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RESUME.

Les bâtiments résidentiels offrent un potentiel important de flexibilité électrique, mais la plupart des évaluations reposent sur des profils simulés ou des données agrégées plutôt que sur des mesures directes. Cet article propose un cadre d'analyse fondé sur les données pour quantifier le potentiel de flexibilité des appareils électroménagers humides à partir de mesures au niveau des équipements. Trois indicateurs sont utilisés : Occurrence, qui mesure la fréquence d'apparition d'une charge pertinente dans la période cible ; Intensity, l'énergie disponible lorsqu'elle apparaît ; et Alignment, la part de l'énergie totale déjà située dans cette période. Appliquée à environ 100 logements suivis toutes les 10 minutes pendant un an, pour des périodes représentatives du tarif français HP/HC, la méthode met en évidence une forte hétérogénéité entre ménages. Les résultats montrent que le potentiel de flexibilité dépend de la période considérée et se concentre sur un sous-ensemble limité de logements. Le cadre proposé fournit une approche transparente et transférable à d'autres jeux de données et périodes de flexibilité.

MOTS-CLÉS : Flexibilité énergétique résidentielle ; équipements électro-ménagers blancs ; évaluation du potentiel de flexibilité..

ABSTRACT:

Residential buildings offer significant demand-side flexibility, yet most assessments rely on simulated or aggregated data rather than direct measurements of when flexible loads are available and how much. This paper proposes a data-driven framework to quantify the flexibility potential of residential wet appliances from appliance-level measurements. Three indicators are used: Occurrence, which measures how often relevant load appears in the target period; Intensity, which measures the energy available when it appears; and Alignment, which measures the share of total energy already located in that period. Applied to about 100 homes with 10-minute appliance-level measurements over one year and periods representative of the French HP/HC tariff, the method reveals strong heterogeneity across households. Results show that flexibility potential depends on the selected period and is concentrated in a limited subset of homes. The framework provides a transparent measurement-based approach transferable to other datasets and flexibility periods.

KEYWORDS: Residential energy flexibility; Wet appliances; assessment of flexibility potential.

1. INTRODUCTION

Rapid electrification and increasing shares of variable renewable generation are strengthening the need for flexibility in power systems (IEA 2025; Li and Pye 2018). As grid reinforcement remains costly and slow, demand-side flexibility is increasingly viewed as a practical complement to supply- and network-side solutions, particularly in sectors with recurring and shiftable electricity uses (Li and Pye 2018; SEDC 2016). In the residential sector, which accounts for a substantial share of final electricity demand, implicit demand response is especially attractive because it requires limited additional infrastructures and preserves household autonomy (SEDC 2016). In France, the combination of Linky smart meters and evolving HP/HC-type tariff structures makes residential flexibility a relevant operational topic (ENEDIS 2024).

Among residential end uses, wet appliances such as washing machines, dishwashers, and tumble dryers are of particular interest because they behave as temporary non-interruptible, or “shiftable atomic” loads: the cycle generally runs to completion, but the start times can be delayed (Degefa et al. 2018). Period-based flexibility potential is understood as the amount and timing of consumption that can be shifted relative to such a flexibility-requested period, independently of behavioral willingness to respond. This flexibility is opportunity-driven: it depends on whether meaningful energy appears in the period and on how much is available when it does (Degefa et al. 2018; D’hulst et al. 2015).

1.1. State of the art and gap

Existing studies assess residential flexibility from several angles. Simulation and bottom-up approaches derive appliance demand from assumed schedules or behavioral models but may miss observed household heterogeneity (Ahmed et al. 2023). (Vellei et al. 2020) explicitly states that occupants' self-reported flexibility often does not coincide with their actual flexibility potential. Behavioral studies quantify routines and willingness to shift, but do not directly measure cycle-appliance flexibility potential (Barsanti et al. 2024). Measured-data studies come closer to operational reality: pilots have quantified appliance flexibility under real conditions (D’hulst et al. 2015), atomic-load formulations have explicitly represented non-interruptible appliance cycles (Degefa et al. 2018), and a recent smart-meter work has proposed multi-dimensional flexibility indicators (Palacios-Garcia et al. 2024). However, many available datasets remain aggregated or hourly and cannot resolve individual wet-appliance cycles (Hofmann and Siebenbrunner 2023). In parallel, operational targeting studies increasingly group or rank customers into flexibility profiles for portfolio selection, but these approaches often rely on composite metrics or clustering outputs that mask the difference between frequent small reductions and single, high-capacity appliance cycles (Petrucci et al. 2025).

1.2. Problem statement

Most assessments treat wet appliances as broadly shiftable, based on simulated schedules, survey responses, or aggregated metering. However, for non-interruptible appliance cycles such as wet appliances, a household may be attractive either because flexibility relevant consumption in the requested period occurs frequently or because they contain substantial energy. Without distinguishing these two dimensions, flexibility potential may be overstated, and household targeting remains limited.

1.3. Contribution

This paper proposes a compact period-based framework to characterize flexibility potential from measured appliance-level energy using three indicators: **Occurrence**, **Intensity**, and **Alignment**. Applied to wet appliances with flexibility requests aligned with the peak hours of the French HP/HC context, this framework provides a transparent basis for household comparison, grouping, and ranking.

Research question: Given measured appliance-level data, how can the flexibility potential of residential temporary cycle-based appliances be characterized using simple indicators, and how can these indicators support household comparison, grouping, and ranking in terms of recurring and sizable relevant consumption in the requested period?

2. METHODOLOGY

2.1. DATASET AND PROCESSING

The proposed method is defined for appliance-level electricity measurements sampled at a regular short time step. Let Δs denote the sampling period and Δd the duration of one day. The proposed method is defined for appliance-level electricity measurements sampled at a regular short time step.

Let's denote $\mathcal{T}$ a set of non-intersecting time periods $T_k = [\check{T}_k, \hat{T}_k[$. For instance, $\mathcal{T}_s = \{[0, \Delta_s[, [\Delta_s, 2\Delta_s[, \dots, [(n-2)\Delta_s, (n-1)\Delta_s[\}$ denotes the consecutive sample periods covering a day. The equivalence is defined by: $\mathcal{T}_1 \leftrightarrow \mathcal{T}_2 \vDash \forall t \in \mathcal{T}_1 \rightarrow t \in \mathcal{T}_2$ and $\forall t \in \mathcal{T}_2 \rightarrow t \in \mathcal{T}_1$. For instance, $\mathcal{T} = \{[0, (n-1)T_s\}$ is equivalent to $\mathcal{T}_s$.

Let $\mathcal{T}_s^F (\subset \mathcal{T}_s)$ be the series of the sample periods where flexibility is requested. Consecutive time period in $\mathcal{T}_s^F$ can be merged to yield an equivalent $\mathcal{T}^F$. Let $\mathcal{D} = (d_1, d_2, \dots d_m)$ be a set of day indices.

For the sake of clarity, we define the operator $\otimes$ on $\mathcal{D} \times \mathcal{T}$ as:

$$\mathcal{D} \otimes \mathcal{T} = \{\cup_{d_i \in \mathcal{D}, T_j \in \mathcal{T}} [d_i \Delta_d + \check{T}_j, d_i \Delta_d + \hat{T}_j[\} \qquad (1)$$

Days with missing data in the relevant appliance channels are excluded from the computation of the indicators. The objective is to characterize flexibility potential directly from measured appliance energy during recurrent daily periods where flexibility is requested.

2.2. FLEXIBILITY-PERIOD DEFINITION

Accordingly, to the above definition of equivalence, requested sample periods can be merged into an equivalent set of continuous intervals denoted $\mathcal{T}^F$. Let D be the set of valid observed days. To map a daily flexibility period to all valid days, the operator $D \otimes T$ is used. It denotes the union of the corresponding time intervals over all days in D. The total energy of appliance a in household h during all requested periods is then defined as:

$$E(h, a, \mathcal{D} \otimes \mathcal{T}^F) = \sum_{T \in \mathcal{D} \otimes \mathcal{T}^F} E(h, a, T) \qquad (2)$$

This quantity represents the total measured appliance energy observed during the recurrent flexibility periods over all valid days.

2.2.1. Operating-state definition

Because wet appliances may exhibit standby consumption, the indicators are based on operating samples only. An appliance is operating during a sample period T if its measured energy exceeds an appliance-specific standby threshold ϵ_a. The operating energy during the requested sample periods is defined as:

$$E^*(h, a, \mathcal{D} \otimes \mathcal{T}_s^F) = \sum_{T \in \mathcal{D} \otimes \mathcal{T}_s^F} \begin{cases} E(h, a, T) & ; E(h, a, T) > \epsilon_a \\ 0 & ; E(h, a, T) \leq \epsilon_a \end{cases} \qquad (3)$$

and the number of operating sample periods inside the requested periods is:

$$O(h, a, \mathcal{D} \otimes \mathcal{T}_s^F) = \sum_{T \in \mathcal{D} \otimes \mathcal{T}_s^F} \begin{cases} 1 & ; E(h, a, T) > \epsilon_a \\ 0 & ; E(h, a, T) \leq \epsilon_a \end{cases} \qquad (4)$$

These two quantities form the basis of the KPI definitions.

2.3. KEY PERFORMANCE INDICATORS

Three complementary indicators are used to characterize flexibility potential at the household–appliance level.

Occurrence measures how often the appliance is active during the requested period. It is defined as the fraction of requested sample periods in which the appliance is operating:

$$\text{Occurrence}(h, a, \mathcal{T}^F) = \frac{O(h,a,\mathcal{D}\otimes\mathcal{T}_s^F)}{|\mathcal{T}|} \tag{5}$$

Occurrence is dimensionless and ranges from 0 to 1. A high value indicates that relevant consumption appears recurrently in the requested period and is therefore more regularly available for a recurring flexibility scheme.

Intensity measures the magnitude of the opportunity when it exists. It is defined as the mean operating energy per active sample within the requested period:

$$\text{Intensity}(h, a, \mathcal{T}^F) = \frac{E^*(h,a,\mathcal{D}\otimes\mathcal{T}_s^F)}{O(h,a,\mathcal{D}\otimes\mathcal{T}_s^F)} \tag{6}$$

Intensity is expressed in Wh per active sample. It indicates how much energy is present when the appliance is effectively operating in the requested period.

Alignment measures the relative importance of the requested period in the appliance's overall use pattern. It is defined as the share of total operating energy that already occurs within the requested period:

$$Alignment(h, a, \mathcal{T}^F) = \frac{E^*(h,a,\mathcal{D}\otimes\mathcal{T}_s^F)}{E(h,a,\mathcal{D}\otimes\mathcal{T}_s)} \tag{7}$$

Alignment is dimensionless and ranges from 0 to 1. Unlike Occurrence and Intensity, it does not describe recurrence or conditional magnitude directly. Instead, it indicates how strongly the appliance's total measured use is already concentrated in the target period.

2.3.1. Threshold definition

The operating threshold ϵ_a is introduced to exclude standby or negligible consumption from the analysis. Because appliances differ in their typical operating levels, ϵ_a is defined per appliance type. This preserves appliance specificity while keeping the framework simple and transparent. In the case study, a second appliance-specific threshold is also used to define a meaningful daily opportunity at the aggregation level, following the same logic as in the original implementation.

2.3.2. Household-level comparison

KPIs are first computed at the household–appliance level. For household-level comparison, wet-appliance energy is aggregated across the equipped services within each dwelling, and household indicators are recomputed from the resulting aggregated series. In the implementation used here, the household threshold is taken as the sum of the appliance-specific thresholds of the wet-appliance services present in the dwelling. Households are then represented in a two-dimensional Occurrence–Intensity space, while Alignment or annual wet-appliance energy is used as a secondary descriptor. This representation makes it possible to distinguish households with frequent but small opportunities from those with rarer but larger ones, and to identify the dwellings that are most attractive for recurring activation in each target period.

3. CASE STUDY: ELECDOM WET APPLIANCES UNDER HP/HC – TYPE PERIODS

The proposed framework is applied to the Elecdom dataset, which provides 10-minute appliance-level electricity measurements for about 100 French dwellings (ADEME 2026). The case study focuses on wet appliances, washing machines, dishwashers, and tumble dryers, as representative non-interruptible residential loads.

In this application, each day is partitioned into four fixed recurrent daily periods: night (00:00–06:00), morning (06:00–12:00), afternoon (12:00–18:00), and evening (18:00–24:00). For each target period, the corresponding set of sample intervals $\mathcal{T}_s^F$ is defined, and the equivalent merged period $\mathcal{T}^F$ is used for interpretation. This partition provides a compact way to compare the potential for time-of-day flexibility and to represent households in Occurrence–Intensity space for each period. It is also consistent with the logic of the French HP/HC tariff, since peak and off-peak tariff periods can be approximated by one or several of these recurrent periods. At the same time, the KPI framework itself remains applicable to any user-defined recurrent daily period.

For each appliance type a, an operating threshold ϵ_a is defined using a fixed scaling factor μ=20%. In the base case, ϵ_a is set to 20% of the median positive daily energy of that appliance type. This keeps the definition of relevant operating consumption proportional to typical observed use. Occurrence, Intensity, and Alignment are then computed for each household–appliance pair and each recurrent daily period.

4. RESULT AND DISCUSSION

Figure 1 places households in the Occurrence–Intensity plane considering the high peak hours of the HP/HC tariffs as the flexibility period.

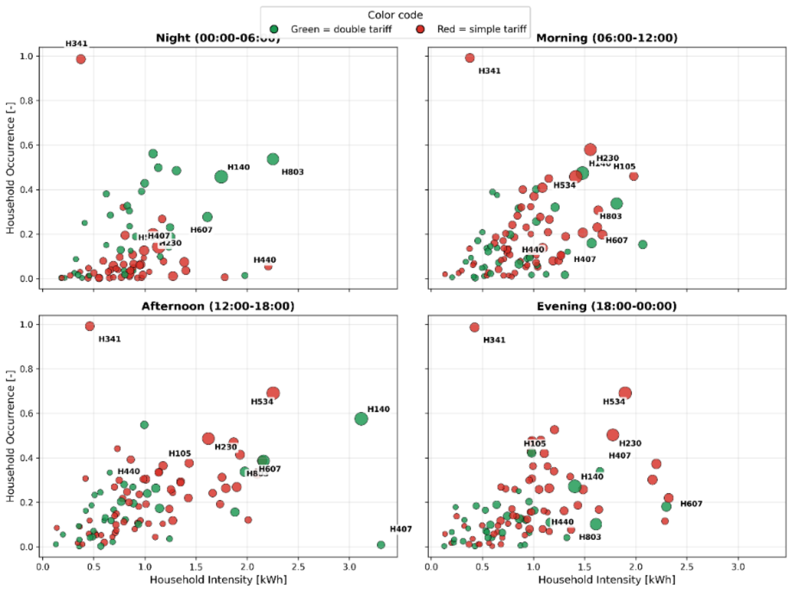

Figure 1. Household representation in the Occurrence–Intensity plane across the four recurrent daily periods. Marker size is proportional to annual wet-appliance energy.

The wide dispersion shows that households with similar appliances can still provide very different flexibility opportunities according to the periods within the day, which have been decomposed into 4 subsets: night, morning, afternoon, and evening. The wide dispersion in each panel shows that households equipped with similar wet appliances can still provide very different flexibility potential. More importantly, household positions change across periods: a dwelling that appears attractive in one period may become much less attractive in another. This confirms that residential flexibility potential is not only household-specific but also period-dependent.

In this representation, households located in the upper-right region combine frequent and large energy availability and are therefore the most attractive candidates for recurring demand-response actions. By contrast, households in the lower-left region show both low recurrence and low conditional energy and thus offer limited potential. Intermediate positions remain operationally relevant, distinguishing households with recurrent but modest availability from those with rarer but larger energy volumes. Marker size indicates annual wet-appliance electricity use and provides a secondary indication of the total load concerned.

To make this targeting logic explicit, households are classified separately in each period using the sample median of household Occurrence and the sample median of household Intensity for that period. This produces four relative groups: frequent-large, frequent-small, rare-large, and rare-small. The grouping is intended to identify the most attractive households within each period by jointly considering how often meaningful energy appears and how much energy is available when it does.

Figure 2 examines how stable the most attractive households remain across the day by counting, for each household, the number of periods in which it is classified as frequent-large. Most households never belong to this group, while only a limited subset appears in it repeatedly across several periods. This result shows that the highest flexibility potential is concentrated in a relatively small share of dwellings and that attractive households are not fully the same from one period to another. In practice, this supports adaptive targeting strategies rather than uniform activation of all households.

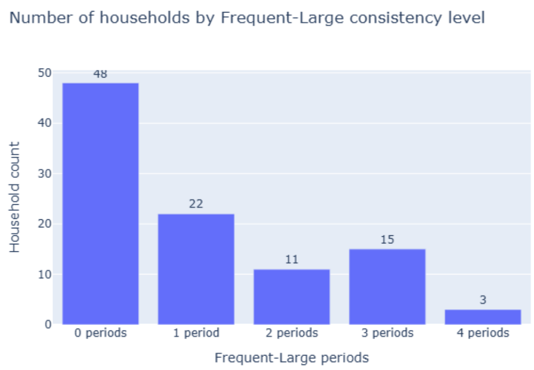

Figure 2. Number of periods in which each household is classified as frequent-large, showing the consistency of the most attractive households across the day.

A secondary analysis focuses on the Alignment indicator and compares households according to their tariff subscription type. Figure 3 shows the distribution of Alignment across the four recurrent daily periods for households subscribed to simple and double tariffs.

Alignment reflects how much of a household's wet-appliance energy is naturally concentrated in each period before any explicit demand-response activation. In this sense, it reveals the temporal structure of appliance-use behavior.

Households subscribed to simple tariffs exhibit very low Alignment during the night period, indicating that wet-appliance usage is naturally concentrated during daytime and evening hours. By contrast, households on double tariffs show substantially higher night Alignment, suggesting that off-peak pricing incentives are associated with a partial shift of appliance use toward night periods.

However, variability remains large within both groups. Some double-tariff households exhibit very strong night Alignment, while others remain close to the behavior observed under simple tariffs. This heterogeneity indicates that tariff structures alone do not produce uniform behavioral responses across households.

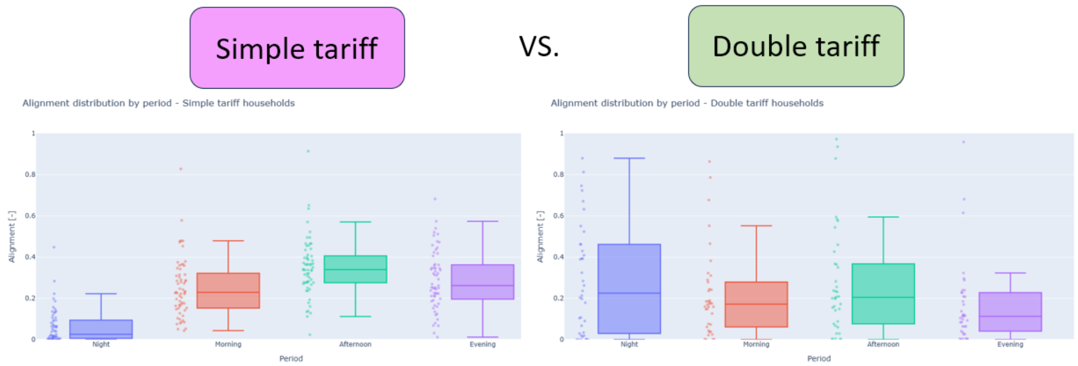

Figure 3. Distribution of Alignment across recurrent daily periods for households subscribed to simple and double tariffs.

These results suggest that residential flexibility should not only be characterized in terms of technical availability, but also through the diversity of behavioral adaptation to price signals. Understanding this response, diversity represents an important direction for future work.

5. CONCLUSION AND PERSPECTIVES

This paper proposed a compact period-based framework to characterize the flexibility potential of residential wet appliances from measured appliance-level energy data. The three indicators: Occurrence, Intensity, and Alignment, capture complementary dimensions of potential: how often relevant consumption appears in a requested period, how much energy is available when it does, and how much of total consumption is already concentrated in that period. Applied to the Elecdom dataset, the framework highlighted substantial heterogeneity across appliances, households, daily periods, showed that the households appearing most attractive for recurring activation depend on the requested period.

These indicators are useful for screening, comparing, and ranking residential flexibility potential when the request is defined over recurrent daily periods, such as tariff periods or regularly repeated system-service periods. They provide a simple first-level characterization of where and when flexibility potential is present in measured load data, rather than a prediction of realized demand response.

The framework has clear limits. It is designed for recurrent daily periods and does not directly address one-off events, non-recurrent requests, inter-period constraints. It characterizes availability in measured load data, but not behavioral acceptance, control feasibility, realized shifting, or economic value.

Future work should compare appliance-specific behaviors in more detail, test robustness under alternative period definitions and threshold choices, and, most importantly, assess whether similar indicators can be approximated from total household load without appliance-level sub-metering.

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