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Improving Energy Consumption Coordination in Renewable Energy Communities through Nudging

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Abstract—We use nudging to increase the renewable energy consumption of an energy community, extending previous work focusing on individual households. We identify periods with available excess production through load forecasting. We introduce coordinators, which selectively notify the members of the community about these periods, by thriving to match forecasted excess with members consumption flexibility. The aim is to maximise the community self-consumption rate. We evaluate the efficiency of our pipelines on numerical simulations using semi-real data, based on public consumption datasets. Results show that our coordinators are superior to the naive strategy, notifying all members about all green periods. Second, they prove efficient with respect to the so called OMEGAAlpes benchmark (a reference approach using a Mixed Integer Linear Programming Solver and knowing all the information for making an appropriate use of the flexibility of the community members). Third, by refining our coordinators based on additional information about the members consumption, we show we can further improve the self-consumption rate. Finally, we discuss the implications of our results for real-world deployment.

Keywords—Renewable energy; Energy self-consumption; Energy Coordination; Information Communication Technologies; Nudges; System control; Energy system optimization

I. INTRODUCTION

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 ([1], 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 [2]. Moreover, energy distribution infrastructure is very costly [3].

The concept of “renewable energy community”, introduced by the European Union in 2018 [4], 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” ([5], 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 ([6], 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 [7], the authors 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 related works, and stating our contributions, in Section II. Next, we introduce our model in Section III, before introducing the coordinators in Section IV. We then present our numerical simulations results in Section V. Finally, we discuss our results, and their practical implications for the real-world deployment of our pipelines, in Section VI.

II. BACKGROUND MATERIAL AND CONTRIBUTIONS

We first discuss related works (Section II-A), before making our problem statement (Section II-B), and stating our contributions (Section II-C).

A. Related Works

The potential of Energy Communities in helping using greener, more local, energy, is great. However, fully taking advantage of it is not entirely straightforward, and much work has been devoted to maximising this potential. Some works focus on single buildings, often linked to a microgrid. [8] present a smart-home energy management system able to conduct fast optimization. [9] 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. [10] 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. Likewise, [11] also optimize the exchanges of a building possessing a battery with a microgrid, but also take into account energy conversion possibilities. Other works apply directly to energy communities. [12] assess the financial viability of an energy community inspired by the French collective self-consumption setting. [13] 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. [14] study a demand-response scheme, where a coordinator informs prosumers of the price they may get to sell their excess production at specific times, and prosumers submit bids in returns, depending on the way they are willing to reschedule their consumptions. The coordinator then selects the bids maximising the utility of the community. [15] study a peer-to-peer energy sharing mechanism. Their results show that no household would be worse-off when participating in the scheme. Moreover, the self-consumption may increase, depending on the storage facilities. [16] build an energy sharing mechanism based on game theory, and validate its efficiency on real world data. [17] analyze the self-consumption of a community in the Spanish framework. They test different scenarios, assessing in particular the impact of consumption shifting on the performance. Fully automated control of microgrids is also an active area of research [18]. Finally, to help conduct all these studies, free or open-source simulation tools have been developed [19], [20]. They allow to test scenarios quicker than by conducting real-world experiments.

To ensure adoption of these techniques by users, and active participation in general to the energy community from users,

it is important to obtain high levels of users engagement. Moreover, [21] emphasise the importance of a “human-in-the-loop” approach to fully exploit the potential of smart buildings. [22] develop a framework to associate users to every stage of the development of a project. Enabling and driving up engagement was at the core of the Trent basin project in Nottingham, UK [23]. The authors also note that the importance of user engagement is often underestimated. User engagement and participation was an explicit intention of the legislator, in the case of the European Union, when they defined the energy communities framework [24], [25]. Key inhibitors of user engagement are administrative complexity and lack of time [26]. Indeed, it has been observed that retired households are more likely to reduce their energy consumption when given feedback than working age households, probably because they have more time to devote to it [27]. Nudging, which consists in suggesting behavioural changes in a non-mandatory way [28], offers a promising way to help drive user involvement [29]. It has been shown to be effective in increasing solar energy adoption [30], or to help households reduce their consumption during strained electricity generation periods [31]. Finally, gamification may also represent an interesting tool [32].

B. Problem Statement

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 favorable consumption periods to the households within the operation, in order to help them optimise their usage of solar energy?

C. Contributions

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 [33] and IDEAL [34] 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 OMEGAlpes model [19] (see Appendix A 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 [7], 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 [7], 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.

III. MODEL

We first describe globally our nudging pipeline in Section III-A, before describing precisely each component in Section III-B. For convenience, Table I compiles all the key notations we use.

TABLE I
MAIN NOTATIONS

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

A. Nudging pipeline

On Figure 10, 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 III-B) 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 article, dispatches these green periods to the different households, according to specific rules aiming at maximising impact (Section IV). Finally, upon receiving the nudge, the household people update their consumption accordingly.

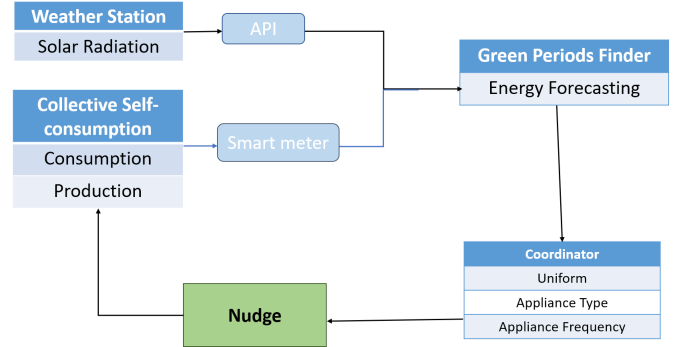


Fig. 1. Nudging pipeline

B. Collective Self-Consumption Operation

We introduce the main notions we use. Several, like that of shiftable appliance, described in [7], 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 [7] 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 II) 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 nonnegative function with compact support.

TABLE II
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

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.

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 [7], we measure the efficiency of solar energy usage with the self-consumption rate [35], [36], 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 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 1 (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:

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

Green periods, nudges. We use the same notions of green periods, and nudges, as in [7], and we recall them here.

Definition 2 (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 [7]. 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 $1 \leq p \leq p_{\max}$. 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 [7]: 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 $g_1, \dots, g_{p_{\max}}$. Therefore, making this dependency explicit, it writes, for $t \geq 0$,

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

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).

IV. COORDINATORS

We first define coordinators (Section IV-A), then present the optimization problem computing the best coordination (Section IV-B). Then, we introduce the available shiftable power

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.

matching coordinator (Section IV-C), and its two practical proxies (Section IV-D).

A. Definition

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 3 (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

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

B. Optimal Green Periods Allocation Problem

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:

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

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 1 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 V).

C. Available Shiftable Power Matching Coordinator

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 4 (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:

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

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.

D. Available Shiftable Power Estimating Coordinators

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.

V. NUMERICAL SIMULATIONS

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

A. Numerical Simulations Set-up

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 [33]. 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 [34] 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 datashare 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 [7] (see Table II).
- 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 A 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 A. 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 Syn1 et Syn2 as follows. Again, choices like the types of shiftable appliances in each house are described in Appendix A.

- 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 [7]. 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 both Syn1 and Syn2.

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 [19]. 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 A. 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 de mémoire, Nvidia RTX6000 GPU with 24 GB of memory). The OMEGAlpes optimization is the computation intensive part, as the number of possible shifts OMEGAlpes considers grows exponentially with the number of households (because each candidate shift for each household has to be considered with respect to all the other candidates shifts of other houses).

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.

B. The Appliance Frequency Coordinator is Better than the Naive Strategy

TABLE III
MEAN SELF CONSUMPTION RATE, EFFICIENCY OF COORDINATORS

Green Periods Finder	Coordinator	Syn1 Mean(%)	Iris Mean(%)	IDEAL Mean(%)
No	No	64.19	67.05	69.41
Load Forecasting	Uniform	72.65	73.88	77.84
	App Frequency	75.82	84.78	87.17

In Table III, 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 Syn1, 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 Syn1 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.

In Figure 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

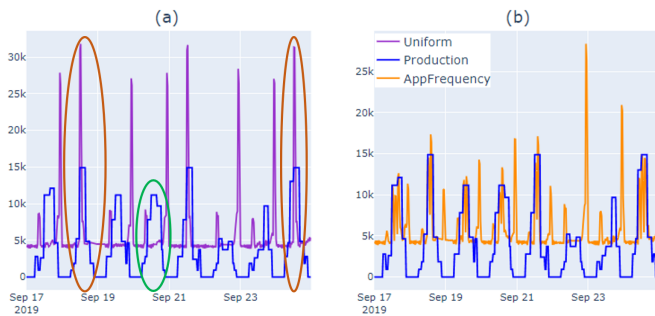


Fig. 2. Self-consumption rates obtained in the reference case, and when forecasting green periods and using the uniform (a), and frequency (b), coordinators. Production curves are in blue, and consumption curves are in dark orchid (uniform coordinator) and dark orange (appliance frequency coordinator).

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.

C. Efficiency of Coordinators

In Table IV, we compare the appliance frequency coordinator performance to those of Optimistic, and Realistic, OMEGAlpes. The simulations are conducted for the Syn1, IDEAL and Iris datasets. The appliance frequency coordinator achieves a 75.82% self-consumption rate for Syn1, 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 Syn1, 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 Realistic OMEGAlpes. Therefore, the appliance frequency coordinator proves efficient, with respect to the OMEGAlpes upper-bounds.

TABLE IV
MEAN SELF CONSUMPTION RATE WITH VARIOUS DATASETS, FOR OMEGAlpes AND THE APPLIANCE FREQUENCY COORDINATOR

Green Periods Finder	Coordinator	Syn1 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

D. The Impact of Available Information on Coordinator Performance

TABLE V
MEAN SELF-CONSUMPTION RATE WITH VARIOUS COORDINATORS

Green Periods Finder	Coordinator	Syn1 : Mean(%)	IDEAL : Mean(%)	Iris : Mean(%)
	Uniform	72.65	77.84	73.88
Load Forecasting	App Type	74.64	83.3	80.58
	App Frequency	75.82	87.17	84.78

In Table V, we compare the performances of the two available power matching coordinators, in order to evaluate the impact the information has on their performances. Recall that the appliance frequency coordinator uses 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 syn1) to approximately 6% (as observed in simulations on Iris). Furthermore, the appliance frequency coordinator shows an additional increase in performance over the appliance type coordinator from 1% (in syn1) to 4% (in the cases of Iris and IDEAL). This shows the value of precise information in enhancing the efficacy of power matching coordinators.

VI. 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 [7]. 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 concerning 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 (therefore, we do not present the results in our simulations part). 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.

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APPENDIX

We use the same optimization tool used in [7] and defined in [19], OMEGAples (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.

A. Self-consumption system modeling

In Figure 3, 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 VI.

Energy balance equation. Equation (1) below depicts the energy balance of household k within the collective self-consumption system. As illustrated in Figure 3, we regard each household as an electric node, and we designate the incoming flux as the total power of household $P_{house}^k(t)$.

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

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

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

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

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

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

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.

TABLE VI
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.
E_{shift}	Total shiftable consumption.
l_{spp}	List of power profiles to shift.

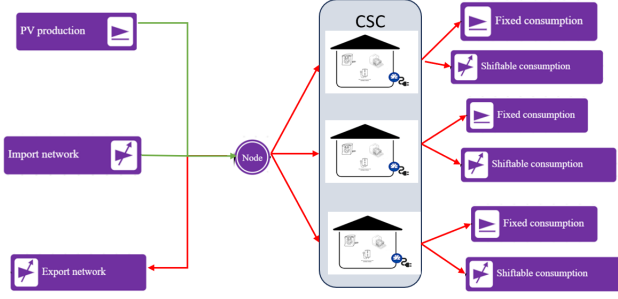


Fig. 3. OMEGAlpes model for a Collective Self-Consumption System

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:

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

$$0 \leq U_{imp}(t), U_{export}(t) \leq 1.$$

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

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

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

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

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.

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

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

Equation (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.

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

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

Objective equation.

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

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

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.

B. Information on the Collective Self-Consumption System Used in Our Study.

We describe here how we construct the collective self-consumption datasets we use in our numerical simulations. These are the synthetic datasets Syn1 (Table IX) and the datasets from real public data, Iris (Table VIII) and IDEAL (Table VII). 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 VII
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 VIII
 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 IX
 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	✓	✓	✓	