Assessing Flexibility Activity in SSEN's Licence Areas phase 2: Implicit Flexibility

Date/version: 15 April 2026 / Final Draft

A Report by ElectraLink in Collaboration with Scottish & Southern Electricity Networks

ElectraLink Ltd.

Registered No: 3271981 VAT Registration No: 698 2336

Contents

Authors: Atzin Madrid (Lead Author & Analysis), Jake Verma (Co-Author & Clusters Analysis)

Contributors: Ian Scougal (Data & analysis support), Smitha Roy (Analysis support)

Introduction

Executive Summary

Flexibility is a critical component of the GB energy system, with policy targets such as Clean Power 2030 and ambitions for up to ~12GW of consumer-led flexibility. However, there remains limited visibility and consistency in how flexibility — particularly implicit flexibility — is defined, measured and understood in practice. This is especially relevant for Distribution Network and System Operators (DNOs/DSOs), where low-voltage networks are directly impacted by changing patterns of domestic demand. Understanding how consumers respond to price signals, and the extent to which demand is already shifting, is therefore key.

As such, the north-star objective of this project is to establish a clear and practical understanding of implicit domestic flexibility within Scottish and Southern Energy Networks (SSEN) areas, including the magnitude, timing and consistency of demand changes translated into consumer behaviour, and how consistent this behaviour occurs in response to underlying signals.

Explicit flexibility refers to demand or generation changes that are actively instructed, contracted or directly controlled in response to a signal, typically through participation in a market or service. Implicit flexibility is understood as changes in consumption or generation that occur in response to market price signals.

This study analyses nine months of Elective half-hourly settled (EHHS) smart meter consumption data across ~60,000 MPANs, focusing on three suppliers with the most complete datasets. While not fully representative of the total population, this EHHS subset of consumers – likely comprising early Low Carbon Technology (LCT) and Time-of-Use (ToU) adopters, more engaged and affluent demographics, etc – provide a strong indication of how demand patterns are likely to evolve as flexibility becomes more widespread and how demonstrated patterns could evolve at scale – a key consideration for DNO/DSO planning.

It's important to note that, at this early stage, the primary aim of this work – particularly for SSEN – is not to define a single metric for implicit flexibility, but to build a robust and data-backed method to more accurately track and understand how consumer behaviour responds to price signals in real conditions with a significant number of users. As such, the analysis focuses on identifying, quantifying and segmenting these patterns, providing a foundation that can be further refined and developed into a more formalised model approach in subsequent phases.

Two complementary analytical approaches were applied to ensure both behavioural interpretability and statistical robustness. A top-down, behaviour-led analysis quantified consumption patterns (e.g. peak/off-peak, overnight and midday behaviour), while a bottom-up clustering approach grouped consumers based on both derived behavioural features and full load profile shapes. Together, these approaches provide complementary lenses investigating and validating the same behavioural patterns.

In the absence of a universally accepted framework (at least publicly available) for measuring implicit flexibility, a pragmatic approach was developed, using ToU signals as a proxy and benchmarking behaviour against standard domestic load profiles derived as baseline.

For the observation/behaviour windows selection, most suppliers agree that 16:00 to 19:00 hrs are peak electricity hours, however they differ on their morning peak hours and on their off-peak windows. Whilst it varies per supplier, morning peak is typically considered between 07:00 to 09:00 hrs, so for the purpose of this report we consider as peak hours between 07:00 to 09:00 hrs and 16:00 to 19:00 hrs. Other LCT tariffs, such as electric vehicle (EV) or heat pump tariffs, also vary by supplier, so for the purpose of this analysis we took 00:00 to 06:00 hrs as the overnight window, and 11:00 to 16:00 for midday – which some suppliers consider as super off-peak.

This work delivers **four tangible outputs**:

1. **A method that can be further applied and developed to quantify implicit flexibility**: a structured framework that can be applied and used to test and validate hypothesis and model demand under different scenarios, by applying cluster-level scale factors and observed behavioural differences derived from the analysis. For example, consumption could be modelled under different scenarios where the number of customers on ToU tariffs is varied.
2. **A set of proxy metrics for implicit flexibility within SSEN area providing a robust indication of the magnitude, distribution and consistency.**
3. **Insights to inform and shape existing or emerging frameworks to measure implicit flexibility.**
4. **A thorough interpretation of observed behaviour of a large real-world dataset and key market participants.**

Key Findings

1. **Implicit flexibility is materially present across a significant share of users and is consistent across time.**

Off-peak to peak consumption ratios for the three analysed suppliers are **3.67, 5.95 and 5.86,** compared to a **baseline of ~2.8**, indicating a material redistribution of demand away from peak periods.

This is also reflected in consumption shares, with off-peak usage increasing from ~**74%** from a standard consumer profile, to **~78 – 83%** across all three suppliers. Off-peak consumption is already high**,** but incremental shifts are significant. Even though the majority of electricity consumption already occurs during off-peak hours – reflecting the fact that these hours account for a much larger proportion of the day - peak demand is concentrated in relatively small periods. As such, even apparent modest shifts in percentage terms represent meaningful behaviour.

2. **Implicit flexibility behaviour varies across suppliers, but it's present for all of them, even within the more *traditional suppliers*.** [1]

Importantly, all suppliers exhibit ratios above baseline. Even the supplier showing most traditional patterns shows a ratio of 3.67, suggesting that demand shift is not limited to highly engaged users but is present across broader customer groups.

This is further supported by clustering analysis, which shows that approximately **68%** of MPANs exhibit non-standard behaviour, including elevated overnight consumption, reduced evening peaks or targeted responses to specific signals such as Sundays with free or cheaper electricity offers.

3. **Consistency and distribution across consumers: some behaviours are more uniform across users, and some shifts are concentrated in distinct segments**

The shift to overnight consumption is the most consistent and pronounced pattern. The results show a significant **increase** of **overnight consumption from 14%** from a standard consumer profile, to **39%** for 2 of the suppliers observed (B and C). This shift represents the largest redistribution of demand in both relative and absolute terms.

[1] By *traditional suppliers* this report refers to suppliers whose offering and customer base are largely characterised by standard consumption patterns, with more limited adoption of ToUs, LCTs, smart products or flexibility-oriented services.

By *standard consumption* this report refers to the typical historic domestic electricity usage/curve.

In addition, more targeted behaviours are observed, such as Sunday midday uplift driven by distinct user segments where the magnitude of behavioural change is material. For example, users identified by the clusters with the highest Sunday midday uplift consume up to ~16.6 kWh more than the baseline/standard consumer during this period. Users with the highest overnight concentration consume between ~8 and 13.5 kWh more overnight than a standard profile.

Supplier A shows a clear concentration of consumption during midday periods, particularly on Sundays, with approximately 78% of users in the upper quartiles of midday share, likely reflecting specific tariff incentives (e.g. free or discounted periods). This contrasts with other suppliers, where midday consumption is more limited and more users remain in lower quartiles.

It's important to note that the cluster-derived metrics are not conclusive numbers – they are proxy-based metrics and rely on representative baselines rather than true counterfactuals and are sensitive to methodological choices. However, they provide a strong and practical indication of the magnitude and distribution of implicit flexibility, and can be used to get an estimation, to inform modelling and scenario analysis. For example, the estimated increase of ~16.6 kWh more than the standard consumption on Sundays currently is driven by around 7-9% of the observed MPANs. However, if this number duplicated or triplicated, the impact to low voltage (LV) networks could be significant.

4. Distinct implicit flexibility archetypes are emerging, and the cluster analysis reveals subtle but important variations.

From near-zero daytime demand and high overnight consumption (indicative of full self-consumption, e.g. solar PV with storage) to profiles with reduced – but not eliminated - daytime usage, suggesting active shifting rather than self-supply. Other patterns include sustained or rounded overnight consumption, sharp short-duration charging peaks, ramping behaviours and profiles with elevated and consistent daytime usage – potentially linked to electric heating demand such as heat pumps. These differences are critical, as they reflect not just the presence of LCTs but how and when demand is being shifted, providing a more granular understanding of implicit flexibility and a basis to model its magnitude, timing and system impact within planning frameworks, for instance with Local Area Energy Plans (LAEPs).

5. There are visible behaviours that indicate the presence and response to dynamic pricing

Whilst not fully conclusive, both data inspection and clusters analysis indicate niche and unusual patterns that vary from the historic electricity demand curve, and furthermore from the ToU users baseline behaviour – for example, the variation and very pronounced dip in specifically one supplier, which is likely aligned with dynamic tariffs. This should be explored more in detail in future phases.

6. Implicit flexibility manifests through a range of behaviours and intensities across different segments, and thus its quantification would greatly benefit from a multi-dimensional approach.

Capturing diversity - rather than collapsing it into a single value - provides a more meaningful and accurate representation of how flexibility operates in practice. A multi-dimensional approach not only would better reflect this but would also help avoid double counting across overlapping behaviours or tariff structures.

Background

In Spring 2025, ElectraLink carried out an initial data-led assessment of domestic and small-scale flexibility in collaboration with SSEN - “Estimating Flexibility Activity in SSEN’s Licence Areas”. This work was effectively the first phase towards the ultimate goal of informing and building a model that can generate repeatable and increasingly accurate insights on the LV network activity.

Phase 1 work identified observable reductions in consumption during national (namely Demand Flexibility Service) and local (SSEN-instructed) dispatch events and produced an initial indication of flexibility volume, and potential of demand reduction capacity across SSEN areas. It also surfaced future research opportunities and how to refine and expand the assessment going forward.

The next steps, identified in Phase 1, are to move beyond isolated event insights and strengthen the confidence and evidence base required to generate repeatable and increasingly accurate flexibility insights over time.

One of the main aspects of immediate and key relevance is to further investigate and differentiate implicit flexibility, to better understand how domestic properties respond to economic and behavioural signals and how this differs or impacts explicit response.

For SSEN and the other DNOs/DSOs, this distinction is critical given implicit flexibility is increasingly seen as a potential key lever to manage LV networks. As such, continuing to explore and understand implicit flexibility is key as it may represent a significant but less visible source of flexibility that influences local load patterns and network constraints.

Explicit flexibility refers to demand or generation changes that are actively instructed, contracted or directly controlled in response to a signal, typically through participation in a market or service. Implicit flexibility refers to changes in consumption or generation that occur in response to market signals.

Project overview

Objective

The north-star objective of this project is to establish a clear and practical understanding of implicit domestic flexibility within SSEN areas, including the magnitude, timing and consistency of demand changes translated into consumer behaviour, and how consistent this behaviour occurs in response to underlying signals.

The aim of this work is intended to do more than produce a one-off analytical assessment. It is designed to help establish an analytical approach that can be refined and reused over time.

Approach

Following an initial assessment of potential approaches, including a review of available inputs, key gaps and the feasibility of obtaining additional information, the project refined its direction and selected the approach set out below.

The methodology takes forward two complementary analytical approaches in parallel, followed by quantification and synthesis and interpretation.

1. Top-down behaviour-led analysis

This analysis is used as an exploratory and interpretative layer. It focuses on visually inspecting aggregate and subgroup demand patterns to identify:

- Expected responses to known or plausible implicit price signals
- Anomalous or unusual consumption patterns
- Evidence of peak avoidance or demand shifting
- Recurring patterns that may indicate automated or tariff-driven behaviour

A signal identification and mapping are used to define relevant windows and guide the analysis.

Thus, this approach intends to:

- provide an initial read of whether signal-consistent behaviour is visible in the data,
- surface patterns and hypotheses for deeper testing,
- and support interpretation of findings from bottom-up work.

2. Bottom-up cluster-based analysis

This analysis provides the more structured and quantitative foundation of the work. Work includes analysing domestic properties profiles to identify meaningful profile groupings and likely behavioural or technology-led linked cohorts. A key output of this stage is the clustering of consumption profiles.

The intention is not to claim definitive identification of individual technologies at property level at this point, but to use profile analysis to infer groups of households with characteristics consistent with certain flexible technologies.

The outputs of this analysis are used to assess the extent to which observed consumption patterns are consistent with the behaviour identified through the signal-led analysis. Not only does this include patterns identified through visual inspection, but also the hypothesis that emerged from that process and informed subsequent areas of investigation.

This alignment provides an important validation step, ensuring that both observed patterns and emerging hypothesis are tested through structured analysis, and helping to distinguish between isolated observations and systematic behaviour. The resulting alignment between these two will inform subsequent quantification and interpretation.

3. Quantification of implicit flexibility

The next step is translating observed consumption patterns into measurable indicators of implicit flexibility. There is currently no single fully agreed universal industry standard for measuring it, particularly in relation to domestic and small-consumer behaviour. However, there is convergence around a set of commonly used metrics, including:

- Average demand reduction peak periods
- Peak-hour demand reduction relative to a counterfactual
- Peak-to-off-peak ratios

We propose to use these established metrics as the basis for quantification, while also examining how they can be translated into practical DNO-usable measurement approach. These metrics will be used as the guiding framework for quantification, however the specific methodological approach used to estimate flexibility will be developed and tested as part of this work.

Robustness and sensitivity: Selected are tested for sensitivity to key assumptions.

4. Synthesis and interpretation

This stage synthesises the outputs of all the analysis, and quantification to produce a consolidated view of what implicit flexibility appears to be present in the dataset and an assessment of which properties/profiles are most associated with that behaviour. This can be used to inform or complement practical frameworks for measuring implicit flexibility.

The top-down exploratory approach was used to identify and investigate patterns directly within the EHHS dataset. This involved visual inspections, identifying key behaviours (e.g. overnight, Sunday midday peak, etc.) deriving consumption-based metrics, analysing consumption shares across defined time windows informed by price signals – suppliers' ToU tariffs, segmenting users based on observed behaviour and testing the consistency of these patterns across time and the whole dataset. These observations directly informed the selection of features used in subsequent analyses.

In parallel, the bottom-up, statistical, cluster-led approach was applied using two clustering techniques. First, each MPAN was represented by its average weekly consumption profile over the full observation period, alongside key behavioural features derived from the exploratory top-down analysis and grouped into 10 clusters based on similarity. Second, clustering was applied directly to the full average weekly load profiles, grouping MPANs based on similarity in their time series shapes without pre-defined assumptions.

The use of these two complementary analytical approaches helps ensure both behavioural interpretability and statistical robustness.

Data scope and preparation

As one of the first steps, early interrogation of the EHHS dataset was undertaken. Building on lessons from Phase 1 – particularly around data completeness – care was taken to avoid progressing analysis before confirming data suitability. An initial filtering step was applied to identify MPANs with sufficiently complete data over the study period.

Licence Area	Domestic MPANs	Smart MPANs (SMETS 1 and 2)	Elective HH MPANs	In DTN EHHS data	9-months of data
Total SSEN	3,703,096	2,604,937	313,183	135,245	61,922
Southern England (H)	2,942,912	2,113,561	261,615	117,419	54,728
Northern Scotland (P)	760,184	491,376	51,568	17,826	7,194

Table 1: Breakdown of MPANs within SSEN licence area.

Different options were considered in terms of data coverage and duration balancing:

- A larger number of MPANs with shorter data histories
- Fewer MPANs with more complete and consistent data

Following this assessment, a nine-month observation window was selected as the observable dataset for the analysis with the most appropriate balance.

GSP Group	Supplier A	Supplier B	Supplier C	Total
Total SSEN	**32,826**	**4,312**	**24,784**	**61,922**
North Scotland	4,245	663	2,286	7,194
Southern England	28,581	3,649	22,498	54,728

Table 2: Observable dataset for the analysis – breakdown per supplier

A small number of MPANs were further removed, for instance those with zero values, and as such the sample is marginally smaller.

Approach Development

In parallel, initial work focused on refining key research questions and sub-objectives required to address this objective. These included:

- Can we detect implicit flexibility behaviour in the EHHS consumption data?
- What implicit flexibility behaviour is observable in domestic demand?
- Can we infer which properties likely have flexible/low carbon technologies and whether they are responding to implicit signals? And if so, should we use this as a method?
- Is there an agreed industry approach to measure implicit flexibility?
- What is the potential magnitude of implicit flexibility/voluntary response to price signals?
- Which properties appear to be responding, to what signals and how often?
- How robust are detected flexibility behaviours?
- Can we develop a repeatable method to identify that behaviour?

The initial analytical framing considered whether a signal-led approach – based on known flexibility drivers – would provide a suitable starting point.

This required first establishing what is generally understood within industry as implicit flexibility. As reviews of current practices indicated that, while a single universally adopted framework of implicit flexibility does not exist, there is broad alignment around price signals, and more specifically ToU tariffs, as the primary drivers of implicit flexibility behaviour.

This led to an initial focus on identifying and defining relevant signal windows within the GB context.

In parallel, consideration was given to whether it would be possible to infer the presence of LCTs – such as EVs, photovoltaic (PV) systems and batteries, etc – from consumption patterns and to use this to link behaviour to specific tariff types.

Whilst indicative patterns in consumption data – such as sustained overnight usage or repeated periods of zero demand – are considered within the analysis as potential signals of LCTs, it is important to note that the aim of this work is not to perform LCT detection or to explicitly classify properties by technology type. Instead, these indicators are used as supporting context to aid interpretation of observed behaviours and to explore how different consumption patterns may relate to different tariff structures and retail incentives.

Tariff and signal mapping

Understanding implicit flexibility requires a clear view of the signals that influence consumer behaviour.

While there are other factors that can influence demand – such as automation, operational constraints or behavioural routines – these are typically implemented for reasons such as convenience, comfort or system optimisation. In practice, most implicit flexibility is ultimately driven by price incentives, which shape tariff structures of retail offers, which define when electricity is cheaper or more expensive to use.

Historically, consumption patterns were relatively consistent and predictable, with limited variation driven by simpler tariff structures. However, the increasing adoption of LCTs, TOU tariffs and the Market-wide Half-Hourly Settlement (MHHS) programme underway have introduced a wider range of incentives, encouraging consumers to shift their consumption across different periods of the day.

This section provides an overview of the main current tariff types/categories and associated time windows relevant to this study.

1. Structured / static ToU tariffs (most common)

Fixed daily off-peak windows, commonly overnight.

Lower price window: ~00:00–06:00~

Standard price: rest of day

2. Managed smart tariffs

Device-controlled charging or optimisation, such as Octopus Intelligent Go, ScottishPower EV Optimise, etc.

3. Dynamic ToU pricing

These are half-hourly prices linked to wholesale markets. Prices are published or consumers receive them daily in the afternoon/evening for the following day. The main example, and the only dynamic pricing to the knowledge of the authors, is Octopus Agile.

Reports such as Ofgem's State of the market[2] evidence that the majority of ToU adoption in the GB market is primarily driven by EV tariffs, which are mostly standard, in some cases enhanced with additional off-peak windows. Whilst there is certainly a group of customers who respond to dynamic/agile tariffs, that remains a very small subset of the GB population. As such, this report focuses mainly on standard ToU tariffs as they provide the most representative basis for understanding both current and near-term flexibility behaviour.

Alongside this, a targeted assessment was undertaken to explore whether, and to what extent, behaviour consistent with dynamic pricing signals (e.g. Agile-type tariffs) can be observed within the dataset. This was considered within the context of the available supplier portfolio, to understand whether early indications of response to more dynamic signals are already visible.

[2] Ofgem (2026) *State of the market report*. Available at: https://www.ofgem.gov.uk/sites/default/files/2026-01/State-of-the-Market-Energy-Retail-Highlights-January-2026.pdf (Accessed: 2026)

Most suppliers agree in their websites that 16:00 to 19:00 are considered peak electricity hours. However, they differ on their morning peak hours and on their off-peak windows. Whilst it varies per supplier, morning peak is typically considered between 07:00 to 09:00, so for the purpose of this report we consider as peak hours between 07:00 to 09:00 hrs and 16:00 to 19:00.

A subset of days with unusually high or low wholesale prices was identified and used as support the visual inspection of demand patterns. These were used to assess responsiveness under more extreme system conditions and as windows to more easily distinguish between typical ToU tariff behaviour and additional responses driven by more dynamic price conditions. The table below summarises the days and the potential expected behaviours.

Dates	Behaviour/Context
8 Jan 2026	Extreme high-price spike during cold winter conditions and tight system margin; Expected signal: dip (likely followed by rebound / spike after 18:00)
12 Dec 2025	High evening prices during winter demand peak and low renewable output; Expected signal: reduced evening peak relative to normal days.
13 Dec 2025	Continued high evening prices during winter demand and low wind generation; Expected signal: reduced evening peak relative to normal days
19 Dec 2025	Very low overnight prices due to high overnight wind generation. Expected signal: stronger overnight demand block (e.g. EV charging).
25 May 2025	Deep negative midday prices caused by high solar generation and low spring demand. Expected signal: a bump in demand at compared to normal daytime levels.
25 and 26 Nov	Really high prices beyond peak hours, and highest prices of November and December.
28 Nov 2025	Late evening spike from 21 to 22:30 high prices during the evening.

Table 4: Days with extreme prices

The corresponding results are presented in the results section below.

Top-down behaviour-based analysis

Initial exploration and observations from data visual inspection

Firstly, an initial view of the total consumption per period was carried out for Supplier A, B and C split by day of the week, mainly to have a better understanding of what type of customers are put on EHHS, and to start the top-down visual inspection.

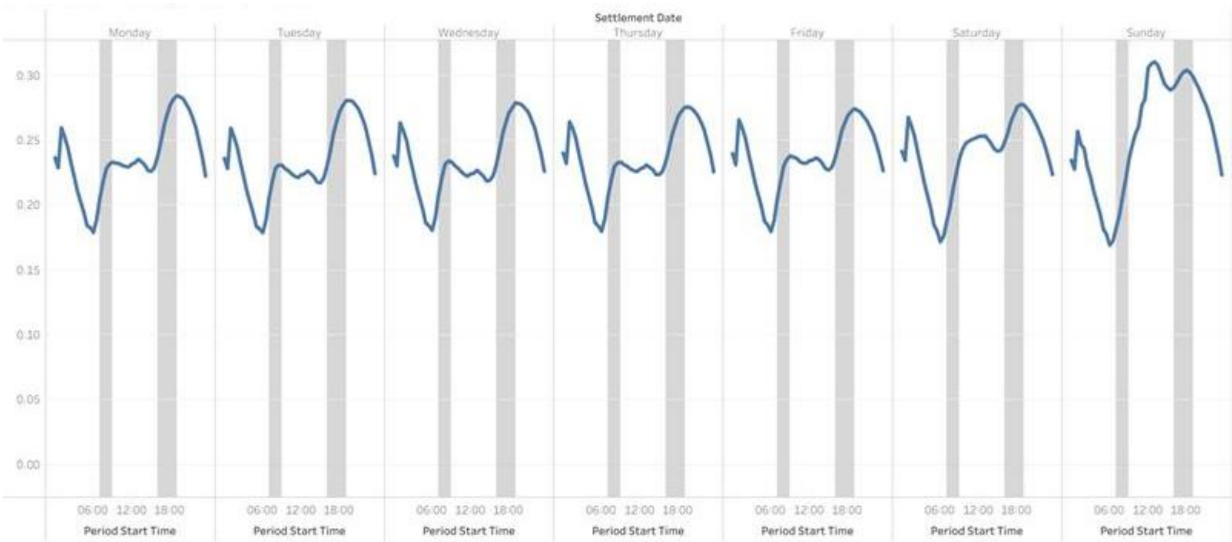


Figure 1: Supplier A weekly average profile

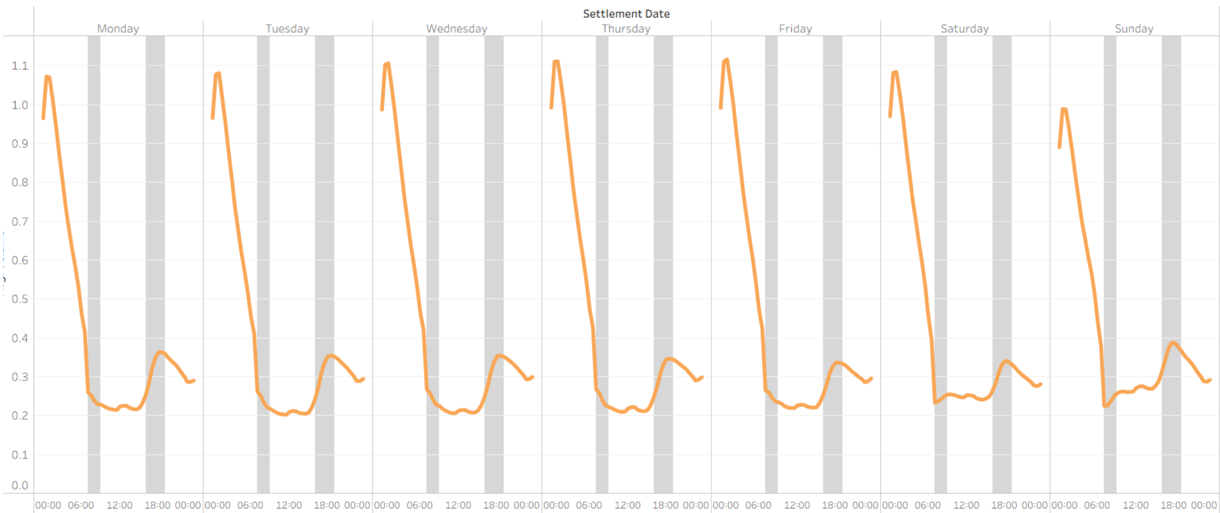


Figure 2: Supplier B weekly average profile

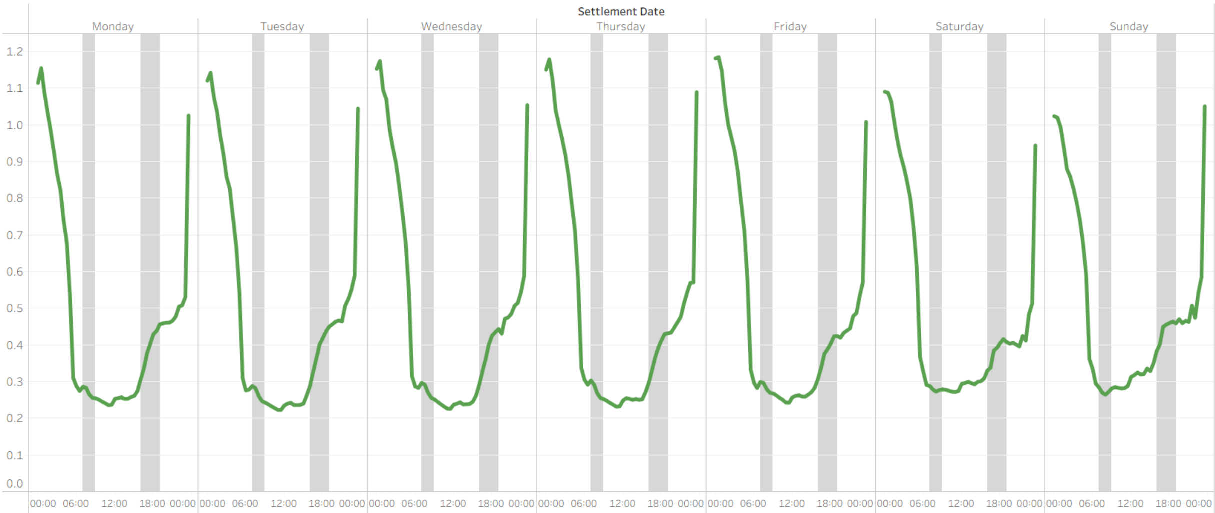


Figure 3: Supplier C weekly average profile

At first sight, three things stand out:

1. These profiles differ from the traditional domestic demand curves used prior to MHHS, where consumption remained low and relatively flat overnight – shown in the figure below – with peaks in the morning and an even larger peak in the evenings, particularly Supplier C and B.

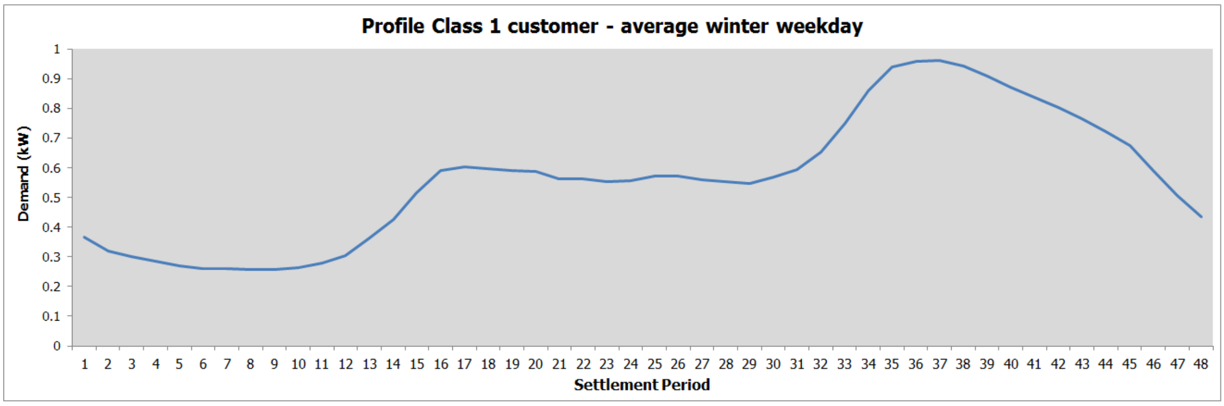


Figure 4: Load Profile for the average Profile Class 1 (domestic unrestricted) customer in a typical winter weekday. Source: Elexon. Normal profile with no ToU uptake (curve for the last 20 years prior to MHHS)

2. In both Supplier C and B observed, the curves reflect overnight peaks consistent throughout the week, which suggest EV charging and potentially battery charging.
3. Supplier A has flatter profiles across the middle of the day than typical domestic use - it looks more similar to a standard profile; however, Sunday consumption is particularly high at midday.

These patterns are further explored in subsequent analysis explained below.

As part of the initial phase of analysis, a series of exploratory observations and targeted analyses were undertaken to understand how flexibility-related behaviour may present within the dataset. These were designed to test different hypotheses, identify observable patterns and inform the direction of subsequent, more structured analysis. The following areas were explored:

- **Event-based comparison of consumption patterns:** consumption on selected days with notably high or low-price signals was compared against typical days. A simple baseline approach was applied at this stage to differentiate event-day behaviour from normal consumption patterns, with more definite baseline methodologies developed subsequently.
- **Peak period consumption analysis:** the proportion of total daily consumption occurring during peak hours (16:00–19:00) was assessed across the three main suppliers, to identify indications of peak avoidance behaviour.
- **Off-peak/EV charging window analysis:** the proportion of daily consumption within typical EV tariff windows (overnight periods) was analysed across the same supplier groups, to explore evidence of load shifting or concentrated overnight demand.
- **Sunday/low-demand window analysis:** consumption patterns during known Sunday saving or low-demand windows were examined to assess whether increased usage is observable during these incentivised periods.
- **Detailed day-level inspection:** a small sample of consecutive days was reviewed at a granular (half-hourly) level to identify patterns that may not be visible in aggregated views, including subtle shifts or irregular behaviours.
- **Identification of "zero" consumption patterns:** an initial screening was conducted to identify MPANs exhibiting consistently low or zero consumption across a proportion of settlement periods (e.g. ≥20%), as a potential indicator of properties with embedded generation or storage.

Results

1.1 Comparison of consumption during observed day (12 December) with extreme prices vs baseline consumption rest of the days

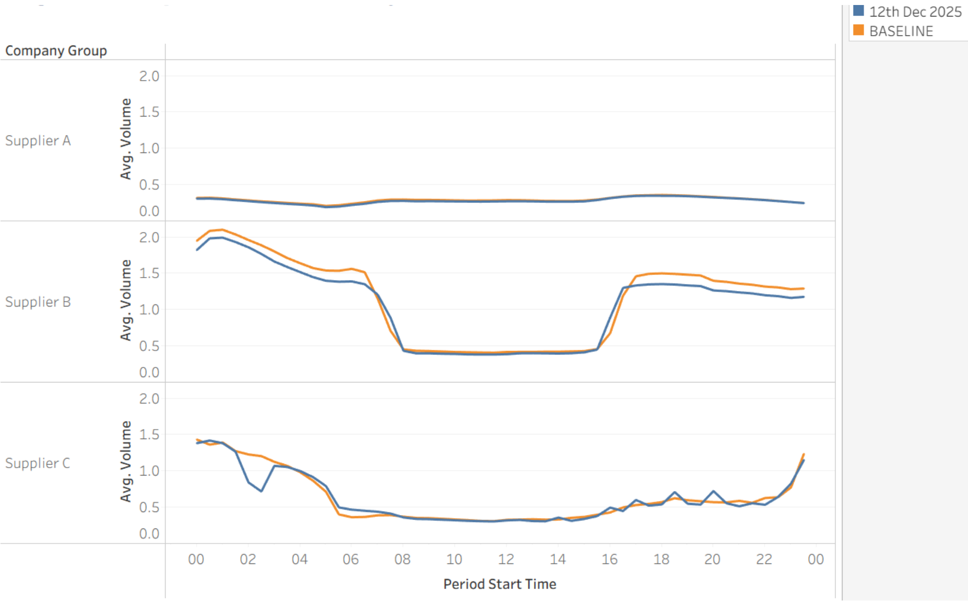


Figure 5: Average consumption on observed day with extreme prices by supplier – 12 Dec 2025

1.2 Comparison of consumption during observed day (28 November) with extreme prices vs baseline consumption rest of the days

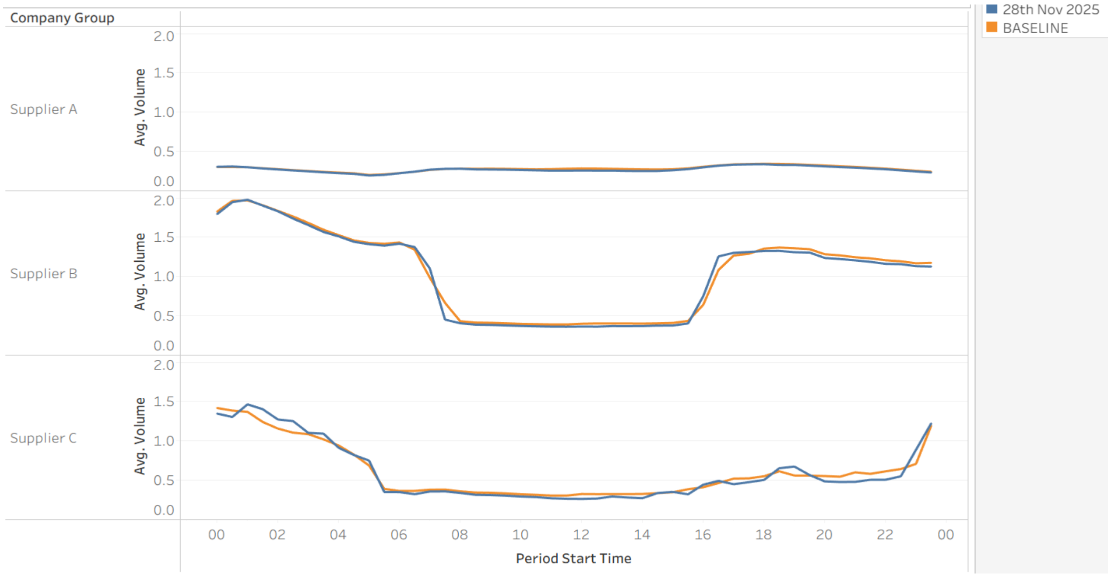


Figure 6: Average consumption on observed day with extreme prices by supplier – 28 Nov 2025

For two selected days, the consumption profile compared to the baseline remains very similar for Supplier A's customers/portfolio, indicating limited deviation from typical demand patterns during these periods.

For Supplier B's group and more notably for Supplier C's group, some variation from the baseline is observed. This may reflect differences in portfolio composition or tariffs structures. In particular, given that Supplier C offers dynamic pricing products, this could be consistent with a degree of responsiveness to more variable price signals throughout the day. This is being taken forward as a hypothesis for further investigation through both the signal-led analysis and more structure data-drive analysis.

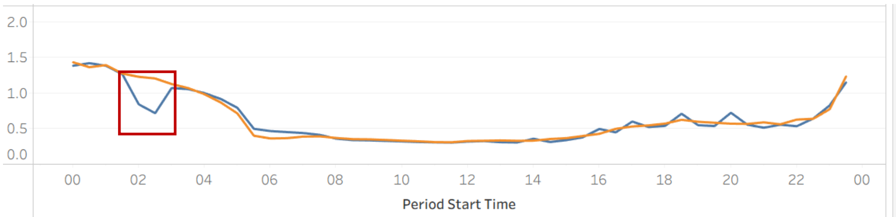


Figure 7: Drop in consumption for Supplier C ~02:00

A significant drop is observed on 12 December that is not present in other days at around 02:00, which is further investigated, but it likely suggests participation in an explicit flexibility event/automated asset optimisation.

2a. Percentage of Daily Consumption during peak hours all suppliers

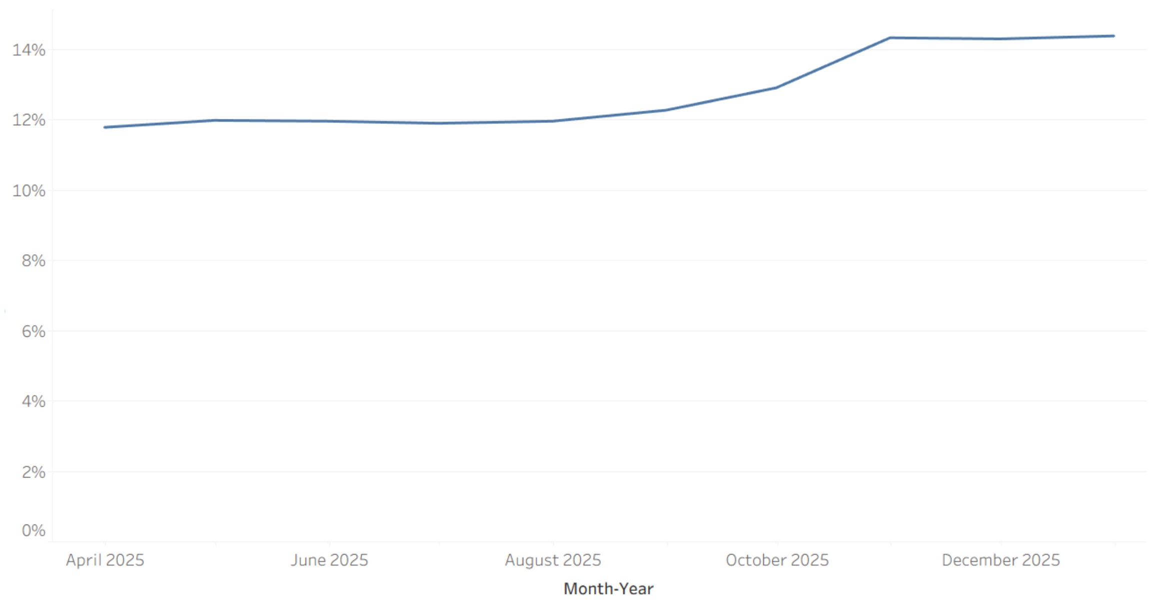


Figure 8: Percentage of daily consumption during evening peak hours – monthly trend

The results show that properties in this dataset are consuming around 13-14% of their daily electricity during peak hours, or in other words around **86% of their consumption happens in off-peak hours**.

2b. Percentage of Daily Consumption during peak evening hours by supplier

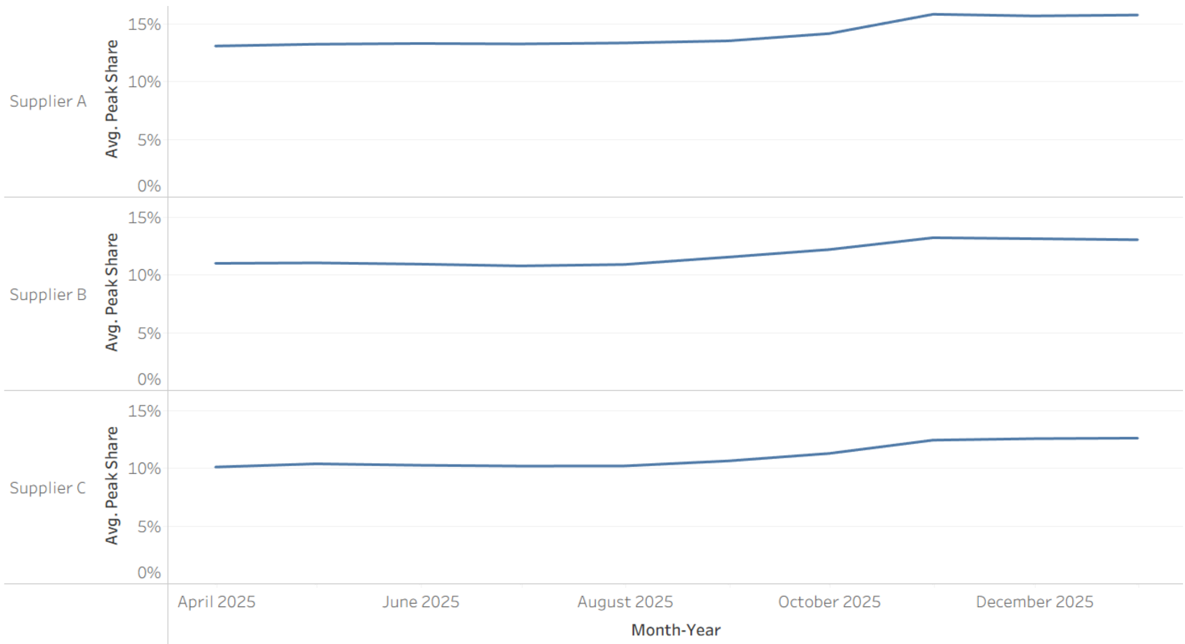


Figure 9: Percentage of daily consumption during peak evening hours by supplier

More specifically, the daily consumption during peak hours per supplier is as follows:

- Supplier A: 13-16%
- Supplier B: 11-13 %
- Supplier C: 10-13%

A slight increase is observed towards October-December consistent with winter time behaviour.

Supplier C's customers/portfolio has marginally less consumption during peak hours compared to Supplier A's.

3c. Percentage of Daily Consumption during EV Tariff Period

We also explored what is the percentage of daily consumption during known EV tariff hours – these vary slightly amongst suppliers.

This indicative results evidence that between **26%-29%** of Supplier C's total portfolio consumption occurs between 00:30-04:30. Similarly, **16-19%** of Supplier A's total consumption occurs between 00:00-05:00.

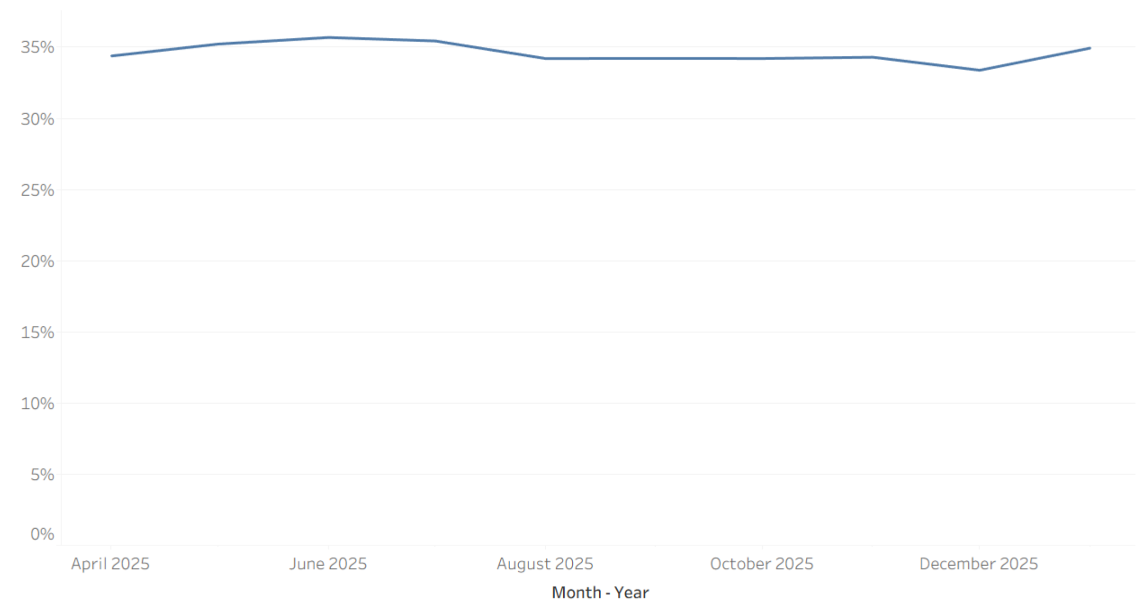


Figure 10: Percentage of Daily Consumption during EV tariff period supplier B

It's important to note that consumption during 00:00 to 05:00 hours can be attributed to EV charging, but also to battery charging.

4. Percentage of Daily Consumption during 11 am – 4 pm – Supplier A

From the figures below, Supplier A shows higher consumption on Sundays than suppliers B and C.

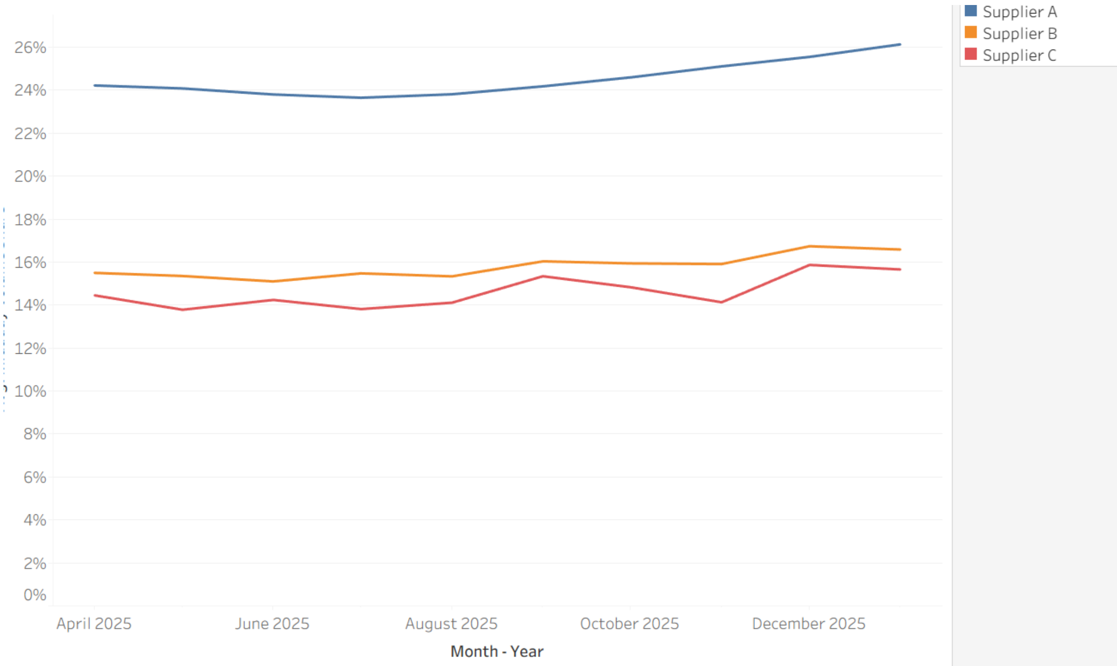


Figure 11: Percentage of daily consumption (11:00-16:00) on Sundays by month

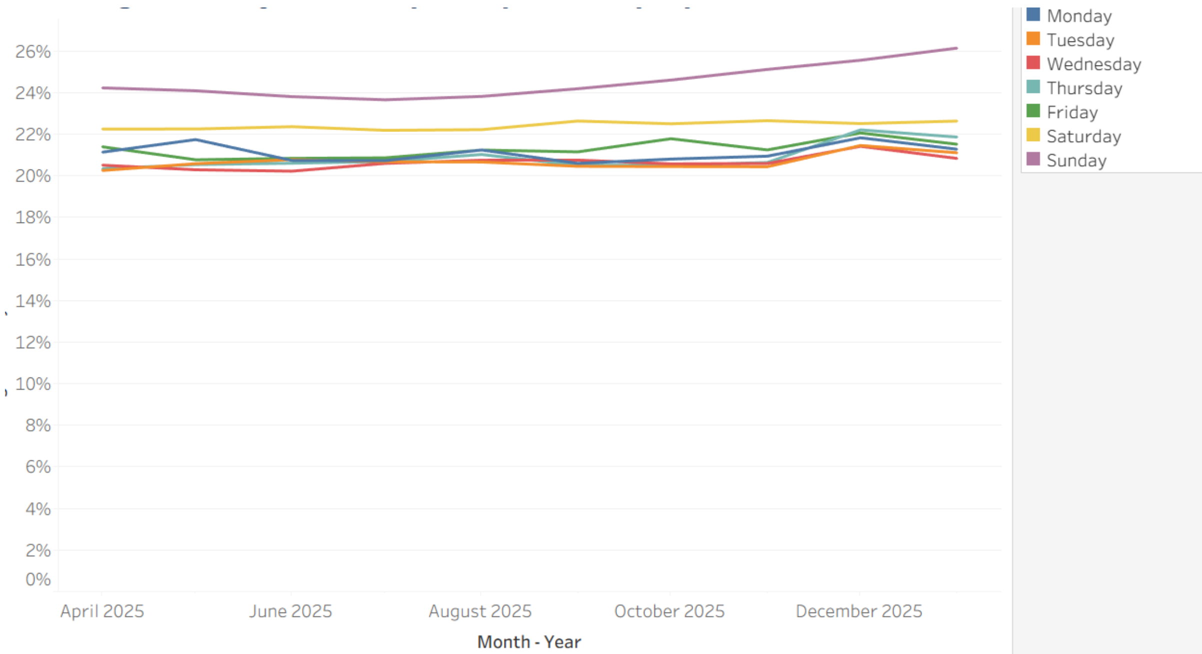


Figure 12: Percentage of daily consumption (11:00-16:00) by day of week for Supplier A

When looking at the share of midday consumption per day for different days of the week, it can be observed that it is higher on Sundays compared to other days of the week, and the difference between Sunday and weekdays is considerable.

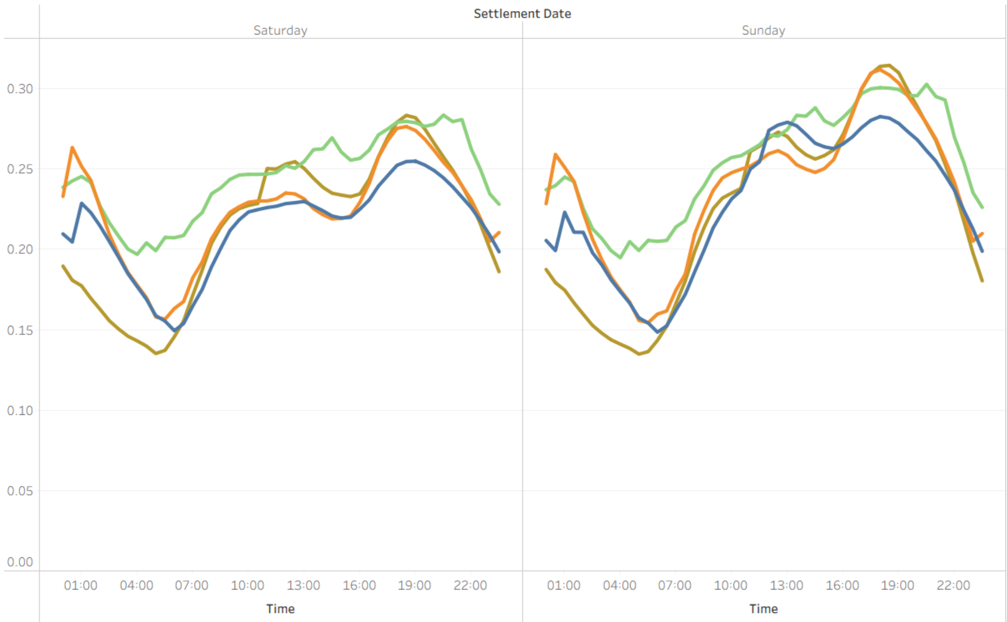


Figure 13: Average weekend elective half-hourly consumption by supplier (non-EV)

Initially when looking at Supplier A (blue line) Sunday behaviour compared to Supplier C and B, the uplift seemed significant, also when comparing midday activity amongst Supplier A's own consumers on other days of the week vs Sunday. The hypothesis was that Supplier A's Sunday has a higher than typical behaviour compared to other suppliers. However, when exploring further the comparison against Suppliers B and C, it wasn't very meaningful because these two suppliers have much higher consumption overnight – likely driven by EVs/batteries/automation. As such, it was compared only with suppliers without a significant overnight profile, and amongst these the uplift is less obvious and significant. However, even though more modest, there is still an uplift on Sunday midday consumption for Supplier A – and also visible in another supplier (olive line) that wasn't in the scope of this report, potentially also offering cheaper or free electricity during these times – caused by a small number of consumers, which is more evident further down in the clusters analysis.

5. Detailed day-level inspection

Half-Hourly Consumption between 12th – 18th Jan – Supplier C

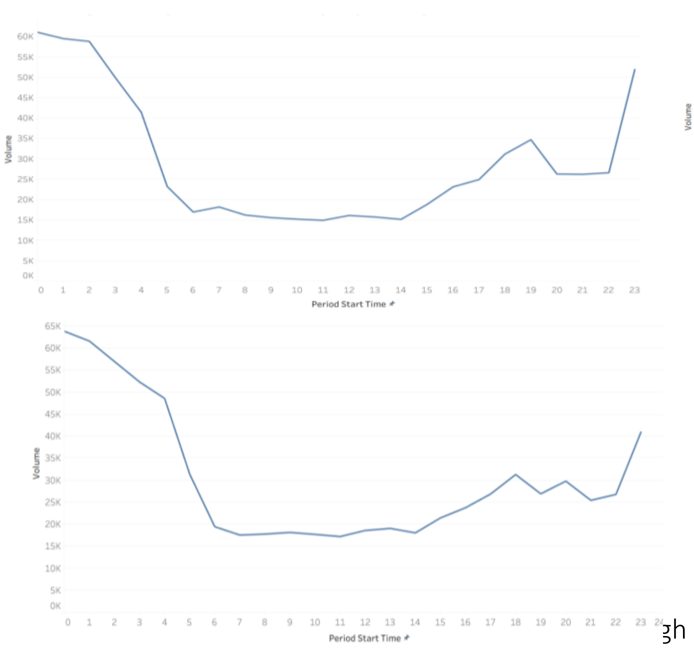


Figure 14: Half-Hourly Consumption between 12th – 18th Jan – Supplier C

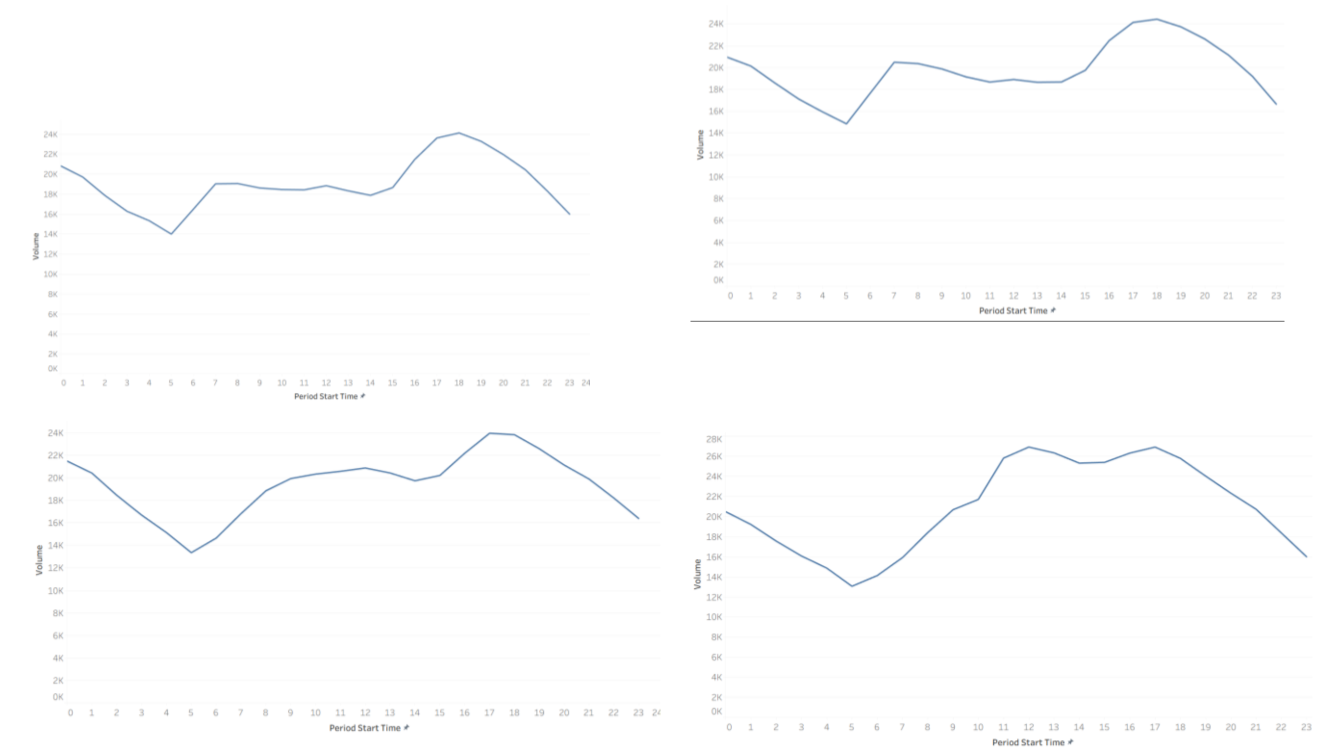


Figure 15: Half-Hourly Consumption between 12th – 18th Jan – Supplier A

Supplier A has a similar behaviour, with the exception that there is a clear peak on Sunday – particularly from 11:00 to 14:00 – that matches their Sunday cheaper electricity offer from 11:00 to 16:00.

6. Identification of low-consumption patterns

Periods of zero consumption are examined as part of the analysis to identify patterns that may indicate the presence of on-site generation or storage, such as solar PV or batteries. While not conclusive, we consider this a supporting indicator that is passed over for the profiling/clustering analysis to be assessed as a feature.

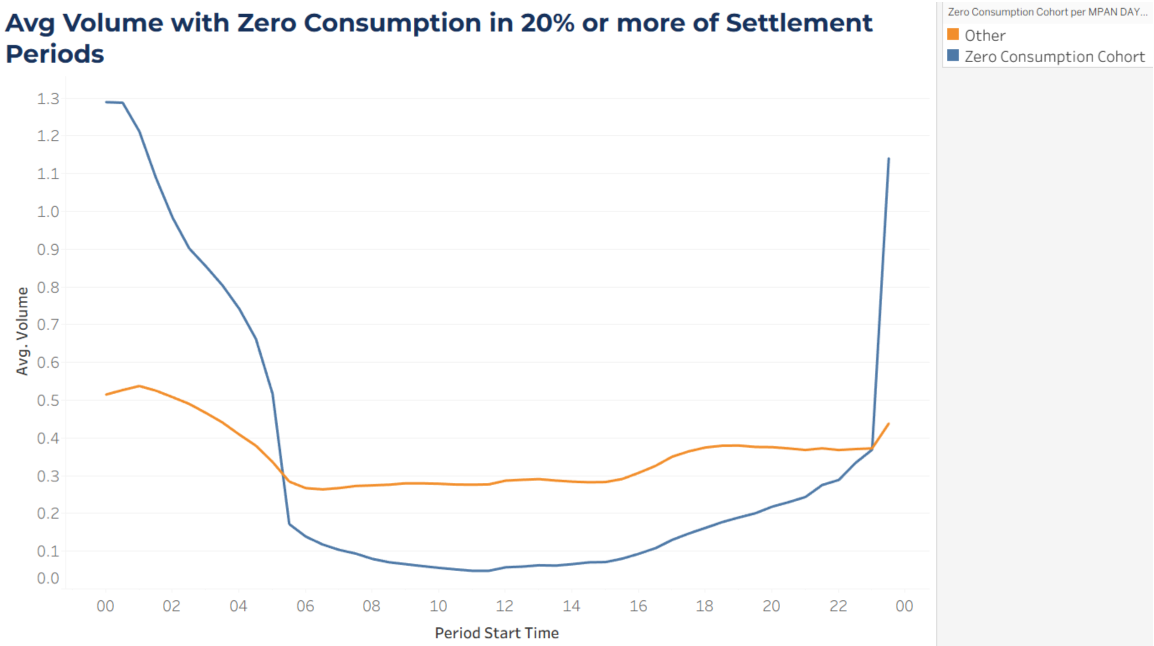


Figure 16: Avg. consumption cohort with Zero consumption vs rest of MPANs

A cohort was created adding customers who have zero volume in 20% or more of the settlement periods and plotted average volume against the settlement period time split by suppliers. This cohort is made up of around 22,000 MPANs from all suppliers, with a majority being Supplier C's customers.

Results are still to be reviewed and refined, but as an early result it was found that around 80% of the customers/MPANs put in this cohort (where at least 20% of their settlement periods = 0) have zero volumes in settlement periods between 11:00 and 15:00.

This is further addressed in the discussion, but it can be attributed to consumers with solar PV and/or batteries, and as such their consumption at midday goes to or close to zero.

Top-down analytical deep dive & refinement

The initial results in the previous section provide a helpful overview of consumption patterns, but without a point of comparison it is not yet clear how materially they deviate from expected behaviour, and thus the following section explores this in more detail.

The following analyses focus on the three key behavioural dimensions: peak vs off-peak consumption, overnight consumption, midday and the uptake of specific incentives such as Sunday cheap/free electricity and dynamic/agile tariffs.

To build on the initial observations, the variability in the results was first assessed, including using standard deviation, to understand whether the observed patterns were consistent across the dataset or driven by a subset.

Consumption shares were calculated using MPAN settlement-date level data, and by dividing the volume of electricity consumed within a given window (e.g. midday 11:00 to 16:00) by the total daily consumption.

Off-peak Consumption

Between 00:00 to 07:00, 09:00 to 16:00 and 19:00 to 00:00 hrs

Supplier	Avg. Consumption (kWh)	Avg. Share (%)	Median Share	STD DEV Share	CoV Share
Supplier A	9.03	77.77%	78.71%	8.52%	10.96%
Supplier B	17.24	81.95%	81.63%	12.11%	14.78%
Supplier C	20.17	83.42%	83.65%	12.31%	14.75%

Table 5: Off-peak consumption metrics

Overnight Consumption

Between 00:00 and 06:00 hrs

Supplier	Avg. Consumption (kWh)	Avg. Share (%)	Median Share	STD DEV Share	CoV Share
Supplier A	2.69	**20.45%**	18.02%	13.23%	64.68%
Supplier B	17.70	**39.18%**	25.92%	29.14%	74.37%
Supplier C	10.46	**38.46%**	27.59%	28.63%	74.44%

Table 6: Overnight consumption metrics

Sunday Midday Consumption

Between 11:00 and 16:00 hrs

Supplier	Avg. Consumption (kWh)	Avg. Share (%)	Median Share	STD DEV Share	CoV Share
Supplier A	2.976	**24.51%**	22.27%	11.95%	48.78%
Supplier B	2.717	**16.08%**	15.63%	12.22%	76.02%
Supplier C	3.209	**14.59%**	13.23%	12.62%	86.45%

Table 7: Sunday midday consumption metrics

Saturday Midday Consumption

Between 11:00 and 16:00 hrs

Supplier	Avg. Consumption (kWh)	Avg. Share (%)	Median Share	STD DEV Share	CoV Share
Supplier A	2.495	**22.43%**	21.18%	10.21%	45.54%
Supplier B	2.471	**15.17%**	14.61%	11.91%	78.51%
Supplier C	2.964	**14.10%**	12.74%	12.34%	87.56%

Table 8: Saturday midday consumption metrics

Weekday Midday consumption

Between 11:00 and 16:00 hrs

Supplier	Avg. Consumption (kWh)	Avg. Share (%)	Median Share	STD DEV Share	CoV Share
Supplier A	2.276	**20.93%**	20.22%	9.76%	46.60%
Supplier B	2.162	**13.41%**	12.48%	10.84%	80.88%
Supplier C	2.508	**12.20%**	10.53%	11.32%	92.78%

Table 9: Weekday midday consumption metrics

In parallel, a range of publicly available baseline profiles were considered to anchor results/benchmark against typical, **non-incentivised behaviour** landing in Elexon's profile class 1[3] load profiles (domestic unrestricted) and Nesta's profile 1 average daily consumption[4]. Nesta's report data, which uses data from the Smart Energy Research Lab, is "focused on the period between July 2023 to June 2024. Results are based on a sample of 5,994 households, designed to represent Great Britain across regions and Index of Multiple Deprivation (IMD) quintiles". Deviations from this baseline were used to assess the extent of behavioural change.

The baseline was applied selectively depending on the analytical approach. For the top-down analysis, Elexon is used as the primary reference, as it provides detailed variation by season and day type. For the clustering analysis, benchmarks derived from Nesta were used, with a more representative sample of typical consumption levels. While different baseline profiles were used, this reflects a deliberate methodological choice based on its suitability to the specific analysis. Importantly, the key behavioural metrics – such as off-peak, overnight and midday shares – were found to be consistent across baselines, reinforcing the validity of the findings.

	Off-peak	Overnight	Midday Sunday	Midday Weekday	Midday Saturday
Share (%)	74%	14%	25%	21%	23%

Table 10: Baseline consumption shares by behaviour (%)

Due to the skewed nature of the data, median values and inter-quartile ranges were used in place of standard deviation for groupings and to provide a more accurate representation of the distribution.

Off-peak consumption

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High	Grand Total
Supplier A	12,596	12,188	6,222	1,820	32,826
Supplier B	536	396	1,261	2,119	4,312
Supplier C	2,378	2,908	8,021	11,468	24,775

Table 11: No. of users per quartile

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High
Supplier A	38.37%	37.13%	18.95%	5.54%
Supplier B	12.43%	9.18%	29.24%	49.14%
Supplier C	9.60%	11.74%	32.38%	46.29%

Table 12: Share of users (%) per quartile

25th percentile	Median	75th percentile
76.94%	79.81%	84.90%

Table 13: Share of consumption at off peak (%) per quartile

[3] Elexon (2024) *Profiling*, Available at: https://www.elexon.co.uk/bsc/settlement/profiling/(Accessed 2026)

[4] Nesta (2025) *Understanding Great Britain's energy consumption patterns through smart meter data*. Available at: https://www.nesta.org.uk/report/understanding-gb-energy-consumption-patterns/average-daily-consumption-curves-show-distinct-consumption-behaviours/ (Accessed 2026)

Overnight

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High	Grand Total
Supplier A	13,875	13,243	3,897	1,811	32,826
Supplier B	351	265	1,141	2,555	4,312
Supplier C	1,261	1,996	10,447	11,069	24,775

Table 14: No. of users per quartile

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High
Supplier A	42.27%	40.34%	11.87%	5.52%
Supplier B	8.14%	6.15%	26.46%	59.25%
Supplier C	5.09%	8.06%	42.17%	44.68%

Table 15: Share of users (%) per quartile

25th percentile (consumption in %)	Median (consumption in %)	75th percentile (consumption in %)
17.29%	24.30%	43.25%

Table 16: Share of consumption overnight (%) per quartile

Midday Sunday

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High	Grand Total
Supplier A	1,667	5,537	11,737	13,885	32,826
Supplier B	1,992	1,453	557	310	4,312
Supplier C	11,730	8,514	3,197	1,334	24,775

Table 17: No. of users per quartile

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High
Supplier A	5.08%	16.87%	35.76%	42.30%
Supplier B	46.20%	33.70%	12.92%	7.19%
Supplier C	47.35%	34.37%	12.90%	5.38%

Table 18: Share of users (%) per quartile

Avg. Q1 - Sunday midday	Avg. Q2 - Sunday midday	Avg. Q3 - Sunday midday	Avg. Q4 - Sunday midday
Below 13.36%	13.36% - 20.09%	20.09% - 25.04%	higher than 25.04%

Table 19: Share of consumption at midday (%) per quartile

Midday Weekday

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High	Grand Total
Supplier A	1,701	4,637	12,204	14,284	32,826
Supplier B	2,023	1,570	466	253	4,312
Supplier C	11,673	9,311	2,830	961	24,775

Table 20: No. of users per quartile

Company Group	Q1 - Low	Q2 - Median	Q3 - High	Q4 Very High
Supplier A	5.18%	14.13%	37.18%	43.51%
Supplier B	46.92%	36.41%	10.81%	5.87%
Supplier C	47.12%	37.58%	11.42%	3.88%

Table 21: Share of users (%) per quartile

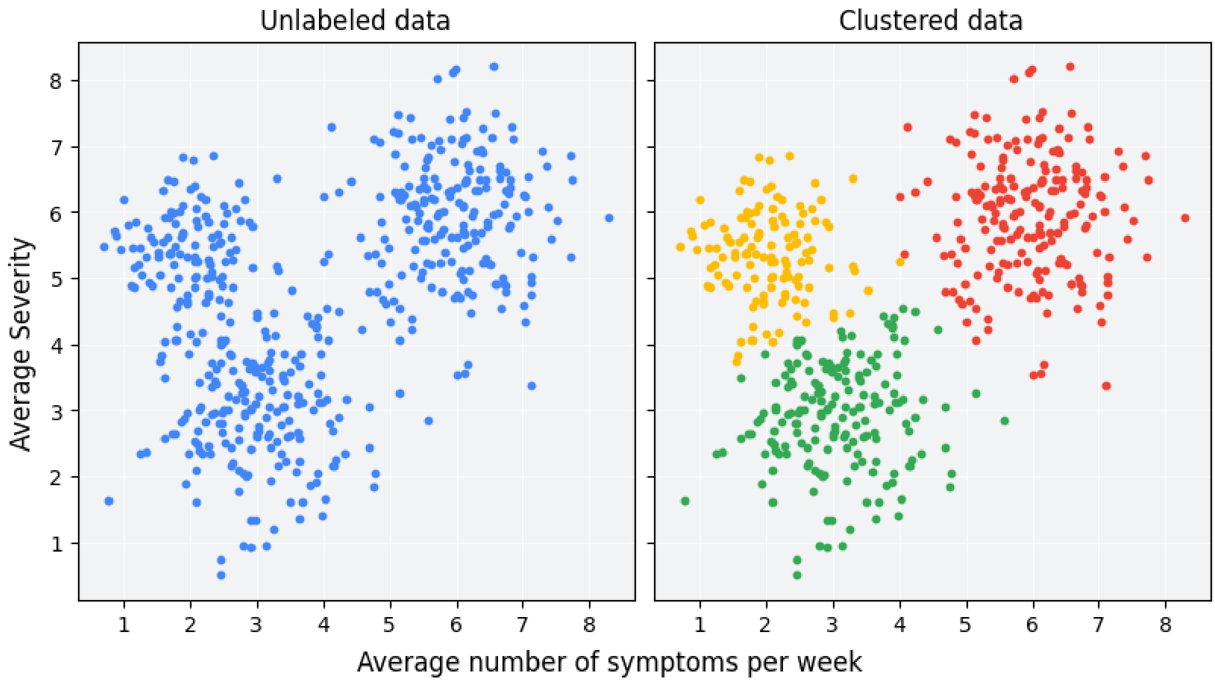
Avg. Q1 - Weekday midday	Avg. Q2 - Weekday midday	Avg. Q3 - Weekday midday	Avg. Q4 - Weekday midday
Below 10.59%	10.59% - 17.30%	17.30% - 22.04%	higher than 22.04%

Table 22: Share of consumption at midday (%) per quartile

Bottom-up cluster-based analysis

Introduction

In contrast to the approach above where we begin with an idea in mind about what patterns we are searching for, in this section we use a clustering-based approach to examine the data and its inherent features from the bottom up. Clustering is a family of machine learning methods that takes data points and measures distance between each of them to understand the underlying similarity between different sets of data. Clustering can be supervised, where a model is trained to understand the specific classification of a new data point in the overall data population, or unsupervised, where there is no pre-conception of classification. In this case, two unsupervised clustering methods are used to tackle flexibility quantification. A visual example of clustering is shown here.



Source: Google Developers

Using clustering in this example helps to unearth the underlying patterns in electricity consumption, and by comparing these clusters within the EHHS data to a typical consumer baseline, the difference can be quantified explicitly.

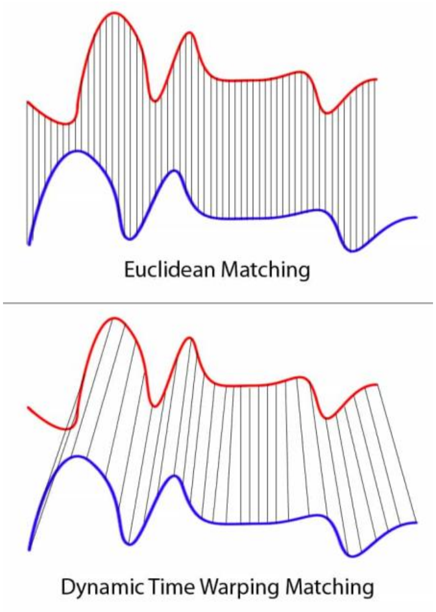
Method

In this analysis, two different clustering algorithms are used:

1. Using the shape of the time series.
2. Using statistical features extracted according to a set of assumptions

The shape clustering is more intuitive and gives some insight into the patterns that are established by different customers on different tariffs. The feature clustering is more abstract but allows a deeper exploration of the characteristics of each household's demand pattern.

Shape Clustering



[5]Shape clustering is done by taking each time series and calculating the distance to another time series by comparing each settlement period value in a weekly profile with its corresponding settlement period value. The sum of those distances between the pair of time series is then added to a running total. The algorithm compares every time series against every other time series in the dataset. Once this is complete, the algorithm then calculates a set of centroids which define each cluster. The centroids calculate the distance metrics between groups of time series and optimise for the number of clusters that are required. To accommodate the fact that the shapes of the time series may be similar but that they are not necessarily in the same settlement period (for example, two customers turning the oven on at 17:00 and 18:00 respectively), a method called "dynamic time warping" is used, which is shown left.

Shape clustering is implemented using the TimeSeriesKMeans package in TSLearn for Python 3.12.

Source: Databricks[6]

Feature Clustering

The aim of the feature clustering is to start to mathematically quantify some of the elements which have been verified by visual inspection in the previous section into 'features' which can then enable the profiles to be clustered according to how similar they are. The features used in this clustering method are partly developed by the visual inspection in the previous section, and partly by the signal mapping of different tariffs. The proposed features are aligned to the features that are related to the quantification of flexibility and the Fourier decomposition. These latter features are the top five frequency and amplitude factors that make up the demand profile according to Fourier analysis.

The features used in the final analysis are:

- Evening peak percentage of total consumption
- Overnight percentage of total consumption
- Sunday afternoon percentage of total consumption
- Settlement period in which the highest consumption occurs
- Settlement period in which the lowest consumption occurs
- Number of 0 consumption values
- Standard deviation of the profile values
- Standard deviation of evening peak consumption

[6] Databricks (2019): *Understanding Dynamic Time Warping. Available at: https://www.databricks.com/blog/2019/04/30/understanding-dynamic-time-warping.html (Accessed 2026)*

- Standard deviation of overnight consumption
- Standard deviation of Sunday afternoon consumption
- The top five frequency and amplitude factors according to Fourier decomposition

Similar to the shape clustering, each of these 15 features contributes to an all-vs-all distance matrix which then are allocated to clusters via the calculation of centroids. The power of this method is that features can be added and removed according to those of interest, but also multiple features can be present in a customer profile at the same time and by visual inspection it may be difficult to decide which is which.

The feature clustering is implemented using the KMeans package in Scikit-learn for Python 3.10.

Quantification

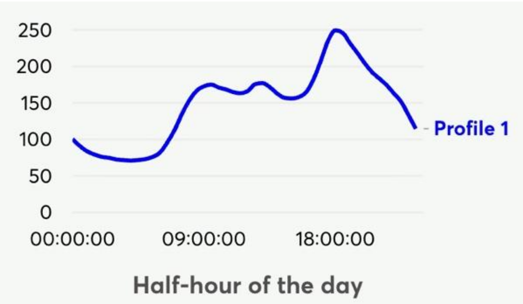
After clustering is completed, the mean value of each cluster for each settlement period in a weekly time series is calculated, then normalised to between 1 and 0 (where 1 is the highest value in the profile and 0 is the lowest value). This normalisation means two clusters can be compared without worrying about scale and makes percentage differences between clusters easier to calculate.

Finally, the quantification step compares each output time series with a normalised baseline of a typical customer and outputs the difference for each time series. The difference between each cluster average and the baseline is the flexibility on that cluster.

Quantification is implemented using the Numpy package for Python 3.10.

Data Processing and model parameters

The base MPAN dataset were aggregated into a weekly profile per settlement period. The weekly profile means that consistent behaviour is emphasised and makes the clustering more computationally efficient. A filter was then applied to remove any that had an incomplete weekly profile (fewer than 336 values, seven lots of 48 settlement periods), had a mean value of 0, or a standard deviation of 0 (i.e. all points are identical). This resulted in 55,881 MPANs for clustering.



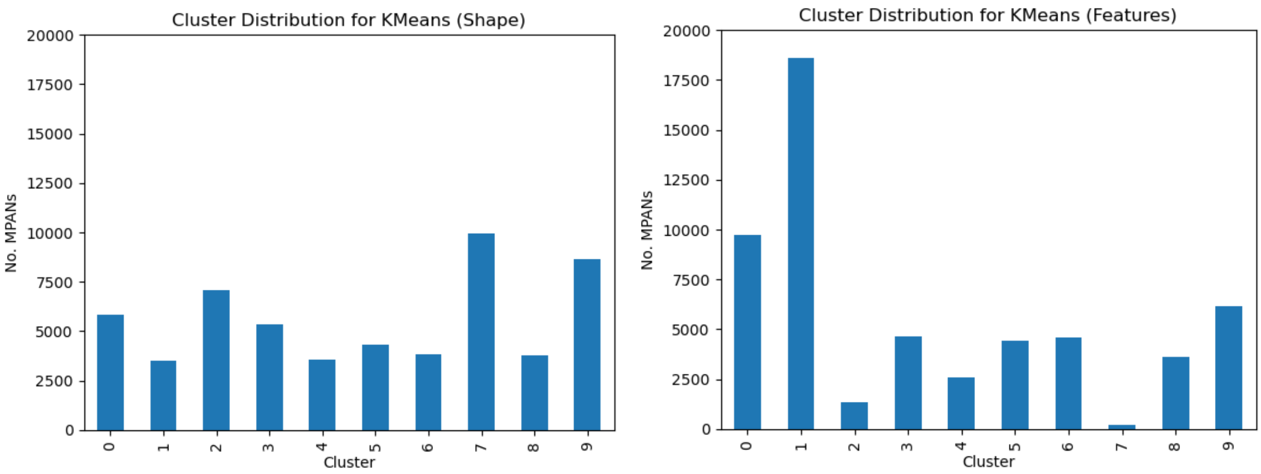
The baseline, in Wh (left) was obtained from a Nesta report using data from the Smart Energy Research Lab. Profile 1 is used as it represents a wide sample of customers and demographics. Using an out of sample baseline is best practice in this case, as all the meters used in this method are biased due to their voluntary participation in half hourly settlement.

For both the shape and feature clustering methods, the number of clusters was set to 10. In data science, a standard rule of thumb is to set the number of clusters as the square root of n, where n is the number of time series. However, in this case, understandability is more important and it would be difficult to draw early conclusions from such a large number of clusters. 10 is therefore a balance between understandability, computing resources needed and explanatory power.

Finally, this analysis was conducted over settlement periods as values, meaning that some of the shifts around daylight savings time are ignored.

Results

The distribution of the MPANs across different clusters are shown in the following graphs (note the clusters are not comparable by cluster number):



Figures 17 and 18: Cluster distribution per Shape and per Features

Shape clustering produces more evenly distributed clusters, whereas feature clustering creates more uneven clusters. For example, cluster 1 in the feature set has just under twice the number of MPANs present in as the next most populated cluster.

Each of the feature shapes represents a mix of implicit and explicit flexibility, as there is no information on the technologies within the household that the MPAN belongs to. However, it is worthwhile using the top-down approach to inform the observations.

Shape clustering commentary

Shape Cluster (SC) 5, 6 and 9 have similar shapes to the baseline, with SC 5 having a higher morning peak on average, and SC 9 having a lower morning peak. SC 9 also has slightly elevated consumption on Sundays vs the rest of its profile. These are likely customers without any behind the meter assets, with the variation down to lifestyle patterns.

SC 1, 2, 3 and 7 have similar characteristics in that they have very large overnight peaks and very low daytime consumption. This could indicate the presence of solar PV and/or batteries, with SC 1 having the widest spread and SC 3 having the narrowest. If this were to be an indicator of batteries, the fact that SC 1 starts to ramp earlier in the day could indicate that the batteries are of a smaller size. Equally, it is common that the battery charging profile is managed by a third party, potentially meaning demand response could be coordinated with the operator rather than the household.

SC 0 and 8 have standard evening peaks, but much lower consumption during the day period than the baseline, plus an overnight spike. These are customers most likely to regularly charge EVs often overnight and potentially be out of the house during the day. SC 4 is an excellent visual example of the potential uplift from a Sunday midday tariff, a lower-than-average demand profile occurs during the week with a large uplift on Sunday.

Feature Cluster commentary

Similarly to the shape clusters, the feature clusters (FC) demonstrate a range of profile shapes, which agree in many cases with the shape clusters. FC 1 and 6 are most similar to the baseline, both with elevated Sunday consumption (FC 6 in particular is most similar to SC 4 which indicates very high proportional Sunday consumption). FC 0, 4 and 9 have similar shapes which are determined by a slow evening ramp up and an overnight peak, and FC 2 ,3 and 8 are similar high narrow curves to SC 1, 2, 3 and 7 which could indicate battery charging and discharging.

To examine the differences in behaviour for each set of clusters, the normalised profiles are plotted vs the baseline.

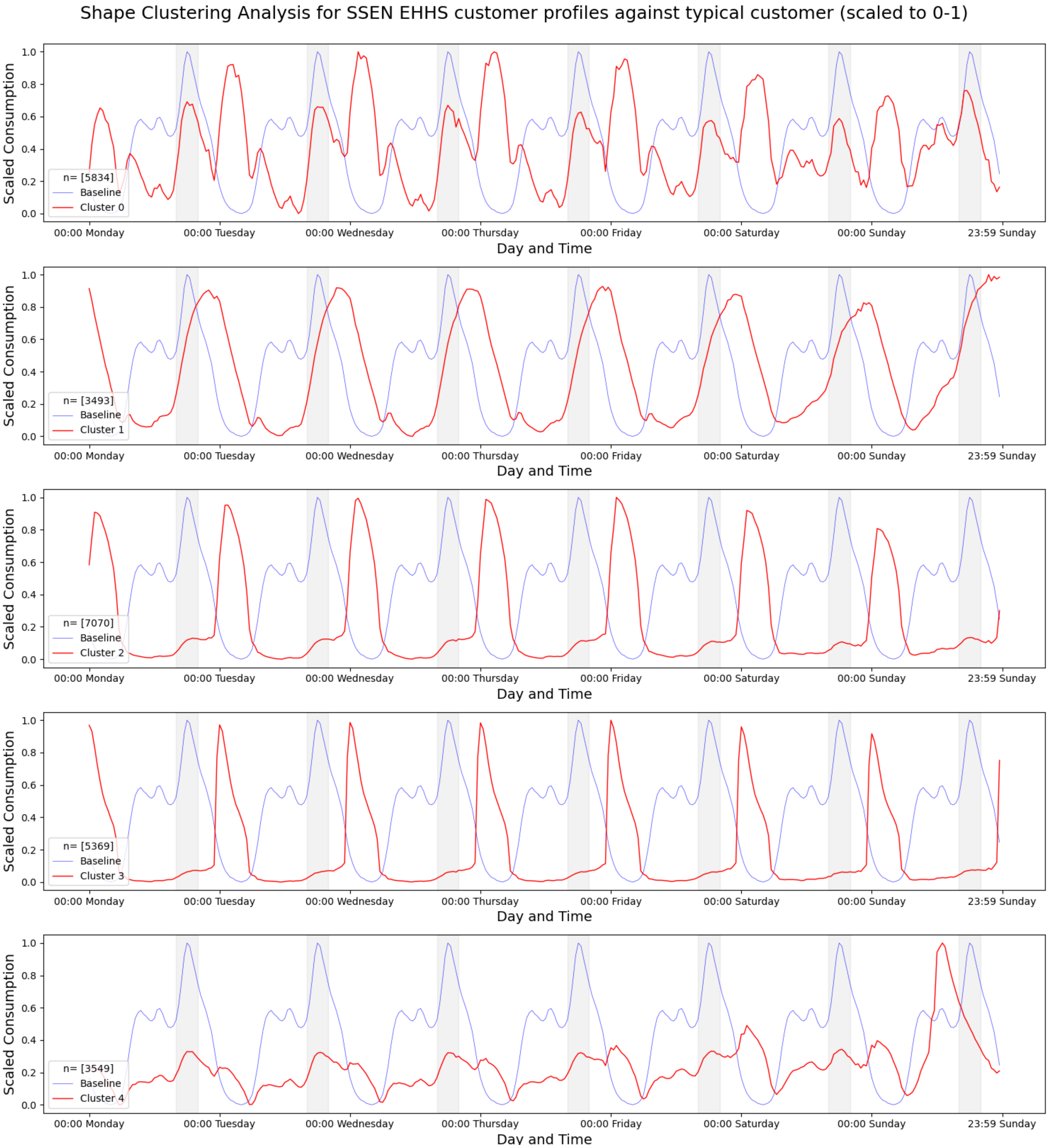


Figure 19: Shape Clusters consumption 0 to 4

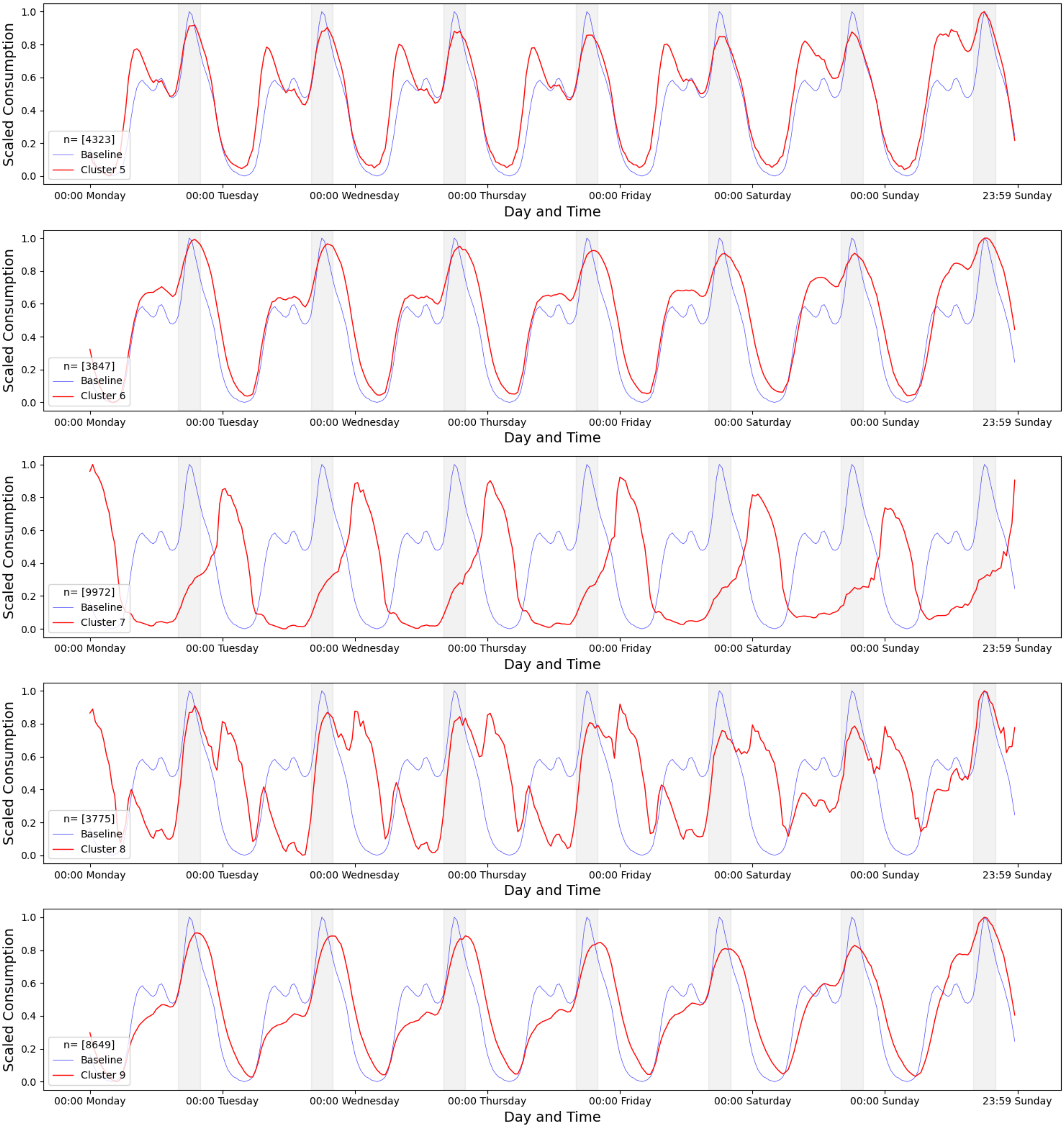


Figure 20: Shape Clusters consumption 5 to 9

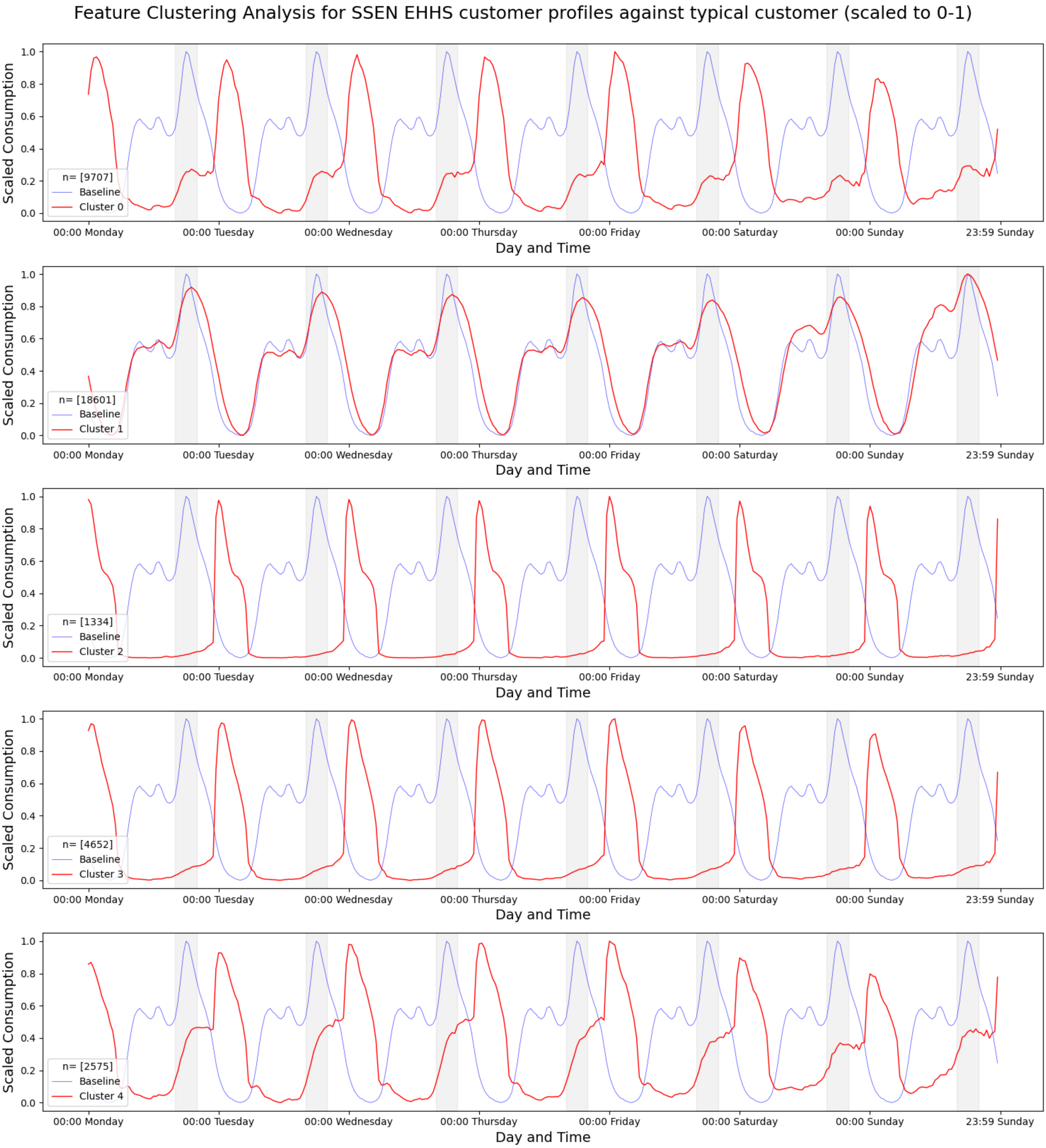


Figure 21: Features Clusters consumption 0 to 4

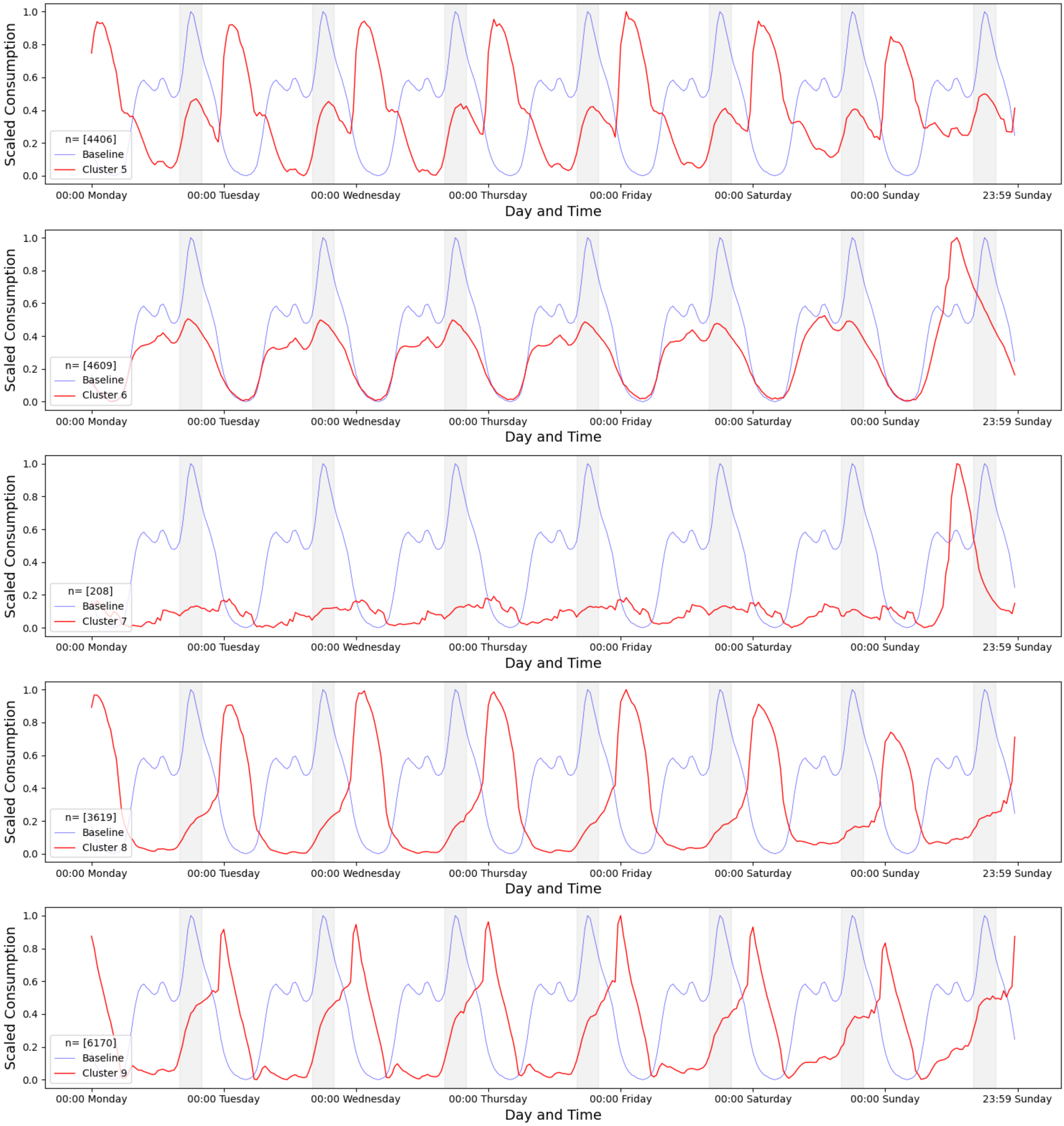
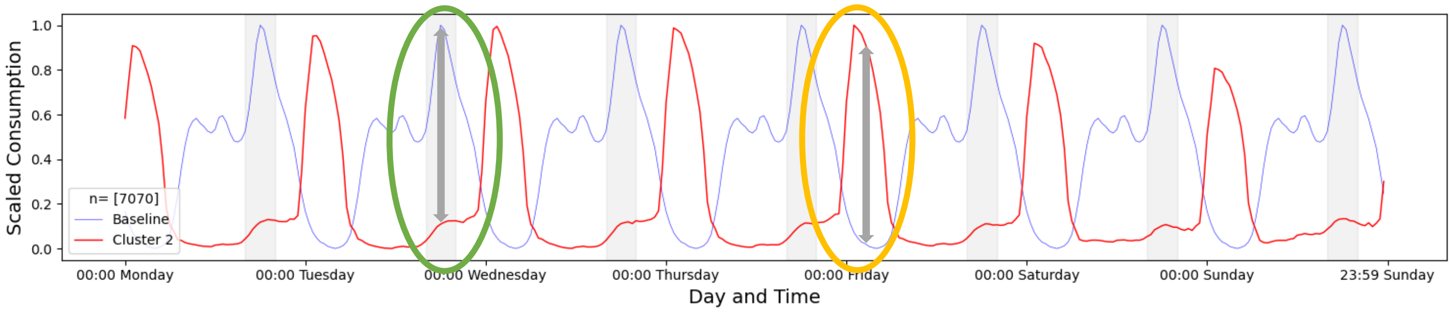


Figure 22: Features Clusters consumption 5 to 9

Quantification method

The difference between the scaled mean volume and the scaled baseline volume gives the percentage difference between the **relative** values. This gives an estimate of the scale factor of flexibility within each cluster which could be applied to a customer's consumption in that period.



To apply the scale factors to any MPAN, two examples are highlighted: one for increase and one for reduction. The green circle in this graph highlights the evening peak for Tuesday. By taking the difference between the two curves during that period, the scale factor for the settlement period is -85%. Therefore, if a customer had a maximum consumption of 5kWh and a minimum of 0.1 kWh under their current profile and they moved to this cluster profile, it would be predicted that their consumption in that settlement period instead would be 5 – (5*0.85) = 0.75kWh. The yellow circle highlights the overnight trough for Friday. The scale factor in this case is +80%, so if they moved to this cluster profile their consumption in that settlement period would be 0.1 + (5*0.8) = 4.1kWh.

The scale factors for each of the periods examined are shown in this table for both clustering methods along with a short commentary on the observed shape.

N.B. – Sunday afternoon is shown for completeness, however the clustering graphs show that what is important for quantification is where there is a significant increase in Sunday consumption, as in shape cluster 4 and feature cluster 6 and 7. Where there is a decrease, it seems to be correlated with overall lower afternoon and evening consumption

Cluster	Commentary	Evening peak	Overnight	Sunday Midday
0	A slightly lower evening peak with a large overnight peak. A lower morning peak with reduced consumption during the midday period	-28.08	70.66	-5.07
1	One large peak, beginning at the evening period and ending at the morning period	-27.09	55.60	-23.47
2	A small bump in the evening, but a high and narrow overnight peak with very low daytime consumption	-72.25	76.82	-46.78
3	Similar to cluster 2, but the peak is sharper on increase and decrease overnight	-76.45	63.52	-50.30
4	Follows a morning – evening peak shape with lower proportional consumption throughout the week until Sunday where there is a large spike in the midday period	-50.22	22.65	28.75

5	A standard profile shape with a higher morning peak and higher consumption on Sunday	-1.00	3.85	30.07
6	A standard profile shape with higher consumption on Saturday and Sunday	5.28	13.15	29.16
7	A single peak starting in the afternoon and continuing overnight until a low point in the morning	-59.72	72.72	-40.15
8	An evening-overnight double peak with lower consumption during the day	-12.40	67.02	-5.77
9	A standard profile shape but with a lower morning peak and higher consumption on Sunday	-4.67	17.14	20.71

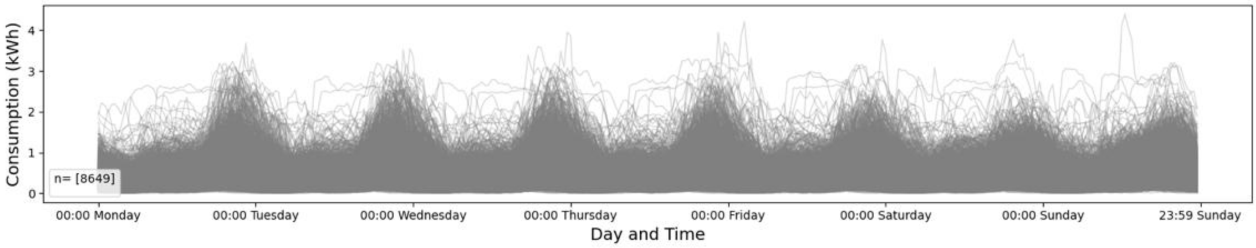
Table 23: Shape clustering

Cluster	Commentary	Evening peak	Overnight	Sunday Midday
0	A single peak starting in the afternoon and continuing overnight until a low point in the morning	-61.21	79.21	-39.85
1	A standard profile shape with higher consumption on Saturday and Sunday	-1.08	10.69	24.75
2	High and narrow overnight peak with very low daytime consumption	-79.87	63.98	-51.79
3	High and narrow overnight peak with very low daytime consumption	-75.96	76.36	-50.32
4	A small bump in the evening, but a high and narrow overnight peak with very low daytime consumption	-49.48	73.50	-36.22
5	A slightly lower evening peak with a large overnight peak. A lower morning peak with reduced consumption during the midday period	-46.05	80.23	-26.61
6	Follows a morning – evening peak shape with lower proportional consumption throughout the week until Sunday where there is a large spike in the midday period	-34.47	0.20	33.60
7	Low consumption during the week overall with very high consumption during the Sunday midday period	-68.37	6.74	23.81
8	A single peak starting in the afternoon and continuing overnight until a low point in the morning	-66.65	80.07	-44.05
9	A small bump in the evening, but a very high and very narrow overnight peak with very low daytime consumption	-48.61	56.35	-34.49

Table 24: Feature clustering

Limitations

Clustering was performed on a weekly profile due to constraints with computing power, and although this was done per profile, it may still smooth out some of the results. Furthermore, a more detailed examination of the confidence intervals (standard deviations or interquartile ranges) would be appropriate to understand the uncertainty around the figures proposed above. This uncertainty would mean that a range of values could be modelled. Running the shape clustering on larger time series would be extremely computing intensive and so feature clustering would be more efficient for this. As was also previously stated, the number of clusters is fairly low for the number of MPANs in the sample, and as a result the means have the effect of smoothing out some of the outliers. An example is shown for shape cluster 9 below where all time series are plotted unnormalised.



The average shape of the cluster can be observed by eye, however there is significant variation across all 8,649 MPANs in this cluster, including some observable outliers.

Although the selection of the baseline from a sample of smart meters is appropriate, it has the unusual downside of having a sample size much smaller than some of the cluster populations. In fact, during the development of this method, it is clear that **there is no commonly understood baseline of what a typical, non-incentivised consumer (profile class 1) looks like, at least not openly accessible.** Elexon allows suppliers to calculate half-hourly profiles using standard settlement methodologies, but it is clear from the EHHS data that the shape of demand is changing significantly. The quantification of flexibility relies on a comparative baseline, if the baseline is higher or lower, then the potential flex will similarly be lower or higher.

Clustering Conclusions

When clustered for shapes and features, a common factor that comes out is the prevalence of overnight peaks in the EHHS dataset. As indicated by the values in the table above, and as is widely known, EVs and battery storage are commonly understood to be sources of flexibility. Although it is not known what assets the customers have behind the meter, this method indicates that overnight consumption can be as high as 80% higher relative to the baseline (SC 0, 2 and 7, FC 0, 3, 4, 5 and 8), a significant opportunity for flexibility. Equally, many customers on EHHS reduce their evening peak, some as part of their overall daytime consumption being reduced (SC 2,3 and FC 2, 3), but some are reduced or shifted as part of discrete daily activities (shape cluster 6 and feature cluster 1).

Using these figures and allocating them to a cluster, an expectation of expected flex from the customer's overall demand profile could be obtained by applying the differences from the table above. For example, demand could be modelled under different scenarios where the number of customers on ToU tariffs is varied. For example, with feature cluster 7, and 1,000 new customers on a Sunday half-price electricity tariff, apply the 33% scale factor to their typical (or estimated) consumption to predict what the increased demand on a Sunday could be. This method therefore provides a significant opportunity to map demand profiles from current to anticipated profile under certain conditions.

Alignment & Quantification

Alignment of observations and analytical outputs

Despite the different approaches, findings are strongly aligned. Both methods identify consistent behavioural segments and similar patterns of demand concentration, with clustering results reinforcing the magnitude of observed effects – for instance, the high overnight concentration relative to baseline and the uplift on Sundays by a subset of consumers.

Differences relate primarily to granularity and sensitivity, rather than overall conclusions. This alignment provides confidence that the observed patterns are not artefacts of a specific methodology or interpretation bias but reflect consistent underlying behaviour across the dataset. The two approaches are complementary: they offer different lenses investigating and validating the same behavioural patterns.

Quantification

In order to produce the proxy metrics presented in this report, a range of calculations and analytical steps were undertaken. These were done to answer different questions.

High level measures, such as **off-peak to peak consumption ratios** and the **share of consumption** occurring in key time windows, were used to quantify overall behaviour of response and patterns of demand shifting.

	Avg Off-peak consumption share (%)	Avg Overnight consumption share (%)	Avg Weekday midday share (%)	Avg Sunday midday share (%)
Supplier A	77.77%	20.45%	20.93%	24.51%
Supplier B	81.95%	39.18%	13.41%	16.08%
Supplier C	83.42%	38.46%	12.20%	14.59%
Standard Consumer/ Baseline profile	74%	14%	21%	25%

Table 25: Consumption Share per observed behaviour compared to baseline

The results show a consistent shift in demand patterns across all suppliers when compared to the baseline/standard profile. In particular, off-peak consumption shares are higher across all portfolios, ranging from ~77% to 84.4%, compared to baseline of around 74%.

A similar pattern is observed for overnight consumption, where shares increase from 14% in the baseline to ~20.45 to 39% across suppliers.

	Total Consumption (MWh) Off-peak hrs	Total Consumption (MWh) Morning peak hrs	Total Consumption (MWh) Evening peak hrs	Total Consumption peak hrs (MWh)	No. of MPANs	Off-peak to Peak ratio
Supplier A	**90,704**	8,727	15,996	**24,723**	32,826	**3.67**
Supplier B	**22,748**	1,290	2,531	**3,820**	4,312	**5.95**
Supplier C	**152,912**	8,487	17,623	**26,109**	24,775	**5.86**
Total all suppliers	266,363.6	18,503.273	36,149.704	54,652.977	61,913	**4.87**
Elexon Profile 1 baseline	5.2173	0.57528	1.263168	1.838448	1	**2.84**
Nesta profile 1 baseline	1.60038	0.172584	0.39168	0.564264	1	**2.84**

Table 26: Off-peak to Peak consumption ratios

In order to estimate the magnitude of change that can be materially higher than portfolio averages suggest, where aggregate metrics do not fully capture behaviour that are driven by distinct user segments, further analysis and more granular metrics were derived from clustering analysis to isolate and quantify behaviours.

The following estimates are provided for each sample in a cluster in absolute terms against the Nesta baseline. The **cluster** where the **proportional effect is most apparent** has been **selected**. The values are presented as the **median values** across the sample, for example, SC 4 Sunday Midday uplift is the median value during the Sunday midday settlement periods of the 3,549 MPANs in that cluster. Bear in mind there is a significant spread in the average values for each settlement period, but this gives some indication of the scale of the change in these clusters.

<u>Sunday effect Clusters</u>

SC 4 **Increase** Sunday Midday – 3.52 kWh Off-peak ratio – 77%

FC 6 **Increase** Sunday Midday -4.91 kWh Off-peak ratio – 75%

FC 7 **Increase** Sunday Midday – 16.26 kWh Off-peak ratio – 76%

<u>Overnight peak Clusters</u>

This is by far the largest increase most proportionally and in absolute terms.

SC 2 Increase Overnight – 8.66 kWh Off-peak ratio – 85%

SC 3 Increase Overnight – 12.89 kWh Off-peak ratio – 92%

FC 2 Increase Overnight – 11.34 kWh Off-peak ratio – 93%

FC 3 Increase Overnight – 13.53 kWh Off-peak ratio – 93%

<u>Evening peak reduction</u>

SC 0 Decrease Evening – 0.71 kWh Off-peak ratio – 83%

SC 8 Decrease Evening – 1.74 kWh Off-peak ratio – 78%

FC 4 *Increase* Evening – 5.96 kWh Off-peak ratio – 79% (note this is due to higher absolute consumption in this cluster)

FC 5 *Increase* Evening – 0.7 kWh Off-peak ratio – 80% (note this is due to higher absolute consumption in this cluster)

Interpretation & Discussion

It's important to note a couple of aspects. One is that whilst these metrics provide a good indication and decision-useful insights, the translation of these patterns into precise and directly comparable system-level metrics remains limited at this stage. This reflects the behavioural and proxy-based nature of the analysis, the use of representative baselines rather than true counterfactuals and sensitivity to methodological choices. Second, the population analysed is likely to be skewed towards early adopters of low carbon technologies and ToU tariffs and may therefore not be a fully representative of the wider domestic consumer base. However, it provides a valuable indication of the direction of travel of consumption patterns as they evolve and become more mainstream.

The following sections reflect on the findings through a set of guiding, key questions focusing on what the results indicate about consumer behaviour and implications for the system and SSEN.

Are consumers responding to price signals/ implicit flexibility?

Yes, the results provide strong evidence that consumers are responding to price signals, specifically responding to ToU tariffs, as per this report. However, there are considerations and caveats discussed below.

Is demand actually shifting? Where? And how does behaviour differ across suppliers?

The results show clear evidence of demand shifting away from peak periods, with the most consistent and pronounced shift towards overnight consumption, which emerges as the dominant pattern across all analytical approaches. In addition, more targeted shifts are observed in specific time windows and driven by a subset of consumers, such as with Sunday's midday uplift.

The results show consistent shift in demand patterns across all suppliers when compared to baseline profile. **Off-peak to peak consumption ratios** for the three analysed suppliers are **3.67, 5.95 and 5.86,** compared to a **baseline of ~2.8**, indicating a material redistribution of demand away from peak periods.

The shares also reflect this – off-peak usage increases **from around 74% from a standard consumer profile, to ~78 – 83%** across all suppliers. Off-peak consumption is already high**,** but incremental shifts are significant. Even though the majority of electricity consumption already occurs during off-peak hours – reflecting the fact that these hours account for a much larger proportion of the day – peak demand is concentrated in relatively small periods. As such, even apparent modest shifts in percentage terms represent meaningful behaviour.

Both Supplier B and C have almost **40% share of overnight consumption** from their customers, which is very significant compared to the **14%** share of standard consumption. Even for Supplier A which reflects a more traditional demand profile, the overnight consumption share is ~**20.5%.** This suggests that implicit flexibility is present even in less responsive or more conventional customer groups

Suppliers B and C show similar patterns, although for Supplier B the number of MPANs is considerably lower, and as such it cannot be inferred that is an accurate representation of the majority of their portfolio (MPANS/consumers outside the EHHS dataset). For Supplier C, half of their observed consumers use more than 84% of their daily electricity consumption at off-peak hours, and specifically 43% or more of their consumption overnight. In contrast, most of their consumers fall within the two lower quartiles both for general off-peak and overnight consumption, but worth noting still above the baseline.

How are behaviours distributed across consumers and across time?

Delving more into it, the analysis indicates that consumer response to price signals is more widespread than a simple segmentation into responders and non-responders would suggest. The magnitude of change varies significantly across groups – for some, consumption patterns differ meaningfully from expected profiles. But importantly, even traditional-looking clusters/consumers with more traditional suppliers show at least small but consistent deviations from baseline.

Implicit flexibility appears to operate along a spectrum, with strong responders driving more visible shifts, while a wider group exhibit smaller but meaningful behavioural adjustment.

Regarding consistency over time, despite the variability at individual level, the overall patterns appear stable across the nine-month observation period.

Are there distinct types of customers responding differently?

Yes, both analytical approaches indicate that distinct types of consumers respond differently to price signals, with clear variation in both the timing and intensity of demand shifts.

Both the quartile distribution analysis and more robustly the cluster-based analysis highlight clear behavioural differences, from segments with strong overnight concentration to those with targeted midday uplift, while still identifying a large group with profiles closer to traditional patterns but with measurable marginal shifts. Shape-based clustering reinforces this by capturing variations in full-load profiles, including differences in peak suppression, secondary peaks and intra-day variability.

The cluster analysis evidenced that a common factor that comes out is the prevalence of overnight consumption. And even though it is not known with certainty what assets the customers have behind the meter, results indicate that overnight consumption can be as high as 80% higher relative to the baseline (as for SC 0, 2 and 7, FC 0, 3, 4, 5 and 8) which likely indicates the presence of EVs and batteries, likely optimised/automated.

What is the nature of the observed implicit flexibility? To what extent is it driven by technology-enabled, automated/optimised or behavioural responses?

This question is very relevant because it helps distinguish whether observed demand shifting is primarily driven by active consumer behaviour or underlying technologies, which has direct implications for scalability, persistence and system value.

The results of this analysis begin to address this question – through both the top-down analysis (zero cohort) and more accurately through the clusters.

Firstly, a significant proportion of the MPANs observed exhibit pronounced overnight consumption. The consistency and timing of this behaviour – concentrated in late night and early morning hours – suggest that it is unlikely to be driven by manual consumer action, and is instead indicative of technology-enabled flexibility, such as EVs or batteries.

Secondly, several clusters show characteristics in that they have very large overnight peaks and very low daytime consumption, in many cases zero or close to, alongside ramping patterns. This is consistent with the presence of solar PV and/or battery storage, where demand from the grid is reduced during daylight hours or shifted to other periods.

In contrast, some MPANs show elevated midday consumption relative to standard consumption. While these were not further investigated, this may indicate the presence of heat pumps or electric heating technologies, particularly when suppliers offer "super off peak" windows of cheaper electricity between 11:00 and 16:00.

Taken together, these results suggest that a meaningful share of the observed implicit flexibility is technology-enabled, with indication of automation and optimisation.

So, whilst this does not allow for definitive attribution, it provides a strong indicator that a significant portion of the observed implicit flexibility is technology-enabled. This represented a valuable starting point and a key area to focus on in future phases.

The analysis highlights the depth of insight that can be extracted from the clusters, while not fully explored within the scope of this phase, these and other insights can be readily applied and further refined in future work.

Where incentives exist (such as Sunday offers or dynamic pricing), is there clear evidence that customers are responding?

Yes, evidenced in both approaches, but this is more specifically driven by a small subset of consumers or very marginal increases from a wider set of consumers.

This is more evident in the cluster analysis clusters, both shape (mainly cluster 4 and more subtly on 8 and 9) and features (mainly on clusters 6, 7 and more subtly in 1).

What does this mean for our network in the next 3-5 years?

The results of this work can be modelled to estimate the impact to the LV network over time. For instance, if current behaviour scale with adoption, peak-period demand could reduce by approximately X-Y%, equivalent to Z MW at network level.

Next steps

From the cluster/statistical analysis perspective, practically speaking, this only scratches the surface of what is achievable with this set of methods. The suggested next steps for the clustering methods could be:

- Increase the variety of features, or tailor the features, to further break down the clusters. For example, this could include other flex windows that are promoted by tariff.
- Cluster on the overall time series – this would need more advanced data engineering to deal with data gaps, outliers and normalisation, and additional computing power to handle the processing for each MPAN.
- A detailed examination of the characteristics of the cluster shapes and what they may mean for SSEN operations and other organisations in the electricity sector.
- Splits into cohorts, between suppliers, between regions, across socio-demographic factors, etc.
- Adding contextual factors, such as EV ownership or solar PV (if available)
- Validate the methodology for calculating the quantification metrics with other flexibility experts in the industry and compare results.
- Further work can be done to explicitly quantify flexibility across and between different clusters, and in addition to this model expected uplift with a future technology or tariff mix.

From a wider perspective, below is a non-comprehensive list on what future work should focus on:

- Comparing response to implicit and explicit flexibility signals.
- Extending the dataset to improve representativeness.
- Including demographic and other contextual factors and datasets. Comparing results amongst DNO/DSOs areas could be very insightful.
- Isolating the impact of specific tariff types, including dynamic pricing.
- Model behaviour using findings to have insights at scale on what is the impact for the network in the short, medium and long term.
- Assessing the most useful ways of expressing implicit flexibility in practice. For instance, should it be measured as behaviour change relative to baseline, measured as difference between tariff cohorts or other?

Conclusions

The analysis provides clear and consistent evidence that implicit flexibility is already present across the observed population. Demand is shifting away from peak periods, with both widespread but moderate behavioural change and more pronounced responses concentrated in specific segments. These patterns are observable across the three suppliers analysed and across time and are supported by both the high-level metrics and the more granular analysis.

At the same time, the findings highlight that implicit flexibility is not uniform. It varies in magnitude, for an underlying driver, with indications that a meaningful share is technology-enabled rather than purely behavioural. This reinforces that implicit flexibility cannot be fully understood or represented through a single metric, but instead requires more nuanced, multi-dimensional views of how different behaviours contribute to overall demand shifting.

This work represents progress in better understating how implicit flexibility manifests and can be quantified by extending the analysis of flexibility beyond explicit – dispatched or contracted flexibility.

While the results are robust and directionally strong, they remain indicative, and there remain limitations that should be explored in future work. It's important to note that the metrics produced rely on representative baselines, rather than exact counterfactuals and reflect a set of methodological choices. This also highlights that there is no single "standard" consumption profile or uniform type of consumer, and the need for baselines to better reflect the diversity of real-world consumption patterns, and for these to be defined, transparent and openly available as industry reference points.

At this stage, implicit flexibility could be captured and expressed in multiple ways and metrics. Further investigating the best way to express implicit flexibility from different perspectives – DNOs, suppliers, Mission Control/Ofgem, etc – is still to be refined and formalised, and this work contributes towards providing a wide range of considerations and indicators that can be easily pivoted or translated into specific metrics.

This document establishes a strong foundation for further development. The approaches applied here – particularly the combination of behavioural metrics and clustering – can already support deeper attribution of flexibility drivers and more granular segmentation of responses. With further refinement, this has the potential to evolve into a more repeatable and scalable model, improving accuracy, consistency and usefulness of insights over time.