use of NILM technology.

8.1.5 Chapter 5: Enhancing Energy Self-Consumption in Individual Residential Buildings through Information and Communication Technology Nudging Pipelines

This chapter has presented a revised approach to enhancing energy self-consumption through simplified nudging pipelines, addressing the limitations faced by Non-Intrusive Load Monitoring (NILM) in real-world applications. By shifting our focus to using prediction modules for informing residents about optimal consumption times without causing user fatigue and confusion, we enable individual decision-making that aligns consumption with local energy production without the need to identify and optimize energy flexibility.

The central question addressed in this chapter is:

How can we best identify consumption-favourable periods to help households align their consumption with solar production while keeping the information comprehensive and limited?

To this end, we conducted several simulations using semi-real data from the Iris and AMPds datasets, demonstrating several key findings:

- **Efficiency with Limited Information:** Even with scarce information and few labeled periods, significant consumption improvements were achieved, validating the effectiveness of our ICT nudging pipelines in individual self-consumption systems.
- **Superiority of Load Forecasting:** Load-forecasting based nudging pipelines consistently outperformed those based solely on weather forecasts, particularly in scenarios where maximum solar production does not coincide with excess production periods.
- **Optimal Production Sweet Spot:** We identified a production sweet spot where nudging is most efficient. Nudging proves less beneficial when production is either too low or too high, indicating that there are optimal conditions for its effectiveness.
- **Impact of labeled Periods:** Increasing the number of labeled periods in nudges improves performance, but the improvement levels off after a certain point. Sig-

nificant gains were observed with only a few labeled periods, which helps mitigate user fatigue.

- **Flexibility and Self-Consumption:** Greater household flexibility enhances the benefits of nudging, suggesting that households with more adjustable consumption patterns can achieve better self-consumption rates.

8.1.6 Chapter 6: Improving Energy Consumption Coordination in Renewable Energy Communities through Nudging

In this chapter, we extended the nudging pipeline from the individual household setting to collective self-consumption systems, addressing the complexities inherent in larger systems. Sending information about consumption favourable periods to all households risks overloading the system or underutilizing renewable energy. Thus, the central question of this chapter is:

How can we efficiently distribute this information to help households optimize their solar energy usage?

We emphasize that accurately estimating energy flexibility is crucial. To address this, we integrated load forecasting and used online surveys to estimate consumption flexibility, developing coordinators that selectively notify community members about optimal consumption periods, based on the estimated energy flexibility. This forms the core of our **Nudging Strategy 2**. Coordinators ensure efficient distribution of information, matching forecasted excess production with members' consumption flexibility. We simulated this new nudging pipeline using semi-real data from the Iris and IDEAL datasets, which demonstrated several key findings:

- **Efficiency of Personalized Notifications:** Coordinators that dispatch personalized information to each household demonstrated significantly higher performance compared to those issuing generic notifications.
- **Benchmark Analysis:** Our system efficiency was evaluated against an ideal case scenario that assumes perfect conditions and a realistic case where constraints identical to those in our simulations are applied. This comparison highlights our system robustness and potential effectiveness in real-world applications.
- **Data Sharing and Efficiency:** The effectiveness of coordinators increases with the volume of consumption data shared by users. However, overly detailed data, such as exact appliance usage days, leads to diminishing returns—where the rate of increased benefits decreases and imposes significant costs on users.

These findings underscore the value of using coordinators to manage notifications, thereby improving self-consumption rates while avoiding issues of overconsumption. Our study highlights the importance of balancing detailed user data with practical implementation to ensure the success of collective self-consumption operations.

8.1.7 Chapter 7: Appliance Level Coordination through Nudges to Improve Self-Consumption in an Energy Community

This chapter revisits the central problem introduced in Chapter 6—optimizing self-consumption within energy communities equipped with solar panels. Here, we present a refined coordinator system that offers more nuanced and effective energy management than the previously discussed approaches.

The refined coordinator stands out due to its granular control, operating at the appliance level rather than at the household level. Instead of generic notifications to shift all energy usage, it specifically informs households about how they should adjust their consumption during peak solar production periods.

Results show that while appliance-level coordination enhances self-consumption rates and can lead to greater energy savings, it also presents challenges such as the complexity of people’s responses to it and the potential for user fatigue due to more frequent notifications. Nevertheless, these challenges can be mitigated by integrating automated devices that respond to notifications without human intervention. However, the refined system may involve higher initial costs, prompting concerns about consumer reluctance to invest. A detailed cost-benefit analysis is essential to demonstrate the value of this upfront investment and to further assess the economic viability of this sophisticated approach.

8.2 Limitations

A major limitation of our nudging Strategy 1 (described in Section 1.4.3), which involves forecasting production and consumption, identifying flexible consumption through non-intrusive load monitoring (NILM), and then rescheduling it by sending recommendations to users, lies in the instability of NILM technology in practical applications. The absence of reliable data in real world settings to verify the success of NILM disaggregation means we cannot confirm its efficiency. Despite our classifier demonstrating good performance in determining whether a household is suitable for a pretrained disaggregation model, the challenge lies in the classifier’s learning process. As noted in Chapter 4, when tested on a 30-minute dataset, the disaggregation models showed very low performance, leading to a potential shortage of successful cases for our classifier to learn from. Additionally, a significant limitation of our approach is the computational intensity required both to pretrain a disaggregation model and to test it on detailed

datasets to label and determine the suitability of a household for the model. Identifying the appropriate disaggregation model for a specific appliance in a particular household can involve testing numerous models, a process that is not only time-consuming but also incurs high computational costs. This substantial computational burden is a major constraint that impacts the feasibility of implementing this strategy on a larger scale. Consequently, this significant limitation led us to ultimately abandon this strategy.

On the other hand, the effectiveness of our energy management strategy 2 hinges on addressing two critical limitations. First, the idealized model of human behavior - each member does all they can to respond to green periods -used in our simulations may not fully capture the complexities and variabilities in real-world responses to nudges, necessitating further research into user compliance rates and strategies to enhance them. Secondly, the limitations of our current energy and weather forecasting modules—owing to their simplistic nature—could introduce inaccuracies in predicting green periods. This may lead to suboptimal shifts in energy consumption and a reduction in user engagement, as the users react to being given bad quality information. To improve reliability and applicability in real-world scenarios, incorporating advanced ensemble forecasting models that synthesize multiple predictions could prove essential in overcoming these limitations and enhancing the overall effectiveness of our energy management strategies.

8.3 Perspectives

Based on the research detailed in this thesis, there are significant opportunities for future work, particularly regarding the real-world application of our Strategy 2. A fundamental challenge in evaluating the effectiveness of these applications in real-life settings stems from the fact that regardless of whether an intervention is implemented or not, only a single consumption profile is obtained. This limitation hinders our ability to determine the impact of the intervention based solely on this data. In contrast, simulations allow us to compare two distinct scenarios—one with the intervention and one without—to assess the difference and thereby evaluate the effectiveness of the intervention. Addressing this challenge in real-world settings will require targeted efforts to develop methodologies that can effectively assess the impact of our nudges with the available data.

Creating a suitable control group is essential for evaluating our interventions. One effective strategy involves comparing our target group to a similar control group. Randomized controlled trials (RCTs) offer a reliable method when large-scale data is available. For instance, studies by Allcott (2011) and Ayres et al. (2013) used randomized assignments to study energy consumption behaviors, demonstrating that households receiving comparative energy feedbacks reduced their electricity consumption. When

RCTs are not feasible, there are still many effective methodologies available. Asensio and Delmas (2017) employed genetic matching¹ techniques to study energy savings and emissions reductions in 178,777 commercial buildings in Los Angeles. Similarly, the matched pair design has proven valuable. Vine (1986) used this method to compare homes built to different energy standards, matching similar properties to underscore efficiency differences. Another robust approach is the Regression Discontinuity Design (RDD), which assigns households to experimental and control groups based on specific thresholds, such as self-consumption rates near 70%. The 70% threshold serves as a critical dividing line for grouping households. Households with self-consumption rates just above 70% are assigned to the experimental group, while those just below 70% are placed in the control group. This strategy ensures that the groups are closely matched, differing only slightly around the 70% threshold, thus facilitating more precise comparisons. Keefer and Rustamov (2018) utilized a sharp RDD to explore the effects of limited attention on residential energy consumption across more than 10,000 customers from a California utility company.

To accurately evaluate interventions across experimental and control groups, various rigorous methodologies have been employed. For instance, Adan and Fuerst (2016) applied difference-in-difference analysis to compare the impact of energy-saving measures like insulation and efficient boilers between the treated homes and their controls. Similarly, Liao and He (2018) utilized super-SBM, cluster analysis, and time and entity fixed effects models to compare energy efficiency across different industrial sub-sectors, considering the effects of technological advancement and structural variables. Moreover, Chui et al. (2015) investigated the effectiveness of energy conservation prompts in university buildings using a paired t-test to compare responses between a group receiving prompts and a control group without any. Karmaker et al. (2023) employs a two-stage least squares random effect model to study the impact of remittances on renewable energy consumption. Findings reveal a positive correlation, suggesting that promoting carbon-neutral energy devices among remittance-receiving households could enhance green energy adoption.

Despite the variety of experimental grouping methods available, practical applications may lead to situations where constructing suitable control groups is not possible, for instance when only a limited number of samples are available with significant variability between them. In such cases, methodologies that do not rely on control groups to assess the impact of interventions are particularly crucial. For instance, Buhl et al. (2017) utilized Interrupted Time Series Analysis (ITSA) to assess the impact of smart home systems and traffic light feedback on energy consumption without a control group. Additionally, Yu et al. (2015) employed a Gaussian Process (GP)-based method for

¹Genetic matching is a statistical technique that optimizes the similarity of covariates between treatment and control groups to ensure comparable conditions.

long-term energy savings estimation in demand-side management programs, adapting to diverse data structures and lengths.

To effectively assess the impact of our nudging system in real-world settings, integrating these methodologies will be essential. Creating a control group where possible, using techniques like RCTs, genetic matching, and RDD, will allow for precise comparisons. In situations where control groups cannot be formed, employing ITSA or GP-based methods will ensure that the impact of interventions is accurately measured. Additionally, gathering user feedback and conducting surveys will enrich our understanding by providing qualitative insights into how users perceive the nudges effectiveness and the behavioral changes they prompt. By integrating these methods, we can establish a detailed and clear framework to evaluate the impact of the nudge, effectively addressing the challenges posed by the absence of reference data.

In summary, the real-world application of our nudging pipeline necessitates conducting social group experiments to ultimately evaluate the impact of the nudges, using a combination of methodologies tailored to the specific context and data availability.

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1. Ling H, Massé P-Y, Rihet T, Wurtz F. Realistic Nudging through ICT Pipelines to Help Improve Energy Self-Consumption for Management in Energy Communities. *Energies*. 2023; 16(13):5105. <https://doi.org/10.3390/en16135105>
2. Haicheng Ling, Pierre-Yves Massé, Thibault Rihet, Wurtz Frederic. Appliance Level Coordination through Nudges to Improve Self-Consumption in a Energy Community. *Conférence IBPSA France 2024*, IBPSA France; Laboratoire LaSIE de La Rochelle Université, May 2024, La Rochelle, France. pp.393. [⟨hal-04653374⟩](#)

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Appendices

Appendix A

IRIS Dataset Characteristics

A.1 Statistic Characteristics of IRIS Dataset

The appliance usage count in the Iris Dataset is provided in Figure A.1, which offers an overview of the appliances installed in the Iris Dataset. Table A.1 displays the statistical characteristics of a subset of the Iris Dataset, specifically for households that concurrently contain the washing machine, dishwasher, and water heater as shiftable appliances.

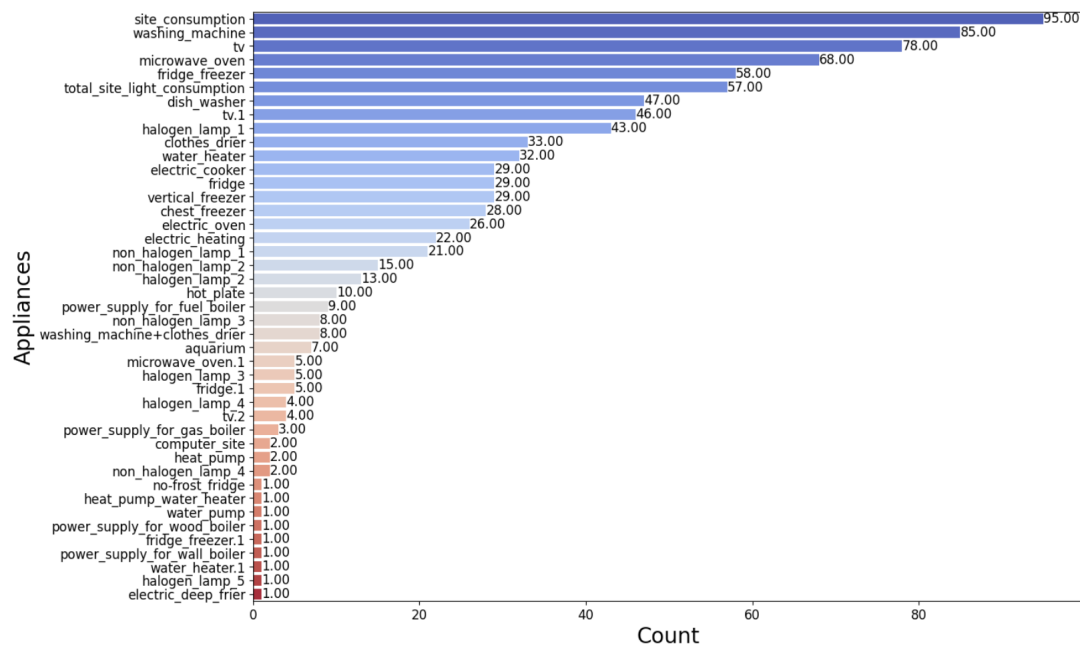


Fig. A.1 Appliance Usage Count in the Iris Dataset

Table A.1 Flexible Appliance Usage Statistics of the Iris Dataset at 30 Minutes Sampling

Target	Iris	Count	ON (%)	OFF (%)	Mean (Watt)	Max(Watt)	STD ¹ (Watt)	AWS ² (min)
Agg ³	907	57.4k	–	–	358	3837	464.7	–
	914	53.4k	–	–	751.3	23337	1070.6	–
	928	53.7k	–	–	519.9	4173	685.9	–
	936	54.5k	–	–	318.1	3498	407	–
	938	56.4k	–	–	791	56259	1395.4	–
	944	53.4k	–	–	753.8	5208	719.8	–
	953	54.8k	–	–	863	6264	817.1	–
	981	50.9k	–	–	303.2	3732	471.5	–
	991	54.6k	–	–	257.6	2922	352.1	–
WM ⁴	907	57.40k	6.11	93.89	18.61	1083	113.41	72.42
	914	53.41k	3.81	96.19	12.63	1113	95	83.64
	928	53.73k	3.16	96.84	5.28	1209	51.93	79.30
	936	54.51k	7.63	92.37	17.43	879	82.02	57.57
	938	56.45k	4.31	95.69	8.91	990	68.10	86.92
	944	53.43k	5.04	94.96	2.82	117	12.55	83.29
	953	54.82k	2.15	97.85	6.06	1140	64.95	88.71
	981	50.92k	5.47	94.53	2.22	126	9.94	62.42
	991	54.56k	5.57	94.43	17.11	1308	126.10	104.41
DW ⁵	907	57.40k	2.71	97.29	16.47	1119	119.71	79.64
	914	53.41k	1.51	98.49	6.98	1062	71.32	74.58
	928	53.73k	1.46	98.54	9.38	1452	97.77	59.69
	936	54.51k	0.80	99.20	7.67	1554	98.54	78
	938	56.45k	1.61	98.39	11.63	1599	116.14	92.58
	944	53.43k	2.17	97.83	12.39	1680	112.68	47.03
	953	54.82k	1.23	98.77	8.46	1647	97.25	61.19
	981	50.92k	3.01	96.99	21.85	1656	152.86	53.68
	991	54.56k	0.76	99.24	4.42	1536	68.55	68
WH ⁶	907	57.40k	10.55	89.45	118.67	1425	359.72	57.36
	914	53.41k	17.14	82.86	174.62	2112	390.56	134.03
	928	53.73k	6.13	93.87	86.87	3087	347.87	99.15
	936	54.51k	10.15	89.85	110.06	1221	333.49	143.78
	938	56.45k	13.27	86.73	124.81	11907	339.71	42.44
	944	53.43k	10.95	89.05	105.37	2190	310.15	65.60
	953	54.82k	11.12	88.88	103.53	1716	318.88	18.05
	981	50.92k	11.54	88.46	137.80	1653	405.87	30.09
	991	54.56k	8.06	91.94	94.45	1260	321.46	108.08

¹ Standard Daviation ² Average Window Size ³ Aggregated Consumption ⁴ Washing Machine ⁵ Dish Washer ⁶ Water Heater

Appendix B

The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes

B.1 Statistic Characteristics of Ukdale Dataset

The statistical characteristics of the flexible load and the aggregated consumption from the three selected buildings, sampled at 30-minute intervals, are detailed in Table B.1.

Table B.1 Flexible Appliance Usage Statistics of the UKDALE Dataset at 30 Minutes Sampling

Target	UKDALE	Count	ON ⁶ (%)	OFF (%)	Mean (Watt)	Max(Watt)	STD ¹ (Watt)	AWS ² (min)
Agg ³	House1	37.7k	—	—	378	3496	293.7	—
	House2	6.8K	—	—	324	3052	349	—
	House5	6.5K	—	—	687	4403	395	—
WM ⁴	House1	37.7k	6.57	93.43	26	1815.49	142	133
	House2	6.8K	1.86	98.14	10.25	1154.4	62.59	98.68
	House5	6.5K	6.95	93.05	40.9	1129	120	161
DW ⁵	House1	37.7k	2.64	97.36	15.7	2355	113	126
	House2	6.8K	4	96	35.62	1616.58	187.55	94.18
	House5	6.5k	2.81	97.19	16	1219	113	126

¹ Standard Daviation ² Average Window Size ³ Aggregated Consumption ⁴ Washing Machine ⁵ Dish Washer ⁶ Activation Rate: calculated as the ratio of activation time to the total time

Appendix C

The Almanac of Minutely Power Dataset

C.1 Statistic Characteristics of AMPDs Dataset

The statistical characteristics of the flexible load and the aggregated consumption, sampled at 30-minute intervals, are detailed in Table C.1.

Table C.1 Flexible Appliance Usage Statistics of the AMPDs Dataset at 30 Minutes Sampling

Target	Count	ON ⁷ (%)	OFF (%)	Mean (Watt)	Max(Watt)	STD ¹ (Watt)	AWS ² (min)
Agg ³	35k	—	—	1112	8370	783	—
WM ⁴	35k	3.56	96.44	4.4	270	24	102
DW ⁵	35k	3.83	96.17	83.35	813	15	129
CD ⁶	35k	2.5	97.5	53	4790.4	389	65.5

¹ Standard Daviation ² Average Window Size ³ Aggregated Consumption ⁴ Washing Machine ⁵ Dish Washer ⁶ Clothes Dryer ⁷ Activation Rate: calculated as the ratio of activation time to the total time

Appendix D

REFIT Electrical Load Measurements Dataset

D.1 Statistical Characteristics and Metadata of the REFIT Dataset

The REFIT Electrical Load Measurements dataset, featuring cleaned consumption data for 20 households, has been refined for optimal accuracy. This refinement process included the merging of duplicate timestamps and capping Individual Appliance Monitor (IAM) readings at 4000 watts to mitigate the effects of sensor errors. IAMs were meticulously calibrated to provide precise readings for single appliances. Furthermore, data entries labeled as Not a Number (NaN) were systematically addressed by either filling them with appropriate values or zeroing them out, depending on the duration of the data absence. This approach was taken to maintain the continuity and integrity of the dataset.

Table D.1 provide detailed information about the dataset, including the appliances contained in the household and the model of each appliance, and Table D.2 present a statistical analysis of the aggregated power consumption across all households and the power consumption of shiftable appliances, with a focus on washing machines.

Table D.1 Meta Data of the REFIT Electrical Load Measurements Dataset

ID	Meter	Appliance Brand	Appliance Model
0	Aggregate		
1	Fridge	Liebherr	KP2620
2	Freezer	Unknown	Unknown
3	Washer Dryer	Zanussi	Unknown
4	Washing Machine		
5	Toaster	Bosch	TAT6101GB/02
6	Computer	Unknown	Unknown
7	Television Site	Sony	KDL-32V2000
8	Microwave	Panasoinc	NN-CT565MBPQ
9	Kettle	Morphy Richards	43615

Table D.2 Flexible Appliance Usage Statistics of the REFIT Dataset at 30 Minutes Sampling

Target	REFIT	Count	ON (%)	OFF (%)	Mean (Watt)	Max(Watt)	STD ¹ (Watt)	AWS ² (min)
Agg ³	House1	30.67k	—	—	520.82	12505.00	499.96	—
	House2	29.64k	—	—	407.72	8343.98	593.52	—
	House3	29.50k	—	—	662.42	34096.00	764.76	—
	House4	30.43k	—	—	374.99	5592.50	275.21	—
	House5	31.12k	—	—	733.03	8715.29	633.64	—
	House6	27.72k	—	—	469.99	3223.36	276.40	—
	House7	29.43k	—	—	522.66	6494.76	640.27	—
	House8	26.64k	—	—	647.74	7603.82	763.48	—
	House9	27.27k	—	—	515.35	8039.27	679.85	—
	House10	28.18k	—	—	733.45	6242.17	699.86	—
	House11	18.82k	—	—	542.50	3648.10	659.94	—
	House12	23.41k	—	—	362.61	5024.53	412.51	—
	House13	23.93k	—	—	537.48	5896.78	617.20	—
	House15	27.23k	—	—	256.38	4975.46	275.59	—
	House16	26.10k	—	—	546.38	11596.30	479.61	—
	House17	22.56k	—	—	397.41	8369.15	501.94	—
	House18	21.27k	—	—	437.57	9198.14	340.30	—
	House19	22.58k	—	—	286.17	2726.04	224.68	—
	House20	22.10k	—	—	372.76	3715.56	309.23	—
	House21	23.51k	—	—	644.58	4998.40	591.33	—
WM ⁴	House1	30.67k	0.60	99.40	1.72	1271.38	29.80	44.27
	House2	29.64k	18.54	81.46	8.51	54.23	17.32	180.72
	House3	29.50k	5.72	94.28	49.10	2460.00	248.53	80.06
	House4	30.43k	0.54	99.46	3.54	2261.56	62.52	92.26
	House5	31.12k	10.83	89.17	54.73	2514.00	209.21	130.60
	House6	27.72k	39.00	61.00	68.68	402.86	83.54	528.35
	House7	29.43k	5.39	94.61	69.36	3440.00	353.12	83.51
	House8	26.64k	4.22	95.78	26.34	2367.24	182.20	95.35
	House9	27.27k	6.81	93.19	40.70	1741.48	182.39	161.13
	House10	28.18k	42.18	57.82	22.58	486.97	29.72	78.48
	House11	18.82k	0.75	99.25	5.04	1949.84	72.88	84.49
	House12	23.41k	10.72	89.28	22.78	1592.43	74.95	36.94
	House13	23.93k	5.02	94.98	19.25	1886.16	141.01	206.72
	House15	27.23k	0.28	99.72	1.25	1861.40	30.68	75.00
	House16	26.10k	0.88	99.12	3.55	1734.00	50.95	83.70
	House17	22.56k	4.54	95.46	29.11	2080.00	211.51	100.43
	House18	21.27k	0.30	99.70	1.38	2149.08	35.02	63.00
	House19	22.58k	2.87	97.13	2.70	703.68	20.66	37.76
	House20	22.10k	3.11	96.89	7.57	1782.82	64.34	116.59
	House21	23.51k	15.66	84.34	44.06	1742.28	172.48	160.35

¹ Standard Daviation ² Average Window Size ³ Aggregated Consumption ⁴ Washing Machine

Appendix E

Results and Visualizations from Intra-Building Model Training and Testing at Varied Frequency Conditions

This appendix presents a comprehensive set of results, including MAE and SAE metrics (Section E.1) and visualizations of disaggregation outcomes (Section E.2), serving as supplementary evidence to support the findings discussed in Section 3.3.2.

E.1 Evaluating NILM Performance: MAE and SAE Results from Intra-Building Model Training and Testing at Varied Frequency Conditions

Table E.1 display the mean absolute error (MAE) and the signal aggregate error (SAE) respectively. The disaggregation of various appliances demonstrated excellent performance in tests conducted with 1-minute sampling intervals. This is evidenced by relatively low MAE values (less than 10) and SAE values that closely approach zero, indicating a minimal relative error of the total energy. However, in tests utilizing 30-minute sampling intervals, the performance of all the models exhibited a decline. This manifested as increases in both MAE and SAE to varying degrees.

Table E.1 MAE and SAE for NILM Algorithm Performance Across Various Datasets and Sampling Frequencies in Intra-Building Train-Test Scenarios (High Predictive Performance Metrics Highlighted in Green.)

Metric	Appliance	Dataset	Frequency	
			1 min	30 min
MAE	WM ¹	UK-DALE	1.22	2.98
		AMPds	2.59	3.21
	DW ²	UK-DALE	0.74	2.65
		AMPds	4.3	7.44
	CD ³	AMPds	6.93	29
SAE	WM	UK-DALE	0.002	0.064
		AMPds	0.047	0.58
	DW	UK-DALE	0.07	0.27
		AMPds	0.02	0.56
	CD	AMPds	0.06	0.49

¹ Washing Machine ² Dish Washer ³ Clothes Dryer

E.2 Visualizing Results: Intra-Building Model Training and Testing at Varied Frequency Conditions

Here, we present visualizations comparing the disaggregation results of the UKDALE washing machine model at 1-minute and 30-minute intervals to demonstrate how high-performance at a 1-minute interval declines to reasonable performance at a 30-minute interval. High-performance metrics are visually represented in Figure E.1, which details the outcomes of the washing machine power disaggregation for the UKDALE dataset. **The figure overlays the actual washing machine consumption with the predicted consumption, illustrating the model's accuracy in capturing consumption patterns.** Then the decline in performance is further exemplified in Figure E.2, which, when compared to Figure E.1, highlights instances where washing machine power consumption was not detected in the ground truth (depicted in red) alongside instances where predicted power was absent (shown in blue).

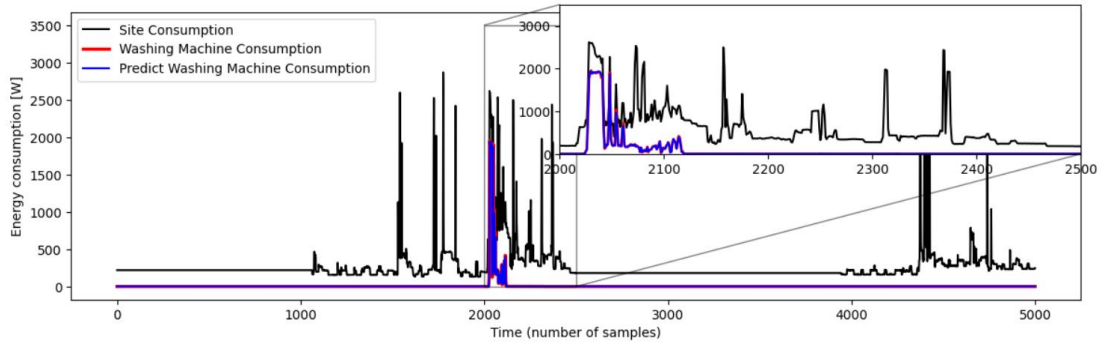


Fig. E.1 High-Performance Disaggregation of 1-Minute UKDALE Washing Machine Data: Overlay of Real and Predicted Consumption

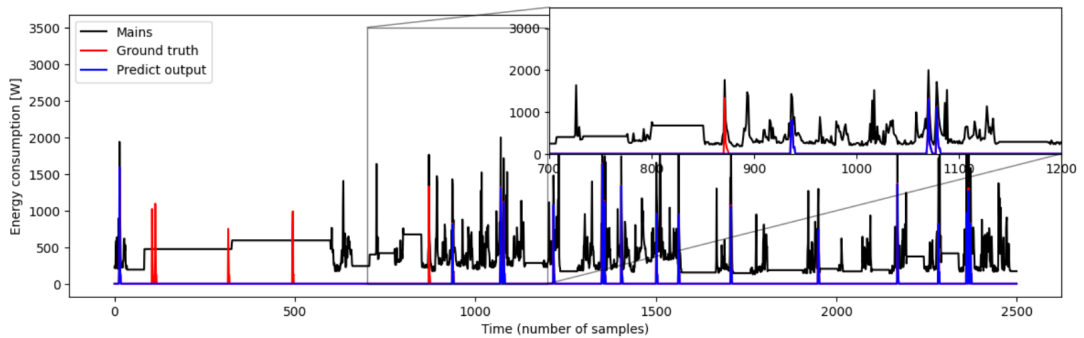


Fig. E.2 30-Minute UKDALE Washing Machine Disaggregation: Challenges in Accurately Predicting Consumption

Appendix F

Exploring the Influence of Feature Sets on Classifier Performance: A SHAP Analysis Approach

In both balanced and imbalanced scenarios, classifiers trained with the simple statistical feature set and with the combined set of statistical and heuristic features consistently exhibit equivalent, superior performance. This observation indicates that the inclusion of simple statistical features is not necessary for achieving optimal classifier performance; rather, it is the heuristic features that significantly enhance classifier efficacy.

To further substantiate this finding, a SHAP values analysis was conducted. The SHAP values for the combined feature set (simple + heuristic) depicted in Figure F.1 reinforce this observation, presenting the top 20 ranking of SHAP values which highlight the significance of each feature in the classification problem. Notably, heuristic features are identified as particularly influential, underscoring their crucial role in boosting the classification performance.

In addition to two simpler feature sets containing heuristics, classification algorithms also demonstrate robust performance with a feature set of nearly 800 features automatically extracted by tsfresh, particularly in balanced scenarios. These tsfresh features achieved an F1 score of over 90% for both classes, as detailed in Table Table 4.2. However, classification using the simple heuristic feature sets still demonstrates superior performance. This could be attributed to the excessive dimensionality of the tsfresh feature set, which may diminish the model's learning effectiveness due to the complexity of managing such a large number of features. Furthermore, augmenting the tsfresh feature set with simple heuristic features does not improve model performance. The lack of improvement is likely due to significant multicollinearity¹ within the combined feature set.

Figure F.2 displays the SHAP values of 818 features within the combined feature set, which includes features extracted by tsfresh and heuristic features. The y-axis lists the features used in the model, sorted by the sum of SHAP value magnitudes over all samples. Features at the top are considered more important for the model's output. No-

¹Multicollinearity refers to the situation in regression analysis where two or more predictor variables have a high linear correlation with each other. In simple terms, this means that one feature in the model can be approximately predicted through a linear combination of one or more other features.

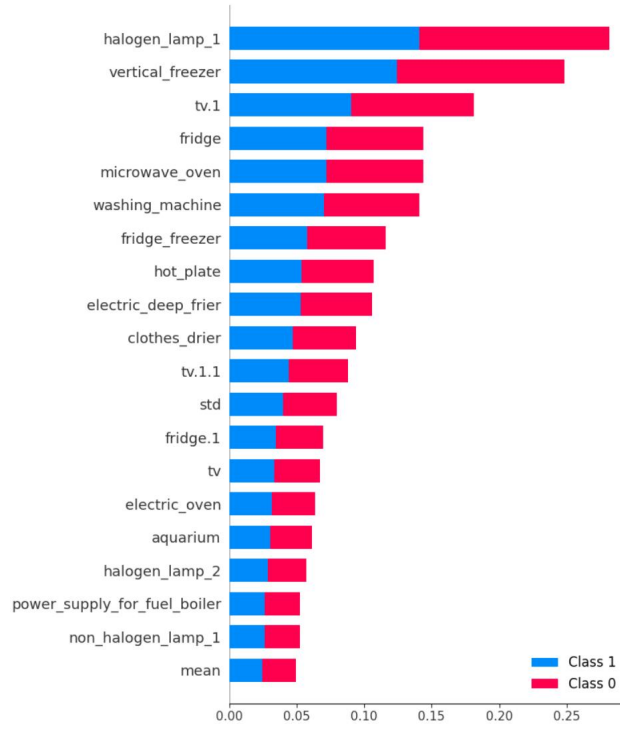


Fig. F.1 SHAP Values: Ranking the Impact of Features within the Simple Stastic and Heuristic Feature Sets on Model Output

tably, even among over 800 features, heuristic information regarding the presence of appliances in a house remains prominently influential, with the top three features all belonging to this category. Consequently, we assert that the influence of heuristic features on the model's performance is significant and cannot be overlooked. To mitigate the effects of multicollinearity among features, we propose that exclusively using heuristic features to train the classification model represents the optimal strategy.

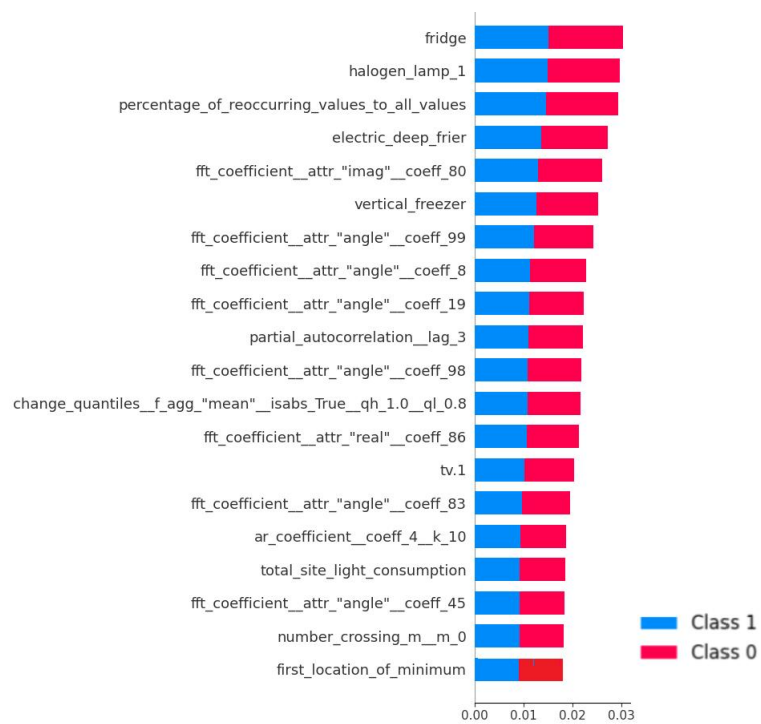


Fig. F.2 SHAP Values: Ranking the Impact of Features within the Tsfresh Heuristic Feature Sets on Model Output

Appendix G

Open Source project : Realistic Nudging Pipelines for Individual Self-Consuming Household

The “Realistic Nudging Pipelines for Energy Consumption” project by Enogrid is an open-source initiative designed to enhance energy efficiency through behavior modification techniques known as nudging. This project offers tools and methodologies for analyzing energy consumption data and applying machine learning to develop strategies that encourage users to adopt more sustainable energy practices. It includes comprehensive code and documentation to facilitate the implementation of these nudging strategies in various scenarios, promoting more efficient energy use. The project has been set up using the Poetry virtual environment (Python environment), and Figure G.1 shows the dependency library of this code.

```
[tool.poetry.dependencies]
python = "^3.10"
pandas = "^1.5.1"
requests = "^2.28.1"
tensorflow = [
    {version = "^2.10.0", python = ">=3.8, <3.11"},
]
pydantic = "^1.10.2"
matplotlib = "^3.6.1"
scipy = "^1.9.3"
keras = "^2.11.0"
joblib = "^1.2.0"
scikit-learn = "^1.1.3"
kaleido = "0.2.1"
omegalpes = "^0.4.3"
pylint = "^2.16.2"
black = "^23.1.0"
jupyter = "^1.0.0"
func-timeout = "^4.3.5"

[tool.poetry.group.dev.dependencies]
pytest = "^7.1.3"
poethepoet = "^0.16.4"
prospector = {extras = ["with_vulture", "with_bandit", "with_mypy"], version = "^1.7.7"}
commitizen = "^2.42.1"
```

Fig. G.1 Dependencies of the Realistic Nudging Pipelines for Energy Consumption Project

In this project, we provide a simple use case example in the notebook named “simple example” and other notebooks that demonstrate the entire simulation process, including data selection, predictor selection, and the final simulation results. Table G.1 showcases

some simulation examples available in our project repository, which also serve as detailed introductions to the simulation specifics and final results discussed in individual sections of this manuscript.

Table G.1 Correspondence Between Notebooks and Manuscript Sections

Notebook Name	Corresponding Section In this Manuscript
Synthetic Data, Efficiency of Nudges	Section 5.4.2
Synthetic data, Production not Predictive of Excess	Section 5.4.3
AMPds Dataset, individual building simulation	Section 5.4.4
Iris Dataset , individual building simulation	Section 5.4.4
Iris dataset, collective runs	Section 5.4.5
Iris dataset, subsets runs	Section 5.4.5
Influence of the Amount of Production	Section 5.4.6
Influence of the Number of Green Periods	Section 5.4.7

Appendix H

Load Forecasting

We use a very simple forecasting model, as it allows us to quickly test our pipelines, while letting open the possibility to improve it, or replace it with more involved models, if the need arises. Indeed, our goal in building the predictor was to assess in principle the relevance of the Combined Controller (Section 5.3.4), that is a controller producing nudges based on forecast excess production. Upon deployment in production, we will probably use more involved forecast models.

As a forecaster for production, we use a linear model whereby:

$$\mathcal{P} = \alpha \times \text{sunshine coefficient},$$

where $\mathcal{P}$ is the predicted solar production, the sunshine coefficient is a value in $(0, 1)$ quantifying how much sun irradiance there is, and α is the regression parameter. We estimate it on past data. Now, in our simulator, solar production is by design a linear function of the sunshine coefficient (see Section 5.4.1). Of course, in real life this will no longer be the case, and a linear model will probably show bad performances for production forecast. We will use more involved models in that case.

As a forecaster for consumption, we create a week consumption profile by averaging past data over a week. Then, the consumption of a time slot is forecast to be that of the same time slot in the profile. For instance, if past consumption data are $L_1, L_2, \dots, L_T$, the forecast consumption for Monday, 10:00am is:

$$\frac{1}{\#\{1 \leq t \leq T \mid t \text{ is a Monday, at 10:00am}\}} \sum_{t=1}^T L_t.$$

Of course, this model is simple, but it already has a relatively correct accuracy, as electricity consumption tends to have some degree of periodicity. One straightforward way to improve it would be to use a weighted average of past consumption values, giving less weight to more ancient values: we will consider such improvements when deploying into production.

To validate our energy forecast models, we use the “mean absolute percentage er-

ror (MAPE)” and “coefficient of determination (R2Score)”. MAPE and R2Score are evaluation metrics that are widely used for regression problems. They are defined as:

$$MAPE(y, \hat{y}) = \frac{1}{n} \sum_{i=0}^{n-1} \frac{|y_i - \hat{y}_i|}{\max(\epsilon, |y_i|)}$$

$$R2Score(y, \hat{y}) = 1 - \frac{\sum_{i=0}^n (y_i - \hat{y}_i)^2}{\sum_{i=0}^n (y_i - \bar{y})^2},$$

where n is size of sample and ϵ in MAPE is an arbitrary small yet strictly positive number to avoid undefined results when y is zero. If MAPE tends to 0 and R2Score tends to 1, we can conclude that we have a very good energy forecast model. A MAPE qualitative criteria table is shown in Table H.1.

Table H.1 MAPE Qualitative Criteria

MAPE(%)	Prediction Capability	R2Score
<10	Highly accurate prediction (HAP)	> 0.9
10 - 20	Good prediction(GPR)	0.7 - 0.9
20 - 50	Reasonable prediction(RP)	0.4 - 0.7
>50	Inaccurate prediction (IPR)	< 0.4

It was used for instance in Eliana Vivas and Salas (2020), Zhao and Guo (2016) to classify accuracy levels depending on different ranges of MAPE. The third column shows the value of R2Score that is equivalent to MAPE for different accuracy levels.

Appendix I

Optimizing Individual Self-Consumption Using OMEGAlpes

We use OMEGAlpes, defined in Hodencq et al. (2021), to provide an upper-bound for the performances of our controllers. To give the reader an idea of how OMEGAlpes computes this bound, we give some elements of context here. We first describe quickly OMEGAlpes (Section I.0.1), then we detail the optimisation model (Section L.0.1).

I.0.1 OMEGAlpes Presentation

OMEGAlpes (Optimization ModELs Generation As Linear Programs for Energy System) is a simulation platform developed by the Grenoble Electrical Engineering Laboratory (G2ELab) at the Grenoble Institute of Engineering and Management. It models and simulates electrical power systems, particularly those using renewable energy sources. It allows users to optimise power generation, distribution, and consumption, while respecting operational constraints. The optimisation module uses mixed integer linear programming¹.

OMEGAlpes uses a modular architecture that allows users to build and customize simulation models according to their specific needs. The platform includes a wide range of simulation tools, such as power flow analysis and optimization algorithms, which can be used to evaluate the performance of power systems under different scenarios and conditions.

OMEGAlpes has been used in numerous research projects and industrial applications, and it is actively developed and maintained by the G2ELab team.

I.0.2 Self-Consumption System Modelling

Figure L.1 presents a diagram of the OMEGAlpes model implemented in the self-consumption system. The system is composed of two fixed energy units: the solar energy production unit, and the non-shiftable part of the total energy consumption. Additionally, the system includes three variable energy units: the energy imported from

¹Mixed integer linear programming (MILP) is a set of mathematical optimization techniques used to solve problems that involve both continuous and integer decision variables in the objective function and constraints.

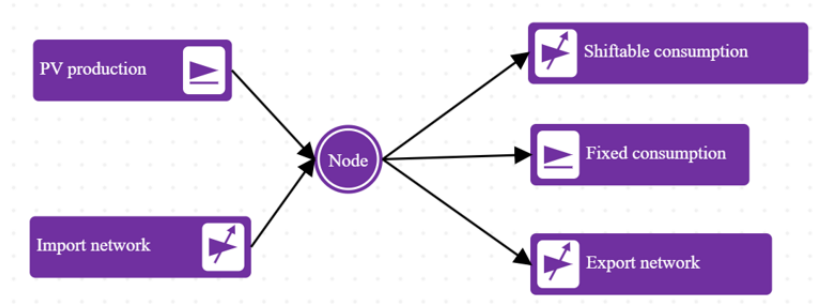


Fig. I.1 OMEGalpes Model for a Self-Consumption System

the grid, the energy exported to the grid, and the aggregated shiftable part of the total energy consumption. The shiftable energy part is subject to changes, affecting the imported and exported energy from the grid accordingly. All energy units are interconnected to an electric node, in which the energy equations are formulated, as shown below. The equation variables are defined in Table L.1.

Table I.1 Energy Equations Variables and their Meaning.

Symbol	Description
t	The time period of optimization, denoted by $t \in [B_t, E_t]$, is defined as starting from B_t , the beginning of optimization, and ending at E_t , the completion of optimization.
δt	The change in time depends on the frequency/sample rate of the energy profile.
P_{imp}	Power imported from the electric grid.
P_{exp}	Power exported to the grid.
U_{imp}	Network import status. It is a binary variable, a value of 1 indicates that the import from the grid is active, while a value of 0 indicates that the import from the grid is inactive.
U_{exp}	Network export status. It is a binary variable, a value of 1 indicates that the export to the grid is active, while a value of 0 indicates that the export to the grid is inactive.
P_{pv}	Power generated by the solar energy unit.
P_{shift}	Power of the shiftable part of the total consumption.
U_{shift}	Shiftable consumption status. It is a binary variable, a value of 1 indicates that the shiftable consumption is active, while a value of 0 indicates that there is no shiftable consumption.
Stp_{shift}	The shiftable consumption start-up is represented by a binary variable. It equals 1 only when the shiftable consumption starts, i.e., when U_{shift} changes from 0 to 1.
	Power of the non shiftable part of the total consumption.

Energy balance equation.

$$\sum_{i=0}^{N_t} (P_{imp}(t)U_{imp}(t) + P_{pv}(t) - P_{exp}(t)U_{exp}(t) - P_{shift}(t) - P_{notshift}(t)) \delta t = 0.$$

The energy balance equation in electrical systems states that the net energy flux across any node must be zero, i.e., the sum of the energy entering the node must be equal to the sum of the energy leaving the node.

Constraints equations.

$$0 \leq U_{imp}(t), U_{exp}(t) \leq 1, \quad \text{integers.}$$

Simultaneous import and export of energy from the grid is prevented through the use of binary values, U_{imp} and U_{export} , which indicate the activation status of importing and exporting energy, respectively. So, the sum of U_{imp} and U_{export} is always equal to 1:

$$U_{imp}(t) + U_{exp}(t) \leq 1.5, \quad \text{integers.}$$

The total energy of a system should remain constant regardless of where the shiftable consumption is allocated within the system.

$$\delta t \sum_{i=0}^{N_t} P_{shift}(t) = E_{shift_{t \in [B_t, E_t]}}.$$

The following equation represents the constraint for detecting the start-up of shiftable consumption. It is defined as a binary value, which equals 1 only when the shiftable consumption starts.

$$U_{shift}(t+1) - U_{shift}(t) \leq Stp_{shift}(t+1).$$

$$\frac{U_{shift}(t+1) - U_{shift}(t) + 1}{2} \geq Stp_{shift}(t+1).$$

The following equation ensures that the sequence of shiftable consumption is respected during optimization. For instance, if a washing machine functions from 8pm to 9:30pm, the “block” it represents will be shifted as a block. It will not be decomposed into several sub-blocks (of 1 hour, or 30 minutes, for instance).

$$P_{shift}(t) \geq l_{spp} Stp_{shift}(t - \text{size}(l_{spp})), \quad \text{for } t \in [\text{size}(l_{spp}), -1].$$

Objective equation.

$$\begin{aligned} \min \sum_{i=0}^{N_t} P_{exp}(t) U_{exp}(t) \delta t \\ = \min \sum_{i=0}^{N_t} (P_{imp}(t) U_{imp}(t) + P_{pv}(t) - P_{shift}(t) - P_{notshift}(t)) \delta t. \end{aligned}$$

The objective of the optimization model is to maximize the self-consumption rate in the self-consumption system, which is equivalent to minimizing the energy exported to the grid.

The shiftable part of the energy consumption can be rescheduled by solving the above equations using OMEGAlpes, with the aim of maximising self-consumption in the self-consumption system. Before optimisation, a TimeUnit of OMEGAlpes must be set to define the time intervals for rescheduling. In our study, we selected a window of three days as the time constraint for rescheduling. This means that all shiftable consumption can only be rescheduled within these time periods. When optimizing over a one-month period, the model maximised the self-consumption rate for each continuous three-days interval.

Appendix J

Load Forecasting

We present here the results concerning the self-productions rates of all our simulations on synthetic data and on semi-real data. They are similar to those about the self-consumption rate, and we only discuss them briefly.

1. **Synthetic Data, Efficiency of Nudges.** We see on Table J.1 that Weather and Combined controllers improve the self-production rate, in the case of synthetic data.
2. **Synthetic data, Production not Correlated with Excess.** When production is no longer correlated with excess production, the Combined controller outperforms the Weather controller: we see it in Table J.2.
3. **Iris Dataset and AMPds Dataset, individual building simulation.** The Table J.3 show the performances in the case of the Iris individual building, and the AMPds building.
4. **Iris Dataset, collective runs.** We see on Table J.4 the results averaged over all the buildings of the Iris dataset. The performances are the same as for the self-consumption rate.
5. **Influence of the Amount of Production.** Figure J.1 shows that, as the production level increases, the improvement in the self-production rate also increases; however, at a certain point (7000-8000 W), the increase in the self-production rate reaches a plateau and stops growing. All daylight consumption is already covered by solar production, so there is no longer room for improvements.
6. **Influence of the Number of Green Periods.** Finally, we can see on Figure J.2 that the efficiency of nudges is already quite good for 4 periods.

Table J.1 Mean Self-Production Rate and Mean Improvement Ratio with Various Controllers: Synthetic Data, General Case

	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)	25.17	28.91	29.01	33.35
Mean of improvement ratio (%)	0	45.9	47.25	100

Table J.2 Mean Self-Production Rate and Mean Improvement Ratio with Various Controllers: Analysis Using Synthetic Data, Uncorrelated Production, and Excess Production

	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)	22.36	22.79	23.53	24.85
Mean of improvement ratio (%)	0	18.53	47.94	100

Table J.3 Mean Self-Production Rate and Mean Improvement Ratio with Various Controllers: A Study Using Iris 966 and AMPds Data

	Reference	Weather Controller	Combined Controller	Omegalpes
Iris: Mean(%)	22.53	23.83	24.25	28.63
AMPds: Mean (%)	34.44	34.84	34.86	35.84
Iris: Mean of improvement ratio (%)	0	21.37	27.99	100
AMPds: Mean of improvement ratio (%)	0	27.74	29.72	100

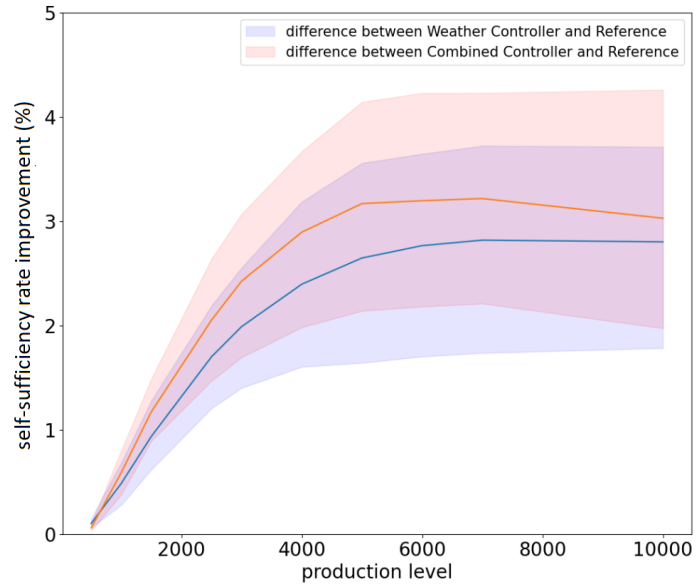


Fig. J.1 Augmentation of the Self-Production Rate Due to the Combined Controller/Weather Controller with Respect to a Reference with No Controller, as a Function of the Production

Table J.4 Mean Self-Production Rate and Mean Improvement Ratio with Various Controllers: Collective Simulation on the Iris Dataset

	Reference	Weather Controller	Combined Controller	Omegalpes
Mean (%)	28.07	28.75	28.93	32.16
Mean of improvement ratio (%)	0	17.22	21.6	100

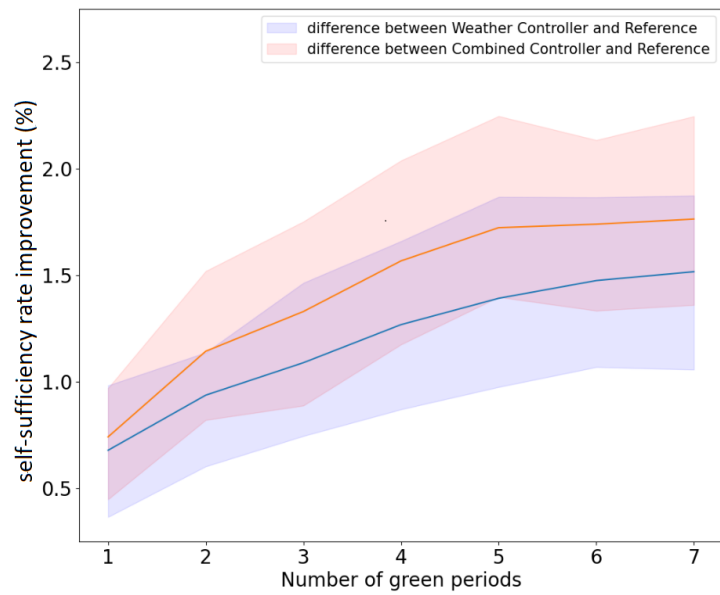


Fig. J.2 Augmentation of the Self-Production Rate Due to the Combined Controller/Weather Controller with Respect to a Reference with No Controller, as a Function of the Number of Green Periods by Nudge

Appendix K

Metadata of Collective Self-Consumption Simulations: Syn1, Iris, and IDEAL

We describe here how we construct the collective self-consumption datasets we use in our numerical simulations. These are the synthetic datasets Syn1 (Table K.3) and the datasets from real public data, Iris (Table K.2) and IDEAL (Table K.1). We present the households contained in each collective self-consumption dataset, and the shiftable appliances available in each household. Additionally, we present the total energy flexibility during the simulation period for each collective self-consumption dataset

Finally, the periods we use in our simulations are the following:

- Syn1: September 8, 2019, to October 13, 2019;
- Iris: July 26, 2020, to July 28, 2020;
- IDEAL: December 31, 2017, to February 01, 2019.

Table K.1 Shiftable Appliance Types in Each House within the Collective Self-Consumption System IDEAL and Total Energy Flexibility of IDEAL During Simulation Periods

List of Household	Washing Machine	Dish Washer	Water Heater	The Ratio of Total Shiftable Energy Outside of Solar Hours to Total Energy
household_01	✓	✓	×	1.3%
household_02	✓	✓	×	
household_03	✓	×	×	
household_04	✓	×	×	
household_05	✓	✓	×	
household_06	✓	✓	×	
household_07	×	✓	×	
household_08	✓	×	×	
household_09	✓	×	×	
household_10	✓	×	×	
household_11	✓	×	×	
household_12	✓	×	×	
household_13	✓	✓	×	

Table K.2 Shiftable Appliance Types in Each House within the Collective Self-Consumption System Iris and Total Energy Flexibility of Iris During Simulation Periods

List of Household	Washing Machine	Dish Washer	Water Heater	The Ratio of Total Shiftable Energy Outside of Solar Hours to Total Energy
household_01	✓	✓	×	5%
household_02	✓	×	✓	
household_03	✓	✓	✓	
household_04	✓	✓	✓	
household_05	✓	✓	×	
household_06	✓	✓	×	
household_07	✓	✓	✓	
household_08	✓	✓	✓	
household_09	✓	✓	✓	
household_10	✓	✓	✓	

Table K.3 Shiftable Appliance Types in Each House within the Collective Self-Consumption System Syn1 and Total Energy Flexibility of Syn1 During Simulation Periods

List of Household	Washing Machine	Dish Washer	Water Heater	The Ratio of Total Shiftable Energy Outside of Solar Hours to Total Energy
household_01	✓	✓	✓	20%
household_02	✓	✓	✓	
household_03	✓	✓	×	
household_04	✓	✓	×	
household_05	✓	×	×	
household_06	✓	×	×	
household_07	✓	×	✓	
household_08	✓	✓	×	
household_09	✓	×	✓	
household_10	✓	✓	✓	
household_11	✓	✓	×	
household_12	✓	✓	✓	

Appendix L

Optimizing Collective Self-Consumption Using OMEGAlpes

We use the same optimization tool used in Ling et al. (2023) and defined in Hodencq et al. (2021), OMEGAlpes (Optimization ModElS Generation As Linear Programs for Energy System), a simulation platform developed by the Grenoble Electrical Engineering Laboratory (G2ELab). A brief description is provided in our prior work. In this section, we focus on describing the differences required to apply the model to a collective self-consumption system.

L.0.1 Self-Consumption System Modelling

In Figure L.1, we present a diagram illustrating the OMEGAlpes model implemented for a collective self-consumption system of three households. This system encompasses both fixed and variable energy units: fixed energy units, like solar panel production units, remain impervious to changes in people's energy consumption behavior and are non-shiftable within individual households.

The variable energy units within our model encompass energy imported from the grid, energy exported to the grid, and the consumption of each shiftable appliance. The shiftable energy component is subject to fluctuations, which impact the energy imported and exported to the grid accordingly. All these energy units are interconnected to an electric node. The energy equations corresponding to this interconnected system are formulated as depicted below. The equation variables are defined in Table L.1.

Energy balance equation. Equation (L.1) below depicts the energy balance of household k within the collective self-consumption system. As illustrated in Figure L.1, we regard each household as an electric node, and we designate the incoming flux as the total power of household $P_{house}^k(t)$.

$$\sum_{i=0}^{N_t} (P_{house}^k(t) - P_{shift}^k(t) - P_{notshift}^k(t)) \delta t = 0. \quad (L.1)$$

The sum of the total power of all households represents the total power of the collective self-consumption system, denoted as $P_{csc}^k(t)$.

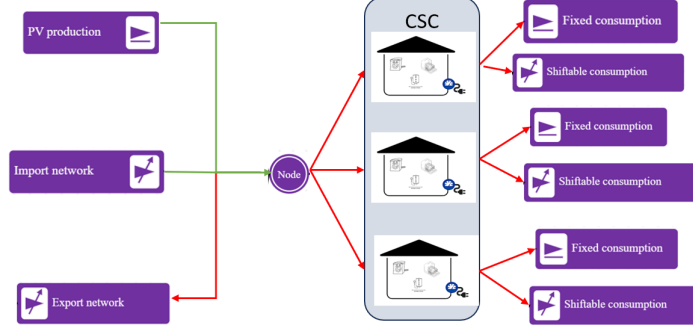


Fig. L.1 OMEGalpes model for a Collective Self-Consumption System

$$P_{csc}(t) = \sum_{k=0}^{N_k} P_{house}^k(t).$$

With the previous equation, we can derive the energy balance equation for the collective self-consumption system,

$$E_{input} - E_{outut} = 0,$$

$$\text{where } \begin{cases} E_{input} = \sum_{i=0}^{N_t} (P_{imp}(t)U_{imp}(t) + P_{pv}(t)) \delta t \\ E_{output} = \sum_{i=0}^{N_t} (P_{exp}(t)U_{exp}(t) + P_{csc}(t)) \delta t. \end{cases}$$

In electrical systems, the energy balance equation dictates that the net energy flow across any node should be zero. This implies that the total energy entering the node must equal the total energy exiting the node.

Constraints equations.

To ensure the simultaneous import and export of energy from the grid is avoided, we employ binary values, denoted as U_{imp} and U_{export} , which indicate the activation status of importing and exporting energy, respectively. Consequently, the sum of U_{imp} and U_{export} is constrained to always be equal to 1:

$$U_{imp}(t) + U_{exp}(t) = 1, \quad U_{imp} \text{ and } U_{exp} \text{ integers,} \\ 0 \leq U_{imp}(t), U_{exp}(t) \leq 1.$$

The total shiftable energy of household k within the collective self-consumption system should remain constant.

Table L.1 Energy Equations Variables and their Meaning.

Symbol	Description
t	The time period of optimization, denoted by $t \in [B_t, E_t]$, is defined as starting from B_t , the beginning of optimization, and ending at E_t , the completion of optimization.
k	The indexing variable for households within the collective self-consumption system.
δt	The change in time depends on the frequency/sample rate of the energy profile.
N_k	The size of the collective self-consumption system, which is the number of households within the collective self-consumption.
P_{imp}/P_{exp}	Power imported from the electric grid / Power exported from the electric grid.
U_{imp}/U_{exp}	Network import / export status. It is a binary variable, a value of 1 indicates that the import from the grid is active, while a value of 0 indicates that the import/export from the grid is inactive.
P_{pv}	Power generated by the solar energy unit.
$P_{shift}/P_{nonshift}$	Power of the shiftable/not-shiftable part of the total consumption.
U_{shift}	Shiftable consumption status. It is a binary variable, a value of 1 indicates that the shiftable consumption is active, while a value of 0 indicates that there is no shiftable consumption.
Stp_{shift}	The shiftable consumption start-up is represented by a binary variable. It equals 1 only when the shiftable consumption starts, i.e., when U_{shift} changes from 0 to 1.
	Total shiftable consumption.

$$\delta t \sum_{i=0}^{N_t} P_{shift}^k(t) = E_{shift_{t \in [B_t, E_t]}}^k.$$

The total energy of a system should remain constant regardless of where the shiftable consumption is allocated within the system.

$$\delta t \sum_{i=0}^{N_t} \sum_{k=0}^{N_k} P_{shift}^k(t) = \sum_{k=0}^{N_k} E_{shift_{t \in [B_t, E_t]}}^k.$$

The following equation represents the constraint for detecting the start-up of shiftable consumption. The start-up is defined as a binary value, which equals 1 only when the shiftable consumption starts.

$$U_{shift}^k(t+1) - U_{shift}^k(t) \leq Stp_{shift}^k(t+1).$$

$$\frac{U_{shift}^k(t+1) - U_{shift}^k(t) + 1}{2} \geq Stp_{shift}^k(t+1).$$

Equation (L.2) guarantees that the sequence of shiftable consumption for household k is moved in a sound way during the optimization process. In practical terms, if a device, such as a washing machine, operates from 8:00 pm to 9:30 pm, the “block” of time it represents will be shifted as a single unit. It will not be fragmented into several smaller sub-blocks, such as one-hour or 30-minute segments.

$$P_{shift}^k(t) \geq l_{spp}^k Stp_{shift}^k(t - \text{size}(l_{spp}^k)),$$

$$t \in [\text{size}(l_{spp}^k), -1]. \quad (\text{L.2})$$

Objective equation.

$$\min \sum_{i=0}^{N_t} P_{exp}(t) U_{exp}(t) \delta t = \min (E_{in} - E_{csc}) \delta t,$$

$$\text{where} \begin{cases} E_{in} = \sum_{i=0}^{N_t} (P_{imp}(t) U_{imp}(t) + P_{pv}(t)) \delta t \\ E_{csc} = \sum_{k=0}^{N_k} P_{shift}^k(t) - \sum_{k=0}^{N_k} P_{notshift}^k(t) \delta t. \end{cases}$$

The objective of the optimization model is to maximize the self-consumption rate in the self-consumption system, which is equivalent to minimizing the energy exported to the grid.