From Social Practices to Load Curves:

A Bottom-Up Framework Based on Time-Use Data

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EES-2026-005

Master Programme:
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Research report of Sofia Maggiora, S5964369

Report: EES-2026-005

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Abstract

Understanding residential electricity demand requires models that reflect how energy use emerges from everyday life. This research presents a bottom-up modelling framework that reconstructs household electricity load curves from time-use data using a social practice perspective. Rather than modelling appliances in isolation, electricity demand is treated as the outcome of daily routines and coordinated household activities.

The model is based on Dutch time-use diaries, from which individual activity patterns are extracted and aggregated into a reduced set of household related practices. Individual behaviour is simulated using time-inhomogeneous semi-Markov chains, allowing the model to capture both time-dependent routines and realistic activity durations. Synthetic households are assembled by combining simulated individuals within socio-demographic cohorts defined by household composition and income group. Electricity demand is then generated by probabilistically assigning appliances and triggering their operation when corresponding practices occur.

The framework produces high resolution daily load curves for different household types, income groups, and day types. Results show that household composition primarily shapes the temporal structure and simultaneity of demand, while income mainly influences demand magnitude through differences in appliance ownership and usage intensity. At the national level, aggregated demand profiles reproduce characteristic weekday evening peaks driven by food related practices and flatter weekend profiles associated with increased daytime presence.

Although the model underestimates absolute annual consumption compared to official statistics, it successfully captures the behavioural structure of residential electricity demand. The results demonstrate the value of integrating social practice theory and time-use data for analysing the environmental implications of everyday household activities.

1 Introduction

1.1 Background and research context

Residential electricity demand represents a substantial share of total electricity consumption and plays a growing role in the energy transition (Eurostat, 2025). As electricity systems integrate increasing shares of renewable generation and electrification expands across sectors, the temporal structure of demand becomes increasingly important (International Energy Agency (IEA), 2024). Peak loads, simultaneity of appliance use, and differences between weekdays and weekends directly influence flexibility requirements, grid stability and infrastructure planning (Lavin and Julienne, 2025).

At household level electricity demand emerges from structured daily routines. People wake up, leave home, prepare meals, clean, relax and sleep. These everyday practices shape when and how electricity is consumed (Mylonas et al., 2024). Residential load curves are therefore not purely technical artefacts, but the aggregated outcome of socially organised activities.

Understanding residential electricity demand thus requires models that can represent both the temporal regularity and variability of daily life. This has led to the development of a wide range of modelling approaches, which are discussed in the following section.

1.2 Literature review and state of the art

Residential electricity demand has been modelled using a wide range of approaches, commonly classified as either top-down or bottom-up methodologies (Grandjean et al., 2012).

Top-down approaches estimate residential consumption from aggregated indicators such as national statistics, macroeconomic variables, demographic projections or appliance saturation rates. These models are relatively simple and can be calibrated against historical consumption data, but they deduce demand from aggregate relationships and therefore provide limited insight about behavioural mechanisms or structural technological change (Swan and Ugursal, 2009).

Bottom-up approaches reconstruct demand by modelling individual households or representative dwellings. They typically combine appliance ownership data, technical characteristics, occupancy patterns, weather information and behavioural assumptions. Their main strength lies in their granularity and their ability to simulate technological transitions and other scenarios, although this comes with higher complexity and substantial data requirements (Kavgic et al., 2010).

Within bottom-up modelling, multiple strands can be distinguished. Engineering-based models focus on physical building properties and end-use technologies (Deb et al., 2017), whereas data-driven approaches rely heavily on historical load measurements and statistical learning techniques (Fida et al., 2024; Yilmaz et al., 2019). Some hybrid approaches attempt to bridge these perspectives (Mylonas et al., 2024).

A particularly influential development has been the integration of occupancy and activity-based modelling into bottom-up frameworks. Widén et al., 2009 demonstrated that stochastic occupancy models based on non-homogeneous Markov chains significantly improve the realism of simulated residential loads in Sweden. Richardson et al., 2008, developed a detailed stochastic occupancy model based on UK time-use data, showing that activity timing strongly determines

electricity demand patterns.

Building on this foundation, several national models have explicitly combined time-use data, appliance ownership statistics and stochastic transition models. In Italy, Bottaccioli et al., 2019, proposed a multi-scale Monte Carlo non-homogeneous semi-Markov framework capable of generating household and national-level load profiles. In Denmark, Foteinaki et al., 2019, linked Danish time-use data to appliance activation probabilities to reconstruct representative daily load curves. In the Netherlands, Nijhuis et al., 2016, implemented a Markov Chain Monte Carlo occupancy model and validated simulated load distributions against smart meter data. These studies demonstrate that stochastic activity-based modelling can reproduce key features of measured residential demand, including diversity, simultaneity and peak formation.

Beyond technical modelling, recent literature increasingly frames residential demand as an outcome of socially embedded practices. Torriti, 2020, shows that the temporal dependence of practices such as cooking, washing and cleaning strongly structures peak demand. This perspective shifts the analytical focus from isolated appliances to coordinated daily routines, highlighting the importance of behavioural heterogeneity (Curtis, 2021).

Despite these advances, the literature offers limited systematic analysis of how household composition and income structure shape electricity demand through differences in activity timing and simultaneity. Moreover, although many models reproduce aggregate load curves, fewer explicitly validate the behavioural layer before translating activities into electricity demand. Finally, linking cohort-level behavioural simulations to national residential demand in a transparent and interpretable way remains a methodological challenge. These issues motivate the research gap addressed in the following section.

1.3 Research gap and objectives

Building on the limitations identified above, this thesis addresses the need for a behaviourally transparent framework capable of reconstructing residential electricity demand from individual daily practices and scaling these dynamics to the national level. The central research question guiding this work is:

How can national residential electricity demand be reconstructed and interpreted as the aggregate outcome of socially structured daily practices?

To answer this question, a time-inhomogeneous semi-Markov model of individual daily activity behaviour is developed and validated against observed presence-at-home profiles. Simulated individuals are aggregated into synthetic households defined by household type and income group, and daily practices are mapped to appliance use to generate high-resolution household load curves. Differences in demand are analysed across household composition, income group and day type, and cohort-level results are aggregated to the national scale for comparison with official statistics from the Centraal Bureau voor de Statistiek.

By reconstructing electricity demand from the temporal organisation of everyday practices, this thesis provides a transparent framework that connects behavioural modelling with national electricity statistics and enables interpretation of residential demand as an outcome of structured social routines.

2 Methods

2.1 Data and preprocessing

This research uses data from a nationally representative time-use survey conducted by the Centraal Bureau voor de Statistiek (CBS) in 2016 on behalf of the Sociaal en Cultureel Planbureau (*Tijdsbestedingsonderzoek 2016*, Sociaal en Cultureel Planbureau (SCP), 2017). The survey collected detailed information on daily activity patterns of Dutch residents across a wide range of socio-demographic and economic backgrounds.

Respondents completed a time-use diary for seven consecutive days, reporting their activity at a temporal resolution of 10 minutes. In addition, respondents filled in structured surveys before and after the diary period, providing information on household composition, income, and appliance ownership. Approximately 5,500 individuals were initially sampled. After data cleaning and preprocessing performed by CBS, a total of 2,260 complete diaries were retained and made available for use in this research project.

2.1.1 Time-use diary structure

Activities reported in the time-use diaries are encoded using a classification scheme including 338 distinct activity codes, grouped into nine macro-categories: work, household and care, personal care, education outside working hours, volunteer work and meetings, social contact, free time, media, and other activities.

For the purposes of this research, the original activity classification was aggregated into a smaller set of 11 activity states related to in-home presence and household practices:

Table 1: Aggregated activity states used in the individual activity model.

State	Activity description
0	Away from home
1	Sleeping
2	Cooking
3	Baking
4	Watching TV
5	Studying
6	Washing dishes
7	Doing laundry
8	Vacuuming
9	Ironing
10	Other activities implying lighting use (e.g. reading)

For each respondent, a sequence of 1,008 time bins is extracted from the diary data, corresponding to seven days at a 10-minute resolution. At each time bin, one of the 11 activity codes is assigned. Respondents are then filtered and grouped according to household type and income quantile.

2.1.2 Cohort definition

Information from the pre- and post-diary surveys is used to define household composition and income. Respondents are grouped according to household type and income level, and these

dimensions are combined to build a set of socio-economic cohorts.

Household income in the time-use surveys is reported using standardised disposable household income categories based on equivalised income. Equivalised income corresponds to the disposable household income adjusted for household size and composition using a standard equivalence scale, with a single-person household as the reference. In the original time-use surveys, income is given in six predefined categories: below €10,000, €10,000–20,000, €20,000–30,000, €30,000–40,000, €40,000–50,000, and above €50,000.

For the purposes of this study, these income categories are aggregated into five income groups by combining the two highest income brackets into a single category. This aggregation is performed to align the income classification with the five-group structure used in a parallel research project that adopts the same cohort definition, to ensure consistency and comparability of results across studies. Even though these income groups do not correspond to population-based income quintiles, they are treated as five income categories for the purpose of cohort definition and aggregation.

The resulting cohort structure consists of five household types and five income groups. Each individual in the population is assigned to one of 25 cohorts corresponding to the cross-classification of these dimensions, which collectively cover all considered socio-demographic and economic categories.

Table 2: Cohort abbreviations used in this study.

Household type	**IQ1**	**IQ2**	**IQ3**	**IQ4**	**IQ5**
Single person, no child(ren)	SP, IQ1	SP, IQ2	SP, IQ3	SP, IQ4	SP, IQ5
Single person with child(ren)	SP+Ch, IQ1	SP+Ch, IQ2	SP+Ch, IQ3	SP+Ch, IQ4	SP+Ch, IQ5
Couple, no child(ren)	C, IQ1	C, IQ2	C, IQ3	C, IQ4	C, IQ5
Couple with child(ren)	C+Ch, IQ1	C+Ch, IQ2	C+Ch, IQ3	C+Ch, IQ4	C+Ch, IQ5
Other multi-person	Other, IQ1	Other, IQ2	Other, IQ3	Other, IQ4	Other, IQ5

2.1.3 Reconstruction of midnight to midnight days

The aim of this research is to model daily activity patterns separately for weekdays, Saturdays, and Sundays, in order to capture systematic differences in behaviour across the week. The original diary sequences are therefore subdivided into three day-type subsets: weekdays (five sequences of 144 time steps each), Saturdays (one sequence of 144 time steps), and Sundays (one sequence of 144 time steps).

Recordings in the time-use diaries start at 04:00 am on Monday and end at 04:00 am on the following Monday. For consistency and interpretability of the simulated results, the diary data are restructured to represent midnight to midnight days. This transformation ensures that simulated daily profiles align with conventional calendar days and facilitates interpretation of daily load curves.

2.2 Step 1: Individual activity modelling

The first step to reconstruct cohorts electricity load curves from social practices is to model behaviour of individuals in each cohorts and for each day (weekday, Saturday and Sunday). The model needs to simulate activities of an individual during a day in 10 minute time steps.

2.2.1 Time inhomogeneous semi-Markov chain

A stochastic modelling approach is adopted rather than a deterministic scheduling framework. Deterministic models impose fixed activity sequences and timings, which would produce identical daily routines for individuals within the same cohort. However, time-use data reveal substantial variability both across days and across households within the same socio-demographic group. Modelling this intra-cohort heterogeneity is important for reproducing diversity in appliance use, simultaneity effects, and peak formation at aggregate level. A stochastic Markov-type framework therefore allows realistic variability to emerge while preserving empirically observed transition structures.

Markov chains are used to model systems that evolve step by step, so they are particularly well suited to model individual human behaviour in the context of this research project. In fact, the considered system (social practices during a day) follows the assumptions needed for a Markov chain: the system is always in one of a finite number of state (in this case, the 11 possible activities), time advances in discrete steps (144 time steps per day), the next state is uncertain (not arbitrary) and which state is next depends only on which state is now. Markov chains are often described as having a "memorylessness" assumption, which means that the future state depends only on the present state and not on the past states. This does not mean that people have no memory and that behaviour is random, but it simply means that the present state already contains all the informations that matter for the next state.

The simulation is built using a time-inhomogeneous semi-Markov chain in order to separately model which activity happens next and how long it lasts. This choice is due to the fact that activities in time-use data typically last for longer periods than a single 10 minute time step, and a plain Markov chain would therefore produce unrealistically frequent state changes.

Two probability distributions are extracted from the time use survey, for each cohort and each day type: a transition probability distribution and a duration (sojourn time) distribution. These distributions are estimated once and cached for later use, as extracting them for all cohorts and day types is computationally expensive.

The transition probability distribution is defined as:

$$P_{ij}(t) = \frac{n_{ij}(t)}{n_i(t)} \tag{1}$$

where $\mathrm{n}_{ij}(\mathrm{t})$ is the number of observed transitions from activity i to activity j occurring at time step t, and $\mathrm{n}_i(\mathrm{t})$ is the total number of transitions leaving activity i at time t. Self transitions are excluded, because staying in one state is handled separately by the sojourn time distributions. The result is a set of time-dependent transition probability matrices with dimensions (144, 11, 11).

The duration probability distribution is estimated to model how long an activity lasts once it has started. For each observed transition from activity i to activity j at time t, the duration k is defined as the number of consecutive time steps spent in activity j before the next transition occurs. The corresponding duration distributions are estimated as:

$$P(D = k \;\mid\; \text{prev} = i, \;\; \text{current} = j) = \frac{n_{ij}(t,k)}{n_i(t)} \tag{2}$$

where $n_{ij}(\mathrm{t,k})$ is the number of times activity j lasts exactly k time steps after being entered from activity i at time t. Duration distributions are therefore conditional on the previous activity, the current activity, and the time of entry.

Together, the time-dependent transition matrices and the conditional duration distributions fully define a time-inhomogeneous semi-Markov process describing individual daily activity sequences for each cohort and day type.

2.2.2 Monte Carlo simulation

For each cohort and day type a 1000 independent daily activity schedules are simulated by repeatedly sampling from the two probability distributions. Together, these trajectories are used to compute average individual behaviour and uncertainty.

The algorithm used is a Markov Chain Monte Carlo (MCMC) algorithm and it goes as follows:

- Initiate the Monte Carlo loop with $n = 1000$ iterations
- Sample initial state i and initial duration k from the empirical distributions estimated at time $t_0 = 0$
- Enter the time inhomogeneous semi-Markov chain loop:
  i. Stay in i for k time steps
  ii. Reach a boundary at time t, when the k time steps are over
  iii. At time t, draw the next state j from the transition probability distribution $P_{ij}(t)$
  iv. Enter state j and draw a new duration $k^{'}$ from the duration distribution $P(D = k \mid \text{prev} = i, \text{ current} = j)$
  v. Stay in state j for $k^{'}$ time steps
  vi. Repeat until $t = 143$ is reached
- Outputs are aggregated across simulations

2.2.3 Validation of Step 1

To validate the individual activity model, simulated and observed presence at home profiles are compared for each cohort and day type. Presence at home is defined as being in any activity state other than state 0 (away from home). For the survey data, presence profiles are computed by evaluating, at each 10 minute time step, the proportion of respondents within a cohort who are at home, and averaging across all available diary days of the corresponding type.

Simulated presence profiles are constructed in an similar manner. For each cohort and day type, presence at home is extracted from 1000 independently simulated daily activity trajectories and averaged across Monte Carlo replications. This ensures that both observed and simulated presence profiles are defined with the same temporal resolution and are directly comparable.

Model performance is assessed using three metrics: the pointwise difference between simulated and observed presence probabilities, the Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE). The difference is defined as simulated minus observed presence; negative values indicate an underestimation of presence at home by the model, while positive values indicate overestimation. The MAE measures the average absolute deviation between simulated and observed profiles across the day, while the RMSE places greater weight on larger deviations and is particularly sensitive to peak mismatches, timing shifts, and systematic bias. Together, these metrics provide a comprehensive assessment of the accuracy and stability of the simulated presence profiles.

2.3 Step 2: Household aggregation

Simulated individual activity profiles are combined to construct household level activity schedules for each cohort and day type. Households are generated according to the cohorts' household type definition by sampling the required number of adult individuals from the corresponding cohort and aggregating their simulated activity sequences at a common 10-minute resolution.

For single-person and single-parent households, the household activity schedule is defined by a single adult individual sampled from the corresponding cohort. For multi-adult household types, individuals are sampled independently and combined without explicit modelling of intra-household coordination. Children are not modelled explicitly; household activity schedules therefore reflect the behaviour of adult household members only. This aggregation allows scalable simulation across cohorts but introduces assumptions regarding independence between household members, the absence of synchronisation mechanisms within households, and the omission of child-specific activity patterns. The implications of these assumptions are discussed in Section 4.4.

As an intermediate diagnostic, aggregated household activity schedules are also summarised using heatmaps that report the probability of performing each activity at each 10-minute time bin, averaged across simulated households within a cohort and day type. These visualisations are used only for descriptive and interpretative purposes and do not affect the load curve construction.

2.4 Step 3: Cohort and national load curves

The first step to construct the load curves is to map the 11 activity states to a corresponding set of household appliances. The mapping is based on functional correspondence between reported activities and typical appliance use (e.g., laundry activities are linked to washing machine and tumble dryer cycles; ironing is linked to iron use). The structure of this mapping is adapted from activity-based modelling approaches presented in Torriti, 2020 and Bottaccioli et al., 2019, and adjusted to reflect the appliance categories available in the Tracebase dataset (Reinhardt et al., 2012). Each activity is associated with at most one appliance, as reported in table 3.

Table 3: Mapping between activity states and associated appliances.

State	Activity	Appliance
0	Away	No appliance
1	Sleeping	No appliance
2	Cooking	Microwave (benchmark)
3	Baking	Oven
4	Studying	Laptop
5	Watching TV	TV
6	Dishwashing	Dishwasher
7	Laundry	Washing machine, Dryer
8	Cleaning	Vacuum cleaner
9	Ironing	Iron
10	Active at home	Lights

Before the diary annotation process, respondents completed a preliminary survey that included questions on household appliance ownership. For each cohort, appliance ownership probabilities are computed as the ratio between the number of respondents reporting owner-

ship of a given appliance and the total number of respondents in that cohort. The resulting ownership rates are reported in table 4.

Table 4: Appliance ownership probabilities by cohort.

Cohort	**Freezer**	**Microwave**	**Dryer**	**Kitchen**	**Dishwasher**	**PC**	**smart TV**
SP, IQ1	0.9091	0.8864	0.3864	0.2727	0.4312	0.9070	0.2791
SP, IQ2	0.8000	0.8222	0.4148	0.2592	0.3407	0.5484	0.2097
SP, IQ3	0.8707	0.8793	0.5517	0.3707	0.5086	0.7632	0.3421
SP, IQ4	0.8837	0.8605	0.6046	0.3023	0.6279	0.6500	0.3500
SP+Ch, IQ2	0.8857	0.9571	0.5714	0.4143	0.5713	0.8226	0.4839
SP+Ch, IQ3	0.9473	0.9474	0.8684	0.4737	0.8180	0.7647	0.5588
C, IQ2	0.8841	0.8963	0.6097	0.3293	0.4939	0.5442	0.2585
C, IQ3	0.9324	0.8897	0.7438	0.4199	0.7295	0.7164	0.3582
C, IQ4	0.9565	0.9068	0.7391	0.4969	0.8944	0.8411	0.5033
C, IQ5	1.0000	0.9388	0.8775	0.5510	0.9796	0.8478	0.6087
C+Ch, IQ2	0.9591	0.9227	0.7727	0.4773	0.8136	0.8186	0.5392
C+Ch, IQ3	0.9638	0.9254	0.8337	0.5608	0.8870	0.8625	0.6037
C+Ch, IQ4	0.9905	0.9238	0.9000	0.5762	0.9286	0.8316	0.6071
C+Ch, IQ5	0.9697	0.9091	0.8333	0.5303	0.9394	0.7846	0.5846

For a small subset of appliances, detailed ownership probabilities by cohort were not available. In these cases, ownership was assumed to be universal (100%), specifically for the vacuum cleaner, iron, and oven. For the washing machines, national Dutch ownership data were available but not differentiated by cohort; a uniform ownership probability of 99.1% was therefore applied across all cohorts (Rozsai et al., 2024).

Appliances are then divided into two categories: *baseload appliances* and *activity-triggered appliances*. Baseload appliances include the fridge and the router, which are assumed to have an ownership probability of 100%, and the freezer, whose ownership probability varies by cohort as shown in table 4. These appliances are assumed to be continuously connected and contribute to household electricity demand according to their operational characteristics, namely compressor cycling for cold appliances and a constant baseline load for the router.

Activity-triggered appliances are activated only when the corresponding activity is performed, the household owns the appliance, and the appliance is not already running an active cycle. An exception is made for the tumble dryer: when present in the household, it is always triggered immediately after a washing machine cycle, independently of the reported activity timing.

Once activities have been mapped to appliances and appliance activations have been scheduled, empirical power consumption traces are assigned to each appliance. These traces are drawn from the Tracebase dataset (Reinhardt et al., 2012), which contains high-frequency (1 Hz) measurements of real household appliances. To match the temporal resolution of the simulated activity profiles, traces are aggregated to a 10 minute resolution. For each household and each time step, total electricity demand is calculated as the sum of the power of all appliances that are active at that moment. In this way, household load curves are built directly from the timing, duration and overlap of appliance cycles.

To avoid artificial synchronisation of baseload demand across households, cold appliances

(fridges and freezers) are modelled using stochastic duty cycles with a random phase offset. Each appliance follows a cyclic on–off compressor pattern derived from the assigned empirical Tracebase trace; however, the initial phase of the cycle is randomised independently for each household. This phase randomisation ensures that compressor start times are de-synchronised across the population, preventing unrealistic aggregate load spikes that would otherwise emerge if identical duty cycles were aligned in time. As a result, households have realistic appliance dynamics, while aggregated cohort and national load curves show smooth and statistically plausible baseload behaviour.

2.4.1 Cohort load curves

Cohort load curves are visualised using two representations: stacked area plots showing the contribution of individual social practices, and total load curves including uncertainty bands and two individual household trajectories.

For each cohort and day type, a fixed number of households is simulated and the mean household load is computed at each 10 minute time step. To estimate average load profiles and associated uncertainty, multiple independent Monte Carlo replications are performed. In the configuration used here, 100 households per cohort are simulated, and the entire simulation is repeated with 5 different random seeds, resulting in 500 independent household realisations per cohort and day type.

Each Monte Carlo replication is initialised with a different random seed, ensuring statistically independent realisations of activity sequences, appliance usage, and resulting load profiles. Repeating the simulation with multiple seeds allows estimation of the expected household demand, quantification of uncertainty arising from stochastic variability, and assessment of the robustness of results with respect to random fluctuations in activity timing and appliance use. Sensitivity analyses showed that increasing the number of random seeds beyond five yielded negligible changes in both the mean load curves and uncertainty estimates, while substantially increasing computational time. Five Monte Carlo replications therefore provide a satisfactory trade-off between result stability and computational efficiency.

The mean load curve is computed by averaging the simulated household trajectories at each time step, and uncertainty is computed using the standard error and corresponding confidence intervals across the set of simulated households. Increasing the number of simulated households or Monte Carlo replications leads to progressively smoother mean curves, as these represent estimates of the expected value of a stochastic process.

To show the effect of aggregation, the total load plots also include two examples of the individual household trajectories. Individual household load profiles are characterised by sharp, high-power peaks resulting from short duration, high-load appliance usage, such as washing machines or irons. When aggregating across households and stochastic realisations, these peaks occur at different times and therefore do not systematically align. As a result, the mean cohort load curve is smoother and shows lower peak values than individual trajectories.

The shaded uncertainty bands further demonstrate this aggregation effect. The outer band represents the 95% confidence interval across simulated households, while the inner band corresponds to the standard error of the mean. Together these elements highlight the variability of individual household behaviour from the smoother expected demand profile at the cohort level and demonstrate that the reduction of extreme peaks comes from statistical aggregation rather than from modelling artefacts.

All simulations are fully reproducible: model code, parameter settings, and the random seeds used for each Monte Carlo replication are stored and can be used to regenerate identical household trajectories and load curves.

Furthermore, to support interpretation at the level of social practices and avoid overly fragmented results, the original activity level electricity contributions are aggregated into four practice bundles reflecting shared meanings and purposes. The practices are: food related practices (cooking, baking, dishwashing), household maintenance practices (cleaning, ironing, laundry and dryer), leisure and ICT-related practices (studying, watching TV and lighting), and baseload demand (fride, freezer, router). Baseload demand is treated separately, as it does not correspond to an activity-based practice but represents continuously operating appliances.

2.4.2 National load curves

National residential load curves are constructed by aggregating the cohort load profiles using household weights derived from official household statistics. The number of households belonging to each cohort is obtained from Statistics Netherlands (CBS), n.d.-a, classified by household type and income groups, as reported in table 5.

Table 5: Number of households per cohort and income group (millions), based on Statistics Netherlands (CBS), n.d.-a.

Cohort	**IQ1**	**IQ2**	**IQ3**	**IQ4**	**IQ5**	**Total**
SP (no child)	1.3809	0.9024	0.5173	0.1340	0.0513	2.9859
SP+Ch	0.0704	0.1673	0.1743	0.1049	0.0450	0.5619
C (no child)	0.0957	0.4045	0.6349	0.6733	0.4191	2.2275
C+Ch	0.0230	0.0929	0.2292	0.6294	0.9949	1.9694
Other (no child)	0.0088	0.0120	0.0231	0.0373	0.0686	0.1498
Total	**1.5788**	**1.5791**	**1.5788**	**1.5789**	**1.5789**	**7.8945**

For each cohort c, the mean household load curve $\bar{L}_c(t)$ is obtained as described in the previous subsection. National load curves are then computed as a weighted sum of the cohort mean profiles, where weights correspond to the number of households N_c in each cohort. Formally, the national mean load curve $\bar{L}_{\mathrm{NL}}(t)$ is given by:

$$\bar{L}_{\mathrm{NL}}(t) = \frac{\sum_c N_c \, \bar{L}_c(t)}{\sum_c N_c} \tag{3}$$

This aggregation maintains differences in load shape across cohorts and ensures that their contribution to national demand reflects their relative prevalence in the population.

National load curves are computed separately for weekdays, Saturdays, and Sundays. To estimate annual residential electricity consumption, the corresponding daily energy demand is first obtained by integrating the national load curve over each day type. Annual consumption is then calculated by weighting these daily values by the number of occurrences of each day type in a year, assuming 52 weeks:

$$E_{\mathrm{year}} = 52 \times (5 \times E_{\mathrm{WD}} + E_{\mathrm{SAT}} + E_{\mathrm{SUN}}) \tag{4}$$

The resulting annual electricity consumption estimate represents the total residential demand given by the simulated activity patterns and appliance usage. This estimate is then

compared with aggregated residential electricity consumption statistics from CBS in order to assess the plausibility and consistency of the simulated national load profiles.

3 Results

3.1 Step 1: Individual behaviour

The tables 6, 7 and 8 below report the validation metrics used to assess the performance of the individual activity model across cohorts for weekdays, Saturdays and Sundays. Results are given in terms of the difference between simulated and observed presence at home probabilities, together with the corresponding MAE and RMSE values.

A clear pattern emerges with respect to sample size. Cohorts with a limited number of survey respondents (highlighted in light red in the tables and characterised by $N \leq 30$) show substantially higher errors than cohorts with larger sample sizes, consistently across weekdays, Saturdays, and Sundays. In these cohorts, both MAE and RMSE values are quite high, indicating that the simulated activity patterns are not able to reliably reproduce observed presence behaviour. To avoid propagating large uncertainties to the next modelling steps, these cohorts are excluded from further household-level simulations. The excluded cohorts represent approximately 0.54 million households, while the retained cohorts account for roughly 7.35 million households, corresponding to about 93% of the Dutch household stock in 2016 (Statistics Netherlands (CBS), n.d.-a). The national aggregation therefore remains representative of the vast majority of residential households, and the exclusion primarily affects small and statistically unstable subgroups.

This effect is particularly pronounced for the household type classified as *Other*, across all income groups. For these cohorts, MAE values frequently exceed 20 percentage points, with RMSE values in some cases exceeding 30 percentage points, reflecting poor agreement between simulated and observed presence profiles. The cohort *Other, IQ5* contains no survey respondents and is therefore excluded from the analysis entirely.

A second systematic pattern concerns differences across day types. Validation performance is generally weaker for weekend days than for weekdays, even for cohorts with a large number of respondents. For example, the cohort *Couple with child(ren), IQ3*, which represents the largest cohort in terms of sample size, exhibits MAE values of approximately 6% and RMSE values around 9% on Saturdays and approximately 4% and 5% on Sundays, compared to lower errors on weekdays. This suggests that weekend activity patterns are more difficult to capture accurately within the current modelling framework, likely reflecting greater behavioural variability and less structured daily routines.

Table 6: Validation metrics per cohort for weekday (WD) presence profiles.
N is the number of survey respondents in the cohort.
Obs WD and Sim WD denote the average observed and simulated probability of being at home.
Diff is the mean difference (Sim Obs).
MAE and RMSE are the Mean Absolute Error and Root Mean Squared Error over the 24-hour profile.

Cohort	**N**	**Obs WD**	**Sim WD**	**Diff**	**MAE**	**RMSE**
SP, IQ1	44	67.30	73.39	6.09	8.03	10.49
SP, IQ2	135	73.62	74.96	1.34	3.56	4.77
SP, IQ3	116	68.53	69.69	1.17	2.76	3.73
SP, IQ4	43	65.68	70.12	4.44	6.62	8.37
SP, IQ5	11	68.24	85.76	17.52	18.66	23.81
SP+Ch, IQ1	12	61.63	83.05	21.42	22.52	30.72
SP+Ch, IQ2	70	68.43	70.38	1.94	5.12	6.65
SP+Ch, IQ3	38	65.90	72.78	6.88	9.50	13.29
SP+Ch, IQ4	8	73.44	84.64	11.20	12.62	16.30
SP+Ch, IQ5	4	70.14	92.62	22.48	25.13	32.59
C, IQ1	14	72.07	84.71	12.64	17.64	24.33
C, IQ2	164	77.74	77.41	-0.33	1.93	2.60
C, IQ3	281	73.76	73.08	-0.68	2.29	2.89
C, IQ4	161	68.36	70.03	1.67	2.56	3.38
C, IQ5	49	69.47	74.56	5.08	6.41	8.76
C+Ch, IQ1	19	69.74	81.22	11.48	13.23	18.51
C+Ch, IQ2	220	68.36	66.92	-1.44	2.76	3.46
C+Ch, IQ3	469	65.14	64.52	-0.63	2.72	3.44
C+Ch, IQ4	210	66.10	64.32	-1.79	3.03	3.91
C+Ch, IQ5	66	62.66	68.96	6.30	9.13	12.61
Other, IQ1	5	56.81	81.56	24.75	27.94	33.88
Other, IQ2	4	60.42	91.84	31.42	37.86	44.87
Other, IQ3	3	49.31	88.96	39.66	41.31	50.18
Other, IQ4	4	78.65	88.47	9.82	14.16	21.37
Other, IQ5						

Table 7: Validation metrics per cohort for Saturday (SA) presence profiles.
N is the number of survey respondents in the cohort.
Obs SA and Sim SA denote the average observed and simulated probability of being at home.
Diff is the mean difference (Sim Obs).
MAE and RMSE are the Mean Absolute Error and Root Mean Squared Error over the 24-hour profile.

Cohort	**N**	**Obs SA**	**Sim SA**	**Diff**	**MAE**	**RMSE**
SP, IQ1	44	59.60	83.40	23.81	23.96	30.78
SP, IQ2	135	75.58	85.77	10.19	10.47	15.25
SP, IQ3	116	73.88	85.80	11.92	13.17	17.05
SP, IQ4	43	70.28	89.57	19.28	19.94	24.74
SP, IQ5	11	86.11	94.01	7.89	9.87	13.25
SP+Ch, IQ1	12	56.37	78.40	22.03	22.99	32.66
SP+Ch, IQ2	70	74.76	82.36	7.60	8.43	13.67
SP+Ch, IQ3	38	74.00	83.42	9.42	10.45	17.22
SP+Ch, IQ4	8	76.22	92.09	15.87	18.25	22.99
SP+Ch, IQ5	4	78.47	98.03	19.56	19.84	25.88
C, IQ1	14	82.44	94.75	12.31	14.74	18.23
C, IQ2	164	85.88	90.24	4.36	4.98	7.71
C, IQ3	281	84.07	90.22	6.14	6.65	9.13
C, IQ4	161	84.26	90.54	6.28	6.81	9.72
C, IQ5	49	82.47	91.61	9.14	9.55	13.03
C+Ch, IQ1	19	77.72	87.37	9.64	10.12	13.44
C+Ch, IQ2	220	73.15	78.74	5.59	6.19	8.59
C+Ch, IQ3	469	72.49	78.53	6.04	6.35	8.79
C+Ch, IQ4	210	72.73	78.63	5.90	6.16	8.43
C+Ch, IQ5	66	71.09	79.14	8.05	8.48	11.95
Other, IQ1	5	61.05	80.11	19.06	21.17	27.33
Other, IQ2	4	58.16	87.49	29.33	31.58	41.67
Other, IQ3	3	55.09	92.64	37.55	38.79	50.83
Other, IQ4	4	69.16	92.34	23.18	25.59	33.05
Other, IQ5						

Table 8: Validation metrics per cohort for Sundays (SU) presence profiles.
N is the number of survey respondents in the cohort.
Obs SU and Sim SU denote the average observed and simulated probability of being at home.
Diff is the mean difference (Sim Obs).
MAE and RMSE are the Mean Absolute Error and Root Mean Squared Error over the 24-hour profile.

Cohort	**N**	**Obs SU**	**Sim SU**	**Diff**	**MAE**	**RMSE**
SP, IQ1	44	70.77	86.70	15.93	17.24	22.70
SP, IQ2	135	79.41	87.33	7.91	8.35	11.71
SP, IQ3	116	75.74	86.68	10.94	11.80	15.70
SP, IQ4	43	74.03	91.25	17.22	18.99	23.87
SP, IQ5	11	83.59	93.62	10.03	12.27	17.25
SP+Ch, IQ1	12	66.88	88.93	22.05	22.92	30.55
SP+Ch, IQ2	70	75.52	87.46	11.94	12.18	15.41
SP+Ch, IQ3	38	77.21	87.55	10.34	12.13	17.33
SP+Ch, IQ4	8	82.67	92.70	10.03	12.05	15.31
SP+Ch, IQ5	4	86.06	96.09	10.03	11.66	14.43
C, IQ1	14	84.09	93.64	9.55	12.76	16.43
C, IQ2	164	89.10	90.90	1.80	2.75	3.56
C, IQ3	281	86.20	90.54	4.34	4.71	6.36
C, IQ4	161	86.42	90.80	4.38	4.71	6.73
C, IQ5	49	85.74	91.93	6.19	6.64	9.13
C+Ch, IQ1	19	78.97	87.63	8.66	9.95	13.59
C+Ch, IQ2	220	73.56	74.95	1.39	3.51	4.45
C+Ch, IQ3	469	71.02	74.47	3.45	4.16	5.32
C+Ch, IQ4	210	71.03	74.50	3.47	4.36	5.70
C+Ch, IQ5	66	69.49	75.86	6.37	6.90	9.74
Other, IQ1	5	64.75	86.55	21.79	24.21	31.73
Other, IQ2	4	58.63	82.37	23.74	28.72	39.40
Other, IQ3	3	56.76	88.56	31.80	34.44	46.28
Other, IQ4	4	74.35	86.39	12.04	18.11	24.46
Other, IQ5						

These patterns are further illustrated in figures 1, 2, 3 and 4, which compare observed and simulated presence at home profiles for four representative cohorts: *Single person IQ3*, *Single person with child(ren) IQ3*, *Couple IQ3* and *Couple with child(ren) IQ3*. For clarity, only these four cohorts are shown here, while the full set of presence profile plots is provided in the Appendix B.1.

Across all cohorts, the agreement between simulated and observed presence profiles is strongest on weekdays, with the model accurately reproducing the timing and magnitude of the main presence peaks and troughs. In contrast, weekend days show larger deviations between simulated and observed profiles, regardless of cohort size. This confirms that the weaker validation performance observed for Saturdays and Sundays is not only driven by limited sample sizes, but reflects structural differences in weekend activity patterns.

In particular, the weekend profiles show a systematic upward shift in simulated presence compared to survey data, indicating a tendency of the model to overestimate time spent at home during weekends. While the overall shape of the daily presence curve is preserved, this bias suggests that weekend behaviour is more heterogeneous and less tightly constrained than weekday behaviour, making it more difficult to capture accurately within the current modelling framework.

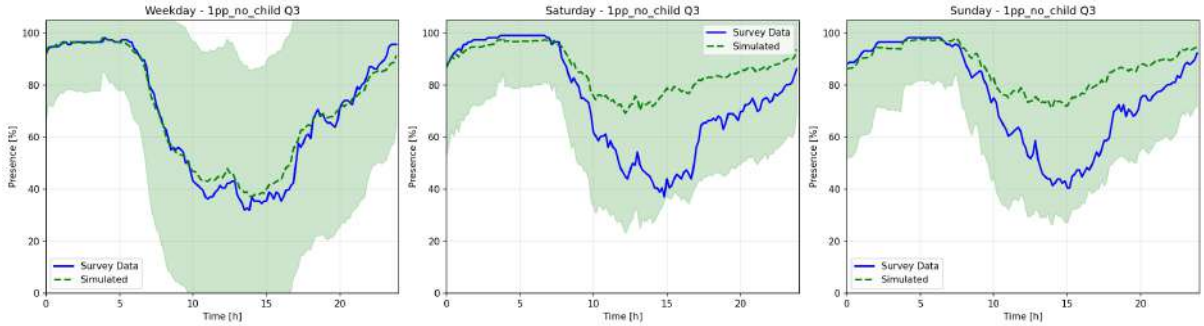


Figure 1: Observed and simulated presence profiles for *Single person, IQ3*.

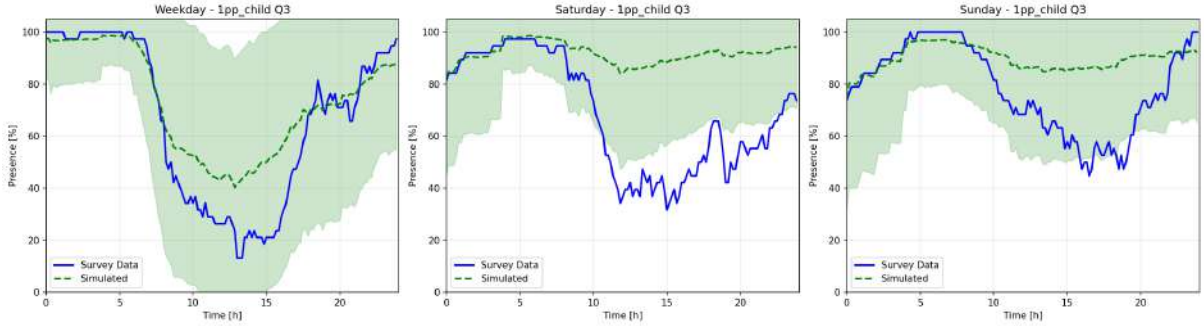


Figure 2: Observed and simulated presence profiles for *Single person with child(ren), IQ3*.

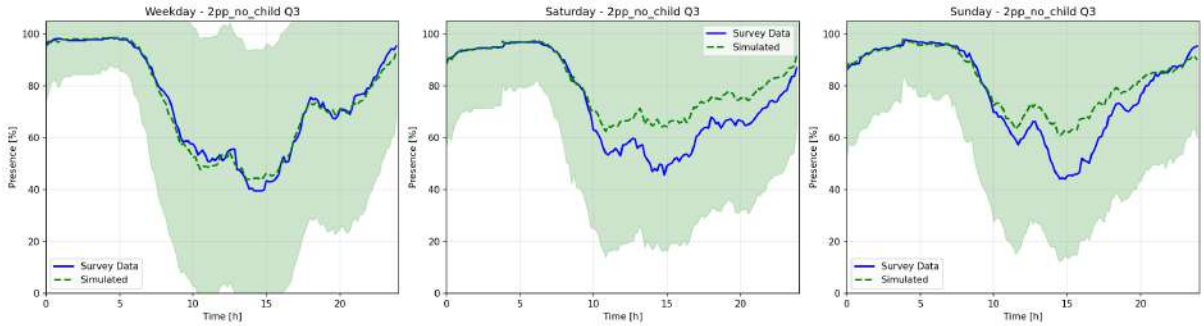


Figure 3: Observed and simulated presence profiles for *Couple, IQ3*.

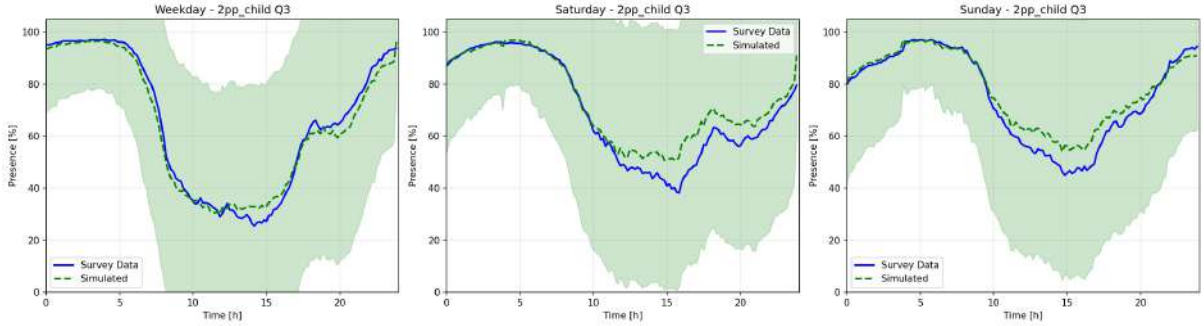


Figure 4: Observed and simulated presence profiles for *Couple with child(ren), IQ3*.

3.2 Step 2: Household behaviour

Figures 5, 6, 7 and 8 present simulated household activity patterns for the same four representative cohorts used in the presence athome analysis: *Single person, IQ3*, *Single person with child(ren), IQ3*, *Couple, IQ3* and *Couple with child(ren), IQ3*. Results are shown separately for weekdays, Saturdays, and Sundays. Heatmap representations are used to visualise the temporal structure and relative intensity of different activities over the course of the day.

The horizontal axis represents time of day, the vertical axis lists the aggregated activity categories, and colour intensity indicates the probability that at least one household member is performing a given activity at a given 10 minute time step. For clarity, only these four cohorts are shown here; the full set of cohort-specific heatmaps is provided in the Appendix B.2.

Because household level activity probabilities span several orders of magnitude, from dominant activities such as sleeping or being away from home to less frequent activities such as ironing or vacuum cleaning, a logarithmic colour normalisation is applied. This scaling makes sure that less probable but behaviourally and energetically relevant activities are visible without saturating the colour scale for high probability states.

As a result, the heatmaps are intended to support qualitative interpretation of daily activity structure and timing rather than precise quantitative comparison of absolute probabilities. This representation allows both common and rare activities to be identified and related to subsequent household electricity demand.

Across both cohorts, clear and interpretable daily activity patterns emerge. On weekdays, sleeping dominates the early morning hours, with high probabilities until approximately 06:00–07:00 am, followed by an increase in the probability of being away from home during typical working hours. During this period, most household activities such as ironing, vacuum cleaning, or laundry display very low probabilities, reflecting limited at home presence.

In contrast, weekend days show higher probabilities of being at home throughout the day, together with later wake up times and a more gradual transition from sleeping to daytime activities. This increased daytime presence is associated with higher probabilities of household and leisure activities, including cooking, watching television, and cleaning related activities, which are more evenly distributed across the day than on weekdays.

For all cohorts, cooking activity shows pronounced peaks during typical evening meal times in the Netherlands, while the probability of watching television increases in the evening hours, particularly after dinner. Despite differences in household composition, the overall temporal ordering of activities is preserved across cohorts, suggesting that the household aggregation procedure keeps realistic daily rhythms while allowing for increased variability during weekends.

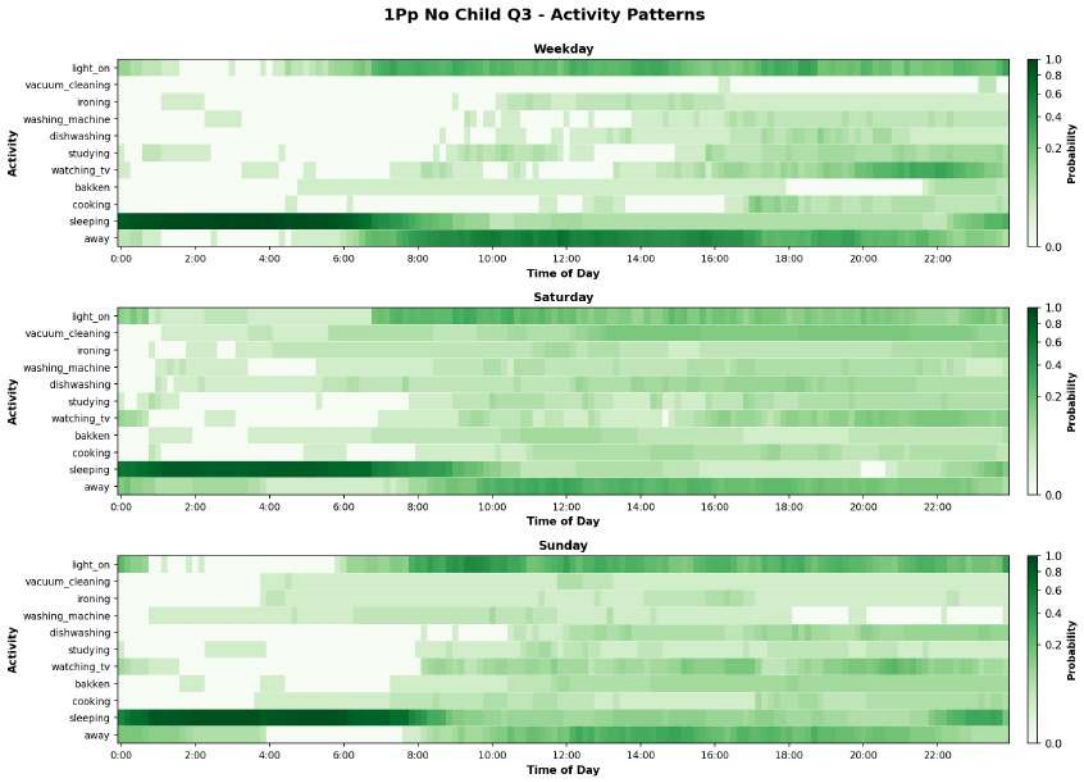


Figure 5: Household activity probabilities for *Single person, IQ3* across weekdays, Saturdays, and Sundays.

Figure 6: Household activity probabilities for *Single person with child(ren), IQ3* across weekdays, Saturdays, and Sundays.

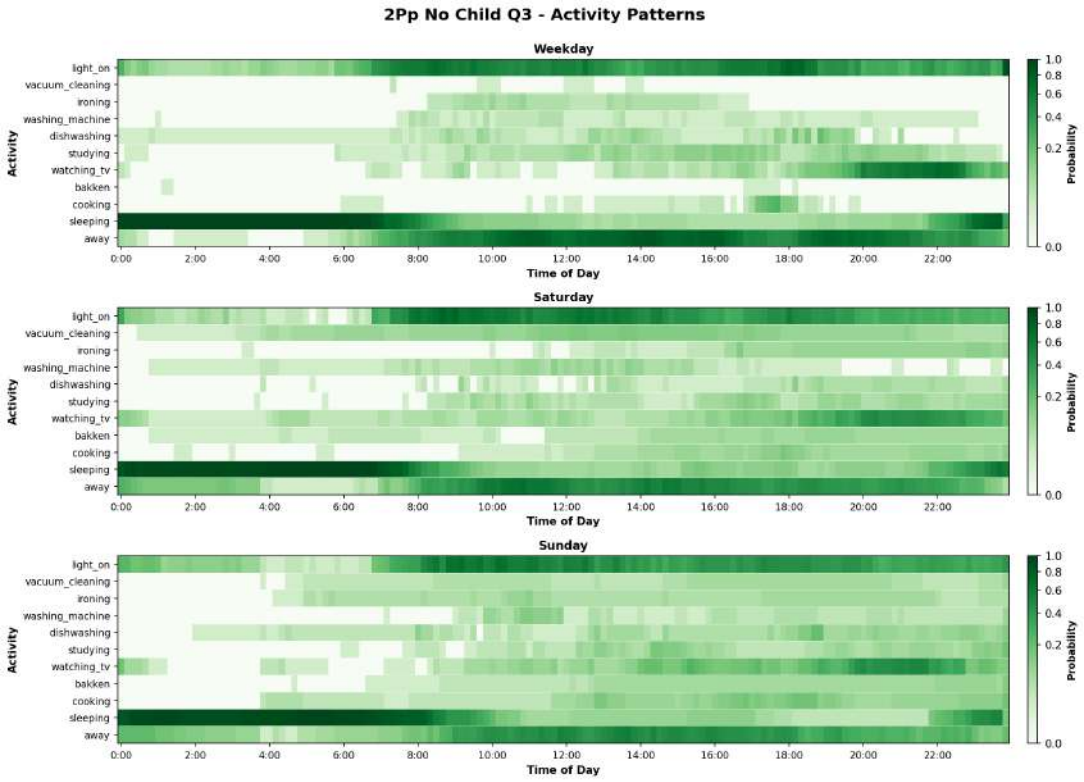


Figure 7: Household activity probabilities for *Couple, IQ3* across weekdays, Saturdays, and Sundays.

Figure 8: Household activity probabilities for *Couple with child(ren), IQ3* across weekdays, Saturdays, and Sundays.

3.3 Step 3: Load curves

The goal of the following analysis is not to test statistical significance between cohorts, but to identify systematic behavioural and structural differences emerging from the simulation framework. Results are therefore interpreted using comparative and descriptive metrics that highlight differences in activity patterns, appliance use, and resulting electricity load profiles across household compositions, income groups, and day types.

3.3.1 Household composition effects, IQ3 baseline

To highlight the effect of household composition on electricity demand, load curves are compared across household types within income group IQ3. IQ3 represents the median income group and contains sufficiently large sample sizes across household types, making it suitable for controlled cross-household comparison. The load curves and load metrics of the other income groups can be found in the Appendix B.3.1.

Differences between household types are analysed by examining how total electricity demand scales with household composition, how often appliances operate simultaneously, and how household activities overlap in time. These effects are visible in Figure 9, which shows simulated weekday load curves for the four representative household types within IQ3.

As reported in Table 9, clear scaling behaviour is observed across household types. Peak demand increases substantially when moving from single person to couple households, reaching above 600 W for couples. Daily electricity consumption follows a similar pattern, with couple households consuming approximately 6.1 kWh per day compared to 3.8 kWh for single-person households. This increase is not purely proportional to household size but reflects higher simultaneity of practices and overlapping appliance use.

Household composition also affects the internal structure of electricity demand, as shown in table 10. Single-person households allocate a larger share of weekday electricity to baseload and leisure-related practices (together exceeding 65%), reflecting a relatively stable and less synchronised demand structure. In contrast, couple households display a clear shift toward activity-driven consumption: baseload decreases from 34.2% (SP) to 21.4% (C), while food-related practices increase from 14.5% to 24.1%, and household maintenance remains substantial. This indicates a stronger concentration of demand in temporally coordinated practices such as cooking and dishwashing, as fixed background loads are diluted within a larger volume of activity-related consumption.

Households with children exhibit a different internal distribution. Although their absolute consumption remains higher than that of single-person households, the relative share of baseload and leisure increases compared to childless couples, while food-related demand decreases. This suggests that additional daytime presence and more dispersed activities redistribute electricity use across the day rather than simply amplifying evening peaks.

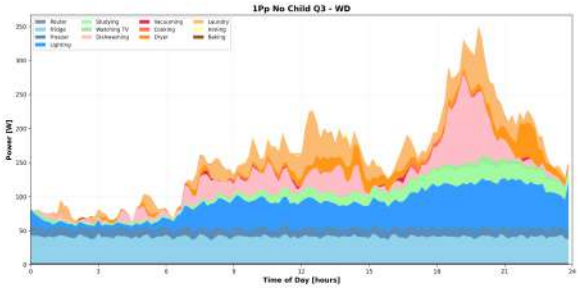
Overall, household composition influences not only the scale of electricity consumption but also its internal organisation across practices. Larger and multi person households exhibit stronger synchronisation of activity-driven demand, leading to higher peaks and a greater contribution of food and maintenance-related practices to total electricity use.

Table 9: Weekday load metrics for cohorts used in the household composition comparison (IQ3 baseline).

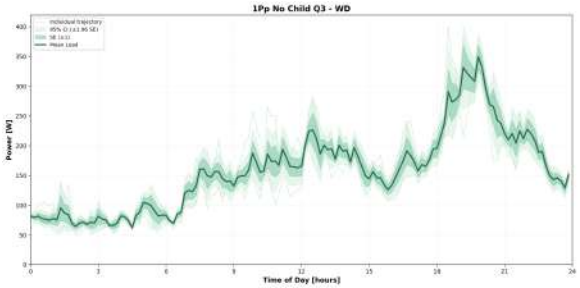
Cohort	**Peak W**	**Peak time**	**Mean W**	**Daily kWh**
SP, IQ3	349.4	19:50	158.4	3.80
SP+Ch, IQ3	248.1	19:30	136.7	3.28
C, IQ3	603.4	19:10	254.0	6.10
C+Ch, IQ3	510.6	18:50	212.8	5.11

Table 10: Macro-practice shares of weekday electricity demand for the household composition comparison (IQ3 baseline). Values are percentages of daily electricity use.

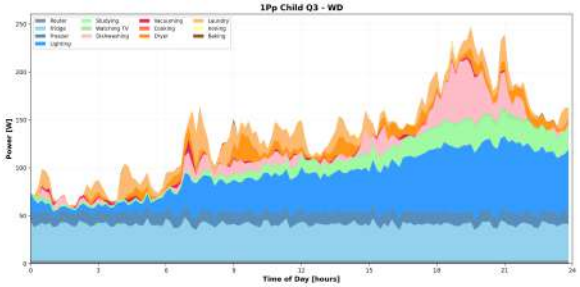
Cohort	**Food (%)**	**Maintenance (%)**	**Leisure+light (%)**	**Baseload (%)**
SP	14.5	18.7	32.6	34.2
SP+Ch	8.1	13.5	38.7	39.6
C	24.1	22.8	31.7	21.4
C+Ch	18.2	23.3	33	25.5



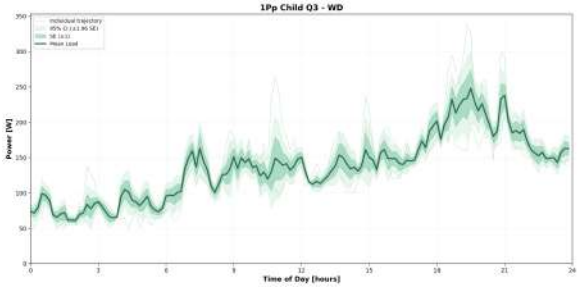
(a) Single person, IQ3, stacked.



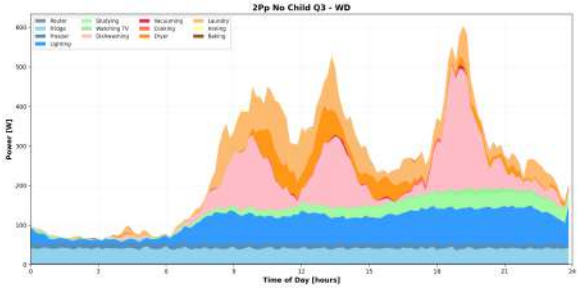
(b) Single person, IQ3, average.



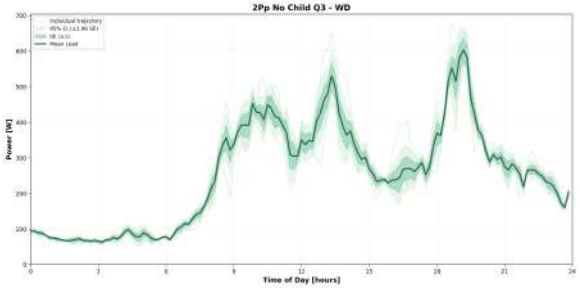
(c) Single person with child(ren), IQ3, stacked.



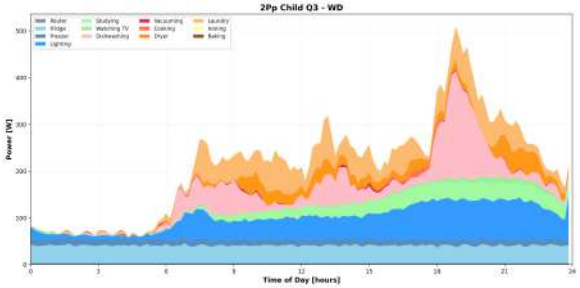
(d) Single person with child(ren), IQ3, average.



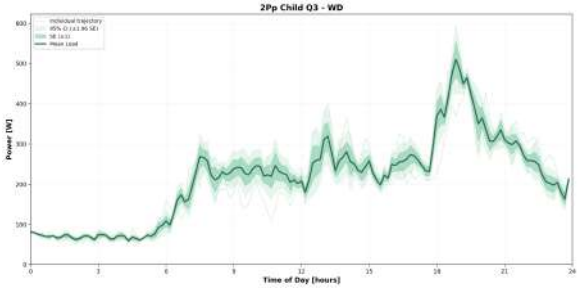
(e) Couple, IQ3, stacked.



(f) Couple, IQ3, average.



(g) Couple with child(ren), IQ3, stacked.



(h) Couple with child(ren), IQ3, average.

Figure 9: Weekday load curves, different household types, fixed income group.

3.3.2 Income effects, *Couple* baseline

To assess the influence of income on residential electricity demand, load curves are compared across income groups for the household type *Couple*. This cohort contains large sample sizes across income groups and represents one of the most prevalent and energy-intensive household structures. Focusing on couples without children also avoids additional behavioural uncertainty related to the absence of explicit child modelling in the activity stage, allowing for a more controlled comparison of income effects. The load curves and load metrics of the other household types can be found in the Appendix B.3.2.

Across income groups, the temporal structure of weekday load profiles remains largely stable. Morning and evening peaks occur at comparable times, indicating that core daily routines such as meal preparation and evening leisure are structurally similar across income categories. Income therefore does not fundamentally alter the ordering or timing of dominant practices.

However, differences emerge in magnitude and internal composition of demand (Table 11). Peak demand ranges from 469 W (IQ5) to 603 W (IQ3), while mean daily power varies between 226 W and 254 W. Notably, these variations do not follow a monotonic income gradient: the highest peak and daily consumption are observed in IQ3 rather than in the highest income group.

The macro-practice decomposition in Table 12 clarifies how income reshapes the internal structure of electricity demand. The share of food-related practices decreases from 24.1% in IQ3 to 18.0% in IQ4 and IQ5, while leisure and lighting increase from 31.7% (IQ3) to 39.0% (IQ5). The baseload share rises slightly with income (from 21.4% in IQ3 to 23.7% in IQ5), whereas household maintenance remains comparatively stable across income groups.

These patterns align with cohort-specific appliance ownership probabilities rather than with income level. As shown in Table 4, appliance ownership does not increase uniformly across income groups. Instead, specific ownership configurations shape differences in aggregate electricity demand. Consequently, income effects in the model are mediated through appliance composition and usage intensity rather than through a simple income–consumption gradient.

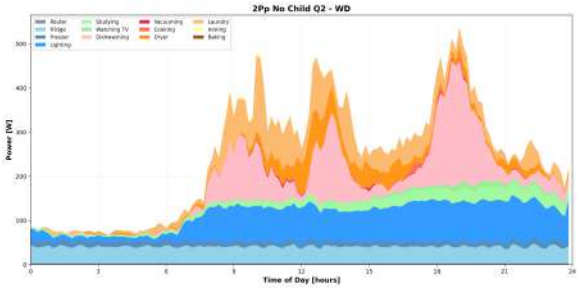
Overall, income influences both the magnitude and composition of electricity demand, while the temporal organisation of daily routines remains stable. The dominant practices persist across income groups, but their relative contributions vary according to the underlying appliance structure of each cohort.

Table 11: Weekday load metrics for cohorts used in the income comparison (Couple baseline).

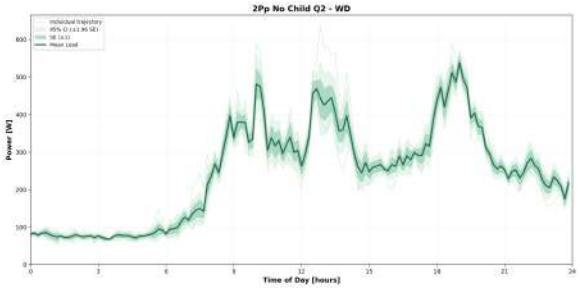
Cohort	Peak W	Peak time	Mean W	Daily kWh
C, IQ2	538.4	19:00	246.9	5.93
C, IQ3	603.4	19:10	254.0	6.10
C, IQ4	507.5	19:10	225.7	5.42
C, IQ5	469.5	19:00	227.8	5.47

Table 12: Macro-practice shares of weekday electricity demand for the income comparison (Couple baseline). Values are percentages of daily electricity use.

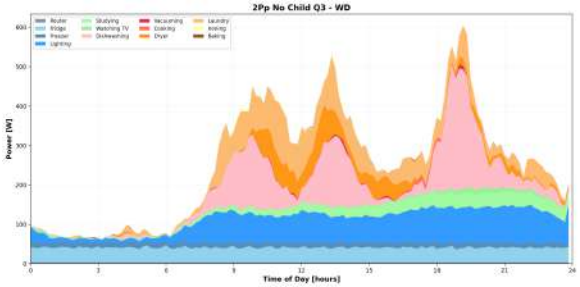
Cohort	**Food (%)**	**Maintenance (%)**	**Leisure+light (%)**	**Baseload (%)**
C, IQ2	22.8	22.9	32.7	21.6
C, IQ3	24.1	22.8	31.7	21.4
C, IQ4	18	22.2	35.5	24.2
C, IQ5	18	19.3	39	23.7



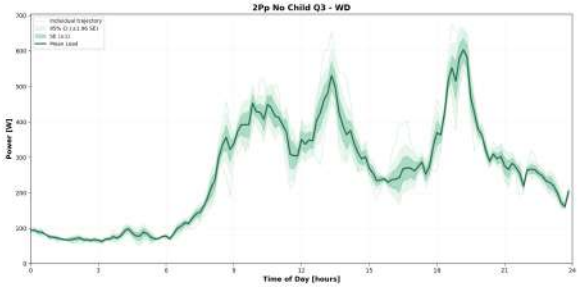
(a) Couple, IQ2, stacked.



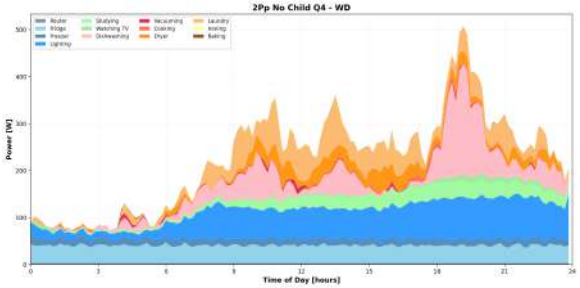
(b) Couple, IQ2, average.



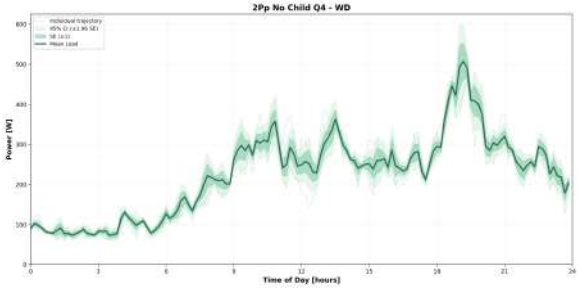
(c) Couple, IQ3, stacked.



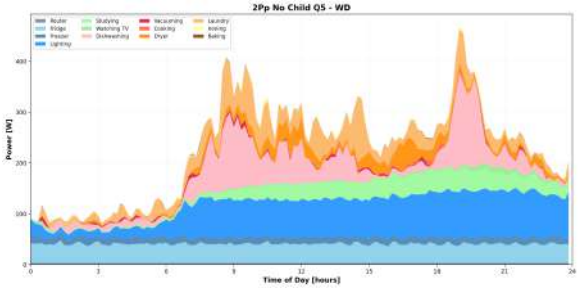
(d) Couple, IQ3, average.



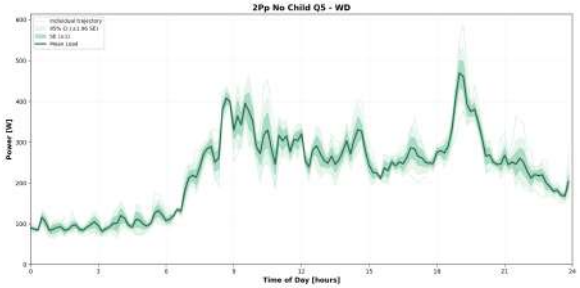
(e) Couple, IQ4, stacked.



(f) Couple, IQ4, average.



(g) Couple, IQ5, stacked.



(h) Couple, IQ5, average.

Figure 10: Weekday load curves, different income groups, fixed household type *Couple*.

3.3.3 Day type effects

To assess the effect of day type on household electricity demand, load curves are compared for weekdays, Saturdays, and Sundays using the same cohort configuration, *Couple, IQ3*. Clear differences emerge in both the temporal distribution and the internal composition of electricity demand across day types.

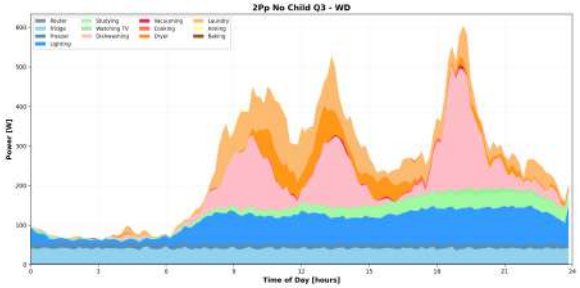
On weekdays, demand profiles closely follow the presence-at-home patterns shown in Figures 3, with pronounced evening peaks occurring after typical dinner times. These peaks are primarily driven by food-related practices, including cooking and subsequent dishwashing, resulting in relatively high peak loads concentrated within a short time window. As shown in Table 13, food-related practices account on average for 24.1% of daily electricity use on weekdays, representing a structurally important driver of peak formation through synchronised activity timing across households.

In contrast, weekend days are characterised by higher overall presence at home and a more even distribution of electricity demand throughout the day. On Saturdays, the share of household maintenance practices increases to 26.7%, exceeding weekday levels, while food-related activities decrease to 16.9%. Leisure and lighting also contribute more strongly compared to weekdays. This redistribution reflects greater flexibility in scheduling activities and a spreading of energy intensive practices across daytime hours, leading to broader and less sharply defined peaks despite comparable total daily consumption. Sundays display a further shift toward leisure-oriented consumption. Leisure and lighting represent 36.7% of daily electricity use on average, the highest among all day types, while baseload contributions also increase slightly. Although food-related activities remain relevant (19.1%), they are less dominant than on weekdays. As a result, electricity demand is flatter and more evenly distributed over the day, with lower peak concentration relative to weekday evenings.

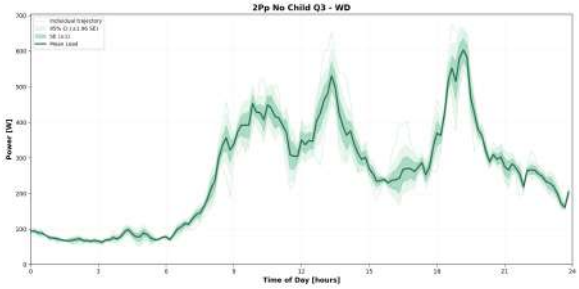
These patterns indicate that while total daily energy use remains of comparable magnitude across day types, the timing and structural drivers of demand vary significantly. Weekdays are characterised by synchronised, practice-driven evening peaks, whereas weekends exhibit greater temporal dispersion and a shift toward maintenance and leisure-related activities. This confirms that differences in residential load profiles across day types are not merely quantitative, but reflect systematic changes in the organisation and simultaneity of everyday social practices.

Table 13: Mean macro-practice shares across all simulated cohorts by day type (simple average across cohorts; not population-weighted). Values are percentages.

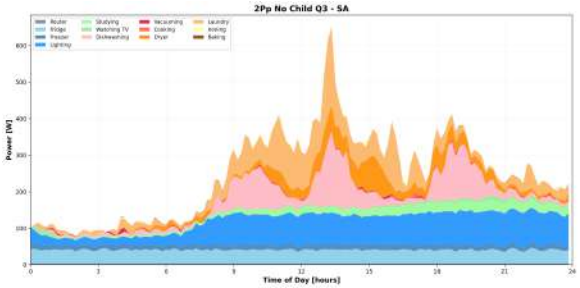
Day type	**Food (%)**	**Maintenance (%)**	**Leisure+light (%)**	**Baseload (%)**
Weekday	24.1	22.8	31.7	21.4
Saturday	16.9	26.7	34.6	21.8
Sunday	19.1	21.2	36.7	23.1



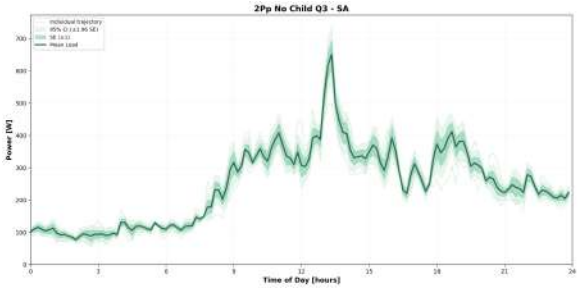
(a) Weekday, Couple, IQ3, stacked.



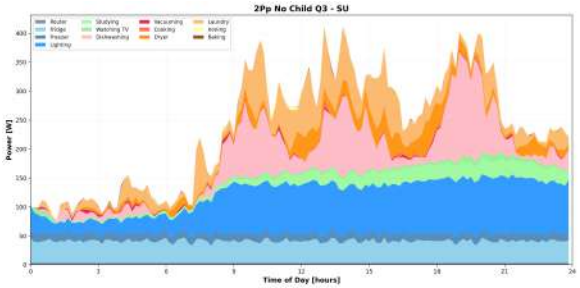
(b) Weekday, Couple, IQ3, average.



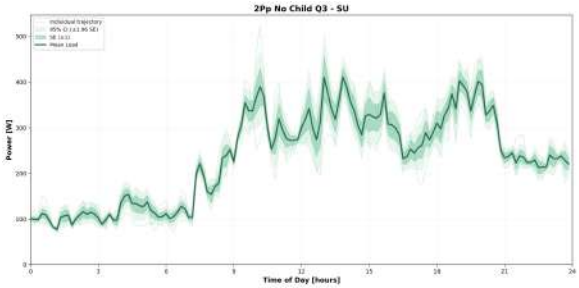
(c) Saturday, Couple, IQ3, stacked.



(d) Saturday, Couple, IQ3, average.



(e) Sunday, Couple, IQ3, stacked.



(f) Sunday, Couple, IQ3, average.

Figure 11: Comparison Weekday, Saturday, Sunday, fixed cohort.

Overall, the results show that household composition primarily shapes the temporal structure and simultaneity of residential electricity demand, while income level mainly affects demand magnitude through differences in appliance ownership and usage intensity.

Larger households exhibit higher peak loads and broader evening demand profiles due to overlapping activity patterns, whereas single-person households display more distinct, activity-driven load signatures. Across income groups, the timing and structure of daily load profiles stays consistent, with differences emerging mainly in baseline and peak demand levels rather than in the ordering of dominant activities. Finally, clear contrasts are observed across day types: weekday demand is more temporally concentrated around evening meal-related activities, while weekend demand is more evenly distributed throughout the day, reflecting increased daytime presence and greater flexibility in scheduling household practices.

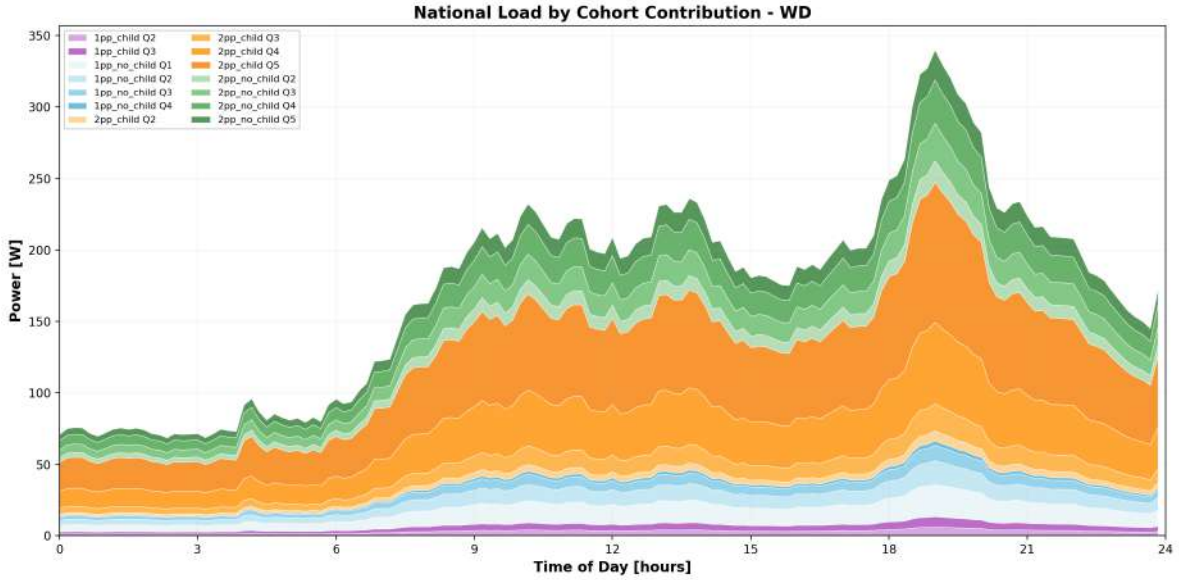
These cohort-level differences form the basis for constructing aggregate residential electricity demand at the national level, which is examined in the following section.

3.3.4 National load curves

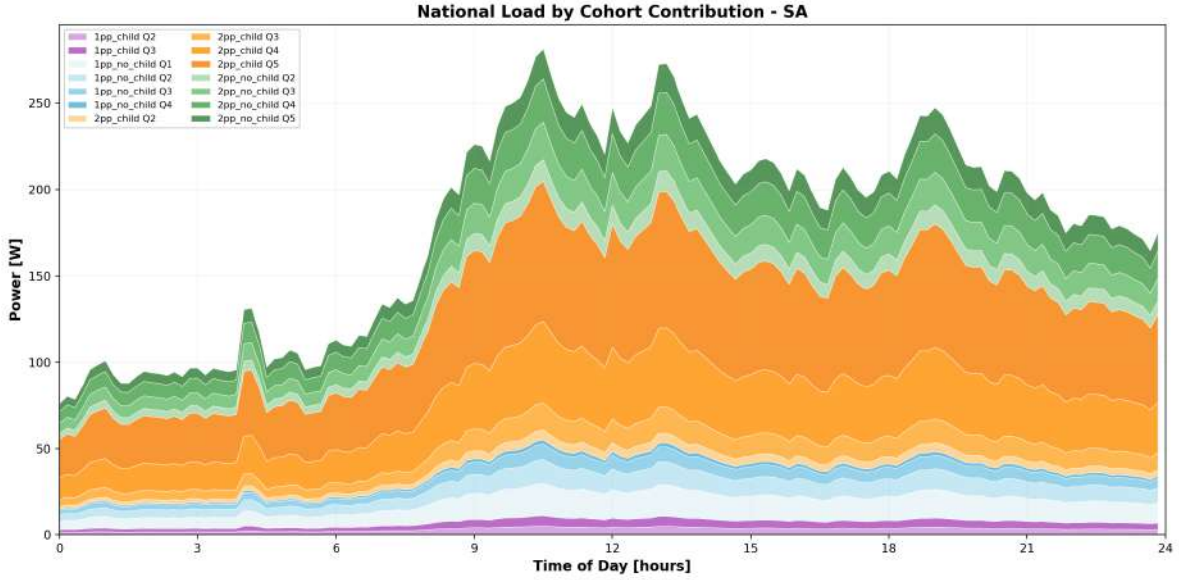
Figure 12 presents the simulated national residential electricity load curves disaggregated by cohort contributions for weekdays, Saturdays, and Sundays. The curves represent population weighted aggregation of cohort level demand profiles and show how heterogeneous household behaviours combine to form national demand patterns.

Across all day types, national electricity demand is dominated by cohorts that are both numerically large and characterised by higher per household consumption, particularly multi-person households and households in middle/higher income groups. As expected, couples and households with children account for a substantial share of total residential demand, reflecting both scaling effects with household size and higher simultaneity of appliance use.

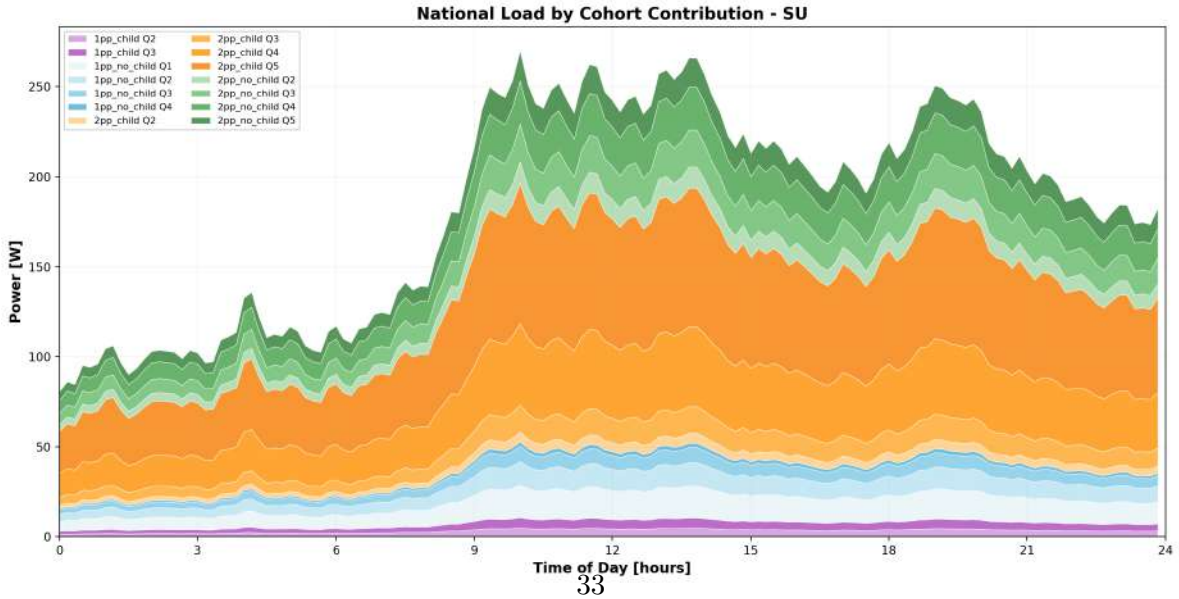
The temporal structure of national demand varies systematically across day types. On weekdays, a pronounced evening peak is observed shortly after typical dinner times, corresponding to coordinated cooking and post meal activities across the population. In contrast, weekend demand profiles show a less defined peak structure, with higher demand during late morning and early afternoon hours.



(a) Cohorts contributions to national load, Weekday.



(b) Cohorts contribution to national load, Saturday.



(c) Cohorts contribution to national load, Sunday.

Figure 12: National load on a Weekday, Saturday and Sunday.

Figure 13 shows the national residential load curves disaggregated by social practice contributions. These stacked representations highlight the dominant role of a limited set of everyday practices in shaping aggregate electricity demand.

On weekdays, the evening peak is largely driven by food related practices, particularly cooking and dishwashing, which are temporally concentrated and very synchronised across households. During weekends, electricity demand is more evenly distributed throughout the day, with increased contributions from leisure and household maintenance activities such as laundry and cleaning. As a result, while overall presence at home is higher on weekends, peak demand levels are lower and less sharply defined than on weekdays, leading to flatter national load profiles.

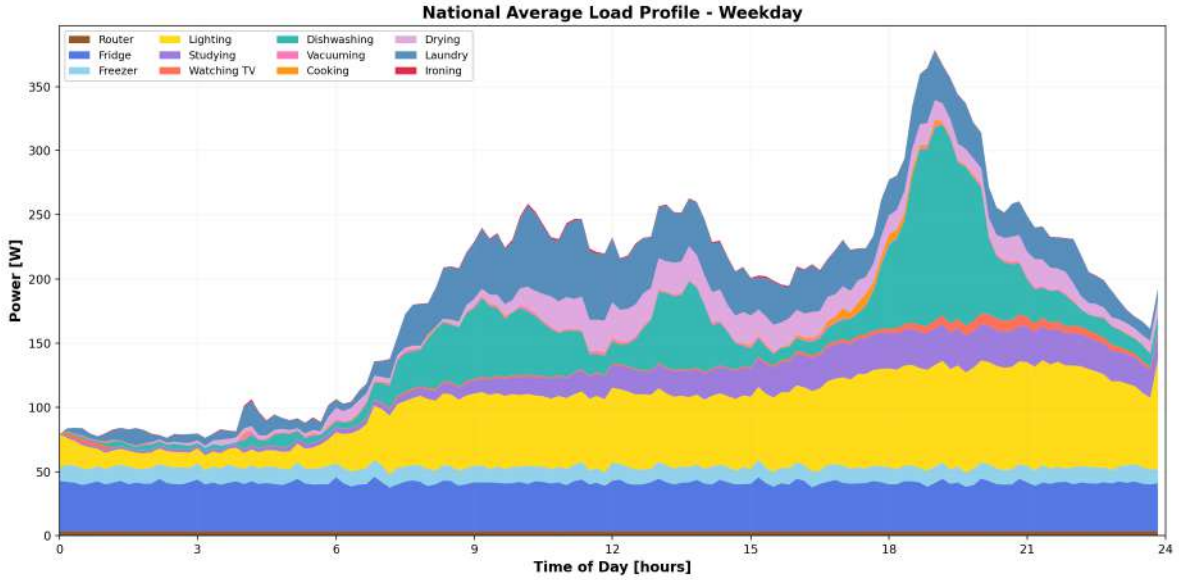
A small but noticeable spike in national demand is observed around 04:00am across all day types. This feature is primarily associated with laundry related activity in the model and reflects the probabilistic nature of activity timing derived from the underlying survey data. The origin and implications of this early morning demand feature are discussed further in Section 4.2.

To assess whether the aggregated cohort-based simulation produces realistic absolute demand levels, the simulated national residential electricity consumption is compared to official statistics from CBS for 2016.

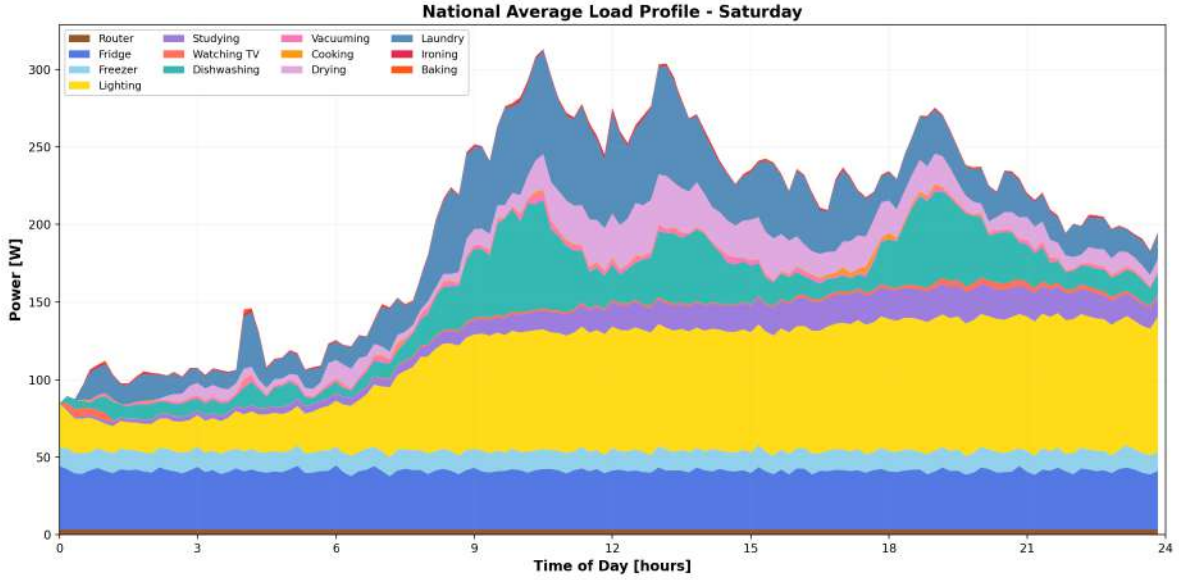
Function 3 weights each cohort by its corresponding number of households and then normalises by the total number of households. The resulting profile therefore represents the average residential electricity demand per household. Using the simulated average daily values (4.61 kWh for weekdays, 4.79 kWh for Saturdays, and 4.88 kWh for Sundays) and applying a standard year composition (261 weekdays, 52 Saturdays, 52 Sundays), the model yields an annual residential electricity consumption of approximately 1,706 kWh per household per year, corresponding to an average of 4.68 kWh per household per day.

According to CBS statistics, average Dutch residential electricity consumption in 2016 was 2,910 kWh per household per year (Statistics Netherlands (CBS), n.d.-b). The model therefore underestimates residential electricity demand by approximately 1,204 kWh per household per year, or about 41%.

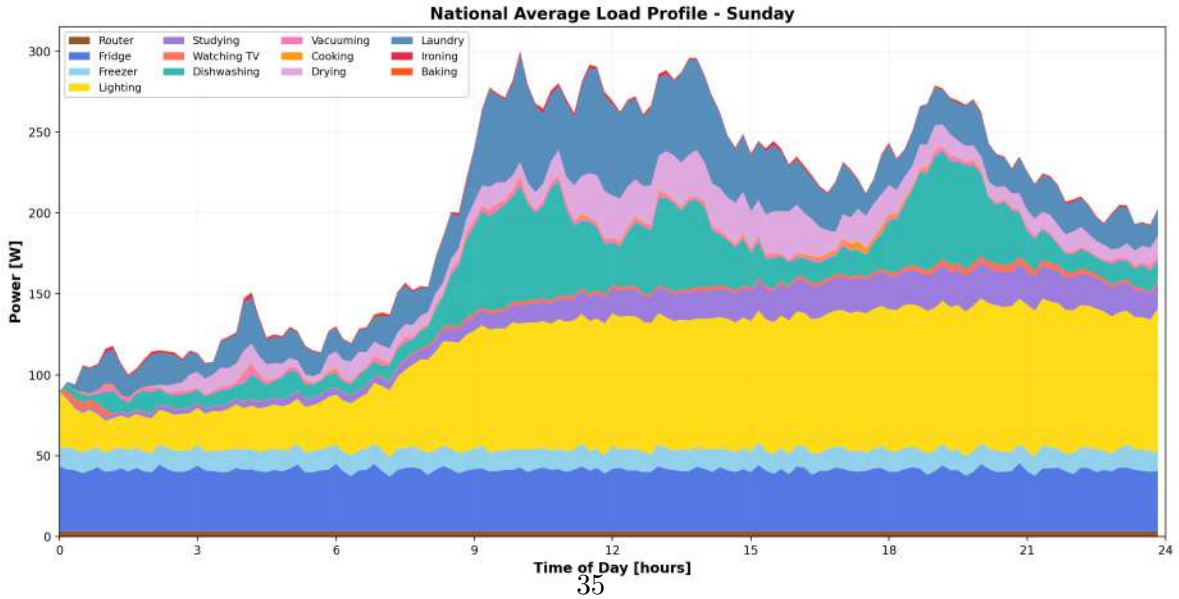
This deviation reflects the fact that several relevant electricity uses are not included in the current modelling framework and other modelling assumptions that will be discussed in section 4.4. Despite this underestimation in absolute magnitude, the model successfully reproduces the temporal structure and relative contribution of dominant practices, which constitutes the primary objective of this research.



(a) Social practices contributions to national load, Weekday.



(b) Social practices contributions to national load, Saturday.



(c) Social Practices contributions to national load, Sunday.

Figure 13: Overall caption describing all panels.

4 Discussion

4.1 Residential electricity demand as coordinated social practice

The central research question of this thesis asked whether national residential electricity demand can be reconstructed and interpreted as the aggregate outcome of socially structured daily practices. The results provide consistent evidence that the temporal structure and internal composition of residential load curves are not arbitrary technical artefacts, but emerge from the organisation, synchronisation, and overlap of everyday activities within households.

Across all analyses, differences in load magnitude and shape can be traced back to differences in practice timing, simultaneity, and appliance composition. Household composition influences not only how much electricity is consumed, but also which practices account for that consumption. Multi-adult households exhibit stronger synchronisation of food-related and maintenance activities, leading to higher evening peaks. In contrast, single-person households display a larger relative contribution of baseload and leisure-related consumption, resulting in flatter and less synchronised demand structures. These findings align with empirical evidence from Dutch households showing that electricity consumption is strongly associated with appliance use duration, food preparation, and cleaning activities, as well as with household size and the use of washing machines and dryers (Bedir et al., 2013).

Similarly, the income comparison showed that load shape remains temporally stable across income groups, while magnitude and composition vary through appliance ownership patterns rather than through a simple income–consumption gradient. This is consistent with Dutch behavioural studies indicating that electricity use clusters around patterns of total appliance use, technology-oriented lifestyles, and cleaning habits rather than income alone (Bedir and Kara, 2017). The present results therefore support the interpretation that income effects are mediated through material configurations and usage intensity, not through fundamentally different daily routines.

The day type analysis further reinforces the practice-based interpretation of peak formation. Weekday peaks are driven by strongly time dependent practices such as cooking and dishwashing, whereas weekend demand is more temporally dispersed and characterised by increased maintenance and leisure activities. Torriti, 2017, demonstrates that washing and cleaning practices exhibit high time dependence, while other activities are more temporally flexible. The present research highlight this distinction: weekday evening peaks emerge from synchronised and socially coordinated practices, while weekend demand reflects greater scheduling flexibility and weaker temporal coupling.

These results also align with literature on flexibility and demand response. Smale et al., 2017, and Lavin and Julienne, 2025, distinguish between practices that are tightly embedded in shared routines (e.g. cooking and eating) and those that are more responsive to time shifting (e.g. laundry and dishwashing). In the simulation, food-related practices are responsible for concentrated peaks, whereas maintenance-related activities contribute to broader demand segments that could theoretically offer greater flexibility potential. This suggests that flexibility is practice-specific rather than uniformly distributed across household electricity use.

The heterogeneity observed across household types and day types cannot be fully explained by socio-demographic variables alone. Cluster analyses of load curves show that appliance ownership, daytime presence, and age structure influence load shape (Yilmaz et al., 2019), yet these structural characteristics ultimately operate through the timing and coordination of activities. By explicitly reconstructing activity trajectories and linking them to appliance use, the present framework makes these underlying mechanisms visible.

At the same time, it is important to acknowledge that activity-based modelling necessarily relies on assumptions when mapping practices to appliances. As highlighted by McKenna et al., 2018, the causal linkage between activities and specific technologies is often not empirically observed but modelled. While this research grounds activity timing in survey data and calibrates appliance ownership probabilities, the activity–appliance connection remains a modelling construction. Nevertheless, the consistency between simulated load structures and empirical findings from Dutch and European studies suggests that practice-based modelling captures key structural drivers of residential electricity demand.

Overall, the results support the view that residential electricity demand should be understood as a socio-technical outcome of coordinated daily practices embedded in material arrangements. Load curves reflect how households organise cooking, cleaning, leisure, and maintenance within temporal constraints and shared routines. National demand, when aggregated, therefore embodies the patterned organisation of everyday life rather than just the statistical sum of independent appliance operations.

4.2 Markov and semi-Markov modelling of daily behaviour

The individual activity model is formulated as a time-inhomogeneous semi-Markov process. This modelling choice reflects three core properties of daily behaviour that are well established in activity-based energy demand modelling. First, routines exhibit strong temporal regularities, which can be represented through time-dependent transition probabilities (Widén et al., 2009). Second, behaviour is variable rather than deterministic: even within the same cohort, no two days and no two households are identical. A stochastic model therefore allows multiple distinct trajectories to be generated while preserving stable cohort-level statistics when aggregated (Richardson et al., 2008). Third, transitions depend strongly on the current activity state and time of day, which aligns naturally with a Markovian dependence structure (Widén and Wäckelgård, 2010).

Explicit duration modelling is particularly important at the 10 minute resolution of time-use diaries. A simple first order Markov chain can produce unrealistically frequent switching because each time step implicitly allows a transition. The semi-Markov formulation separates the selection of the next activity from the duration of that activity once entered, improving realism for long duration states such as sleeping or being away from home (Bottaccioli et al., 2019).

Higher order Markov approaches can improve duration prediction by incorporating information from previous states (Flett and Kelly, 2016). However, empirical comparisons suggest that gains over first-order models are often limited, while parameter requirements increase substantially. Given the limited sample sizes in several cohort/day combinations, a first order time-inhomogeneous structure combined with explicit duration modelling provides a suitable balance between behavioural resolution and statistical reliability.

The limitations of this approach are directly linked to data availability. Transition and duration distributions are estimated from survey counts and are therefore sensitive to sampling variability. This affects not only day-to-day fluctuations but also heterogeneity between sampled households within the same cohort. These effects are visible in the Step 1 validation results **??**, where smaller cohorts exhibit higher MAE and RMSE values and weekend patterns show weaker agreement with observed presence profiles.

Similar modelling constructions appear in the simulated load curves, where rare activities occasionally trigger appliances at implausible times. These arise from stochastic sampling combined with sparse probability mass and household aggregation, which increases the probability that at least one member occupies a rare state at a given time step. Introducing feasibility win-

dows for selected activities would reduce such artefacts while preserving the stochastic structure.

Finally, activity-based demand modelling assumes a mapping between activities and appliance operation. As noted by McKenna et al., 2018, such mappings are often based on modelling assumptions rather than direct empirical evidence. While this framework grounds activity timing in survey data, the activity–appliance linkage remains a structural simplification.

4.3 National load validation: EV, Heat Pumps and Standby Power

The validation of national residential electricity demand shows a substantial gap between simulated practice based demand and the average household electricity consumption reported by CBS. To assess how much specific end-uses not explicitly modelled in the framework can account for part of this discrepancy, three additional components are examined: standby power, residential heat pumps, and electric vehicle (EV) charging.

4.3.1 Standby power

Standby or parasitic consumption represents electricity used by appliances while in standby or off mode. At the European level, standby consumption has been estimated at approximately 7% of residential electricity use in 2021 (Vasiliu et al., 2021), while earlier UK estimates reported values around 12% in 2014 (International Energy Agency (IEA), 2014). A reasonable midpoint estimate for the Netherlands around 2016 is therefore assumed to be approximately 10% of residential electricity consumption.

Applying this share to Dutch households in 2016 suggests an additional load on the order of 291 kWh per household per year. This aligns with Feenstra's overview of standby and parasitic loads, drawing on Milieu Centraal data, which reports approximately 450 kWh per year of "sluipverbruik" for an average Dutch household (Feenstra, 2025).

Recent EU regulations have introduced stricter limits on standby and off-mode consumption, substantially reducing cut-through consumption in newer devices European Commission, 2025. These measures are projected to achieve annual electricity savings of 4 TWh by 2030 at EU level. While standby consumption may have decreased in newer appliances, countervailing trends such as increased device ownership, smart home technologies and higher connectivity could partially offset these gains. Standby consumption therefore represents a structurally relevant component of household demand and plausibly explains a meaningful share of the modelled gap, particularly for earlier years such as 2016.

4.3.2 Heat pumps

Residential heat pumps represent another potential source of additional electricity demand not explicitly included in the simulation. In 2016, total residential heat pump energy input amounted to 1,004 TJ, corresponding to approximately 280 GWh (Statistics Netherlands (CBS), n.d.-c). Assuming as an upper bound that this entire input was electricity (so neglecting hybrid systems using natural gas), this corresponds to roughly 1,550 kWh per heat pump household per year. However, heat pumps were installed in only about 180,000 households in 2016, representing approximately 2.3% of the total Dutch housing stock (Statistics Netherlands (CBS), n.d.-a). When averaged across all households, this yields a contribution of approximately 35 kWh per household per year.

Even under this deliberately conservative assumption of fully electric heat pumps systems, the national average contribution is negligible compared to the approximately 1,200 kWh per household gap between simulated and CBS-reported electricity consumption. Accounting for

hybrid systems would further reduce this estimate. Heat pumps therefore cannot fully explain the discrepancy observed in the model validation for 2016.

It is important to note that this conclusion is specific to the 2016 context. By 2026, the diffusion of heat pumps in the Netherlands has increased substantially (Volt et al., 2024), meaning their contribution to residential electricity demand is no longer marginal and must be taken into account for future work.

4.3.3 Electric vehicles (EVs)

A further missing component is residential EV charging, which is not explicitly linked to time-use practices in the current framework. Using national mobility statistics for 2022, plug-in passenger cars (Fully Electric Vehicles FEV and Plug-in Hybrid Electric Vehicles PHEV) travelled approximately 9.2 billion km per year (Statistics Netherlands (CBS), 2025). Assuming an average electricity intensity of 15–20 kWh per 100 km (ANWB, n.d.) and that roughly half of charging occurs at home (Duurzame Mobiliteit Databank, 2022), the implied electricity delivered via home charging is on the order of 0.69–0.92 TWh per year.

Distributed across the Dutch household stock (circa 8 million households in 2022), this corresponds to approximately 90–120 kWh per household per year on average, with an upper-bound estimate of 175–235 kWh per year if all charging were assumed to occur at home. This indicates that EV charging contributes a non-negligible additional load at the national scale, but by itself is insufficient to close the full gap between simulated and CBS-reported average household electricity consumption.

According to the IEA, home charging remains the dominant charging mode, while public charging infrastructure continues to expand rapidly across Europe International Energy Agency (IEA), 2025. The Netherlands now hosts one of the largest public charging networks in Europe. As EV adoption accelerates, residential charging will increasingly shape household load profiles, particularly through evening charging peaks.

4.3.4 Overall implications

Taken together, these three components suggest that standby consumption likely accounts for the largest structurally missing share in the 2016 model context, while heat pumps and EV charging were still relatively marginal at that time. In more recent years, however, electrification trends imply that EV charging and heat pumps are becoming increasingly relevant for residential electricity demand, not only in magnitude but also in their impact on temporal load patterns.

Nevertheless, even when combined, these additional components do not fully eliminate the observed discrepancy between simulated and reported electricity consumption. This indicates that the remaining gap is likely attributable to a combination of simplified appliance mapping, omitted minor end-uses, behavioural aggregation assumptions, and statistical uncertainty in both modelling and reported data. Rather than invalidating the framework, this analysis clarifies which components are structurally missing and provides a transparent interpretation of their relative importance.

4.4 Limitations and implications for interpretation

A first limitation concerns the representation of children. Children below nine years of age did not provide diary responses, and the number of respondents in the 9–14 age category is too small to allow stable estimation of cohort- and time-dependent transition matrices. As a result,

children are not modelled explicitly in the activity simulation. As a first approximation, this omission is partly alleviated by the fact that children's daily schedules are often strongly coupled to adult routines (school times, meal times, shared presence at home). However, the absence of explicit child behaviour likely reduces realism in specific domains, particularly leisure-related activities and household maintenance patterns in families, and it may contribute to differences between simulated and observed weekend behaviour. Extending the model to incorporate children dynamics would therefore be a valuable direction for future work, but it would require richer data coverage than is available in the current dataset.

A second limitation is the absence of intra-household coordination between adults. In the household construction step, adult individuals are sampled independently and combined without modelling synchronisation mechanisms such as shared meals, coordinated leisure time, or task allocation. Capturing these interactions would require information on realistic household compositions beyond the cohort definition, for example age distributions, number and ages of children, gender composition, and correlations between employment schedules within households. Implementing such coordination would substantially increase model complexity and data requirements. In the current framework, independent sampling allows scalable simulation across cohorts but may underestimate synchronisation of certain practices and may affect peak coincidence, especially for meal-related activities and evening routines.

A third limitation arises from the aggregation of the original 338 activity codes into 11 activity states. This simplification is necessary to make the data more manageable and for linking activities to appliances, but it necessarily introduces arbitrariness and loss of behavioural detail. In particular, the "lighting" category is broad and groups together activities that may differ substantially in timing, duration, and associated electricity use. This aggregation improves interpretability but reduces the specificity with which particular social practices can be analysed. A more refined approach could keep a larger set of activity states or introduce a hierarchical structure where detailed activities map to a smaller set of energy relevant practice categories.

Relatedly, the modelling of lighting demand is simplified. Lighting is triggered as a generic activity category rather than being linked to seasonal daylight conditions. A more realistic lighting component could be implemented using solar irradiance or daylight availability, for example using KNMI weather data for 2016 at 10 minute resolution and activating lighting only when irradiance falls below a defined threshold (commonly reported around 60 W/m^2). Such an extension would improve physical realism and would allow analysis of seasonal differences not only in electricity demand but potentially also in the timing of practices.

A fourth limitation concerns the mapping from activities to appliances and the completeness of the appliance set. Some mappings are pragmatic rather than behaviourally exact. For instance, cooking is currently linked to the microwave because empirical traces and ownership probabilities are available, while cooking in practice may be dominated by other technologies (e.g. electric hobs or induction stoves) whose load signatures and ownership structures differ. Many appliance categories that can create short, high-power peaks (e.g. electric kettles) are not represented because the time-use activity codes do not provide a clear trigger. In addition, appliance ownership probabilities are incomplete for some devices, and for a subset of appliances (oven, vacuum cleaner and iron) ownership is assumed universal. These choices may lead to overestimation of appliance activations for cohorts with lower ownership rates and should be interpreted accordingly.

Finally, the exclusion of 11 cohorts due to small sample sizes reduces population coverage and slightly limits representativeness in the national aggregation. The retained cohorts account for approximately 93% of the Dutch household stock in 2016, meaning that the vast majority of

households is represented in the weighted national average. Because the comparison with CBS statistics is performed on a population weighted per-household basis, the exclusion does not automatically imply an underestimation of total residential demand. Such a bias would occur only if the omitted cohorts constituted a substantial share of households and systematically exhibited higher electricity consumption than the retained groups. The main implication of their exclusion is therefore a small reduction in representativeness, potentially omitting specific niche household configurations, rather than a deterministic downward bias in national results. Accordingly, the aggregated outcomes should be interpreted mainly in terms of load structure, timing, and relative practice contributions rather than as a fully exhaustive accounting of absolute national consumption.

An additional limitation concerns the temporal representativeness of the input data. The time use diaries reflects Dutch behaviour in 2016, whereas this analysis is conducted a decade later. Over this period, societal routines and work practices have likely changed, notably due to the COVID-19 pandemic and increased prevalence of remote and hybrid work. Such changes may shift presence-at-home patterns, the timing of practices, and the resulting electricity load profiles. The results of this thesis should therefore be interpreted as a reconstruction of residential demand consistent with 2016 behavioural patterns. Updating the model with more recent time-use data, or calibrating key behavioural parameters using contemporary measurements, would be necessary to produce nationally representative load curves for the current period.

5 Conclusion

This thesis set out to answer the following research question: How can national residential electricity demand be reconstructed and interpreted as the aggregate outcome of socially structured daily practices?

To address this question, a modelling framework was developed that links time-use diary data to appliance activation and the generation of high resolution load curves. The model combines a time-inhomogeneous semi-Markov representation of daily activity patterns with an explicit mapping from practices to appliances and a cohort-based household aggregation procedure. Instead of modelling electricity demand directly as a technical time series, the framework reconstructs it from the timing, duration and overlap of everyday activities, allowing residential load profiles to be interpreted as the aggregated result of structured daily routines.

The results demonstrate that the temporal structure of residential load curves is strongly shaped by the organisation and synchronisation of everyday practices. Evening peaks emerge primarily from food-related activities and their associated appliance use, confirming that peak demand is a social phenomenon before it is a technical one. Differences across household compositions reveal that larger households do not simply consume more electricity; they exhibit higher simultaneity of activity-driven practices, which amplifies peak formation. Income effects, in contrast, primarily influence demand magnitude and internal composition through differences in appliance ownership rather than through systematic shifts in daily routines. Across day types, weekday demand is characterised by synchronised evening peaks, while weekend demand is more temporally dispersed due to increased daytime presence and greater flexibility in scheduling practices.

At the national level, the model underestimates by 41%absolute annual electricity consumption compared to CBS statistics. However, this discrepancy could be largely attributed to omitted end-uses (such as standby consumption, EV charging and heat pumps in later years) and simplifying assumptions in appliance mapping. Nonetheless, the model succeeds in reproducing the temporal structure and relative contribution of dominant practices, which is the main objective of this research. The findings therefore support the central premise that residential electricity demand can be meaningfully interpreted as the aggregated outcome of socially structured daily behaviour.

Several limitations must be acknowledged. The model relies on aggregated activity states, simplified appliance mappings, and independent sampling of household members. Children's behaviour is not explicitly modelled due to data constraints. Moreover, the behavioural foundation of the model is based on Dutch time-use data from 2016. Since then, societal routines have likely evolved substantially, particularly in light of increased remote working, digitalisation, and electrification trends. As a result, the model should be interpreted as a reconstruction of residential electricity demand consistent with 2016 behavioural patterns rather than as a representation of current demand structures.

These limitations also point toward promising directions for future research. Updating the framework with more recent time-use data, integrating richer appliance level information, modelling intra-household coordination, and explicitly incorporating electrification technologies would allow for a more comprehensive and contemporary representation of residential demand. In particular, applying the model to post 2020 behavioural data could reveal how shifts in work patterns and domestic routines reshape the temporal organisation of electricity use.

Ultimately, this thesis demonstrates that residential electricity demand is not merely a function of technologies or socio-demographic categories, but the emergent expression of coordinated, time-dependent social practices. Understanding and modelling these practices is therefore essential for designing demand-side management strategies, planning grid infrastructure, and navigating the transition toward a more flexible electricity system.

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Appendix A Research Data Management Plan

This section is mandatory as an appendix.

A.1 Data Collection

A.1.1 Type of data

(i.e. observational, experimental, simulation, derived)

This thesis uses secondary observational data and derived simulation data.

The primary input dataset is the Dutch Time Use Survey (TBO), which consists of observational diary data reporting individual daily activities at 10-minute resolution. In addition, high-frequency empirical appliance power traces from the Tracebase dataset were used to assign realistic load profiles to appliance activations.

Supplementary statistical data from Statistics Netherlands (CBS) were used for contextualisation and national-level comparison (e.g., average household electricity consumption and household stock figures).

All simulation outputs, processed datasets, transition probability matrices, and generated load curves constitute derived data produced within the scope of this research.

A.1.2 Format

CSV format

A.2 Data Storage and Back-up

A.2.1 Data documentation

The original TBO and Tracebase datasets are accompanied by their respective official documentation, including variable descriptions and metadata provided by the data owners. These were used to interpret and preprocess the raw input data.

A.2.2 Primary and intermediary data information

The raw time-use dataset was kept unchanged. Processed datasets were generated for the purpose of activity aggregation, transition probability estimation, and simulation input preparation. These processed files were derived programmatically from the raw data and can be regenerated using the provided code.

A.2.3 Name and location of the data

A.2.4 Back-up strategy

All data, simulation code and intermediate processing scripts were developed and stored locally on the researcher's personal laptop. Versioned backups were maintained through periodic manual copies to an external storage device.

A.2.5 Data deposition

Was the data deposited to the Y-drive with a READ ME file before handing in the thesis? Yes/No
No

A.3 Data Access and Ownership

A.3.1 Privacy and security

A.3.2 Accessibility

The TBO time-use dataset was accessed through formal permission from the data provider. Access was granted upon submission of a research proposal specifying the intended use of the data. The dataset was used strictly for academic purposes within the scope of this thesis.

Appendix B Appendix

B.1 Step 1: Individual behaviour

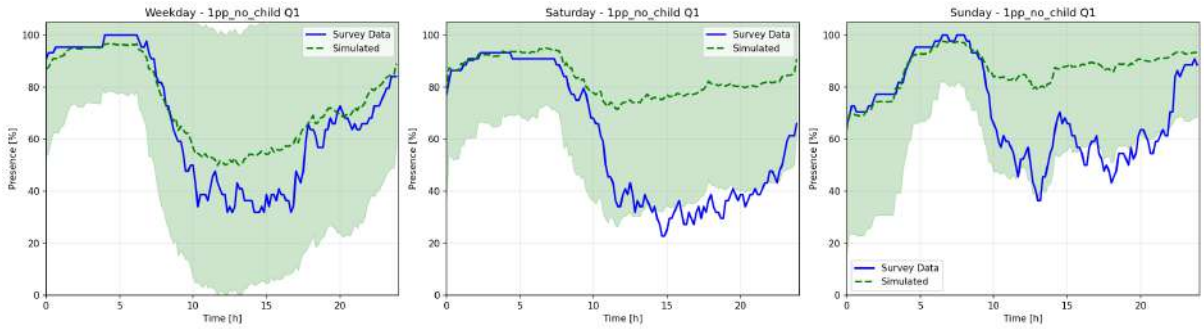


Figure 14: Observed and simulated presence profiles for *Single person, IQ1.*

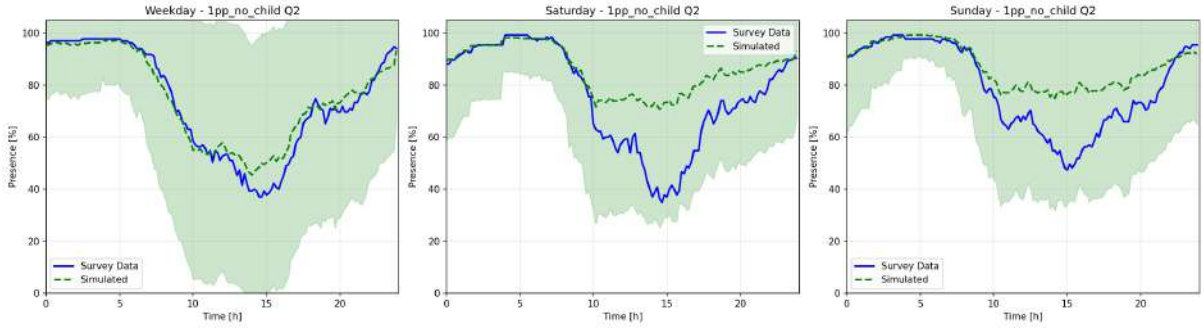


Figure 15: Observed and simulated presence profiles for *Single person, IQ2.*

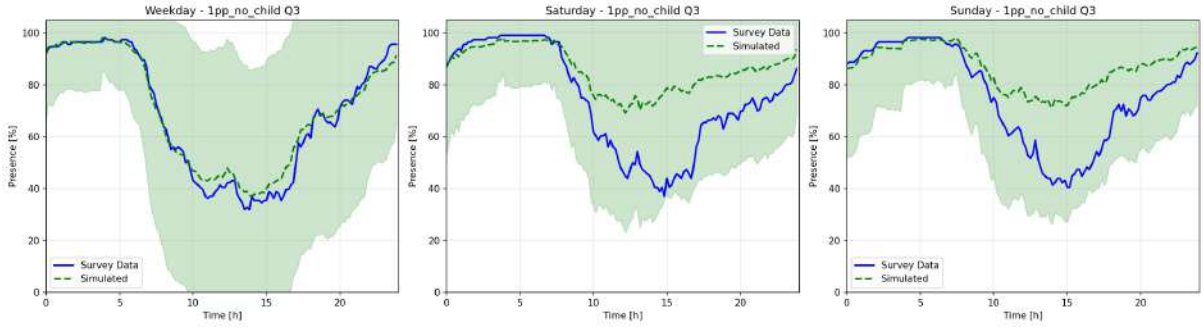


Figure 16: Observed and simulated presence profiles for *Single person, IQ3.*

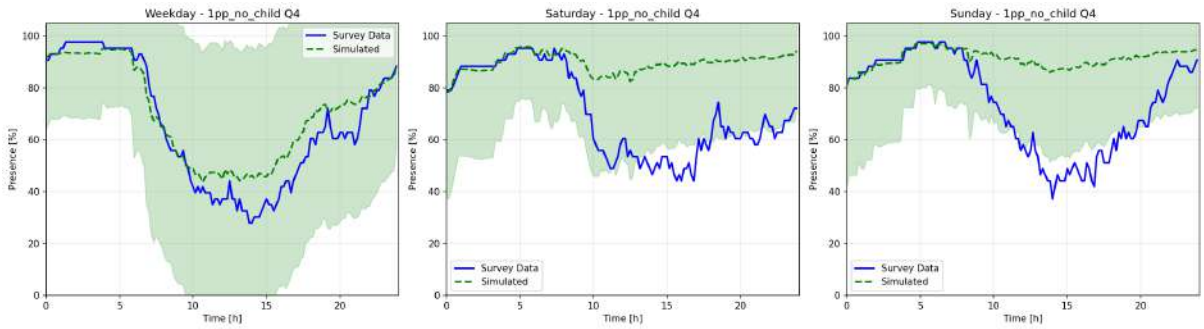


Figure 17: Observed and simulated presence profiles for *Single person, IQ4.*

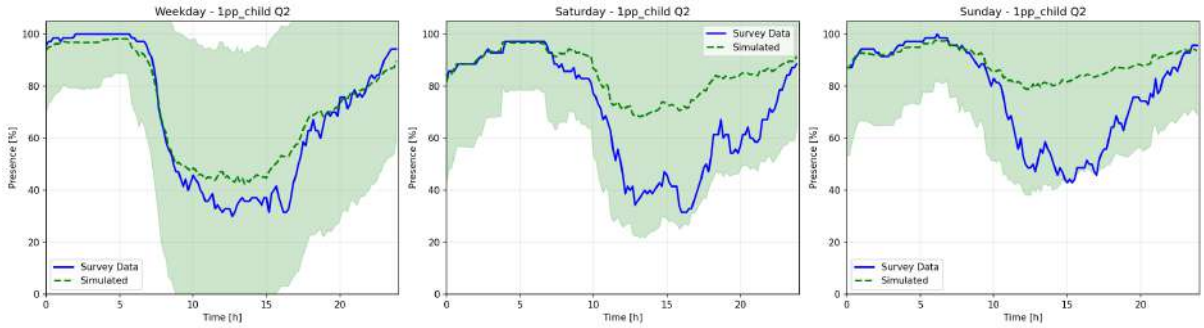


Figure 18: Observed and simulated presence profiles for *Single person with child(ren), IQ2.*

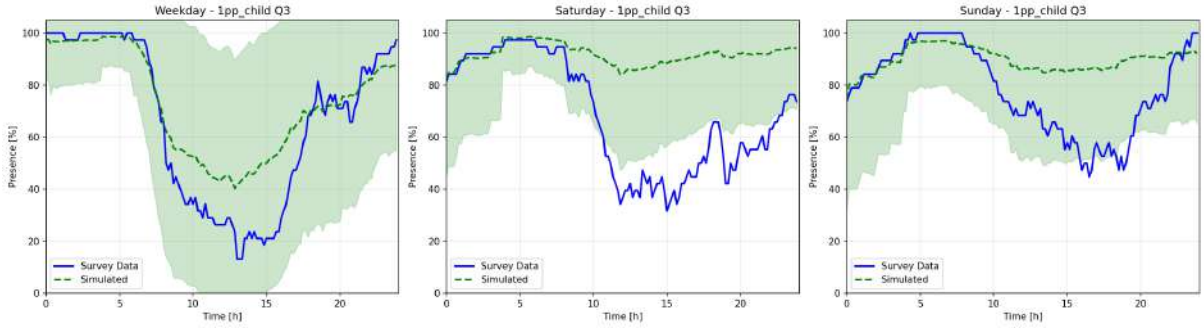


Figure 19: Observed and simulated presence profiles for *Single person with child(ren), IQ3.*

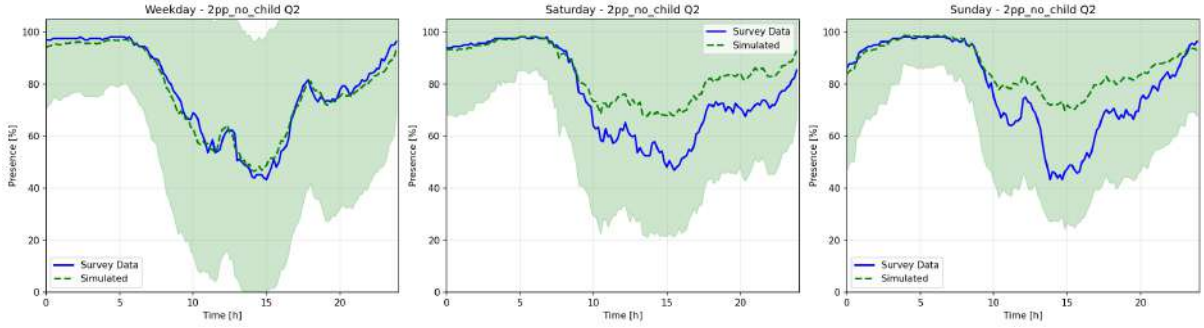


Figure 20: Observed and simulated presence profiles for *Couple, IQ2.*

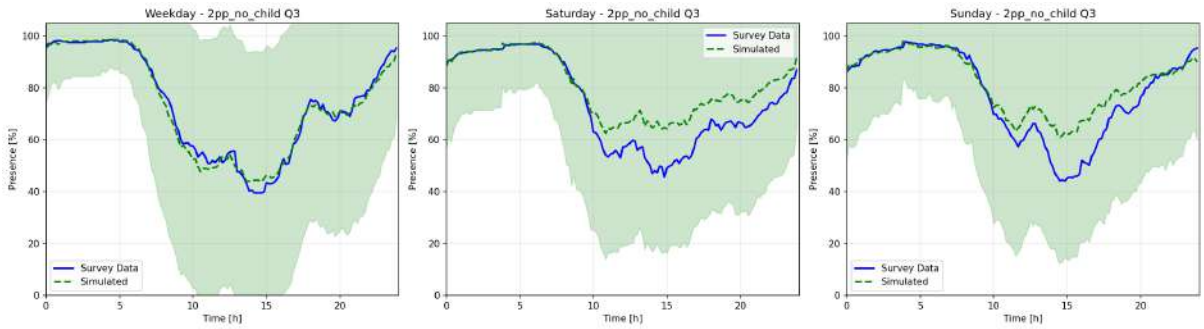


Figure 21: Observed and simulated presence profiles for *Couple, IQ3*.

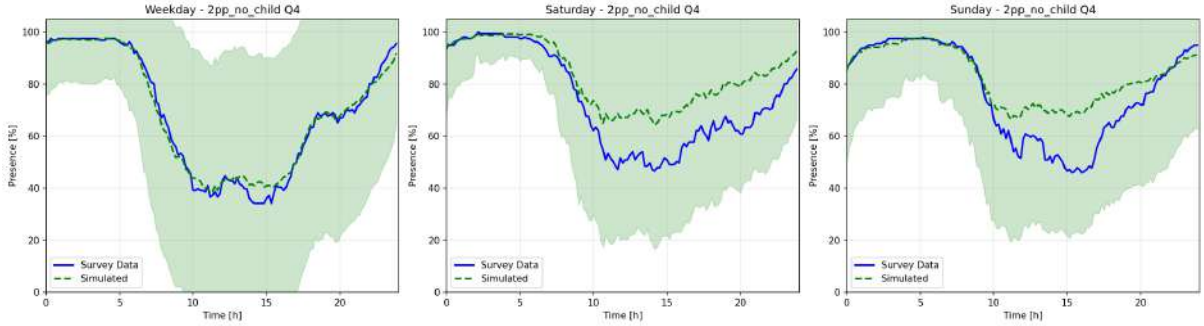


Figure 22: Observed and simulated presence profiles for *Couple, IQ4*.

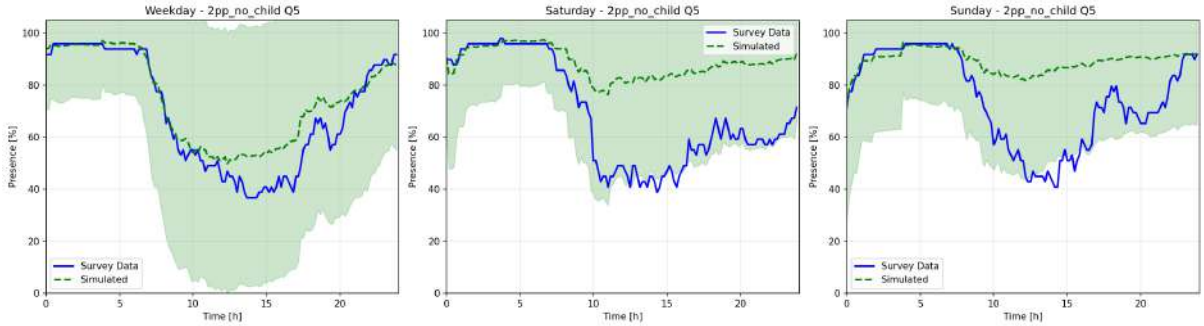


Figure 23: Observed and simulated presence profiles for *Couple, IQ5*.

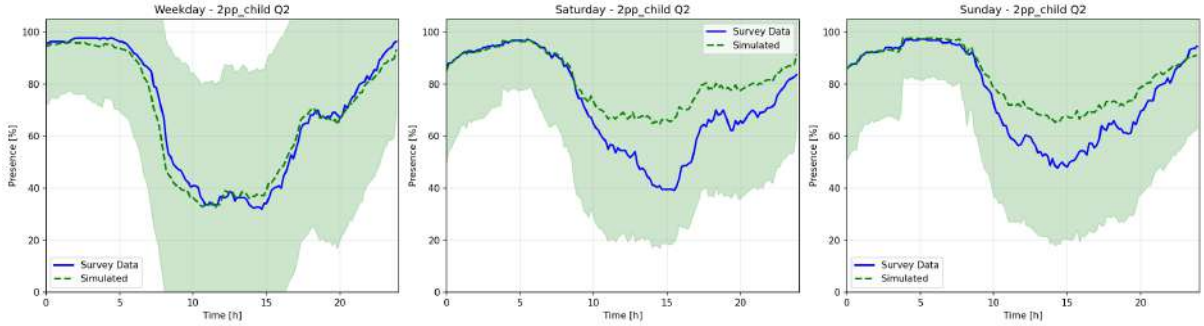


Figure 24: Observed and simulated presence profiles for *Couple with child(ren), IQ2*.

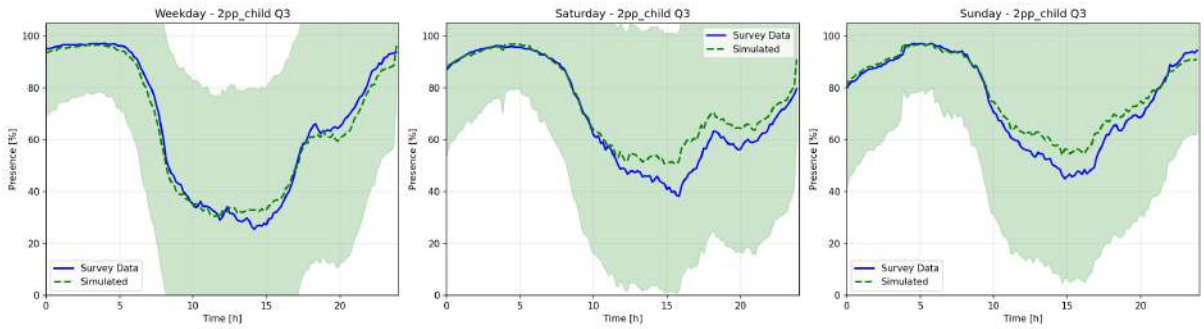


Figure 25: Observed and simulated presence profiles for *Couple with child(ren), IQ3.*

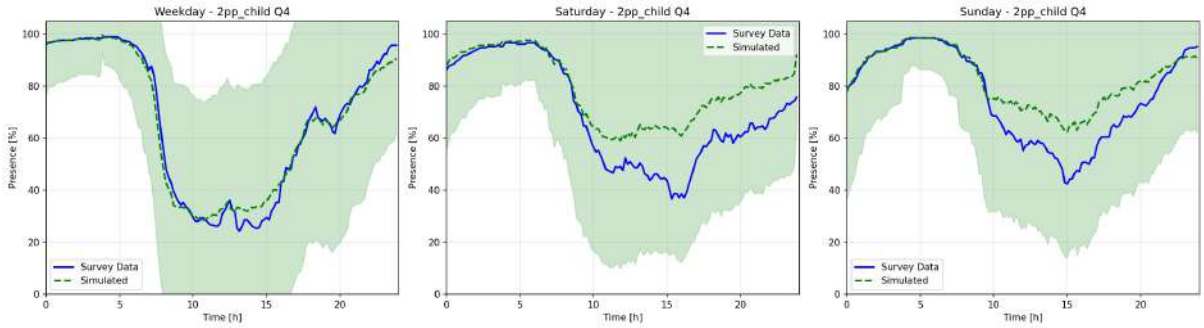


Figure 26: Observed and simulated presence profiles for *Couple with child(ren), IQ4.*

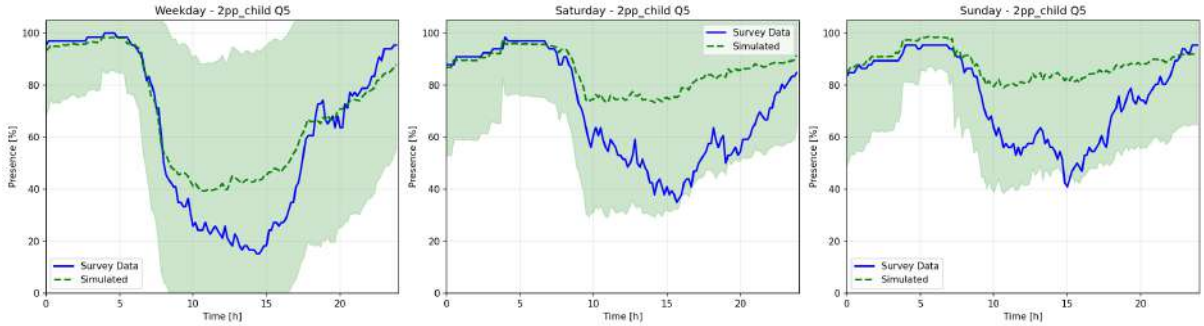


Figure 27: Observed and simulated presence profiles for *Couple with child(ren), IQ5.*

B.2 Step 2: Household behaviour

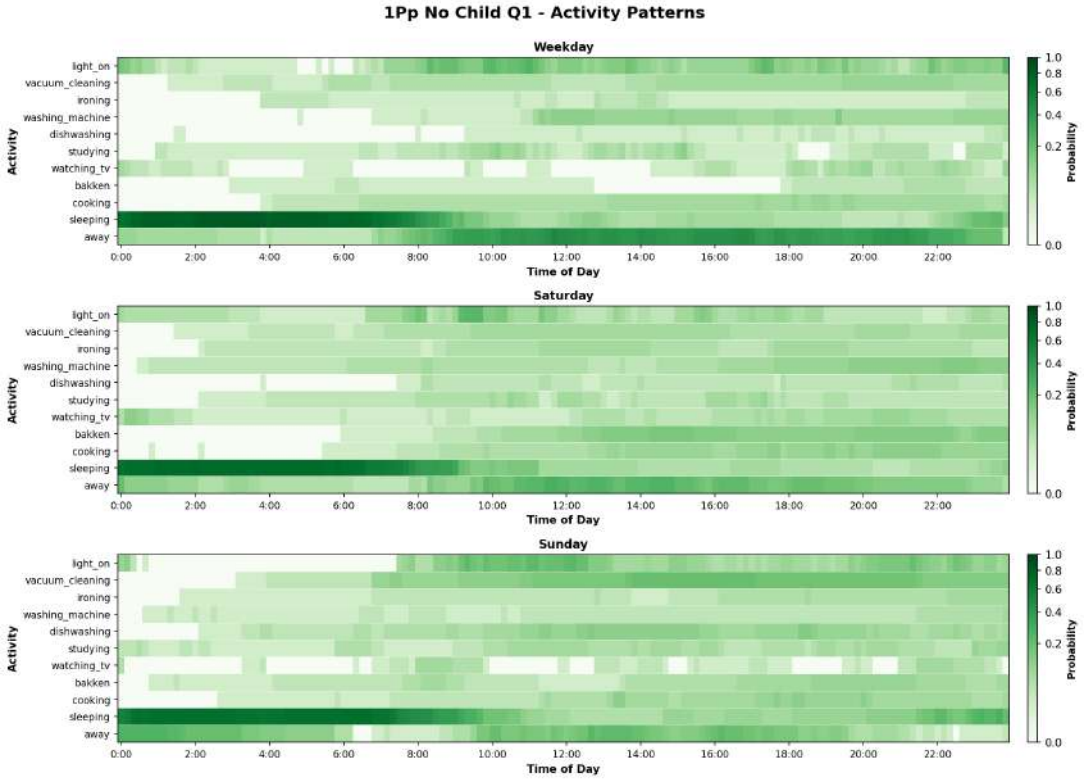


Figure 28: Household activity probabilities for *Single person, IQ1* across weekdays, Saturdays, and Sundays.

Figure 29: Household activity probabilities for *Single person, IQ2* across weekdays, Saturdays, and Sundays.

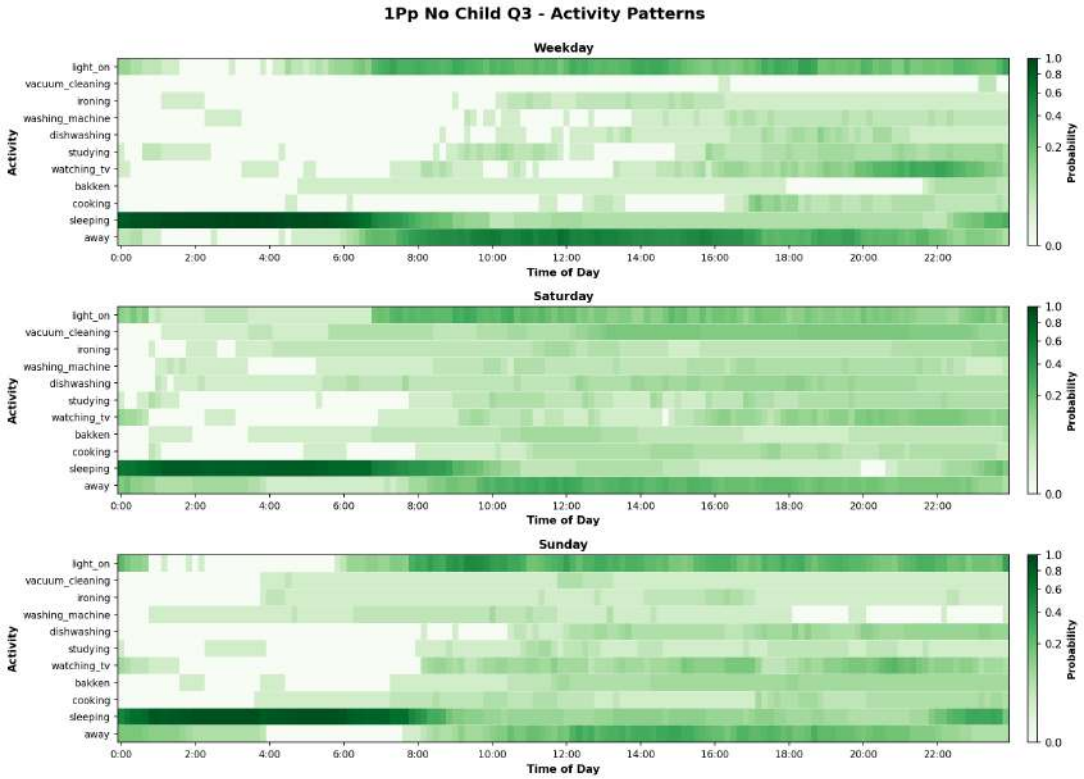


Figure 30: Household activity probabilities for *Single person, IQ3* across weekdays, Saturdays, and Sundays.

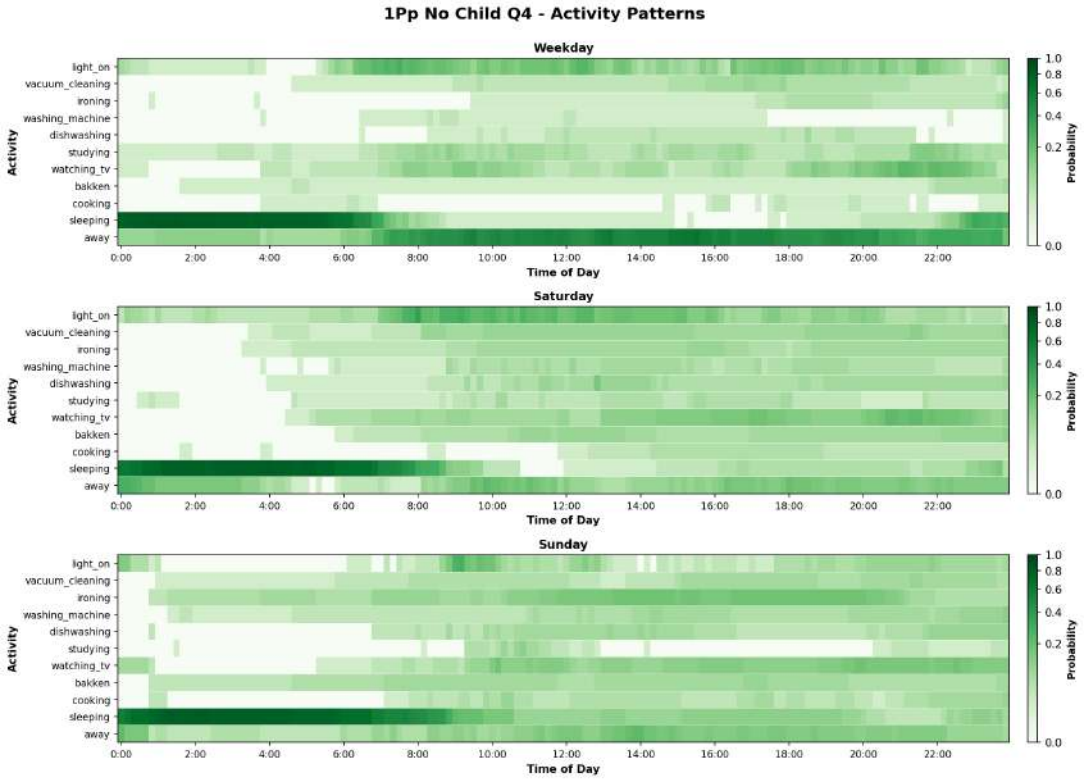


Figure 31: Household activity probabilities for *Single person, IQ4* across weekdays, Saturdays, and Sundays.

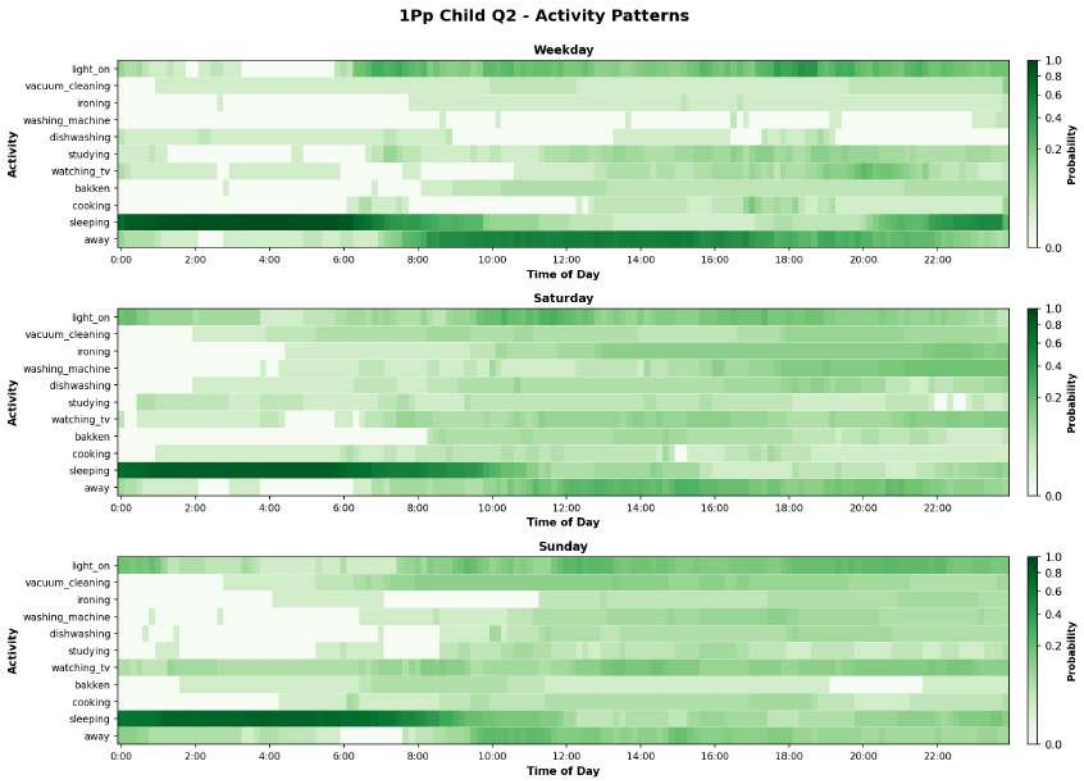


Figure 32: Household activity probabilities for *Single person with child(ren), IQ2* across weekdays, Saturdays, and Sundays.

Figure 33: Household activity probabilities for *Single person with child(ren), IQ3* across weekdays, Saturdays, and Sundays.

Figure 34: Household activity probabilities for *Couple, IQ2* across weekdays, Saturdays, and Sundays.

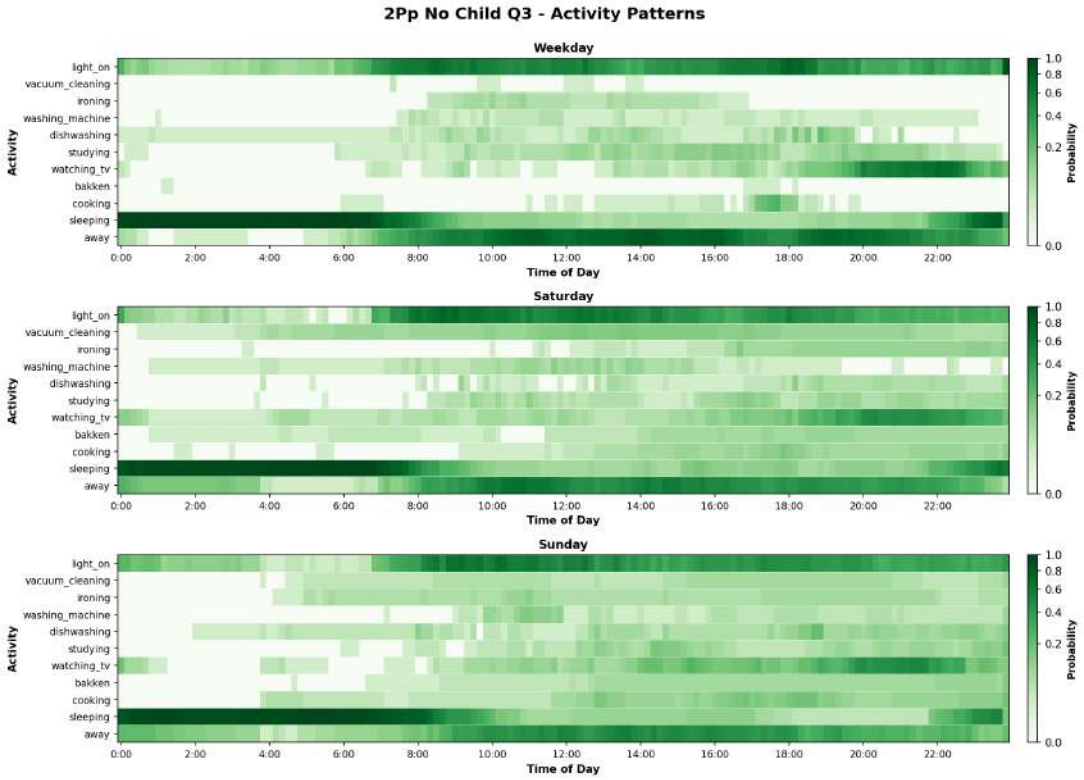


Figure 35: Household activity probabilities for *Couple, IQ3* across weekdays, Saturdays, and Sundays.

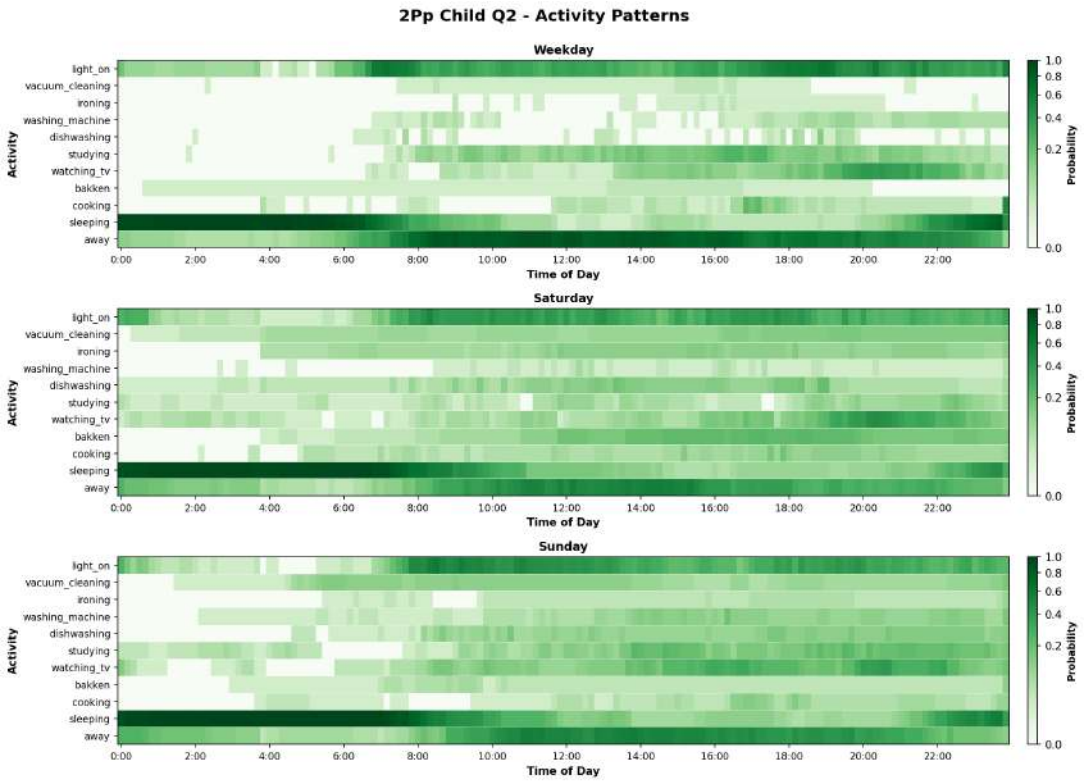


Figure 36: Household activity probabilities for *Couple with child(ren), IQ2* across weekdays, Saturdays, and Sundays.

Figure 37: Household activity probabilities for *Couple with child(ren), IQ3* across weekdays, Saturdays, and Sundays.

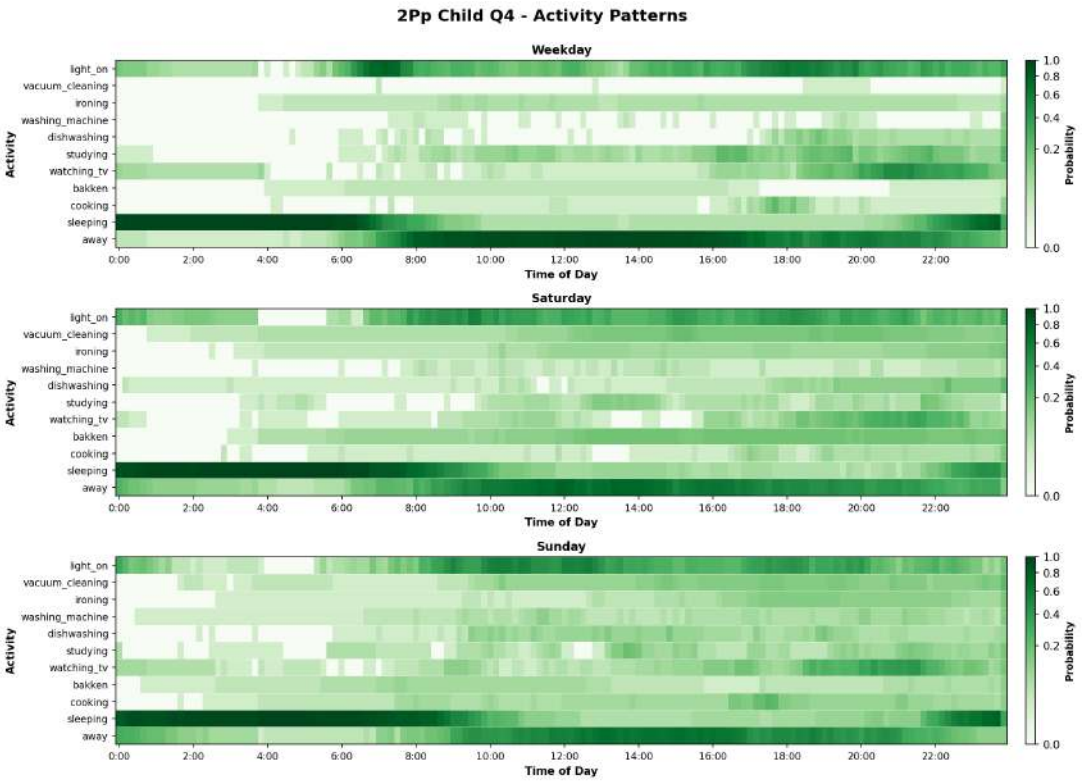
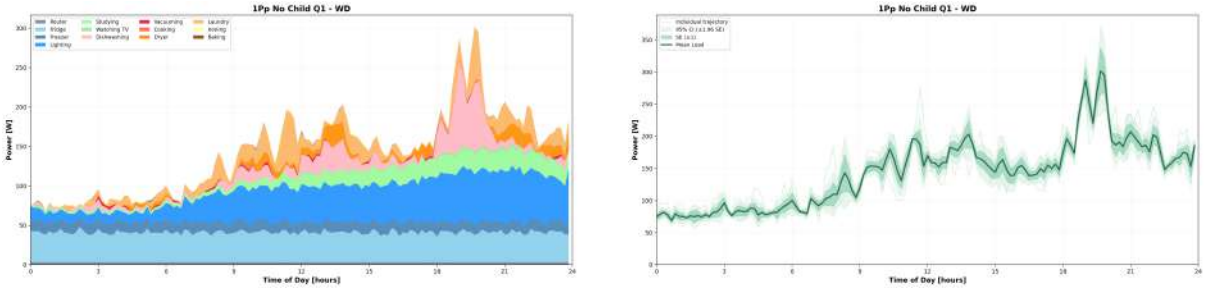


Figure 38: Household activity probabilities for *Couple with child(ren), IQ4* across weekdays, Saturdays, and Sundays.

Figure 39: Household activity probabilities for *Couple with child(ren), IQ5* across weekdays, Saturdays, and Sundays.

B.3 Step 3: Load curves

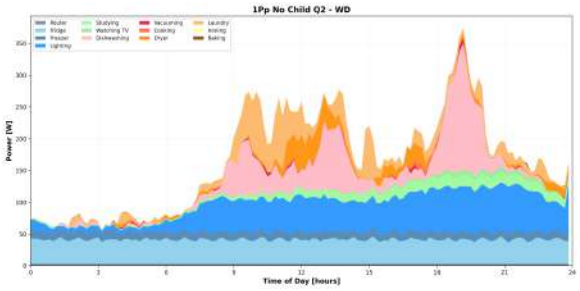
B.3.1 Household composition effects, fixed income groups



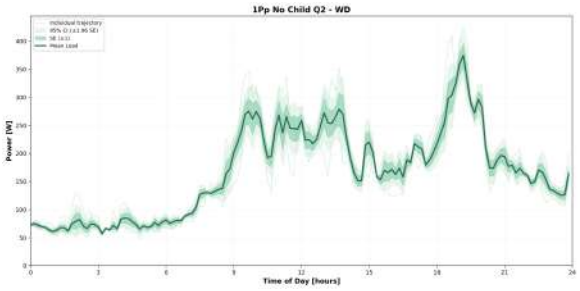
(a) *Single person, IQ1*, stacked.

(b) *Single person, IQ1*, average.

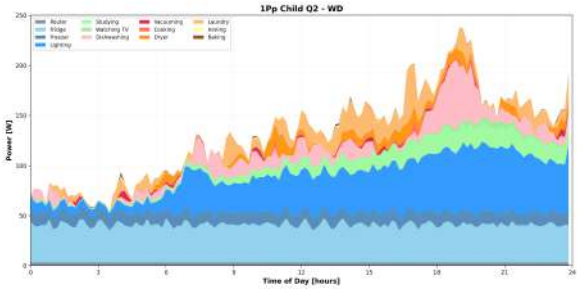
Figure 40: Weekday load curves, different household types, income group 1.



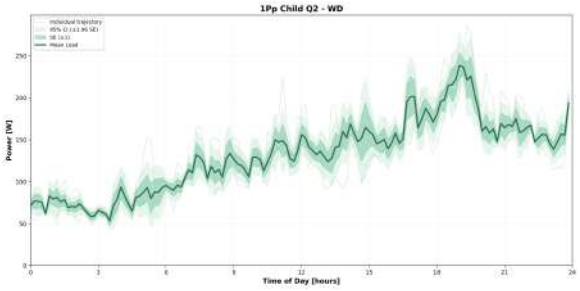
(a) *Single person, IQ2*, stacked.



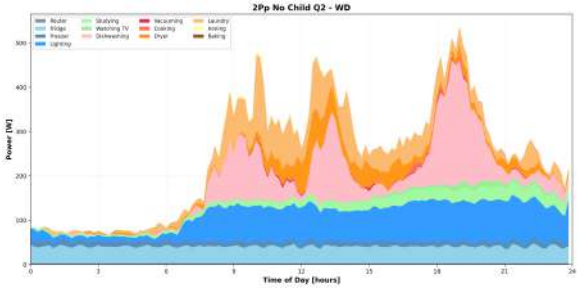
(b) *Single person, IQ2*, average.



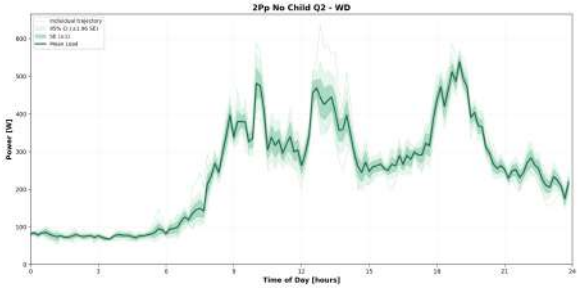
(c) *Single person with child(ren), IQ2*, stacked.



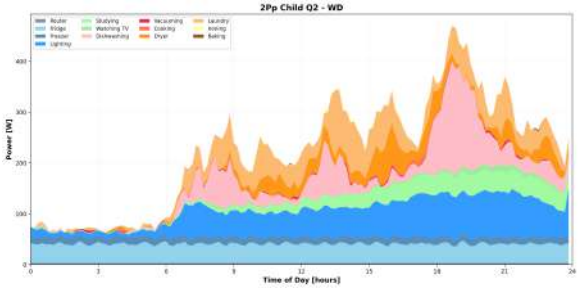
(d) *Single person with child(ren), IQ2*, average.



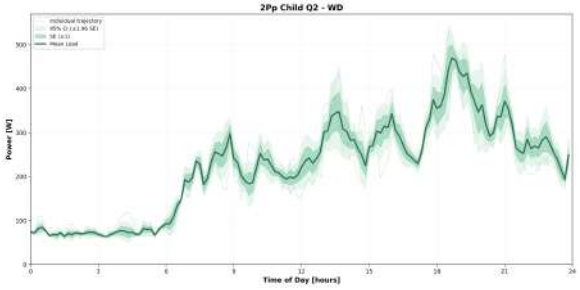
(e) *Couple, IQ2*, stacked.



(f) *Couple, IQ2*, average.

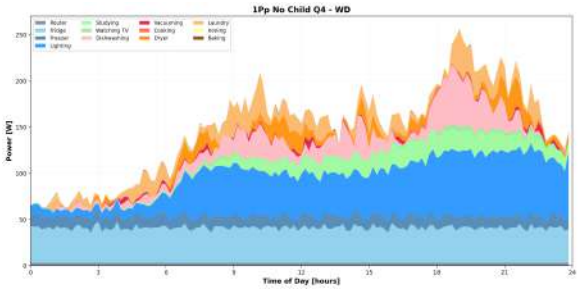


(g) *Couple with child(ren), IQ2*, stacked.

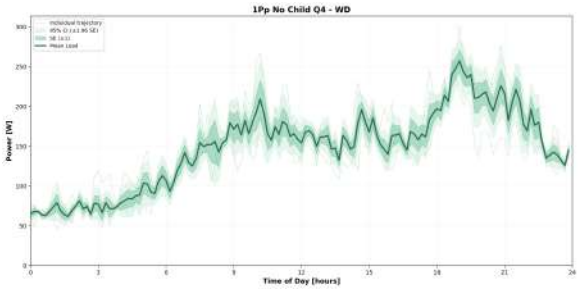


(h) *Couple with child(ren), IQ2*, average.

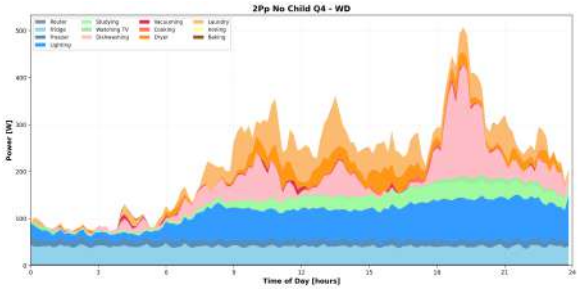
Figure 41: Weekday load curves, different household types, income group 2.



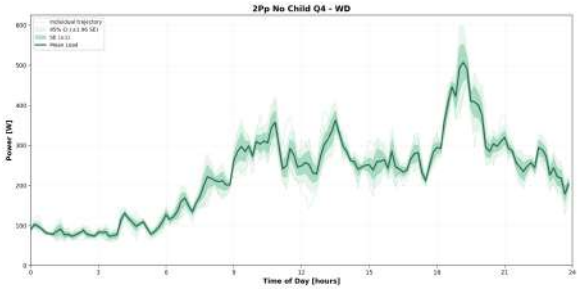
(a) *Single person, IQ4*, stacked.



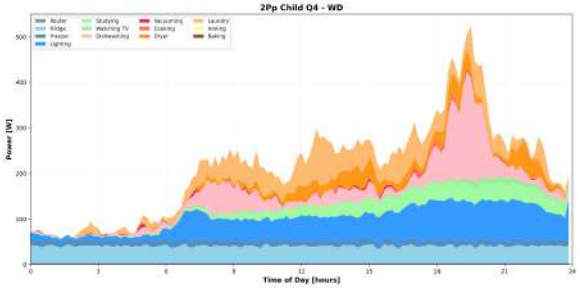
(b) *Single person, IQ4*, average.



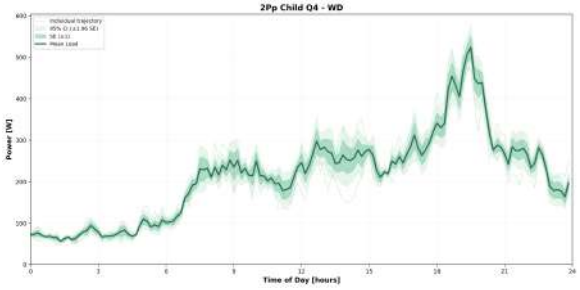
(c) *Couple, IQ4*, stacked.



(d) *Couple, IQ4*, average.

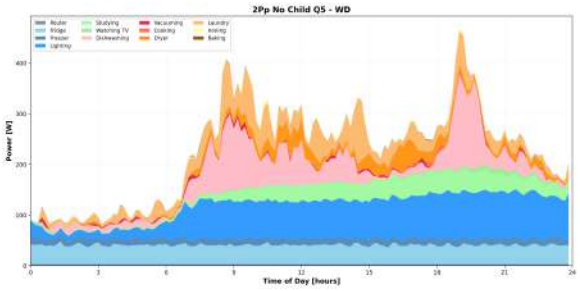


(e) *Couple with child(ren), IQ4*, stacked.

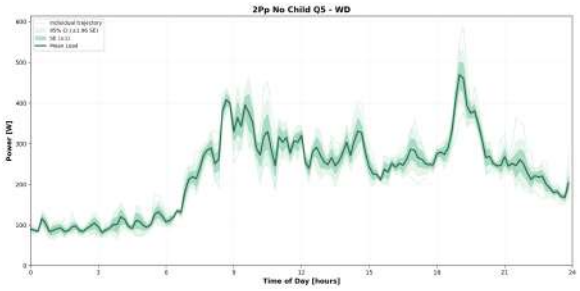


(f) *Couple with child(ren), IQ4*, average.

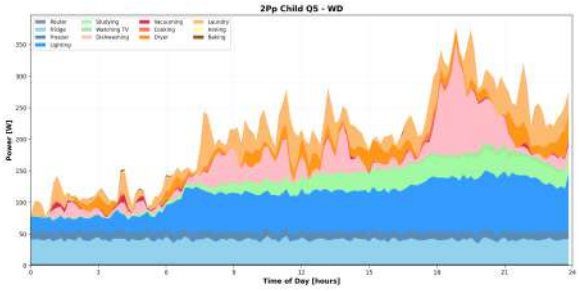
Figure 42: Weekday load curves, different household types, income group 4.



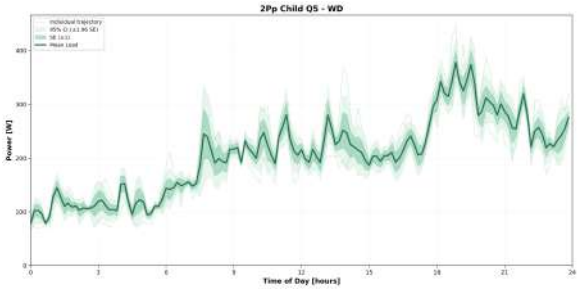
(a) *Couple, IQ5*, stacked.



(b) *Couple, IQ5*, average.



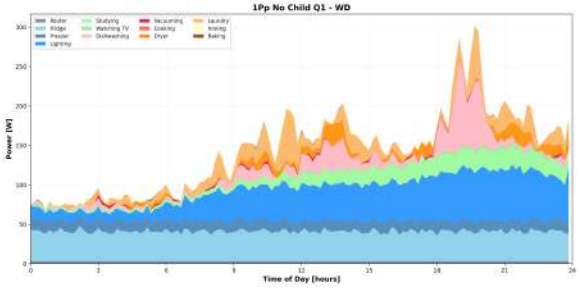
(c) *Couple with child(ren), IQ5*, stacked.



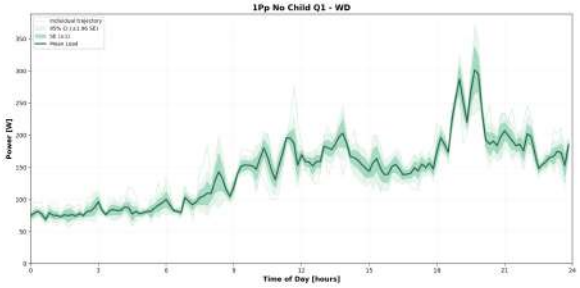
(d) *Couple with child(ren), IQ5*, average.

Figure 43: Weekday load curves, different household types, income group 5.

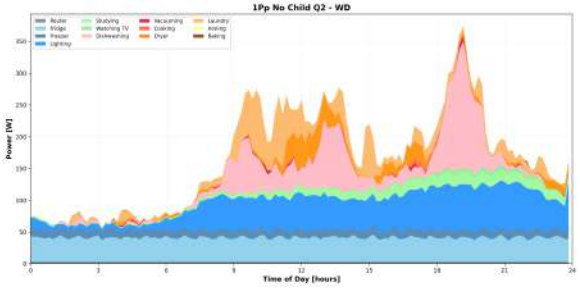
B.3.2 Income effects, fixed household composition



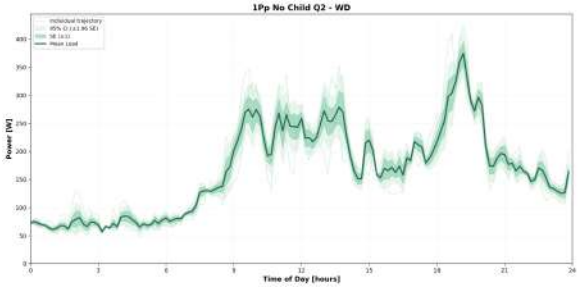
(a) *Single Person, IQ1*, stacked.



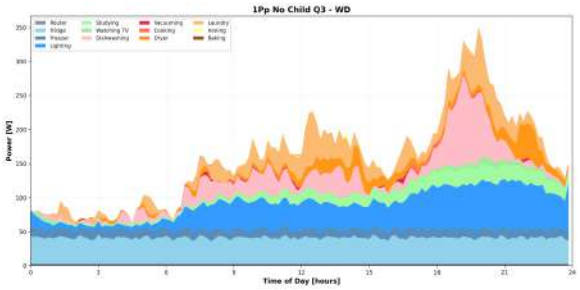
(b) *Single Person, IQ1*, average.



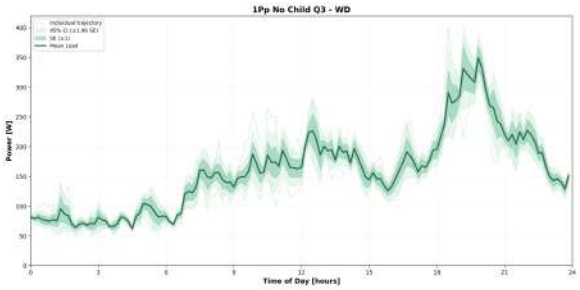
(c) *Single Person, IQ2*, stacked.



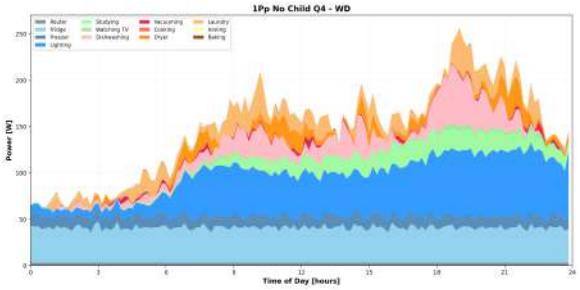
(d) *Single Person, IQ2*, average.



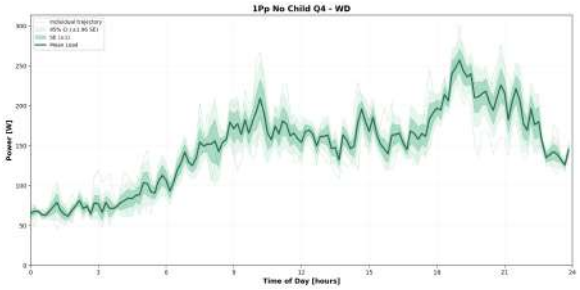
(e) *Single person, IQ3*, stacked.



(f) *Single Person, IQ3*, average.

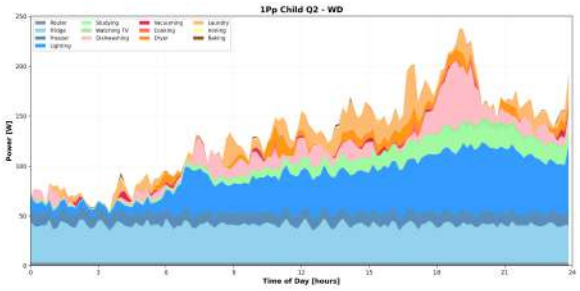


(g) *Single Person, IQ4*, stacked.

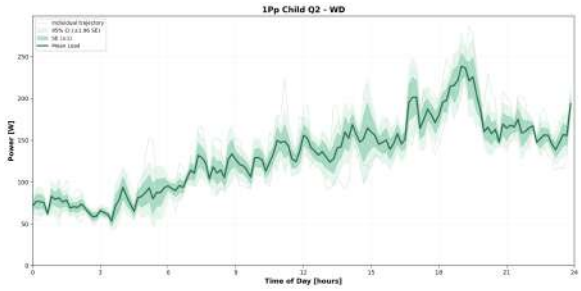


(h) *Single Person, IQ4*, average.

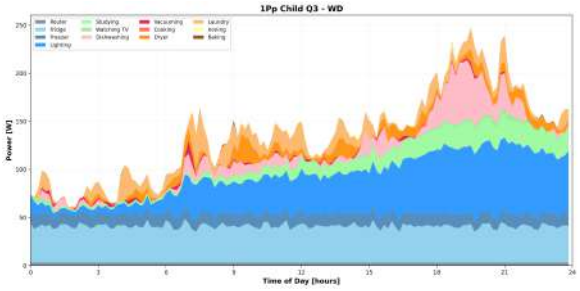
Figure 44: Weekday load curves, different income groups, fixed household type *Single Person*.



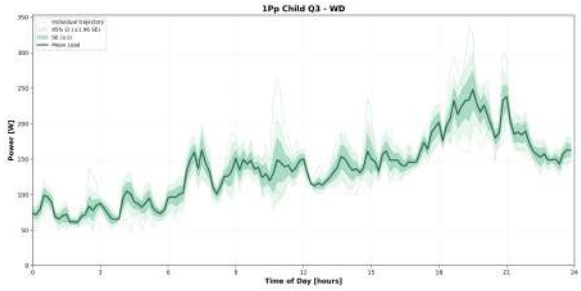
(a) *Single Person with child(ren), IQ2*, stacked.



(b) *Single Person with child(ren), IQ2*, average.

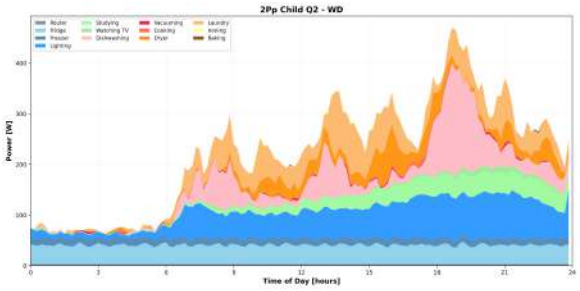


(c) *Single Person with child(ren), IQ3*, stacked.

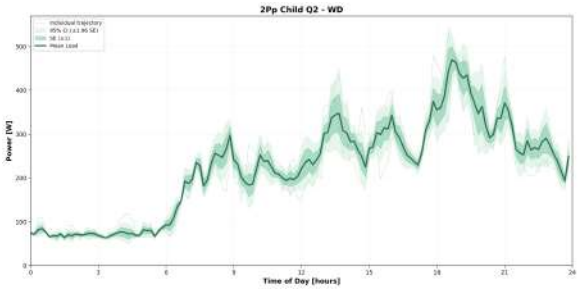


(d) *Single Person with child(ren), IQ3*, average.

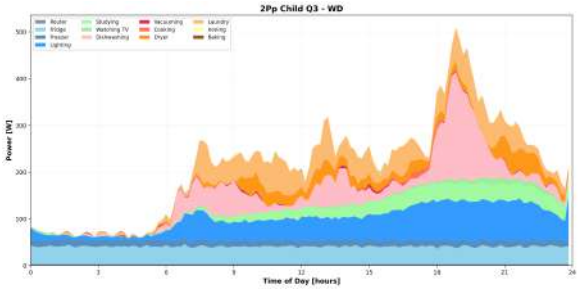
Figure 45: Weekday load curves, different income groups, fixed household type *Single Person with child(ren)*.



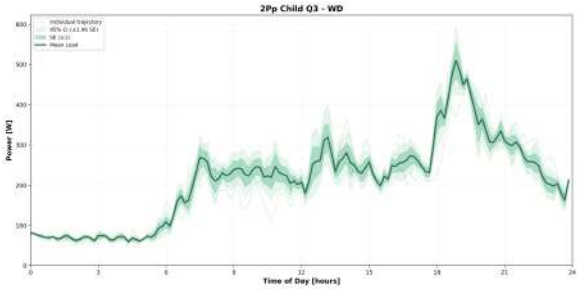
(a) *Couple with child(ren), IQ2*, stacked.



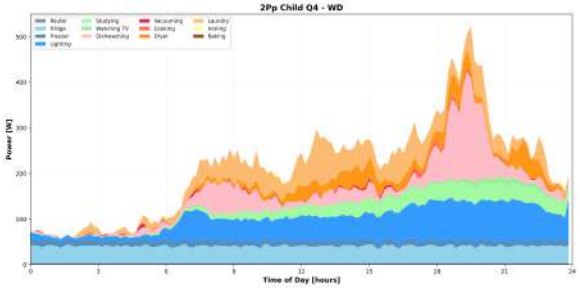
(b) *Couple with child(ren), IQ2*, average.



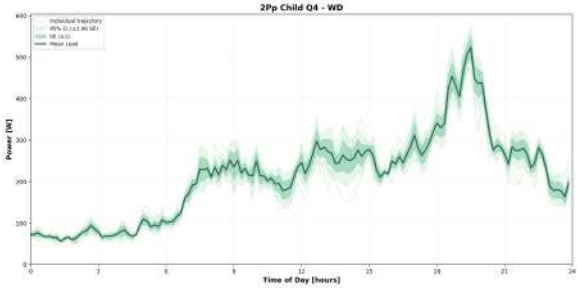
(c) *Couple with child(ren), IQ3*, stacked.



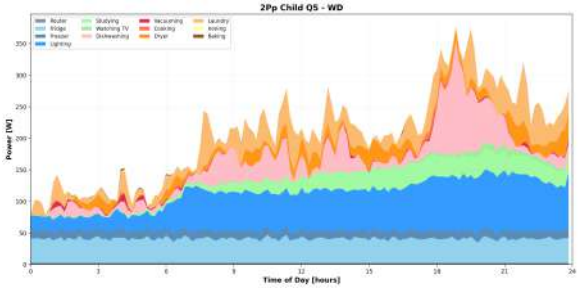
(d) *Couple with child(ren), IQ3*, average.



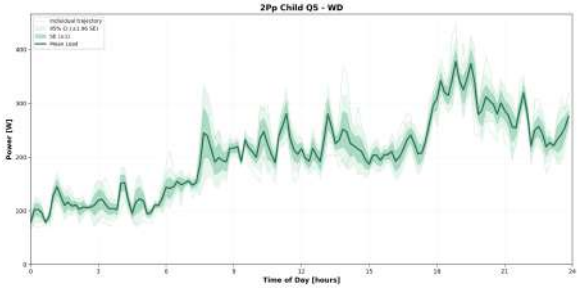
(e) *Couple with child(ren), IQ4*, stacked.



(f) *Couple with child(ren), IQ4*, average.



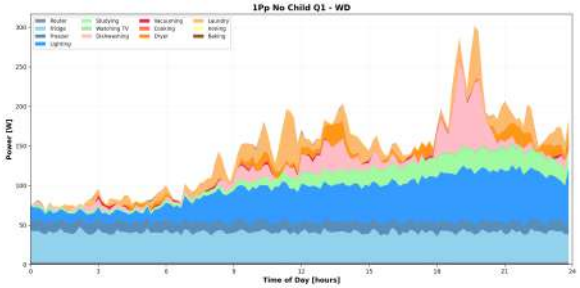
(g) *Couple with child(ren), IQ5*, stacked.



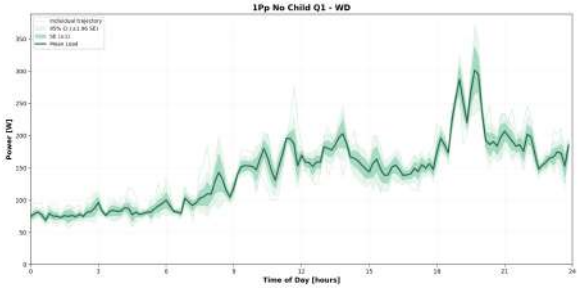
(h) *Couple with child(ren), IQ5*, average.

Figure 46: Weekday load curves, different income groups, fixed household type *Couple with child(ren)*.

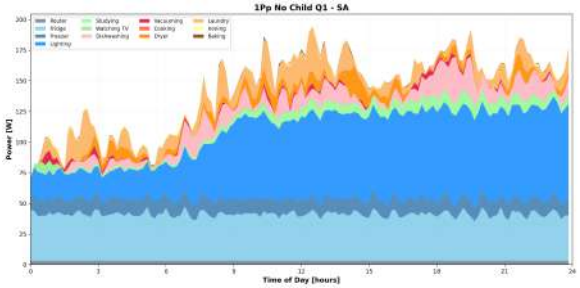
B.4 Day type effects



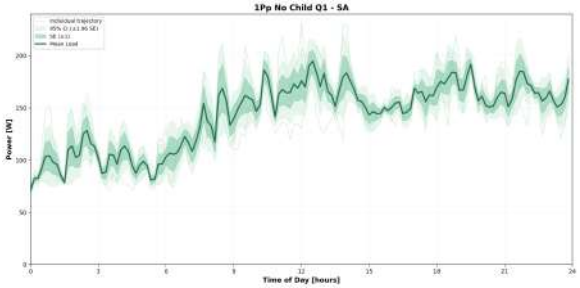
(a) Weekday, Single Person, IQ1, stacked.



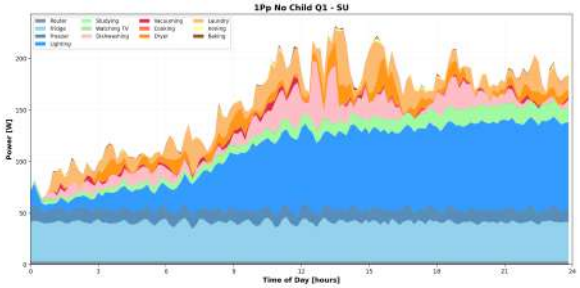
(b) Weekday, Single Person, IQ1, average.



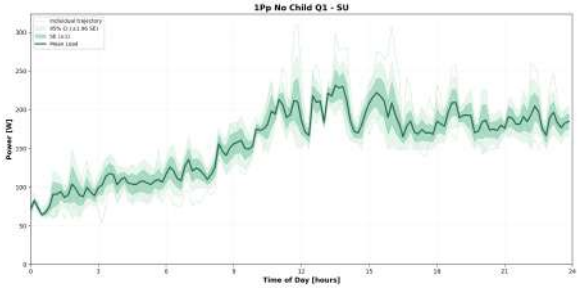
(c) Saturday, Single Person, IQ1, stacked.



(d) Saturday, Single Person, Q1, average.

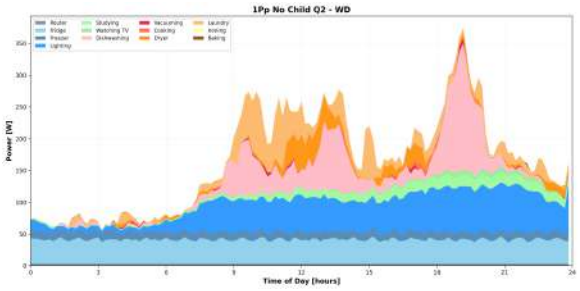


(e) Sunday, Single Person, IQ1, stacked.

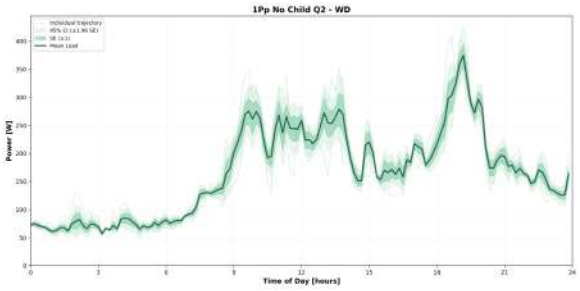


(f) Sunday, Single Person, IQ1, average.

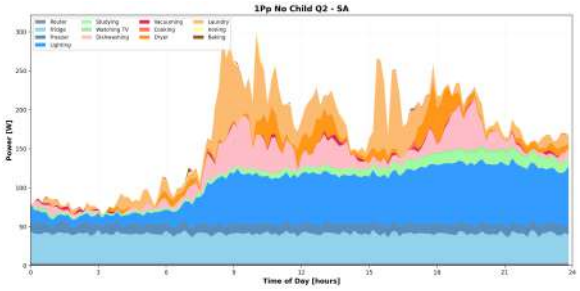
Figure 47: Comparison Weekday, Saturday, Sunday, fixed cohort *Single Person, IQ1.*



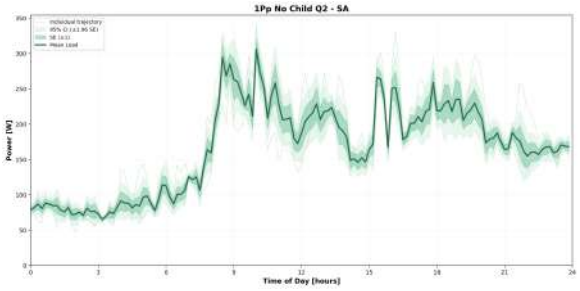
(a) Weekday, Single Person, IQ2, stacked.



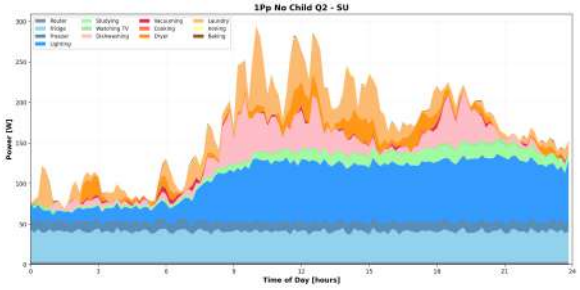
(b) Weekday, Single Person, IQ2, average.



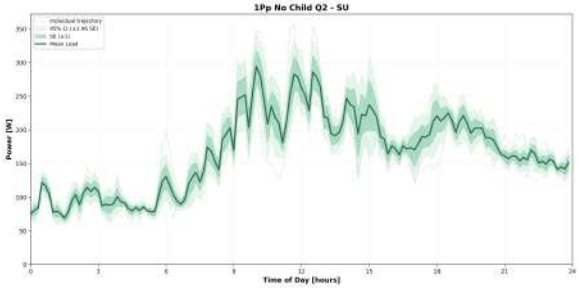
(c) Saturday, Single Person, IQ2, stacked.



(d) Saturday, Single Person, Q2, average.

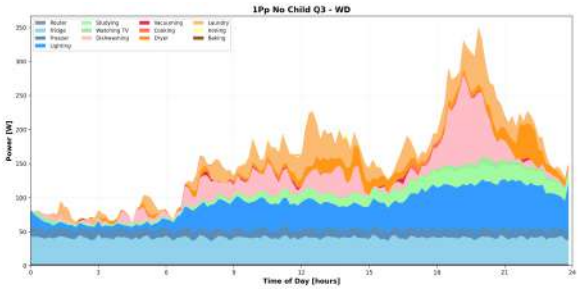


(e) Sunday, Single Person, IQ2, stacked.

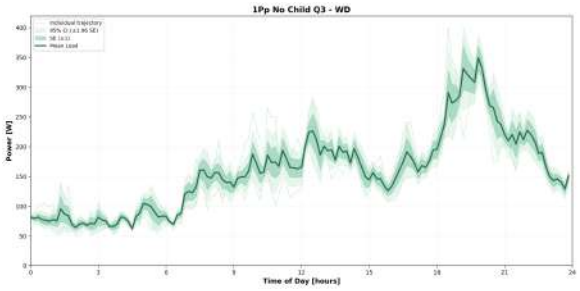


(f) Sunday, Single Person, IQ2, average.

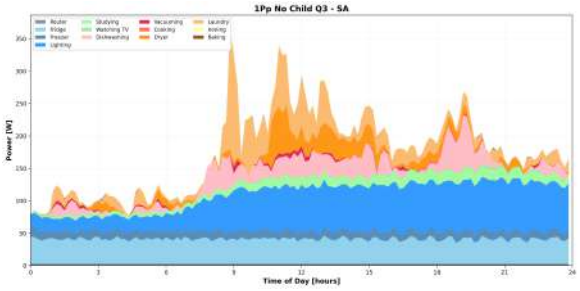
Figure 48: Comparison Weekday, Saturday, Sunday, fixed cohort *Single Person, IQ2*.



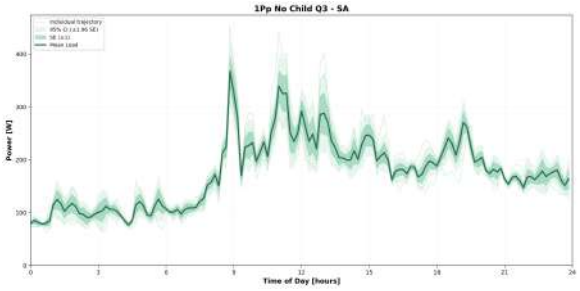
(a) Weekday, Single Person, IQ3, stacked.



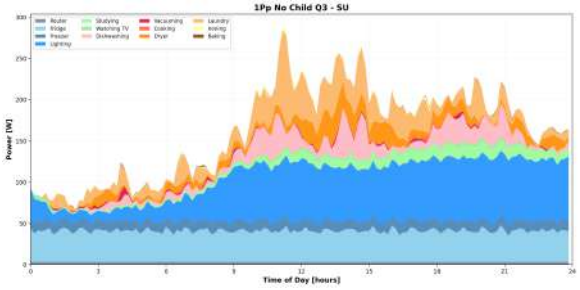
(b) Weekday, Single Person, IQ3, average.



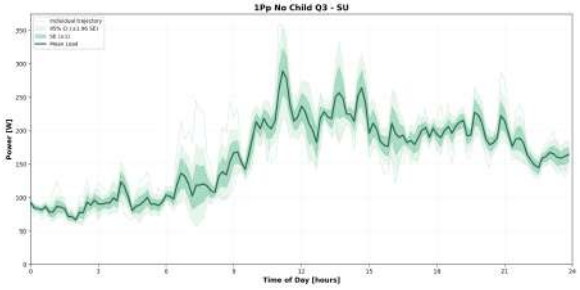
(c) Saturday, Single Person, IQ3, stacked.



(d) Saturday, Single Person, Q3, average.

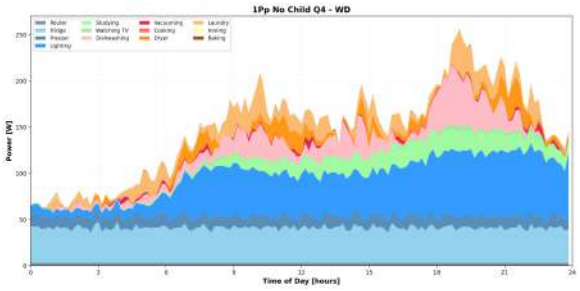


(e) Sunday, Single Person, IQ3, stacked.

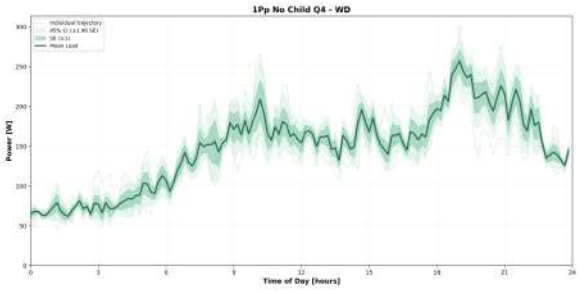


(f) Sunday, Single Person, IQ3, average.

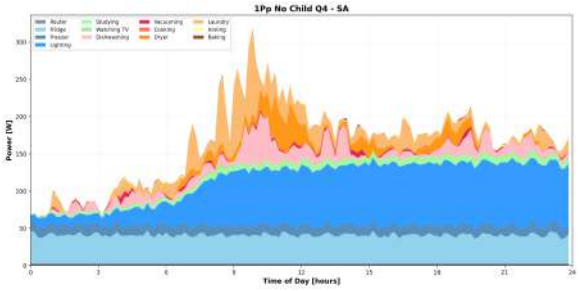
Figure 49: Comparison Weekday, Saturday, Sunday, fixed cohort *Single Person, IQ3*.



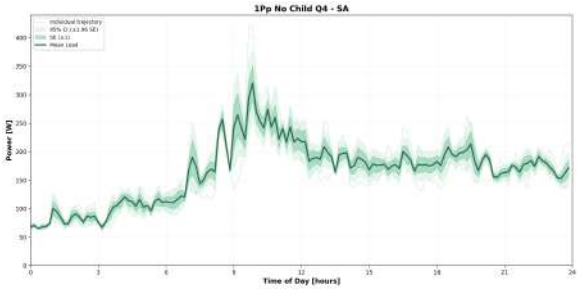
(a) Weekday, Single Person, IQ4, stacked.



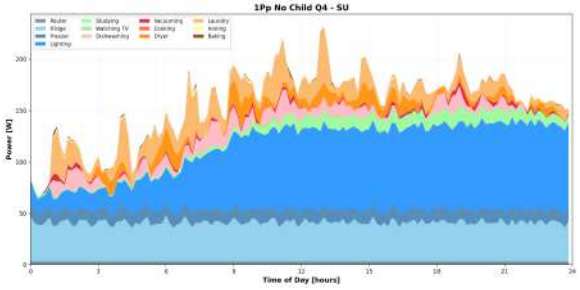
(b) Weekday, Single Person, IQ4, average.



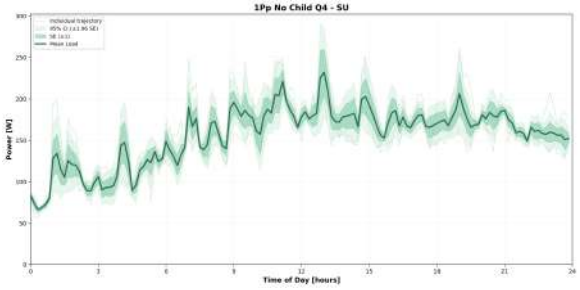
(c) Saturday, Single Person, IQ4, stacked.



(d) Saturday, Single Person, Q4, average.

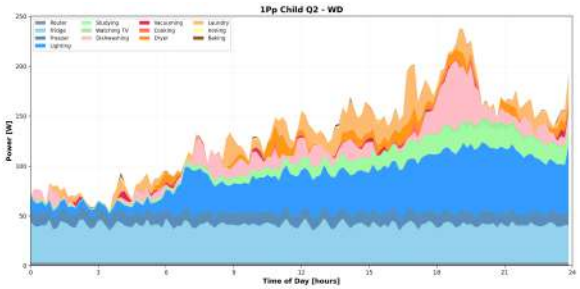


(e) Sunday, Single Person, IQ4, stacked.

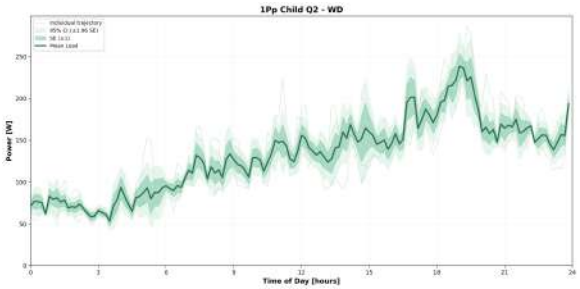


(f) Sunday, Single Person, IQ4, average.

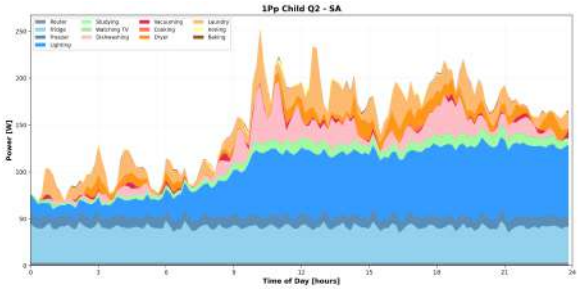
Figure 50: Comparison Weekday, Saturday, Sunday, fixed cohort *Single Person, IQ4*.



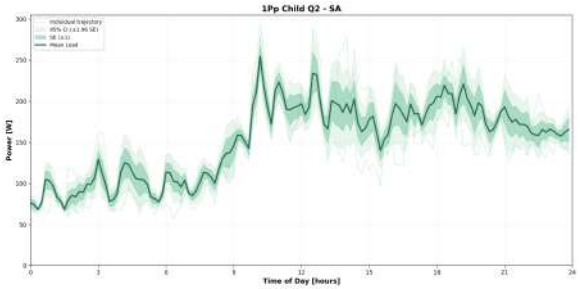
(a) Weekday, Single Person with child(ren), IQ2, stacked.



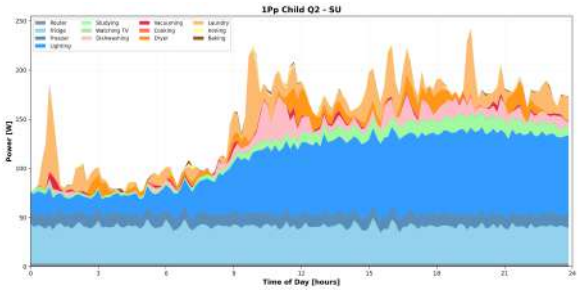
(b) Weekday, Single Person with child(ren), IQ2, average.



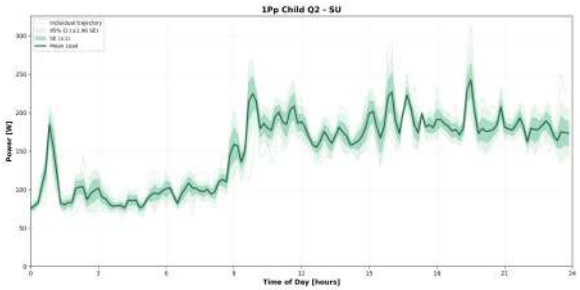
(c) Saturday, Single Person with child(ren), IQ2, stacked.



(d) Saturday, Single Person with child(ren), Q2, average.

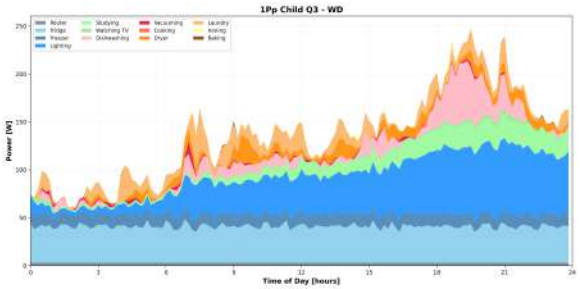


(e) Sunday, Single Person with child(ren), IQ2, stacked.

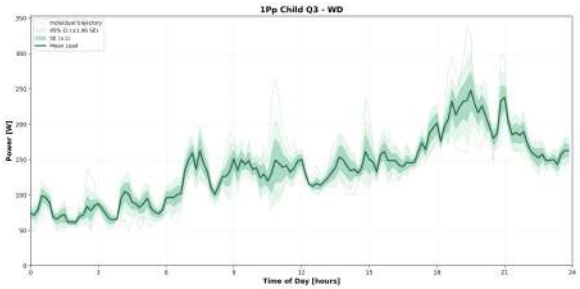


(f) Sunday, Single Person with child(ren), IQ2, average.

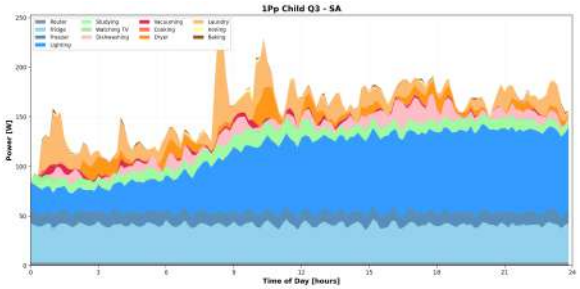
Figure 51: Comparison Weekday, Saturday, Sunday, fixed cohort *Single Person, with child(ren) IQ2*.



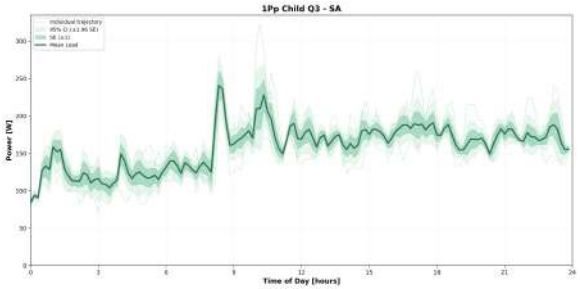
(a) Weekday, Single Person with child(ren), IQ3, stacked.



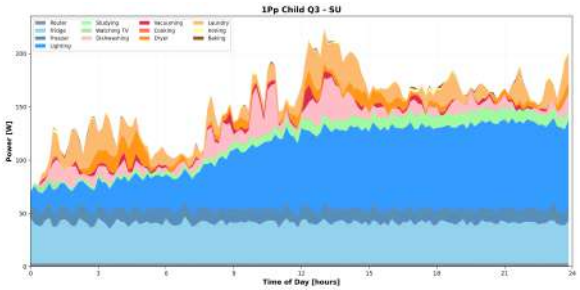
(b) Weekday, Single Person with child(ren), IQ3, average.



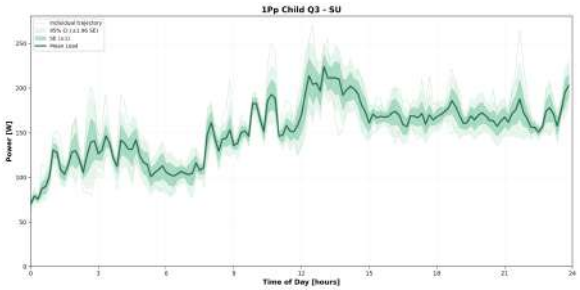
(c) Saturday, Single Person with child(ren), IQ3, stacked.



(d) Saturday, Single Person with child(ren), Q3, average.

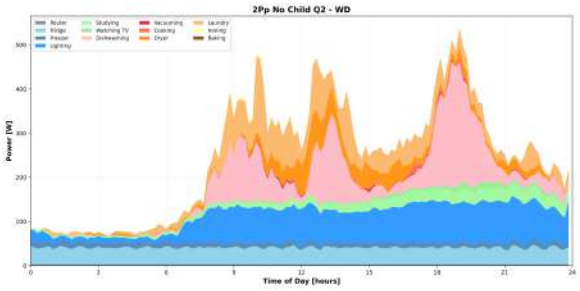


(e) Sunday, Single Person with child(ren), IQ3, stacked.

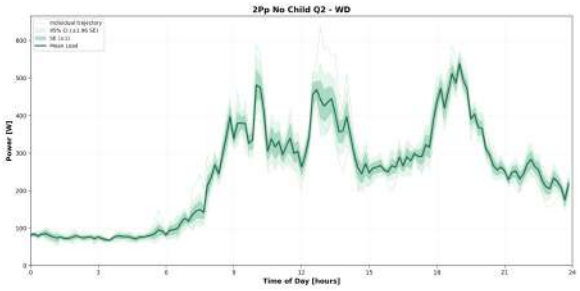


(f) Sunday, Single Person with child(ren), IQ3, average.

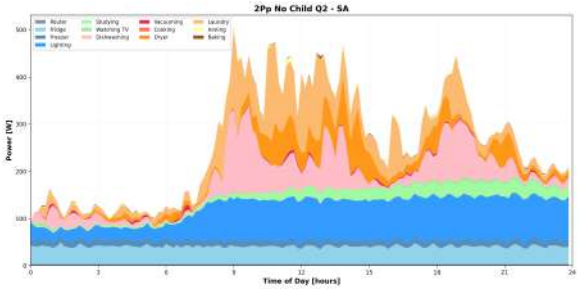
Figure 52: Comparison Weekday, Saturday, Sunday, fixed cohort *Single Person, with child(ren) IQ3*.



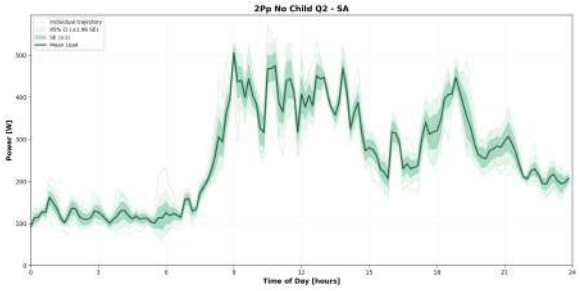
(a) Weekday, Couple, IQ2, stacked.



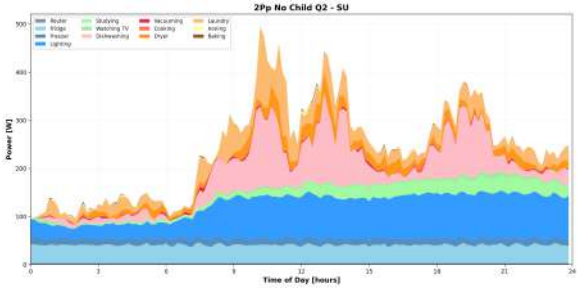
(b) Weekday, Couple, IQ2, average.



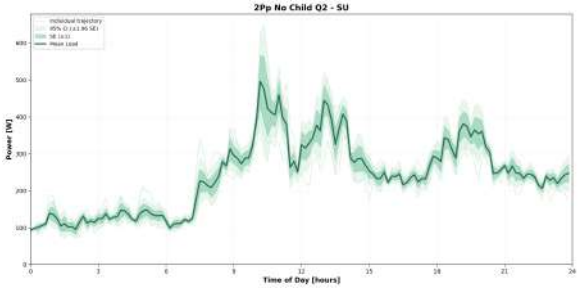
(c) Saturday, Couple, IQ2, stacked.



(d) Saturday, Couple, IQ2, average.

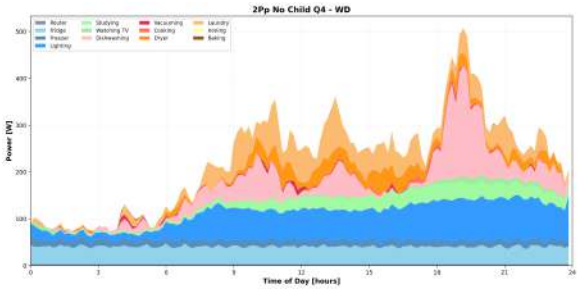


(e) Sunday, Couple, IQ2, stacked.

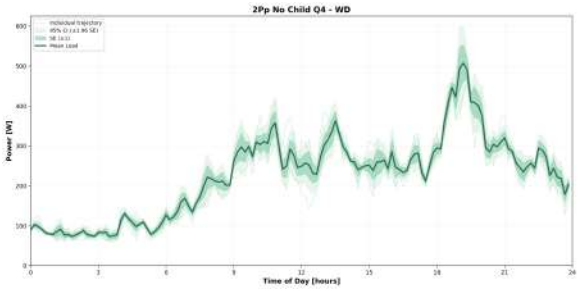


(f) Sunday, Couple, IQ2, average.

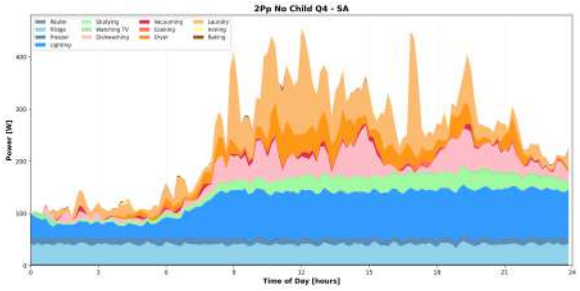
Figure 53: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple, IQ2*.



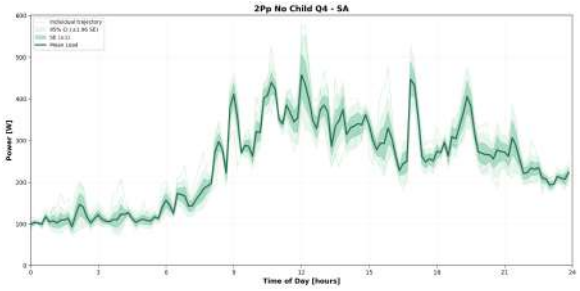
(a) Weekday, Couple, IQ4, stacked.



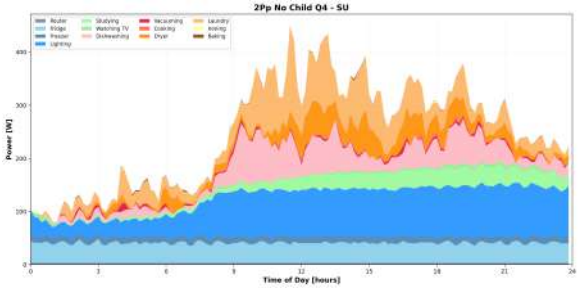
(b) Weekday, Couple, IQ4, average.



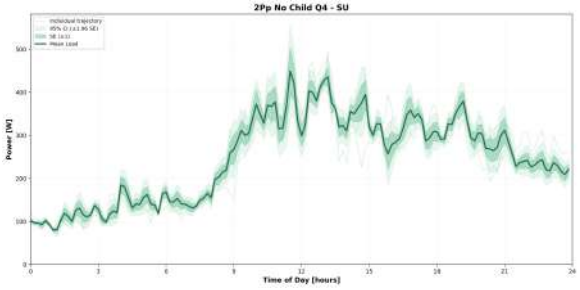
(c) Saturday, Couple, IQ4, stacked.



(d) Saturday, Couple, IQ4, average.

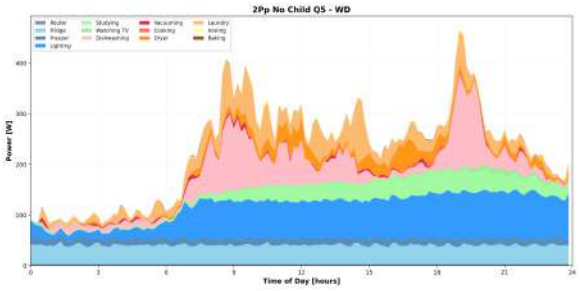


(e) Sunday, Couple, IQ4, stacked.

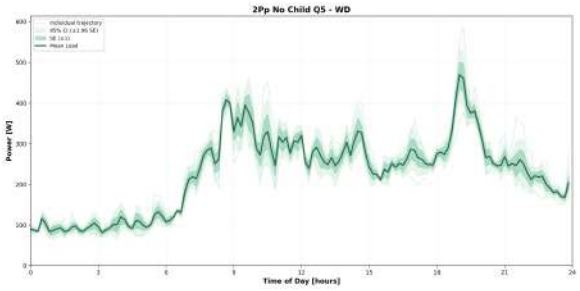


(f) Sunday, Couple, IQ4, average.

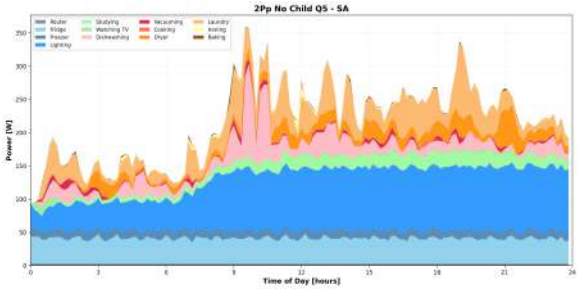
Figure 54: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple, IQ4*.



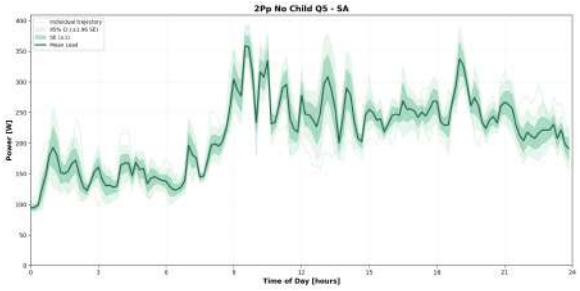
(a) Weekday, Couple, IQ5, stacked.



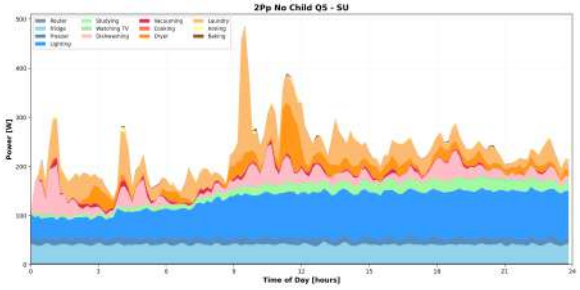
(b) Weekday, Couple, IQ5, average.



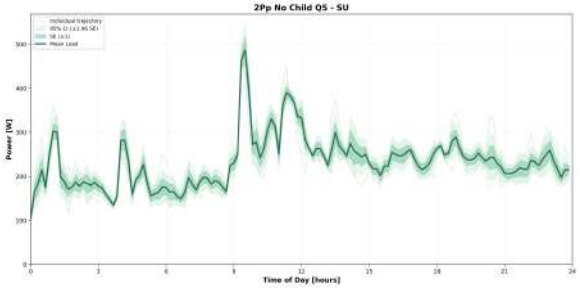
(c) Saturday, Couple, IQ5, stacked.



(d) Saturday, Couple, IQ5, average.

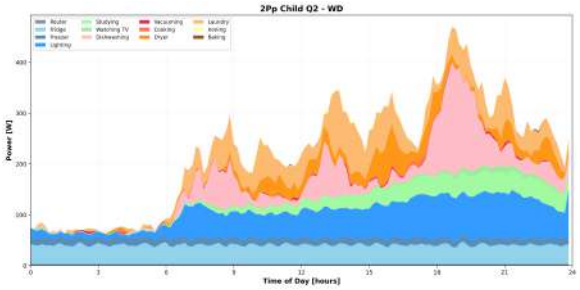


(e) Sunday, Couple, IQ5, stacked.

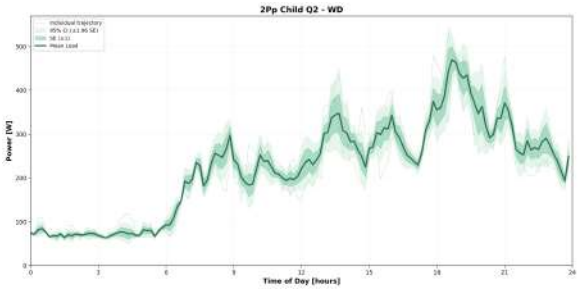


(f) Sunday, Couple, IQ5, average.

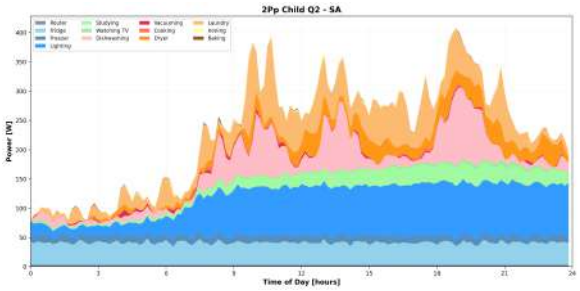
Figure 55: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple, IQ5*.



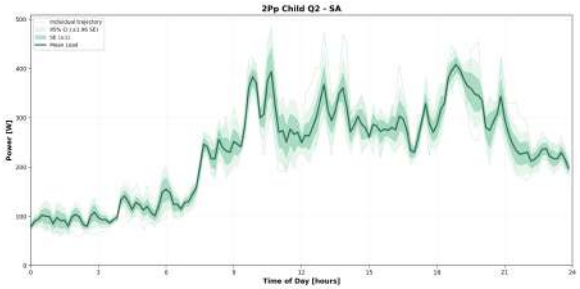
(a) Weekday, Couple with child(ren), IQ2, stacked.



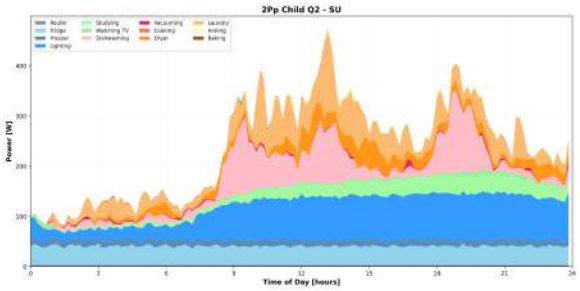
(b) Weekday, Couple with child(ren), IQ2, average.



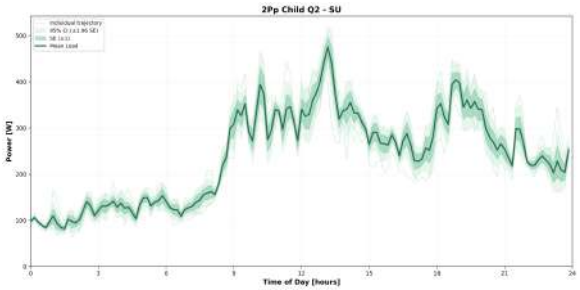
(c) Saturday, Couple with child(ren), IQ2, stacked.



(d) Saturday, Couple with child(ren), IQ2, average.

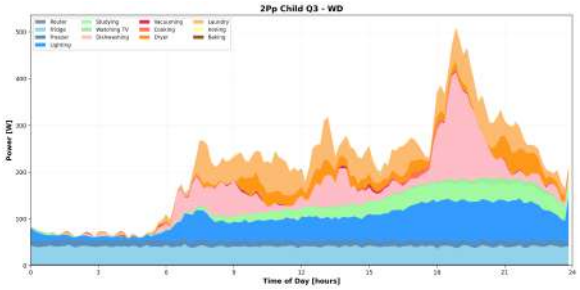


(e) Sunday, Couple with child(ren), IQ2, stacked.

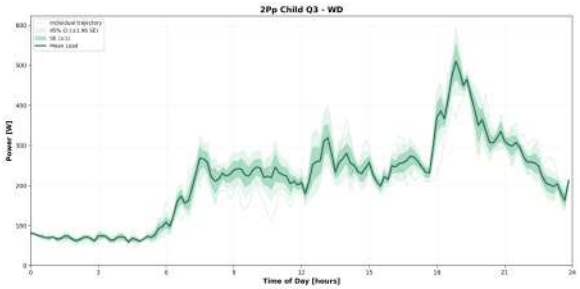


(f) Sunday, Couple with child(ren), IQ2, average.

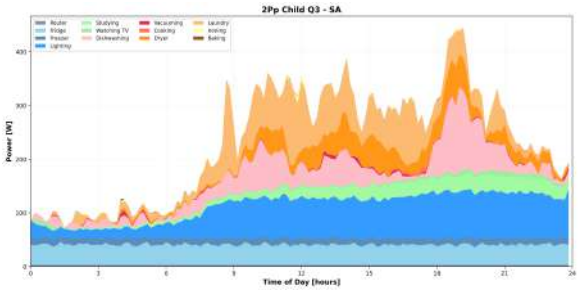
Figure 56: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple with child(ren), IQ2.*



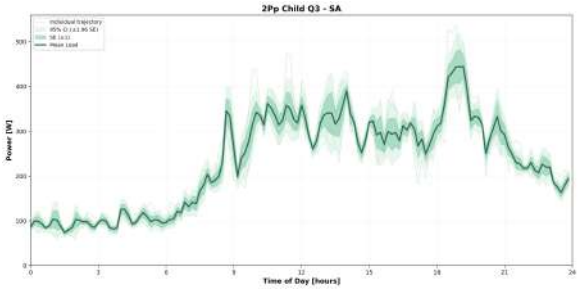
(a) Weekday, Couple with child(ren), IQ3, stacked.



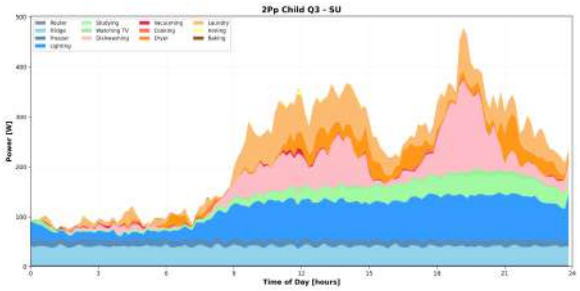
(b) Weekday, Couple with child(ren), IQ3, average.



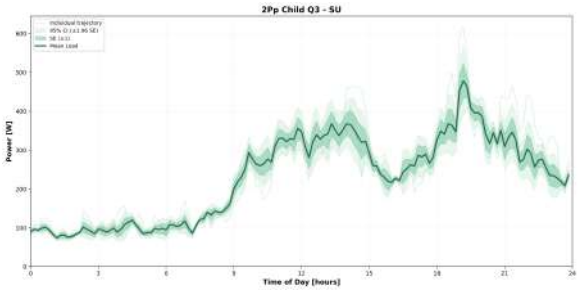
(c) Saturday, Couple with child(ren), IQ3, stacked.



(d) Saturday, Couple with child(ren), IQ3, average.

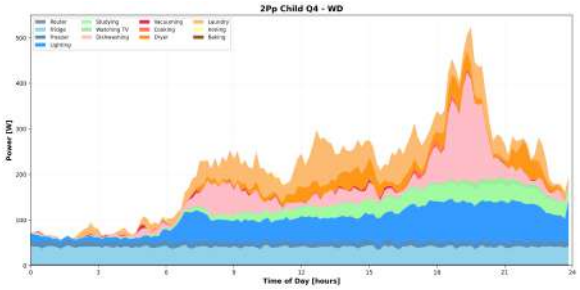


(e) Sunday, Couple with child(ren), IQ3, stacked.

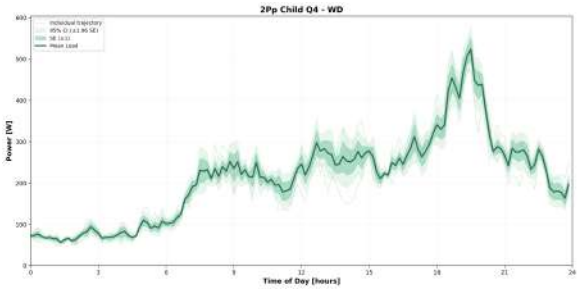


(f) Sunday, Couple with child(ren), IQ3, average.

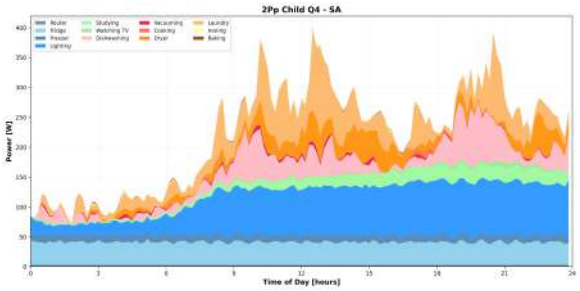
Figure 57: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple with child(ren), IQ3*.



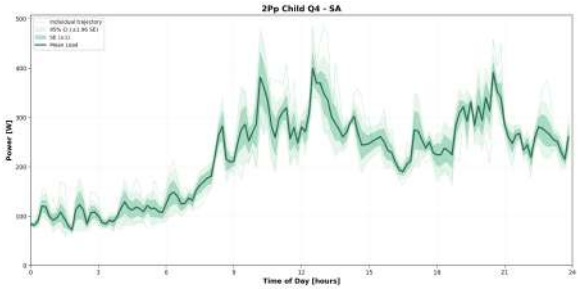
(a) Weekday, Couple with child(ren), IQ4, stacked.



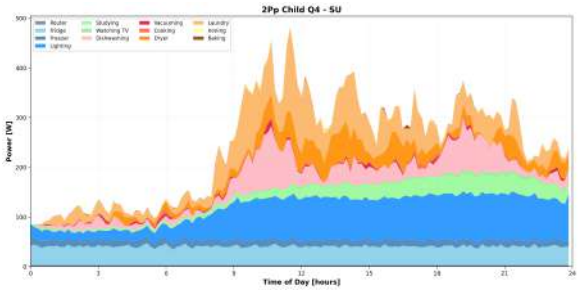
(b) Weekday, Couple with child(ren), IQ4, average.



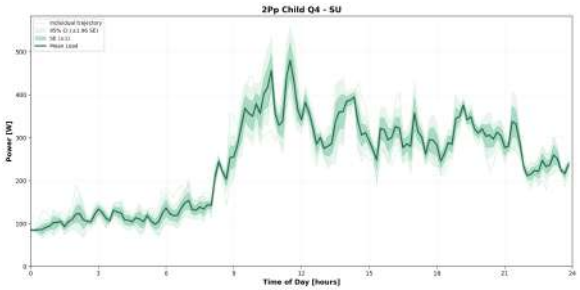
(c) Saturday, Couple with child(ren), IQ4, stacked.



(d) Saturday, Couple with child(ren), IQ4, average.

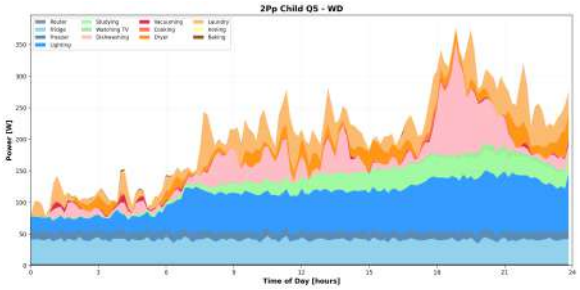


(e) Sunday, Couple with child(ren), IQ4, stacked.

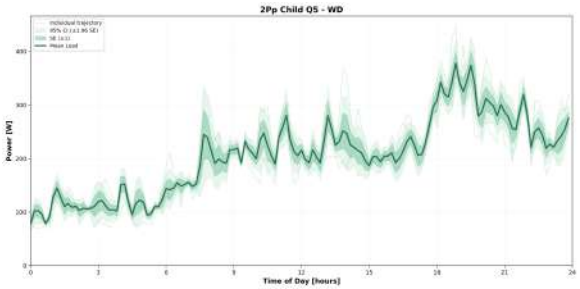


(f) Sunday, Couple with child(ren), IQ4, average.

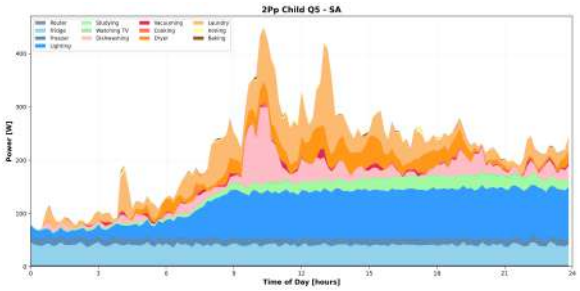
Figure 58: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple with child(ren), IQ4.*



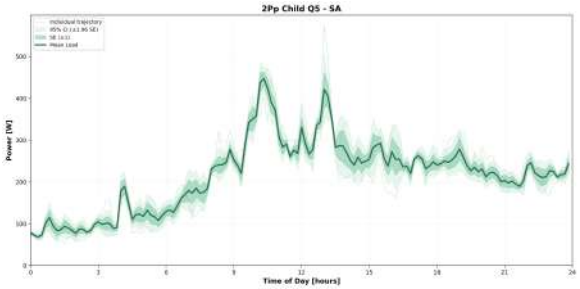
(a) Weekday, Couple with child(ren), IQ5, stacked.



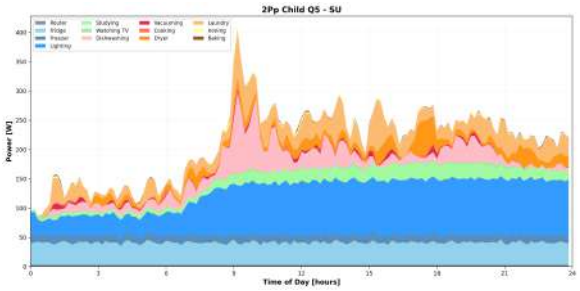
(b) Weekday, Couple with child(ren), IQ5, average.



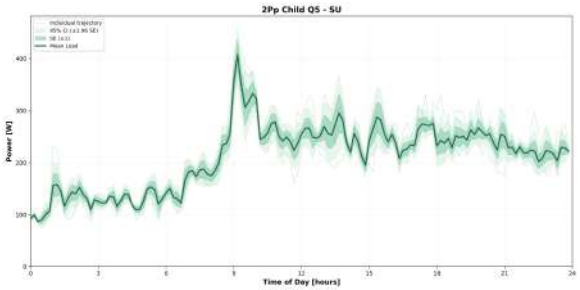
(c) Saturday, Couple with child(ren), IQ5, stacked.



(d) Saturday, Couple with child(ren), IQ5, average.



(e) Sunday, Couple with child(ren), IQ5, stacked.



(f) Sunday, Couple with child(ren), IQ5, average.

Figure 59: Comparison Weekday, Saturday, Sunday, fixed cohort *Couple with child(ren), IQ5.*

B.4.1 Summary metrics

Table 14: Load metrics per cohort for weekdays.

Cohort	Peak W	Peak time	Mean W	Daily kWh
SP, IQ1	301.5	19:40	143.1	3.43
SP, IQ2	374.5	19:10	166.5	4.00
SP, IQ3	349.4	19:50	158.4	3.80
SP, IQ4	257.5	19:00	148.0	3.55
C, IQ2	538.4	19:00	246.9	5.93
C, IQ3	603.4	19:10	254.0	6.10
C, IQ4	507.5	19:10	225.7	5.42
C, IQ5	469.5	19:00	227.8	5.47
C+Ch, IQ2	469.6	18:40	221.9	5.33
C+Ch, IQ3	510.6	18:50	212.8	5.11
C+Ch, IQ4	523.7	19:30	213.4	5.12
C+Ch, IQ5	377.9	18:50	205.5	4.93
SP+Ch, IQ2	238.4	19:00	131.9	3.17
SP+Ch, IQ3	248.1	19:30	136.7	3.28

Table 15: Load metrics per cohort for Saturdays.

Cohort	Peak W	Peak time	Mean W	Daily kWh
SP, IQ1	194.8	12:30	143.1	3.43
SP, IQ2	306.3	10:00	167.2	4.01
SP, IQ3	368.1	08:50	176.2	4.23
SP, IQ4	320.2	09:50	165.0	3.96
C, IQ2	505.9	09:00	258.5	6.20
C, IQ3	650.8	13:20	247.5	5.94
C, IQ4	457.5	12:00	246.2	5.91
C, IQ5	358.8	09:30	216.2	5.19
C+Ch, IQ2	408.0	18:50	231.0	5.54
C+Ch, IQ3	444.3	19:10	232.3	5.58
C+Ch, IQ4	399.6	12:30	219.7	5.27
C+Ch, IQ5	447.9	10:20	216.1	5.19
SP+Ch, IQ2	254.5	10:10	152.3	3.65
SP+Ch, IQ3	240.5	08:20	158.3	3.80

Table 16: Load metrics per cohort for Sundays.

Cohort	Peak W	Peak time	Mean W	Daily kWh
SP, IQ1	231.6	13:30	157.7	3.78
SP, IQ2	294.5	10:00	167.4	4.02
SP, IQ3	289.3	11:10	162.7	3.91
SP, IQ4	232.1	13:00	156.4	3.75
C, IQ2	495.9	10:10	241.3	5.79
C, IQ3	410.9	13:50	236.3	5.67
C, IQ4	449.0	11:30	247.8	5.95
C, IQ5	486.2	09:30	232.8	5.59
C+Ch, IQ2	475.3	13:10	238.9	5.73
C+Ch, IQ3	478.1	19:10	228.7	5.49
C+Ch, IQ4	480.4	11:30	243.1	5.84
C+Ch, IQ5	407.4	09:10	211.3	5.07
SP+Ch, IQ2	242.9	19:30	151.0	3.62
SP+Ch, IQ3	223.9	13:00	152.8	3.67

Table 17: Aggregated practice-bundle contributions to daily electricity demand by cohort (Weekdays).

Cohort	Food (%)	Maintenance (%)	Leisure+light (%)	Baseload (%)
SP, IQ1	9.8	14.0	37.7	38.4
SP, IQ2	18.4	16.4	32.6	32.6
SP, IQ3	14.5	18.7	32.6	34.2
SP, IQ4	11.1	14.1	38.3	36.6
SP+Ch, IQ2	10.5	12.1	36.8	40.6
SP+Ch, IQ3	8.1	13.5	38.7	39.6
C, IQ2	22.8	22.9	32.7	21.6
C, IQ3	24.1	22.8	31.7	21.4
C, IQ4	18.0	22.2	35.5	24.2
C, IQ5	18.0	19.3	39.0	23.7
C+Ch, IQ2	17.7	24.4	33.4	24.6
C+Ch, IQ3	18.2	23.3	33.0	25.5
C+Ch, IQ4	16.8	24.1	34.3	24.8
C+Ch, IQ5	14.7	20.0	38.6	26.7

Table 18: Aggregated practice-bundle contributions to daily electricity demand by cohort (Saturdays).

Cohort	Food (%)	Maintenance (%)	Leisure+light (%)	Baseload (%)
SP, IQ1	7.0	12.4	42.9	37.8
SP, IQ2	11.3	20.8	35.9	32.1
SP, IQ3	10.8	20.2	38.3	30.7
SP, IQ4	8.4	16.8	41.7	33.0
SP+Ch, IQ2	9.2	16.8	38.9	35.0
SP+Ch, IQ3	5.3	14.8	45.5	34.3
C, IQ2	17.6	27.4	34.1	21.0
C, IQ3	16.9	26.7	34.6	21.8
C, IQ4	12.6	27.9	37.7	21.8
C, IQ5	10.4	22.4	42.4	24.8
C+Ch, IQ2	14.9	24.8	37.3	22.9
C+Ch, IQ3	15.2	27.7	33.9	23.2
C+Ch, IQ4	13.4	25.5	36.6	24.6
C+Ch, IQ5	10.6	25.6	38.5	25.3

Table 19: Aggregated practice-bundle contributions to daily electricity demand by cohort (Sundays).

Cohort	Food (%)	Maintenance (%)	Leisure+light (%)	Baseload (%)
SP, IQ1	8.2	15.2	42.3	34.3
SP, IQ2	11.2	17.8	38.9	32.2
SP, IQ3	8.8	20.0	38.2	33.0
SP, IQ4	5.8	15.4	44.3	34.5
SP+Ch, IQ2	5.7	15.3	43.1	35.9
SP+Ch, IQ3	7.4	14.2	42.7	35.7
C, IQ2	21.2	18.8	37.7	22.3
C, IQ3	19.1	21.2	36.7	23.1
C, IQ4	14.6	26.2	37.6	21.6
C, IQ5	10.8	24.9	41.2	23.1
C+Ch, IQ2	16.6	23.7	37.1	22.7
C+Ch, IQ3	17.3	23.1	36.1	23.6
C+Ch, IQ4	13.7	28.6	35.8	21.9
C+Ch, IQ5	11.7	19.4	43.2	25.6