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

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RÉSUMÉ. *Nous essayons de maximiser l'autoconsommation d'une communauté énergétique dotée de panneaux solaires. Nous étendons le pipeline de recommandations introduit dans (Ling et al., 2024). Le pipeline commence par prévoir les périodes avec du surplus de production, puis indique ces périodes de manière sélective aux membres de la communauté, pour les encourager à consommer de l'énergie pendant celles-ci. La logique de notification est gouvernée par un module "coordinateur". Dans (Ling et al., 2024), le coordinateur estime la flexibilité au niveau des logements entiers. Dans notre travail, nous le faisons au niveau des appareils électriques individuels, ce qui offre un niveau de contrôle plus fin. L'efficacité de notre approche est évaluée par des simulations numériques utilisant des données semi-réelles dérivées de jeux de données de consommation publics. Les résultats indiquent que notre coordinateur (au niveau des appareils) surpasse la stratégie naïve qui notifie tous les membres à propos de toutes les périodes propices à la consommation. Il surpasse également le coordinateur opérant au niveau des logements lorsque un nombre arbitraire de notifications peut être envoyé à chaque logement. Cependant, ce n'est plus le cas lorsque les notifications sont limitées en nombre. Nos résultats suggèrent que, pour tirer avantage du coordinateur travaillant au niveau des appareils individuels, ceux-ci devraient être dotés de dispositifs domotiques capables de les activer à la réception d'un signal.*

MOTS-CLÉS. *communauté d'énergie renouvelable, nudges, coordination, optimisation du système énergétique, system autoconsommation*

ABSTRACT. *We try to maximise the self-consumption of an energy community endowed with solar panels. We extend the nudging pipeline introduced in (Ling et al., 2024). 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 (Ling et al., 2024), 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 indicate that our appliance-level coordinator outperforms the naive strategy which notifies all members about all consumption favourable periods. It also outperforms the corresponding household-level coordinator when any number of notifications may be sent. However, this is no longer the case when the notifications are restricted in numbers. 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.*

KEYWORDS. *renewable energy community, nudges, coordination, energy system optimization, energy self-consumption*

1. INTRODUCTION

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 (Ling et al., 2024), the authors 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 discuss related works (Section 2.), before presenting our model (Section 3.). Then we present our experimental results (Section 4.). Finally, we conclude, and discuss our results (Section 5.).

2. RELATED WORKS

Power systems are evolving with an increased integration of renewable energy sources (Tang et al., 2022). This brings challenges related to the variability of power supply. To address these, (Nosair and Bouffard, 2015) emphasize the importance of assessing the potential for operational flexibility of individual power system assets. To take full advantage of energy system flexibility, some works focus on single buildings. (Azizi et al., 2021) present a novel unsupervised non-intrusive load monitoring (NILM [1]) method to characterize the energy flexibility of a single building by extracting the consumption pattern of shiftable appliances via analyzing the active and reactive power. (Aslam et al., 2020) develop an effective energy management

1. Non-Intrusive Load Monitoring (NILM) is a technique used to disaggregate a building's total energy consumption into individual appliance usage without the need for installing dedicated meters for each appliance, allowing for detailed energy analysis and efficiency improvements through a single monitoring point.

strategy using Mixed Integer Linear Programming (MILP [2]). 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. Other works apply directly to energy communities. (Contreras-Ocaña et al., 2021) assess the financial viability of an energy community inspired by the French collective self-consumption setting. (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. (Ling et al., 2024) introduce a coordination strategy within a nudging pipeline to select which household within the collective self-consumption should consume when there is excess production. The coordination strategy showed a maximum of 18% improvement in the self-consumption rate in a simulation environment, utilizing semi-real data supplemented by available real-world information.

Achieving high user engagement is crucial for the successful adoption and active participation in renewable energy initiatives and collective consumption efforts. Effective engagement methods are essential for the success of collective energy projects, promoting energy justice and democracy (Shortall et al., 2022), yet challenges such as administrative complexity and time constraints can hinder user involvement (Aydin et al., 2018). Nudging, the technique of encouraging behavior change in a non-mandatory way (Thaler and Sunstein, 2008), is considered promising for increasing user engagement in energy conservation. It has been shown to boost solar energy adoption (Neumann et al., 2023) and help reduce consumption during peak demand times (Salman Shadid et al., 2020).

3. MODEL

We use the same framework introduced in (Ling et al., 2024), in which we introduce a new coordinator. This coordinator works at appliance level, while that in (Ling et al., 2024) works at household level. We start by briefly presenting our model in Section 3.1For more detailed and comprehensive insights, we refer readers to (Ling et al., 2024). Then, we introduce the appliance level coordinator in Section 3.2.

3.1. NUDGING PIPELINE

On Figure 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 (Table 1) from the original desired time slot.

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 by (Ling et al., 2023), to identify optimal usage times, called “green

2. Mixed Integer Linear Programming (MILP) 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. Several variables are integer, which makes it more complex to solve than standard linear programming approaches.

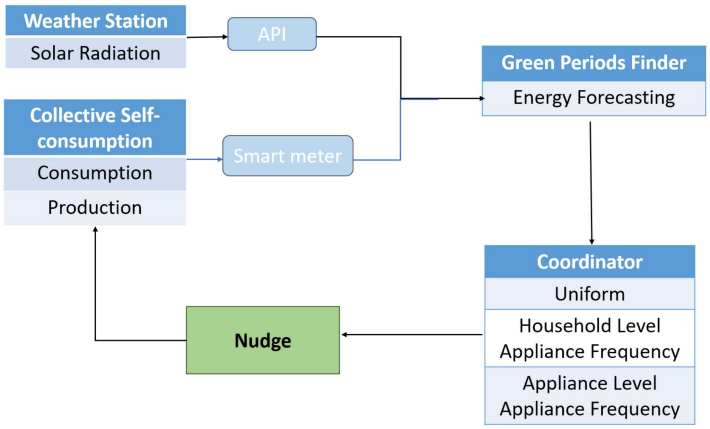

Figure 1 : *Nudging pipeline*

periods" (Ling et al., 2023), 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.

Tableau 1 : *Shiftable appliances maximum shift delays (Lucas et al., 2019)*

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

3.2. COORDINATOR

Once we have identified green periods, we need to notify them to the households of the collecive 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 (Ling et al., 2024).

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 1 (Appliance Frequency Coordinator at Appliance Level) *For each day d, let $e_1, \ldots, e_{p_{d,\max}}$ 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 :*

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

This differs from the appliance frequency coordinator in (Ling et al., 2024) in that the allocation variables also depend on the appliances (through the k index), while in (Ling et al., 2024), 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.

4. NUMERICAL EXPERIMENTS

We first give a brief presentation for the simulation set-up (Section 4.1.). Then, we present the simulation results (Section 4.2.)

4.1. SET-UP

The simulation set-up is similar to the one in (Ling et al., 2024), and we only give some brief explanations here. We start by describing the datasets, real and synthetic, we use. Each dataset is used to model one collective self-consumption operation.

Consumption and production datasets preparation. For the consumption simulation, we use the same datasets as in (Ling et al., 2024) : the Iris dataset which was collected as part

of the REMODECE (Residential Monitoring to Decrease Energy Consumption) project (Ene, 2008), the IDEAL dataset (Pullinger et al., 2021), and a synthetic dataset, named Syn, which we generated based on some real consumption. For the Iris dataset, we selected the 10 houses with the most shiftable appliances (defined in Table 1). Then, we added an electric vehicle charging profile with random activation frequencies during the evening hours to enhance the flexibility potential. Likewise, for the IDEAL dataset, we selected the 12 households with the highest number of shiftable appliances. Additionally, we incorporated a water heater profile, programmed to activate in the evening at random frequencies. For the synthetic dataset, we used a non-shiftable base consumption pattern sourced from the Iris dataset. This pattern was then replicated across 13 households, with the addition of realistic shiftable appliances usage, randomly distributed to each household's, and thus constituting varied morning and evening routines, to reflex varied energy consumption behaviors.

For the production simulation, we employ the same Markov chain model used in the works (Ling et al., 2023) and (Ling et al., 2024). This model generates a synthetic production profile by considering the time of day, month of the year, and a random amount of cloud coverage.

Simulation. The simulations are performed on G2ELAB's computation server, 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. The simulations are carried out by selecting data for a one-month period from the dataset. We make 50 runs for each simulation set-up, to adequately account for the stochastic nature of production generation, and average the results.

The input of the simulations includes essential parameters extracted from the datasets, such as maximum power and the frequency of appliances usages. These are additional information required by coordinators. To compute the green periods, we also need the historical consumption and production data for the houses, as well as future weather forecasts. The output of these simulations is the average self-consumption rate for the collective self-consumption operation, which depends on the coordinator used. We compare the self-consumption rate achieved by the appliance-level coordinator to the reference scenario, where there are no nudges (no shifts in consumption patterns), and also to the household-level coordinator from (Ling et al., 2024).

4.2. RESULTS

4.2.1. The Appliance Level Coordinator is Better than the Naive Household-Level Coordinator (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 2.

Tableau 2 : *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**

Our results show the following.

— 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.

4.2.2. 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 et al., 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 3 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.

Tableau 3 : *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

4.2.3. Suboptimal Performance of Appliance-Level Coordinators Compared to Household-Level 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 4. 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 coordina-

tor, 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.

Tableau 4 : *Average self consumption rate, Appliance-Level Coordinators vs Household-Level Coordinators when Considering 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**

5. 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 et al., 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 aim is to deploy our solution in real-world settings. We identify two main challenges in that respect, one linked with actual customer behaviour, and the second linked with load forecasting. First, human behaviour is complex, and prone to unpredictability. While our simulations assume idealized compliance with suggested nudges, real-life conditions often reveal wide variances in individuals' responses. Additionally, the effectiveness of our models can be compromised when individuals adjust the settings of their shiftable appliances without notification (for instance, replacing their washing-machine with a new one, with different consumption profile, or adding a new equipement). Therefore, future research should estimate the "compliance" rate of users to nudges, and assess their overall willingness to cooperate efficiently with the scheme, accepting the (mainly time) costs entailed in order to best benefit from it. Second, our model relies on accurate forecasting of production, and consumer consumption. Despite the availability

of various models in the literature (Yang et al., 2016; Pappas et al., 2008; Fan et al., 2019), the accuracy of weather forecasts, especially over longer periods, remains a challenge. Prediction errors could misidentify green periods, resulting in suboptimal consumption shifts and possibly deterring consumers from further participating in the scheme. Using ensemble models, which combine multiple forecasts for a more reliable aggregated prediction, could address this concern (A.Lahouarab, 2015).

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)(oec,) 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 highlighs 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.

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