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Daily operating states of residential electricity demand in India: Within-household variation, thermal conditions and peak demand

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Abstract

Residential electricity demand exhibits substantial variation in both load timing and peak intensity, with consequences for demand forecasting and power system operation. Characterising the temporal structure of residential electricity demand is therefore important for understanding how household loads evolve across operating conditions. Using 15-minute whole-house electricity records from 133 households across five monitoring locations in India, this study examines day-to-day demand alongside household survey information and daily weather. Recurring household-day demand patterns are evaluated in relation to weather, air-conditioner ownership, electric water heater ownership, within household transitions and high peak events. Four operating states emerged: concentrated morning peak, diffuse morning-led operation, concentrated daytime peak and extended evening-to-night operation. Individual households typically occupied several states over the monitoring period, indicating substantial within household variation in daily electricity use patterns. Under hotter conditions, the share of days characterised by concentrated morning operation decreased by approximately 11–14 percentage points, with redistribution across the remaining states. Households with air conditioners showed substantially stronger increases in active electricity use with increasing outdoor temperature. Electric water heater ownership was associated with greater morning concentration and 1.05 kW higher peak excess after adjustment for region and season. Concentrated morning and daytime states represented about one-third (34.08%) of all household-days and accounted for 70.12% of the pooled top 5% of peak excess days. The findings show that recurring daily operating states capture within household variation in the timing, weather response and peak characteristics of residential electricity demand.

Keywords: residential electricity demand; smart meters; daily load profiles; residential energy consumption; peak demand

1. Introduction

Buildings account for around 30% of global energy demand, with the residential sector contributing about 70% of energy use in buildings [1]. Global electricity consumption in buildings increased by more than 600 TWh in 2024, a 5% annual increase that accounted for nearly 60% of the growth in global electricity demand; rising air-conditioning demand during periods of high temperature was among the drivers [2]. The contribution of cooling is also evident in electricity system peaks. In India, peak electricity load increased from 148 GW in 2014 to 250 GW in 2024, and cooling was estimated to contribute 60 GW to peak load in 2024 despite air conditioners being present in fewer than 20% of households [3]. The additional daily peak demand associated with each 1 °C increase in daily average temperature rose from about 4 GW in 2019 to more than 7 GW in 2024 [3]. These developments make the temporal organisation of residential electricity demand relevant to understanding how household loads contribute to temperature sensitive system peaks.

At the household scale, electricity demand varies with environmental conditions, household characteristics, appliance ownership and electricity service conditions. Smart-meter studies have modelled total electricity consumption, maximum demand, load factor and peak timing against household, dwelling, appliance and climatic variables, with different factors associated with different demand metrics [4,5]. Longitudinal records further show that the same household can exhibit distinct load profiles on different days, and that aggregation to a household average profile reduces this within household temporal variation [6,7]. The prevalence of recurring daily profiles can also vary with outdoor temperature, season and day type [8]. Analysis at the household-day scale therefore retains changes in demand timing and concentration that occur within individual households over time and permits these changes to be examined in relation to thermal conditions and peak demand.

Research on residential load profile variation differs in both the temporal representation of demand and the analytical approach applied to it. Profiles may represent annual or seasonal household patterns, an average day, individual household-days, or a defined high demand period such as the evening peak [6–8,12,14]. Within these temporal units, electricity demand may be represented by the complete interval load curve, a normalised profile, or a smaller set of features describing timing, concentration and peak characteristics [7,10]. These representations retain different aspects of temporal variation. Household-day profiles preserve changes between days within the same household [6,7], whereas peak period profiles restrict the analysis to a defined high demand window [12]. The analytical approach determines how this temporal information is subsequently examined. Cluster analysis is widely used to identify recurring structures in interval electricity data [9]. Segmentation of individual household-days before aggregation has been used to characterise diurnal, intra-day and seasonal variation [6], while feature based representations have improved cluster separation relative to raw

profile representations [7]. Daily profile classification has also been extended to transition probabilities, peak probabilities and consumer level peak risk measures [10]. Linked smart-meter, weather, building and survey data have been analysed using mixed effects models to quantify variation in daily household energy demand [11]. Peak period clustering combined with activity data has related differences in temporal demand patterns to occupant activities [12]. Multi-year household-day clustering has tracked changes in profile prevalence with temperature and temporal conditions [8], while Indian multi-city analysis has used climate correction, dimensionality reduction and mixture modelling to examine changes in residential peak timing and magnitude [13]. Comparative analyses further show that the inferred profile structure depends on the clustering algorithm and validity criterion applied [14].

Table 1. Selected residential electricity demand studies relevant to household-day profile analysis, temporal variation and peak demand

Study context		Temporal representation		Analytical approach	Analytical contribution
Ireland; households; months [6]	3,941 six	Individual profiles	household-day	K-means, k-medoid, self-organising maps; multinomial logistic regression	Segmentation before aggregation retained within household temporal variation and linked profile classes with household characteristics.
Switzerland; households; year [7]	656 one	Household average and household-day profiles; raw and feature based representations		K-means; comparison of aggregation and feature representations	Household-day analysis retained variation suppressed by household averaging; feature representation improved cluster separation.
India; consumers [10]	171	Feature based daily load profiles		Empirical feature selection; K-means; transition-probability and peak risk analysis	Extended daily profile classification to transitions, peak probability and consumer level peak risk.
Great Britain; 1,418 and 682 households [11]		Daily electricity and gas consumption		Linear mixed-effects modelling using smart-meter, weather, building and survey variables	Quantified day-level demand variation using weather, building and household characteristics within one statistical model.
United Kingdom; 269 households [12]		Normalised cumulative evening peak period profiles		Hierarchical agglomerative clustering; elastic-net logistic regression; random forests	Linked differences in peak period load shape with occupant activities.
Great Britain; ~13,000 homes; three years [8]		Normalised home-fuel-day profiles at 2-h resolution		K-means clustering with longitudinal prevalence analysis	Tracked recurring daily profile prevalence across temperature and temporal conditions.
India; 13 cities [13]		Daily load curves across dwelling typologies		Degree-day climate correction; multidimensional scaling; Gaussian mixture modelling	Quantified changes in residential peak timing and magnitude across periods and dwelling groups.
Hungary; nearly 1,000 households [14]		Daily and annual electricity profiles		K-means, fuzzy K-means, agglomerative hierarchical clustering; elbow, silhouette and Dunn indices	Showed that profile structure and cluster selection depend on clustering method and validity criterion.

Residential electricity demand varies within the same household from day to day, and this variation can be expressed through recurring daily load patterns that persist or transition over time [6–8,10]. The occurrence of these patterns also varies with outdoor temperature and temporal context [8], while peak demand analyses show that high load periods are associated with particular load shapes and timings [10,12,13]. Within household variability, thermal conditions and peak demand are therefore connected through the temporal organisation of daily electricity use. Across the existing literature, these relationships have been examined using different profile definitions, temporal windows and analytical endpoints. A common household-day representation provides a basis for examining them together and for determining whether recurring daily states that describe within household variation also change in prevalence across thermal conditions and differ in their representation during high peak events.

This study uses linked 15-minute whole-house electricity measurements, household-survey information and daily weather data from a multi-site Indian sample. Recurring household-day demand patterns are treated as operating states and identified from normalised daily active load profiles, separating temporal profile structure from daily demand magnitude during classification. The study aims to identify recurring household-day electricity-demand states and examine their within-household dynamics, associations with appliance ownership and temperature-responsive demand, and representation during high-peak events. Five research questions guide the current analysis: (1) which recurring operating states characterise daily residential electricity demand; (2) how do individual households occupy and transition among these states over time; (3) how does state prevalence vary across thermal conditions; (4) how is appliance ownership associated with temperature response, time-of-day demand concentration and peak demand; and (5) which states are disproportionately represented during high peak events?

2. Data and methods

This study analyses high resolution residential electricity data to identify recurring household-day operating states and examine how those states vary within households, across thermal conditions and appliance-ownership groups, and during high peak events. The analysis proceeded in five stages: (1) reconstruction and quality control of household-day electricity records; (2) separation of persistent and active demand and construction of normalised daily load profiles; (3) identification and internal validation of recurring household-day operating states; (4) analysis of within household state occupancy, transitions, thermal-condition variation and appliance-ownership associations; and (5) evaluation of operating state representation during high peak events.

2.1 Study data and analytical sample

The study used data from the Monitoring and Analysis of Residential Electricity Consumption (eMARC) programme developed by Prayas (Energy Group) to examine residential electricity use in India [15]. The programme monitored volunteer households in Maharashtra and Uttar Pradesh in India and was designed to include variation in economic conditions and appliance ownership. The public eMARC archive used in this study provides whole-house electricity records at 15-minute resolution, together with household-survey information on dwelling characteristics and appliance ownership [15]. Only main-line whole-house meter records were retained for analysis; appliance-submeter records were excluded.

Monitoring records covered five locations: Pune city, Pune district and Aurangabad district in Maharashtra, and Gonda district and Kanpur Rural in Uttar Pradesh. After application of the household-day data-quality and operating-day eligibility criteria described below, the analytical sample comprised 44,571 household-days from 133 households. Survey information was available for 126 households. To limit the influence of households with longer monitoring periods on estimation of the operating state centroids, the clustering model was fitted using a household-balanced training subset of 17,747 household-days, with a maximum of 180 eligible days per household. The resulting centroids were subsequently used to assign operating states to all 44,571 retained household-days. Site specific sample retention and data-quality diagnostics are reported in Supplementary section.

The household-day was the principal observational unit, allowing changes in electricity use patterns within individual households to be examined over the monitoring period. Three primary data sources were linked for the analysis: 15-minute whole-house electricity records, household-survey information and daily weather data. A separate daily electricity-consumption file was used only to verify calendar alignment and consistency with the interval-meter records. All electricity use, peak demand and operating state measures were calculated from the 15-minute whole-house records. Weather data were matched to the electricity records by monitoring location and local calendar date using the Asia/Kolkata time zone.

2.2 Household-day processing and profile construction

Each household-day was reconstructed on an expected grid of 96 - 15-minute intervals. Duplicate observations within an interval were averaged. Missing readings and recorded zeros were repaired only when they satisfied predefined limits on the number, duration and position of affected intervals and on the change in reconstructed daily electricity use. Days exceeding these limits were excluded. The complete reconstruction rules and sample progression are provided in Supplementary section.

Daily whole-house electricity use was calculated by integrating the 15-minute average power observations. A persistent power level was estimated separately for each household-day to represent the continuously present component of whole-house demand. Active power was defined as the portion of observed demand above this level, and active electricity was obtained by integrating active power over the day. Peak excess was defined as the difference between the maximum observed whole-house power and the corresponding daily persistent-power level. Household-days that did not satisfy the decomposition and minimum active demand criteria were excluded from temporal classification. Definitions and eligibility thresholds for these measures are provided in Supplementary section. Operating states were identified from the within day distribution of active demand, independent of daily electricity magnitude. For household h , day d and 15-minute interval t , the normalised active load share was defined as:

$$q_{hdt} = \frac{P_{hdt,active}}{\sum_{u=1}^{96} P_{hdu,active}}, \quad \sum_{t=1}^{96} q_{hdt} = 1. \quad (1)$$

where $q_{(h,d,t)}$ is the share of the day's active load occurring in interval t and $P_{act(h,d,t)}$ is active power for household h on day d during that interval. The 96 values of $q_{(h,d,t)}$ sum to one for each eligible household-day. Normalisation therefore preserves the timing and concentration of active demand while removing daily active electricity magnitude from the clustering input. Absolute active electricity, persistent demand and peak excess were retained as separate variables for subsequent characterisation of the identified states. Time-of-day periods used in the profile features were defined as night (22:00–04:59), morning (05:00–09:59), daytime (10:00–15:59) and evening (16:00–21:59).

2.3 Identification and validation of household-day operating states

Recurring operating states were identified from the normalised temporal distribution of active electricity demand. Six representations of each household-day profile were evaluated: the original 96-point quarter-hour profile, an hourly smoothed profile, a cosine-normalised hourly profile, an hourly principal-component representation, a compact feature representation and a hybrid representation. For each representation, K-means solutions with $k=2-8$ were fitted to the household-balanced training sample described in Section 2.1.

The compact representation was selected for the final model. It comprised seven features describing morning, daytime and evening shares of active demand, circular peak timing, concentration within the two highest load

hours and the number of local peaks. Features were standardised before clustering. Candidate solutions were assessed using silhouette separation, the proportion of observations with negative silhouette values, the Davies–Bouldin and Calinski–Harabasz indices, cluster-size balance and reproducibility across repeated initialisations. Agreement between alternative solutions was quantified using the adjusted Rand index (ARI). The solution that provided stable assignments while preserving distinct differences in the timing and concentration of daily active demand was retained. The final K-means model was fitted using 60 initialisations, a maximum of 1,000 iterations and random seed 42. Internal robustness was examined by repeating the classification under alternative data-processing and representation choices. These checks included removal of zero-value repair, stricter and more permissive day-quality criteria, alternative persistent-demand quantiles, different temporal smoothing windows, restriction to a common monitoring period, repeated model initialisation, household-level bootstrap resampling and region-balanced resampling. Robustness was evaluated from agreement in household-day assignments and similarity of the resulting state profiles. These analyses were used to distinguish features of the state structure that were consistently reproduced from those that were more sensitive to sampling or representation choices. The fitted centroids were applied to all 44,571 eligible household-days, assigning each day to one of four operating states. State labels were subsequently interpreted from the temporal characteristics of the resulting profiles. Absolute active electricity, persistent demand, peak excess and peak timing were retained outside the clustering model and evaluated after state assignment.

2.4 Household dynamics, weather response, appliance-service signatures and peak analysis

Household state mixtures and transitions

For each household, state occupancy was calculated as the proportion of retained household-days assigned to each operating state. Within household diversity in state occupancy was quantified using normalised Shannon entropy,

$$H_h = - \frac{\sum_{s=1}^4 p_{hs} \ln(p_{hs})}{\ln(4)}, \quad (2)$$

where p_{hs} is the proportion of retained days for household h assigned to state s . $H_h=0$ indicates that all retained days are assigned to a single state, whereas $H_h=1$ indicates equal occupancy of all four states. The primary entropy analysis was restricted to households with at least 30 retained days spanning at least two calendar months and two seasons.

State transitions were evaluated only between retained observations on consecutive calendar days. For each transition, the state on day d was treated as the origin state and the state on day $d+1$ as the destination state. Two transition matrices were calculated. The pooled matrix was estimated from all eligible consecutive-day transitions and therefore weighted households according to the number of transitions they contributed. The household-balanced matrix was calculated by first estimating transition probabilities separately for each household and origin state and then averaging these probabilities equally across households contributing transitions from that origin state.

Weather exposure and paired thermal contrasts

Daily weather data were obtained from the Open-Meteo Historical Weather application Programming Interface (API) [16] and matched to each household-day by monitoring location and local calendar date. Cooling degree days (CDD) were calculated using a 24 °C base temperature as:

$$\text{CDD}_{24,d} = \max(0, T_{\text{mean},d} - 24^\circ\text{C}), \quad (3)$$

where $T_{\text{mean},d}$ is daily mean outdoor temperature in °C. CDD_{24} therefore represents the daily exceedance of the 24 °C base temperature and was used as an indicator of outdoor thermal exposure.

Air-conditioner ownership and temperature responsiveness

The association between air-conditioner ownership and temperature related electricity use was evaluated from household-specific responses of daily active electricity to CDD_{24} . For each eligible household h , daily active electricity was modelled as

$$E_{hd}^{active} = \alpha_h + \beta_h CDD_{24,d} + \varepsilon_{hd}, \quad (4)$$

where E_{hd}^{active} is daily active electricity and β_h is the household-specific change in active electricity per 1 °C·day increase in CDD_{24} . Households were included when they had at least 30 eligible household-days, at least 10 distinct CDD_{24} values, a CDD_{24} range of at least 5 °C·day and known air-conditioner ownership. Detailed eligibility and sensitivity criteria are provided in Supplementary Section.

Electric water heater ownership and morning/peak signatures

Electric water heater associations were evaluated at the household-season level. For each eligible household-season, the median share of daily active electricity occurring during the morning period (05:00–09:59) and the median daily peak excess were calculated. Household-seasons were included when they contained at least 14 eligible days and water heater ownership was known.

Separate linear models estimated ownership associated differences in morning active electricity share and peak excess, with adjustment for region and season. Confidence intervals were obtained by bootstrap resampling at the household level. Seasonal variation in the ownership association was evaluated using water heater-by-season interaction terms, with summer as the reference season. Sensitivity analyses examined household-equal weighting, and alternative minimum numbers of eligible days per household-season. Full model specifications and sensitivity analyses are reported in the Supplementary section.

3. Results

The final analytical sample comprised 44,571 household-days from 133 households across the five monitoring locations. First, the analytical sample and operating state representation are established and the four recurring daily states are characterised. Second, changes in state prevalence and demand characteristics are examined across thermal conditions and appliance-ownership groups. Finally, within household state diversity, consecutive-day transitions and the occurrence of states on high peak days are evaluated.

3.1 Analytical sample and selection of the operating state representation

Following household-day reconstruction, data-quality screening and active/persistent load decomposition, 44,571 household-days from 133 households were retained from 71,038 candidate household-days (62.74%). Survey information was available for 126 households. K-means clustering was fitted using a household-balanced subset of 17,747 days, in which each household contributed a maximum of 180 eligible days to reduce the influence of unequal monitoring duration on state identification.

K-means clustering with $k=2-8$ was evaluated across six representations of the normalised active load profile: the raw 96-interval profile, smoothed hourly profile, cosine-normalised hourly profile, hourly principal components, a compact temporal-feature representation and a hybrid representation. The compact temporal-feature representation described each household-day using seven variables capturing morning, daytime and evening load shares, peak timing, concentration in the two highest load hours and the number of local peaks. Across the tested state counts, this representation provided the clearest separation among temporally distinct daily patterns and was retained for state selection. For the compact representation, the mean silhouette coefficient was 0.32 for both $k=2$ and $k=3$, compared with 0.29 for $k=4$. However, increasing from three to four states reduced the proportion of observations with negative silhouette values from 1.92% to 1.60%, reduced the Davies–Bouldin index from 1.31 to 1.28, and reduced the largest state share from 52.09% to 47.77%. Reproducibility across repeated initialisations remained high, with mean adjusted Rand index (ARI) values of 1.00 at $k=3$ and 0.98 at $k=4$. The four-state solution was therefore selected based on the combined evidence from cluster separation, state size balance, reproducibility and the additional temporal distinction provided by the fourth state.

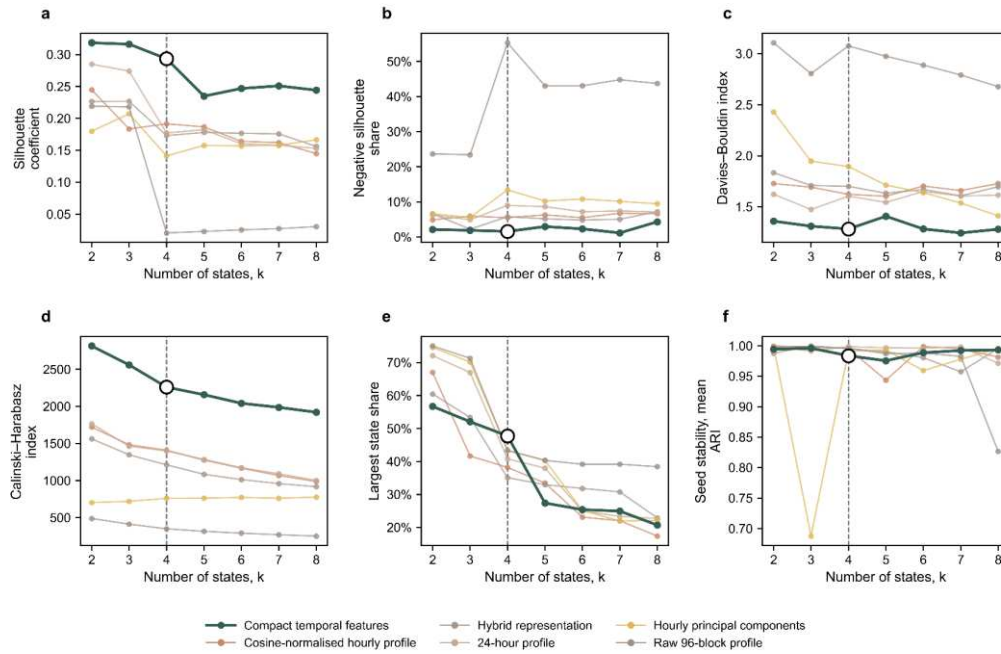


Figure 1. Evaluation of K-means clustering across six active load profile representations and $k=2-8$ states. **(a)** Mean silhouette coefficient. **(b)** Percentage of observations with negative silhouette values. **(c)** Davies–Bouldin index. **(d)** Calinski–Harabasz index. **(e)** Largest state share. **(f)** Mean adjusted Rand index (ARI) across repeated initialisations.

The selected solution was then evaluated under alternative sample and preprocessing specifications. Restricting the analysis to the common monitoring period yielded an ARI of 0.96 relative to the primary solution, indicating that differences in monitoring periods across locations did not determine the state assignments. Complete day analysis produced an ARI of 0.98, and omission of zero-value repair produced an ARI of 0.99. Replacing the primary fifth-percentile persistent load definition with first- and tenth-percentile definitions gave minimum matched state profile correlations of 0.996 and 0.994, respectively. The state specific robustness results and additional sensitivity analyses are reported in the Supplementary Information.

3.2 Characteristics of the four operating states

The selected four state compact-feature solution separated the 44,571 retained household-days according to differences in the timing and concentration of normalised active demand. The temporal profile distribution and peak time characteristics of each resulting cluster were then used to characterise the four operating states (Fig. 2): S1, concentrated morning peak; S2, diffuse morning-led operation; S3, concentrated daytime peak; and S4, extended evening-to-night operation. As classification was performed at the household-day level, individual households could contribute days to more than one state.

The concentrated morning-peak state (S1) was observed on 7,150 household-days (16.04%) from 81 households and showed a narrow concentration of active demand in the early morning, with a median peak time of 07:45. The diffuse morning-led state (S2) occurred on 8,462 days (18.99%) across 121 households and had the same median peak time of 07:45, although active demand was distributed more broadly across the morning, daytime and evening periods. The concentrated daytime-peak state (S3) comprised 8,040 days (18.04%) from 118 households and was concentrated around late morning and midday, with a median peak time of 11:45. The extended evening-to-night state (S4) accounted for 20,919 days (46.93%) from 130 households and showed sustained late-day demand, with a median peak time of 19:15 and a peak time interquartile range of 13:30–21:00. Household counts are non-exclusive because the same household could occupy different states on different days.

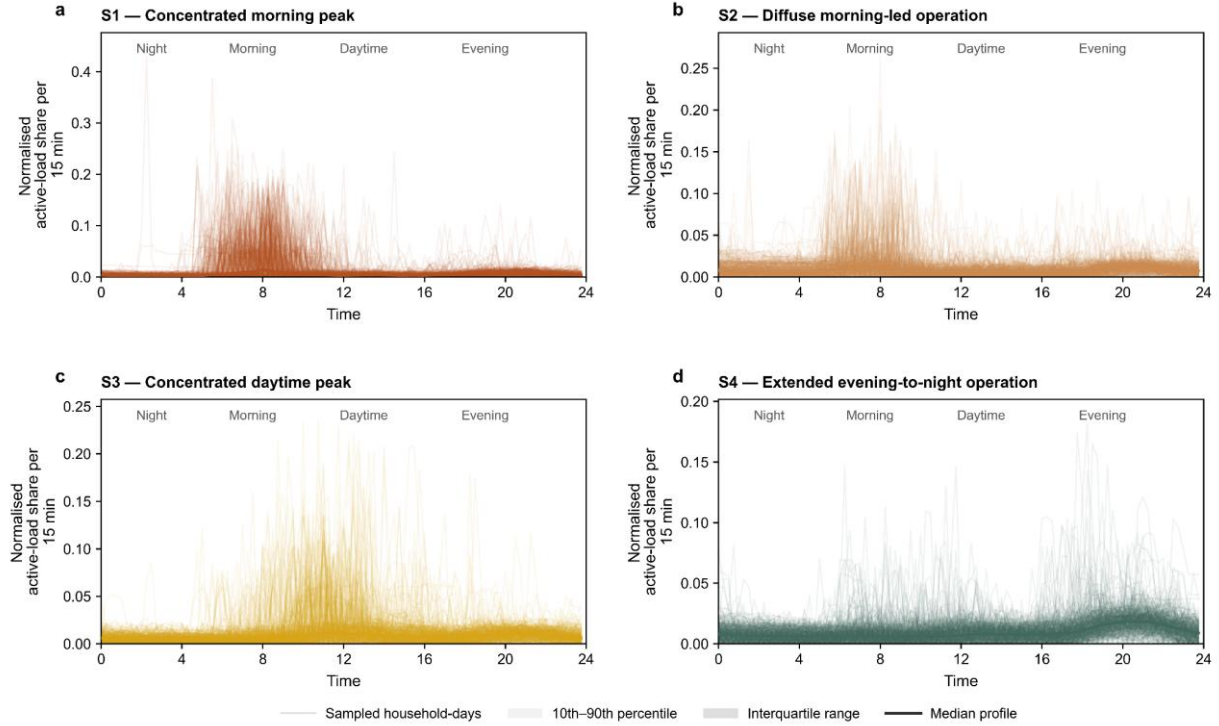


Figure 2. Temporal profiles of the four recurring household-day operating states. **a**, Concentrated morning-peak state (S1), characterized by a narrow early-morning concentration of active demand and a median peak time of 07:45. **b**, Diffuse morning-led state (S2), with a morning maximum at 07:45 and active demand distributed across a longer portion of the day. **c**, Concentrated daytime-peak state (S3), characterised by concentration around late morning and midday and a median peak time of 11:45. **d**, Extended evening-to-night state (S4), characterised by sustained late-day demand and a median peak time of 19:15.

Absolute demand characteristics were examined after state assignment (Fig. 3). Median active electricity was 4.06 kWh in the concentrated morning-peak state (S1), 3.43 kWh in the diffuse morning-led state (S2), 3.38 kWh in the concentrated daytime-peak state (S3), and 2.48 kWh in the extended evening-to-night state (S4). Median peak excess followed a similar ordering, at 2.02, 1.24, 1.25 and 0.35 kW, respectively. The diffuse morning-led state (S2) and concentrated daytime-peak state (S3) therefore had nearly identical median active electricity and peak excess despite clear differences in demand timing. The combined distribution of active electricity and peak excess also showed substantial overlap between states, with the concentrated morning-peak state (S1) extending toward higher peak-excess values and the extended evening-to-night state (S4) concentrated at lower peak-excess values (Fig. 3a–c). Peak timing separated the states more clearly: the concentrated morning-peak state (S1) and diffuse morning-led state (S2) had median peaks at 07:45, the concentrated daytime-peak state (S3) at 11:45, and the extended evening-to-night state (S4) at 19:15 (Fig. 3d).

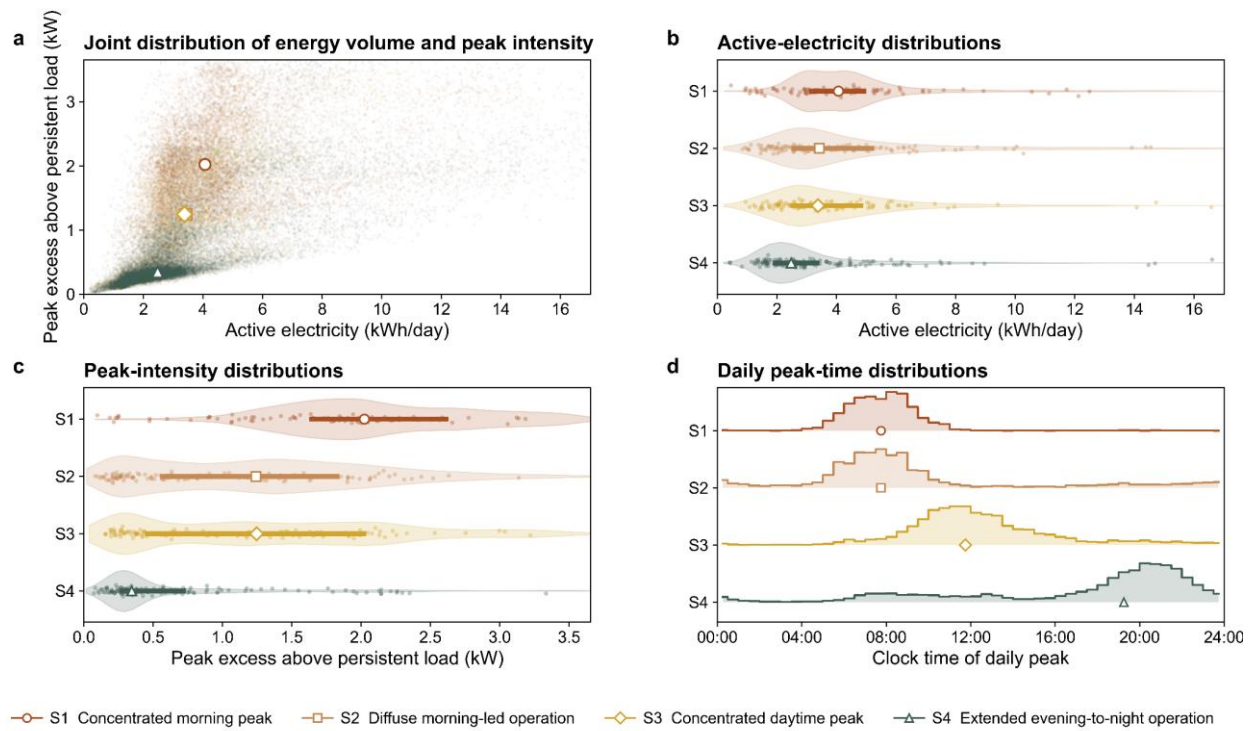


Figure 3. Active electricity, peak excess and peak timing across the four household-day operating states. **a**, Joint distribution of daily active electricity and peak excess for household-days assigned to the four states. **b**, State specific distributions of daily active electricity. **c**, State specific distributions of peak excess above the estimated household-day persistent power level. **d**, State specific distributions of daily peak time across the 24-h period. State assignment was based on normalised active load profiles; the absolute electricity and peak quantities shown here were evaluated after classification.

The four operating states distinguished temporal demand structure from absolute demand magnitude. This was most evident for the diffuse morning-led state (S2) and concentrated daytime-peak state (S3), which had similar active electricity and peak excess distributions despite different peak timing and within day demand concentration. Normalisation of the active load profiles therefore allowed household-days with comparable electricity use and peak magnitude to be differentiated by the timing and distribution of demand across the day.

3.3 Appliance ownership and whole-house demand characteristics

The four operating states differed in the timing, concentration and peak characteristics of daily electricity demand. To examine whether related whole-house demand characteristics varied with appliance ownership, survey-reported ownership was linked to the interval-meter records. Air-conditioner ownership was examined in relation to the response of daily active electricity to CDD_{24} , and electric water heater ownership was examined in relation to morning active electricity share and peak excess. As the outcomes were derived from whole-house meters, the estimated differences represent demand characteristics associated with appliance ownership rather than appliance specific electricity consumption.

Among the 105 households included in the air-conditioner analysis, the median household-specific CDD_{24} response was 0.64 kWh/day per $^{\circ}C \cdot day$ for the 28 air-conditioner owners and 0.08 kWh/day per $^{\circ}C \cdot day$ for the 77 non-owners (Fig. 4). The median difference between the ownership groups was 0.56 kWh/day per $^{\circ}C \cdot day$ (95% confidence interval [CI] 0.19 to 0.79). Over the common monitoring period, the separation in daily active electricity between owners and non-owners increased with CDD_{24} , with the larger increase occurring among air-conditioner-owning households. Household-specific response coefficients showed the same group-level difference, although the owner and non-owner distributions overlapped. Adjustment for regional composition produced an ownership associated difference of 0.62 kWh/day per $^{\circ}C \cdot day$ (95% CI 0.39 to 0.85), and restriction to regions containing both ownership groups produced an estimate of 0.63 kWh/day per $^{\circ}C \cdot day$ (95% CI 0.40 to 0.88). Air-conditioner ownership was therefore associated with greater whole-house active electricity responsiveness to increasing CDD_{24} .

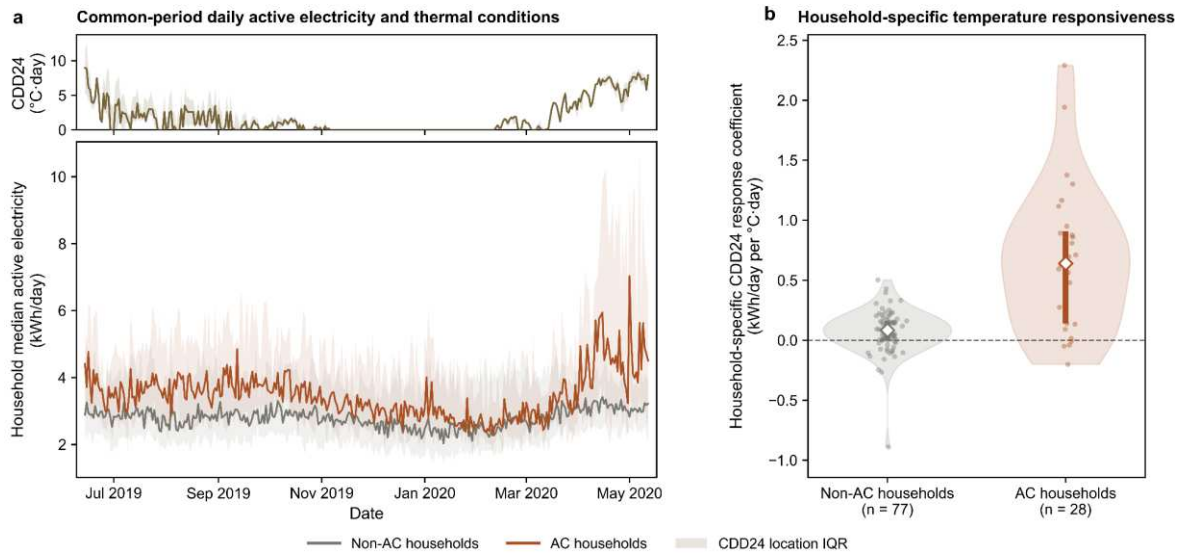


Figure 4. Air-conditioner ownership and temperature responsiveness of whole-house active electricity. **a**, Common-period variation in CDD₂₄ and daily whole-house active electricity for air-conditioner-owning and non-owning households across the monitoring period. **b**, Distribution of household-specific CDD₂₄ response coefficients for non-owners and owners.

The electric water heater analysis included 110 households, comprising 38 owners and 72 non-owners. Water heater-owning households had a greater share of daily active electricity concentrated in the morning period (05:00–09:59), with a larger owner–non-owner separation in winter than in summer (Fig. 5). The owner–non-owner profile difference was concentrated in the morning. As the profiles were normalised to total daily active electricity, the larger morning share was accompanied by negative proportional differences during much of the later day. After adjustment for region and season, electric water heater ownership was associated with a 15.30-percentage-point greater morning active electricity share (95% CI 9.42 to 20.28) and 1.05 kW greater peak excess (95% CI 0.76 to 1.35). The ownership associated difference in morning share was 7.65 percentage points greater in winter than in summer (95% CI 3.50 to 11.79), and the corresponding difference in peak excess was 0.38 kW greater in winter (95% CI 0.07 to 0.66).

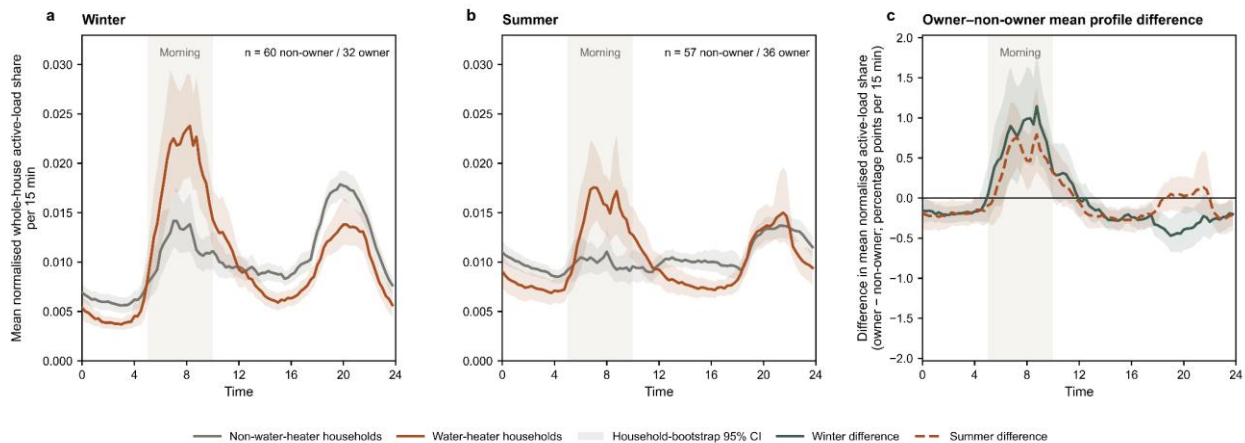


Figure 5. Whole-house active load profiles by electric water heater ownership in winter and summer. **a**, Winter mean normalised active load profiles for water heater owners and non-owners. **b**, Corresponding summer profiles. **c**, Owner–non-owner difference in the mean normalised active load profile for winter and summer.

3.4 Within household state diversity and consecutive-day transitions

To determine whether the four operating states represented stable household-level patterns or changing daily operating conditions, their distribution within individual households and their persistence across consecutive days were evaluated. Within household diversity was summarized using normalised state entropy, which ranges from 0 when a household’s days are concentrated in a single state to 1 when its days are distributed evenly across all four states. Consecutive-day behaviour was examined using two transition summaries. The pooled transition matrix combined all eligible consecutive-day transitions across households, so households with longer

monitoring records contributed more observations. The household-balanced matrix first calculated transition probabilities separately for each household and then averaged households equally within each origin state.

Operating state assignments were distributed across multiple states within individual households over the monitoring period (Fig. 6). The extended evening-to-night state (S4) occurred in 130 households, the diffuse morning-led state (S2) in 121, the concentrated daytime-peak state (S3) in 118 and the concentrated morning-peak state (S1) in 81. The extended evening-to-night state (S4) was the dominant state in 82 households (61.7%), compared with 23 households for the diffuse morning-led state (S2), 15 for the concentrated morning-peak state (S1) and 11 for the concentrated daytime-peak state (S3); two households had tied dominant states. Among the 109 households meeting the entropy-analysis criteria, median normalised state entropy was 0.71, indicating that retained days were distributed across several operating states for majority of the households.

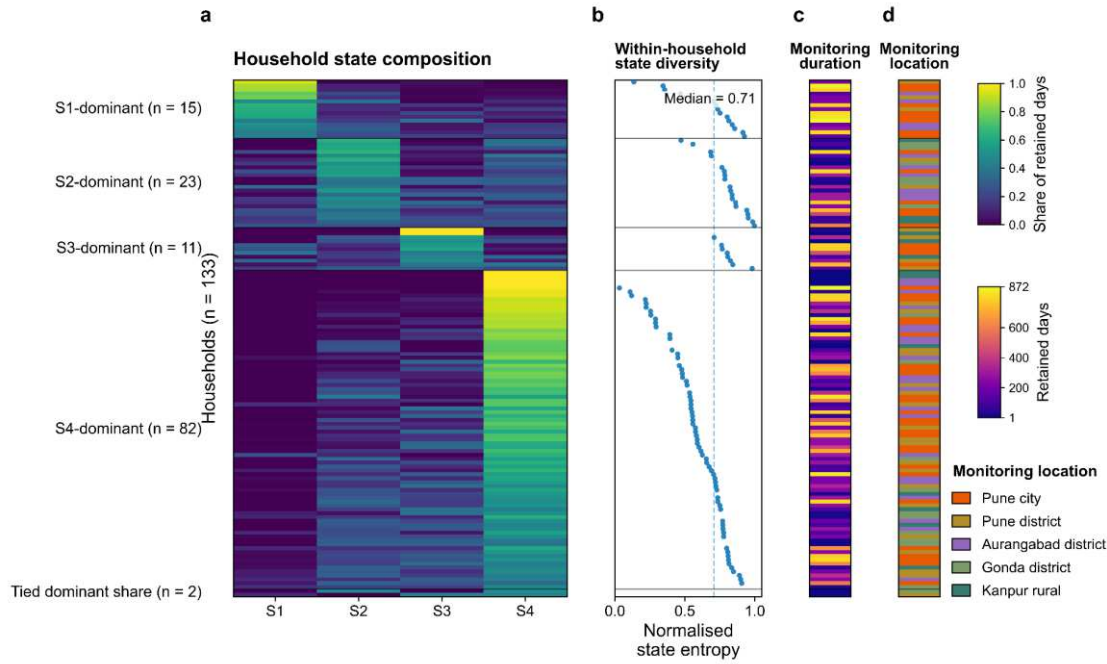


Figure 6. Household-level operating state composition and within household diversity. **a**, Proportion of retained household-days assigned to the concentrated morning-peak state (S1), diffuse morning-led state (S2), concentrated daytime-peak state (S3) and extended evening-to-night state (S4) for each household, grouped by dominant state. **b**, Normalised Shannon entropy of state occupancy for each household. **c**, Number of retained household-days contributing to the analysis for each household. **d**, Monitoring location of each household.

Consecutive-day transitions differed across the four operating states (Fig. 7). In the household-balanced analysis, the probability of remaining in the same state on the following day was 59.13% for the extended evening-to-night state (S4), 47.55% for the concentrated morning-peak state (S1), 33.93% for the diffuse morning-led state (S2) and 30.49% for the concentrated daytime-peak state (S3). For the diffuse morning-led state (S2) and concentrated daytime-peak state (S3), transition to the extended evening-to-night state (S4) was more frequent than same state persistence: 39.84% of S2 days and 40.21% of S3 days were followed by S4. From the extended evening-to-night state (S4), transitions occurred most frequently to the diffuse morning-led state (S2; 19.10%) and concentrated daytime-peak state (S3; 17.00%), while transition to the concentrated morning-peak state (S1) occurred on 4.8% of occasions.

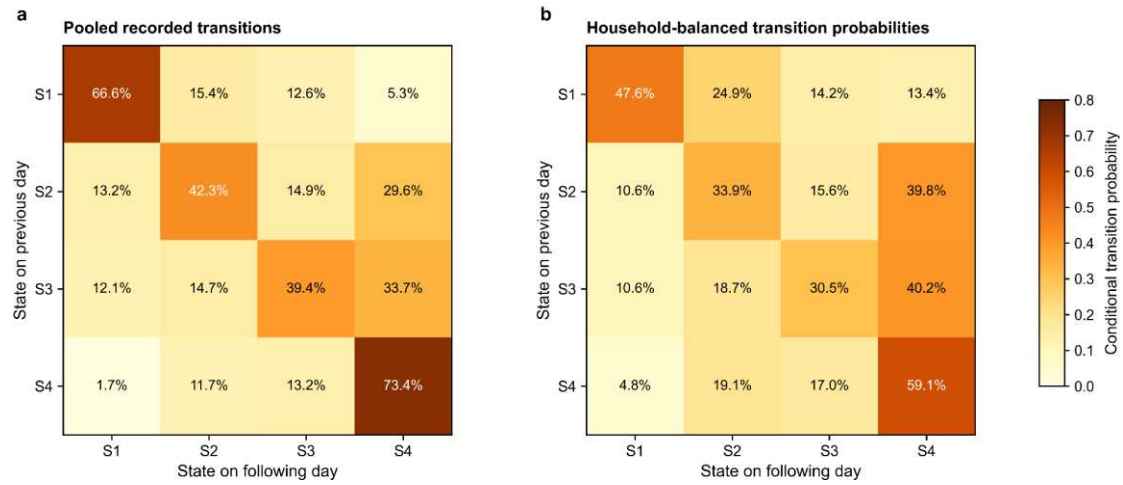


Figure 7. Consecutive-day transition probabilities among the four household-day operating states. **a**, Pooled transition matrix calculated from all eligible consecutive-day transitions. **b**, Household-balanced transition matrix obtained by calculating transition probabilities within each household and averaging households equally within each origin state.

Same state persistence was higher in the pooled analysis than in the household-balanced analysis for all four states. Pooled persistence was 66.62% for the concentrated morning-peak state (S1), 42.35% for the diffuse morning-led state (S2), 39.42% for the concentrated daytime-peak state (S3) and 73.40% for the extended evening-to-night state (S4), compared with 47.55%, 33.93%, 30.49% and 59.13%, respectively, in the household-balanced analysis.

3.5 Operating states associated with high-peak days

To examine how high demand events were distributed across the four operating states, daily peak excess was evaluated along with the timing of the daily maximum. The global high peak threshold, defined from the upper 5% of peak excess values across all retained household-days, was 2.975 kW and identified 2,229 household-days (Fig. 8). High peak timing differed across the operating states. High peak events assigned to the concentrated morning-peak state (S1) occurred mainly during the morning, those assigned to the concentrated daytime-peak state (S3) extended through late morning and midday, and those assigned to the extended evening-to-night state (S4) occurred predominantly later in the day. The timing of the largest peak events therefore followed the temporal structure of the operating states.

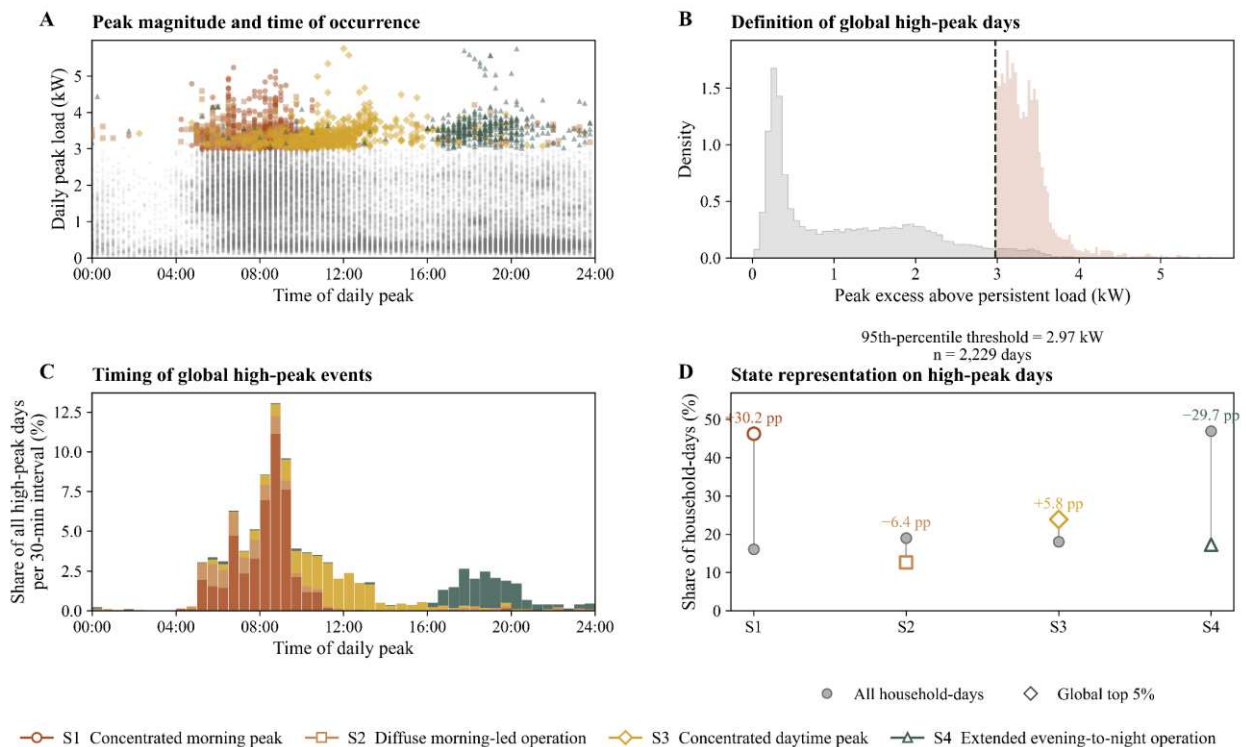


Figure 8. Magnitude, timing and operating state representation of global high peak days. **a**, Daily peak excess plotted against the time of the daily maximum for all retained household-days, with global high peak days identified by operating state. **b**, Distribution of daily peak excess across the complete household-day sample; threshold of 2.975 kW used to define global high peak days. **c**, Time-of-day distribution of global high peak events, separated by the concentrated morning-peak state (S1), diffuse morning-led state (S2), concentrated daytime-peak state (S3) and extended evening-to-night state (S4). **d**, Operating state composition of all retained household-days compared with the global high peak subset.

The operating state composition of global high peak days differed from that of the complete household-day sample. The concentrated morning-peak state (S1) accounted for 46.25% of high peak days compared with 16.04% of all retained days, an increase of 30.21 percentage points. The concentrated daytime-peak state (S3) increased from 18.04% to 23.87%, a difference of 5.83 percentage points. In contrast, the diffuse morning-led state (S2) decreased from 18.99% to 12.61%, and the extended evening-to-night state (S4) decreased from 46.93% to 17.27%. The concentrated morning-peak state (S1) and concentrated daytime-peak state (S3) represented 70.12% of global high peak days, compared with 34.08% of all retained household-days. Thus, the largest daily peak events were disproportionately represented by the two states characterised by concentrated morning or daytime demand.

When high peak days were defined relative to each household's own peak excess distribution, the prevalence of the concentrated morning-peak state (S1) and concentrated daytime state (S3) also increased. Among 99 eligible households, S1 increased by 8.82 percentage points (95% CI 5.75 to 12.52) and S3 by 5.71 percentage points (95% CI 2.12 to 9.49) on each household's own top-5% peak days. The diffuse morning-led state (S2) decreased by 3.91 percentage points and the extended evening-to-night state (S4) by 10.63 percentage points. The greater representation of concentrated morning and daytime operation during high peak events was therefore observed both across the full sample and within individual households.

4. Discussion

This study examined day-to-day variation in residential electricity demand within individual households using 15-minute whole-house electricity data. Four recurring household-day electricity demand states were identified: concentrated morning peak, diffuse morning-led operation, concentrated daytime peak and extended evening-to-night operation. Individual households commonly occupied several states during monitoring, showing that a household average profile can obscure day-to-day variation. This is consistent with residential smart-meter analyses showing that aggregation reduces the intra-household temporal variation retained in daily profiles [6,7]. Extended evening-to-night operation was the most prevalent and persistent state, whereas diffuse morning-led and concentrated daytime operation persisted on approximately one-third of consecutive days and frequently transitioned to the evening-to-night state. The operating states consequently describe recurring daily demand conditions that change within households over time. Large-scale smart-meter analysis has reported similar within household variation; among 60,000 households observed for one year, 73% exhibited more than one energy lifestyle across the year [17].

The operating states also distinguished demand characteristics of household electricity consumption. Diffuse morning-led and concentrated daytime operation had similar median active electricity (3.43 and 3.38 kWh) and peak excess (1.24 and 1.25 kW), although their median peak times differed by four hours. Concentrated morning-peak and diffuse morning-led operation shared a median peak time of 07:45, with median peak excess of 2.02 and 1.24 kW, respectively. This distinction is consistent with load profile analyses that use temporal and peak related features to characterise residential demand [10,18]. The concentrated morning-peak, concentrated daytime-peak and extended evening-to-night states were reproduced across the alternative specifications, whereas diffuse morning-led operation was more sensitive to regional balancing, zero treatment and temporal smoothing. Sensitivity of load profile classifications to preprocessing and clustering choices has also been documented in previous analyses [9,14].

The thermal analysis showed a consistent reduction in the prevalence of concentrated morning-peak operation across the cooling-degree, seasonal and direct-temperature contrasts (Supplementary Table S11 and Supplementary Fig. S6). Temperature and season-related changes in the prevalence of residential load profiles have also been reported in longitudinal smart-meter analyses [8,19]. In the present data, air-conditioner-owning households showed a median CDD₂₄ response of 0.64 kWh/day per °C·day, compared with 0.08 kWh/day per °C·day among non-owners. Previous Indian analyses have similarly reported heterogeneity in household electricity response to high temperature [20] and increased residential air-conditioning demand during summer,

with substantial night-time air-conditioning use [21]. Electric water heater ownership was associated with a distinct temporal component of whole-house demand. After adjustment for region and season, owners had a 15.30-percentage-point greater morning active electricity share and 1.05 kW greater peak excess, with the ownership associated morning difference increasing by 7.65 percentage points in winter relative to summer. Appliance-wise residential load profile simulations in previous work have similarly placed electric water heating demand around the morning secondary peak and air-conditioning demand at the evening system peak [22]. The ownership analyses consequently identify different whole-house demand characteristics associated with cooling and water heating equipment: temperature responsiveness in daily active electricity for air-conditioner ownership and morning concentration and peak excess for electric water heater ownership.

The high peak analysis shows that temporal demand structure is relevant to the occurrence of large household peaks. The concentrated morning-peak and concentrated daytime-peak states represented 34.08% of all household-days but 70.12% of the pooled top 5% of peak excess days. Concentrated morning-peak operation increased from 16.04% of all days to 46.25% of high peak days, whereas extended evening-to-night operation decreased from 46.93% to 17.27%. Residential peak profile research has similarly shown that differences in peak demand are associated with the timing and concentration of household activities [12]. The present analysis extends this comparison across complete household-days. On each household's own top-5% peak days, concentrated morning-peak and concentrated daytime-peak states increased by 8.82 and 5.71 percentage points, while diffuse morning-led and extended evening-to-night operation decreased by 3.91 and 10.63 percentage points. The within household analysis shows that the enrichment of concentrated morning and daytime states during high peak events remained when each household was evaluated relative to its own peak excess distribution. Cluster-specific load shape characteristics have also been used to identify residential consumers with different potential for demand-side management and net-metering programmes [23]. The present results add a within household temporal dimension: the operating state associated with a household's high peak days can differ from its most frequent operating condition. This distinction is relevant when high resolution meter data are used to identify demand-response periods or households contributing to peak demand.

4.1 Study scope and transferability

The findings apply to the longitudinal eMARC volunteer sample, with monitoring duration and household representation varying across five locations. Household-balanced fitting, resampling and common-period analyses were used to limit the influence of unequal records; population prevalence across Indian households was not estimated. Weather was assigned by location and date, while indoor conditions, occupancy, tariffs, outages and appliance operation were unavailable at comparable temporal resolution, so air-conditioner and electric water heater results represent ownership associated whole-house demand characteristics. The operating state classification was robust across the principal alternative specifications, although the diffuse morning-led state was more sensitive to regional balancing, zero treatment and temporal smoothing. Validation using independent Indian smart-meter datasets with broader climatic, dwelling and appliance diversity, along with occupancy and appliance-level measurements, would allow wider testing of state reproducibility, prevalence and the processes underlying high peak events.

5. Conclusion

This study used 44,571 household-days from 133 households to examine day-to-day variation in residential electricity demand structure and its relationship with appliance ownership and high peak events. Four recurring household-day operating states were identified: concentrated morning peak, diffuse morning-led operation, concentrated daytime peak and extended evening-to-night operation. Individual households occupied multiple states across the monitoring period, confirming substantial within household variation in daily demand patterns.

- Household-day operating states captured distinct temporal demand structures. Diffuse morning-led and concentrated daytime-peak operation had similar median active electricity (3.43 and 3.38 kWh) and peak excess (1.24 and 1.25 kW), despite median peak times of 07:45 and 11:45. State occupancy also changed across consecutive days, with same state persistence ranging from 30.49% for concentrated daytime-peak operation to 59.13% for extended evening-to-night operation in the household-balanced analysis.
- Appliance ownership was associated with distinct whole-house demand characteristics. Air-conditioner-owning households had a median CDD₂₄ response of 0.64 kWh/day per °C·day, compared

with 0.08 kWh/day per °C·day among non-owners. Electric water heater ownership was associated with a 15.30-percentage-point greater morning active electricity share and 1.05 kW greater peak excess after adjustment for region and season, with the morning difference larger in winter.

- Operating state composition differed during high peak events. Concentrated morning-peak and concentrated daytime-peak states represented 34.08% of all household-days but 70.12% of the pooled top 5% of peak excess days. The same direction was observed within households: on each household's own top-5% peak days, concentrated morning-peak and concentrated daytime-peak states increased by 8.82 and 5.71 percentage points, while diffuse morning-led and extended evening-to-night operation decreased by 3.91 and 10.63 percentage points.

These findings show that residential electricity demand is characterised by both magnitude and temporal structure. Household-day operating states retain differences in demand timing, concentration and peak occurrence that are reduced when demand is represented only by consumption totals or household average profiles. Representing households as sequences of recurring daily operating states therefore provides a more informative basis for examining within household variation and identifying the temporal conditions associated with high residential peaks.

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CRedit authorship contribution statement

Krithika Panicker: Conceptualization, Methodology, Software, Formal analysis, Data curation, Visualization, Writing – original draft. Prashant Anand: Conceptualization, Methodology, Supervision, Writing – review and editing. Abraham George: Conceptualization, Methodology, Supervision, Writing – review and editing.

Data availability

The household electricity and survey data analysed in this study are publicly available through Harvard Dataverse as *Household energy consumption data: Processed data* (Prayas Energy Group, 2021; <https://doi.org/10.7910/DVN/YJ5SP1>). Historical weather data were obtained from the Open-Meteo Historical Weather API. Derived results and robustness analyses are reported in the article and Supplementary Information.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics statement

This study is a secondary analysis of anonymised, publicly available eMARC electricity and household-survey data by Prayas (Energy Group) and involved no recruitment, intervention or collection of identifiable personal information by the authors. Prayas (Energy Group), were informed of the present secondary use of the dataset.

Declaration of generative Artificial Intelligence (AI) and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist with language editing, manuscript organisation and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Figure and Table Legend

Item	Legend
Figure 1	Evaluation of K-means clustering across six active-load profile representations and $k = 2-8$ states. (a) Mean silhouette coefficient. (b) Percentage of observations with negative silhouette values. (c) Davies–Bouldin index. (d) Calinski–Harabasz index. (e) Largest state share. (f) Mean adjusted Rand index (ARI) across repeated initialisations.
Figure 2	Temporal profiles of the four recurring household-day operating states (a) Concentrated morning-peak state (S1), characterised by a narrow early-morning concentration of active demand and a median peak time of 07:45. (b) Diffuse morning-led state (S2), with a morning maximum at 07:45 and active demand distributed across a longer portion of the day. (c) Concentrated daytime-peak state (S3), characterised by concentration around late morning and midday and a median peak time of 11:45. (d) Extended evening-to-night state (S4), characterised by sustained late-day demand and a median peak time of 19:15.
Figure 3	Active electricity, peak excess and peak timing across the four household-day operating states. (a) Joint distribution of daily active electricity and peak excess for household-days assigned to the four states. (b) State-specific distributions of daily active electricity. (c) State-specific distributions of peak excess above the estimated household-day persistent-power level. (d) State-specific distributions of daily peak time across the 24-h period. State assignment was based on normalised active-load profiles; the absolute electricity and peak quantities shown were evaluated after classification.
Figure 4	Air-conditioner ownership and temperature responsiveness of whole-house active electricity. (a) Common-period variation in CDD24 and daily whole-house active electricity for air-conditioner-owning and non-owning households across the monitoring

Item	Legend
	period. (b) Distribution of household-specific CDD24 response coefficients for air-conditioner non-owners and owners. Positive coefficients indicate increasing daily active electricity with increasing CDD24.
Figure 5	Whole-house active-load profiles by electric water-heater ownership in winter and summer. (a) Winter mean normalised active-load profiles for water-heater owners and non-owners. (b) Corresponding summer profiles. (c) Owner–non-owner difference in the mean normalised active-load profile for winter and summer.
Figure 6	Household-level operating-state composition and within-household diversity. (a) Proportion of retained household-days assigned to the concentrated morning-peak state (S1), diffuse morning-led state (S2), concentrated daytime-peak state (S3) and extended evening-to-night state (S4) for each household, grouped by dominant state. (b) Normalised Shannon entropy of state occupancy for each household. (c) Number of retained household-days contributing to the analysis for each household. (d) Monitoring location of each household.
Figure 7	Consecutive-day transition probabilities among the four household-day operating states. (a) Pooled transition matrix calculated from all eligible consecutive-day transitions. (b) Household-balanced transition matrix obtained by calculating transition probabilities within each household and averaging households equally within each origin state. Rows represent the origin state and columns represent the following-day state; diagonal values indicate same-state persistence.
Figure 8	Magnitude, timing and operating-state representation of global high-peak days. (a) Daily peak excess plotted against the time of the daily maximum for all retained household-days, with global high-peak days identified by operating state. (b) Distribution of daily peak excess across the complete household-day sample; the 2.975 kW threshold defines the global top-5% high-peak subset. (c) Time-of-day distribution of global high-peak events separated by the concentrated morning-peak state (S1), diffuse morning-led state (S2), concentrated daytime-peak state (S3) and extended evening-to-night state (S4). (d) Operating-state composition of all retained household-days compared with the global high-peak subset.
Table 1	Selected residential electricity-demand studies relevant to household-day profile analysis, temporal variation and peak demand.

Supplementary Files

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