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COMPARATIVE ANALYSIS OF ELECTRICITY CONSUMPTION PATTERNS ACROSS FOUR K-MEANS CLUSTERS OF SMALL AND MEDIUM ENTERPRISES

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The paper presents a comparative analysis of the electricity consumption profiles of four consumer clusters identified by k-means segmentation of hourly smart-meter data from small and medium enterprises (SMEs) in Latvia. The four clusters were developed using data acquired from 3,016 metering points representing structurally distinct archetypes of temporal consumption behaviour: Cluster 0 (n = 382, evening entertainment), Cluster 1 (n = 1,712, continuously operating infrastructure), Cluster 2 (n = 323, daytime-active retail), and Cluster 3 (n = 599, nocturnal operations). The analysis demonstrates key dimensions of difference across clusters: peak hour of day, day-of-week seasonality, weekend-to-weekday load ratio, diurnal amplitude, and night-time baseload behaviour. These four distinct SME types account for the full range of SME load profile variability observed in the dataset. Implications for demand-side management, time-of-use tariff design, distribution network planning, and short-term load forecasting are discussed for each cluster and comparatively across the full typology.

Keywords: *Demand-side management, diurnal pattern, load profile typology, k-means clustering, smart metering, SME electricity consumption, weekly seasonality.*

1. INTRODUCTION

The understanding of electricity consumption patterns among small and medium enterprises has emerged as a priority research area in applied energy analytics, driven by the proliferation of smart metering infrastructure, the growing importance of demand-side flexibility in distributed energy systems, and the need for more granular load forecasting at the distribution network level [1], [2]. Consumer segmentation through unsupervised clustering methods, particularly k-means, has been widely demonstrated as an effective approach for identifying groups of metering points that share coherent temporal consumption signatures, enabling the development of group-level demand-response programmes, differentiated tariff structures, and cluster-specific forecasting models [3], [4].

Earlier studies have established various frameworks for characterising electricity consumption profiles of commercial and residential consumers. Figueiredo et al. [5] introduced a data-mining-based characterisation framework for energy consumers. McLoughlin et al. [6] developed clustering approaches for domestic load profile characterisation using smart metering data, and Räsänen et al. [7] demonstrated data-based methods for creating electricity use load profiles from large customer datasets. A comprehensive review of low-voltage load forecasting methods and applications further confirms the importance of cluster-level analysis for accurate and scalable demand modelling. These methodological foundations underpin the present research.

The present paper integrates the findings from four individual cluster analyses conducted on a common hourly SME metering dataset from Latvia, providing a direct comparative context and drawing on consistent data representations and a unified analytical framework to illuminate structural differences and operational interpretations across the four consumer archetypes [8]. The analytical framework applied two-pass daily-mean shape Z-score normalization to energy consumption data acquired from 3,016 metering points. This procedure standardises each client's hourly consumption shape relative to their own daily mean, followed by k-means clustering with Silhouette-coefficient-based selection of the optimal number of clusters [9]. The resulting four-cluster solution distributes the 3,016 metering points as follows: Cluster 0 (n = 382), Cluster 1 (n = 1,712), Cluster 2 (n = 323), and Cluster 3 (n = 599). Cluster 1 is by far the largest, representing 56.8 % of the total consumer population, while Cluster 2 is the smallest at 10.7 % [9].

2. MATERIALS AND METHODS

2.1 Theoretical Basis

The k-means clustering algorithm partitions *n* observations into *k* clusters by minimising the within-cluster sum of squared distances from each observation to its cluster centroid. The algorithm iterates between assignment of data points to the nearest centroid and recalculation of centroids until convergence. Formally, for a dataset $X = \{x_1, ..., x_n\}$, k-means minimises the objective function:

$J = \Sigma^k \Sigma_i \|x_i - \mu k\|^2$,

where μk is the centroid of cluster *k*. Cluster quality is evaluated using the Silhouette coefficient, which measures cohesion and separation for each data point and ranges from −1 (poor assignment) to +1 (ideal assignment). The optimal number of clusters *k* is selected as the value maximising the mean Silhouette score across all data points [9].

Before clustering, each consumer's 24-hour load profile is normalized using a two-pass daily mean shape Z-score procedure. In the first pass, the hourly consumption values for each day are normalized by the daily mean, producing a shape vector that is scale-invariant. In the second pass, these daily shape vectors are standardised across days using the Z-score transformation. This procedure removes absolute consumption magnitude as a clustering dimension while preserving the temporal structure of each consumer's load profile [10], [16].

2.2 Research Object and Dataset

The dataset consists of hourly smart-meter data from 3,016 SME metering points operated within the TET Ltd distribution network in Latvia. The data encompass a representative cross-section of Latvian SME electricity consumers across multiple economic sectors, including retail, hospitality, logistics, manufacturing, and service industries. All data were collected via automatic meter reading (AMR) infrastructure with hourly temporal resolution.

The analysis was conducted using an automated load profile clustering and forecasting pipeline specifically developed for SME electricity data [8]. The pipeline implements the two-pass Z-score normalisation, k-keans clustering with automated *k* selection, and a suite of post-clustering diagnostic visualisations including diurnal profiles, day-of-week aggregations, and statistical comparison metrics.

The four-cluster solution was selected on the basis of the Silhouette coefficient, which achieved its maximum value at k = 4. This solution distributes the 3,016 metering points into four structurally distinct consumer archetypes with non-overlapping temporal signatures, confirming the validity of the segmentation. Cluster memberships, peak characteristics, and summary statistics are presented in the Results section.

2.3 Analytical Dimensions

Each cluster is characterised across six primary analytical dimensions: (1) peak hour of the day, the hour at which mean consumption is the highest; (2) peak day of the week, the day on which aggregate daily consumption is the highest; (3) a weekend-to-weekday mean load ratio, the ratio of mean consumption on Saturday and Sunday versus Monday through Friday; (4) diurnal coefficient of variation (CV), the standard deviation of the 24-hour mean profile expressed as a percentage of its mean; (5) diurnal amplitude, the difference between the maximum and minimum hourly mean values; and (6) night-time baseload behaviour, the relationship between night-time and daytime consumption levels. These dimensions collectively define each cluster's position in the temporal consumption space [11], [12].

3. RESULTS AND DISCUSSION

3.1 Cluster Overview and Summary Statistics

Table 1 provides a high-level summary of the four clusters, including membership size, identified consumer archetype, peak hour of day, peak day of week, weekend-to-weekday mean load ratio, diurnal coefficient of variation, and diurnal amplitude. These six dimensions collectively define the position of each cluster in the temporal consumption space and form the analytical backbone of the comparative analysis presented in subsequent sections [11].

Table 1. Comparative Summary of the Four SME Consumer Clusters Identified by K-Means Segmentation. Note: Diurnal amplitude for Cluster 0 is reported in normalized Z-score units; all others in kWh/h.

Metric	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Archetype	Evening Entertainment	Continuous Operations	Daytime Retail	Nocturnal Operations
Members (n)	382	1,712	323	599
Share of total (%)	12.7%	56.8%	10.7%	19.9%
Peak Hour	19:00–21:00	09:00 (flat)	15:00	01:00–02:00
Peak Day	Friday	Thursday	Sunday	Thursday
Weekend/Weekday Ratio	0.928	1.019	1.052	0.803
Diurnal CV (%)	22.5	1.56	17.21	16.22
Diurnal Amplitude (kWh/h or Z)	0.641 (Z)	0.055	0.714	0.615
Night Baseload Behaviour	Below the daily mean	Equal to daytime	Deep trough	Above daytime

3.2 Comparative Diurnal Load Profiles

Figure 1 presents the mean 24-hour diurnal load profiles for Clusters 1, 2, and 3 on a common absolute scale (kWh/h), enabling direct visual comparison of both shape and relative magnitude. The three profiles occupy entirely distinct regions of the hour-of-day versus consumption space, confirming the discriminative validity of the K-Means segmentation [9].

Cluster 1 (n = 1,712) presents a near-horizontal profile oscillating between 0.971 and 1.027 kWh/h — a diurnal amplitude of only 0.055 kWh/h (5.5 % of mean). This near-flatness is unique in the dataset and reflects a consumer population whose operational activities are uniformly distributed across all 24 hours, consistent with the baseload behaviour documented for continuously operating commercial facilities such as food retail, logistics hubs, and hospitality establishments [13]. Cluster 2 (n = 323) presents the archetypal daytime-active commercial profile, rising steeply from a 06:00 morning minimum (1.176 kWh/h) to a broad afternoon peak plateau at 14:00–17:00 (maximum 1.889 kWh/h at 15:00), then declining progressively through the evening. The diurnal amplitude is 0.714 kWh/h (48.3 % of mean), consistent with afternoon-peak patterns documented for retail and service-sector SMEs [13].

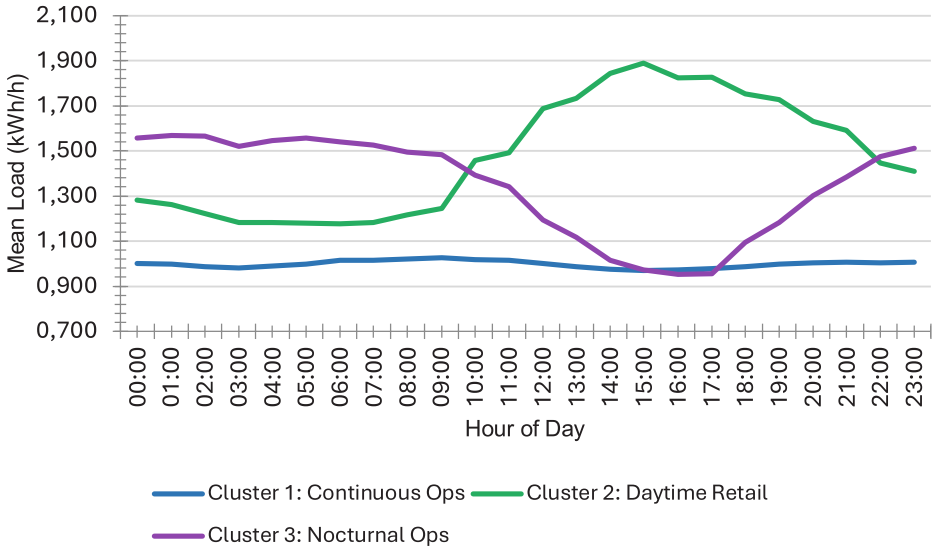

Fig. 1. Mean 24-hour diurnal load profiles for Clusters 1, 2, and 3 (kWh/h). Cluster 1 (blue) is near-flat at ~1.0 kWh/h. Cluster 2 (green) peaks at 15:00. Cluster 3 (purple) peaks at 01:00–02:00 and troughs at 16:00.

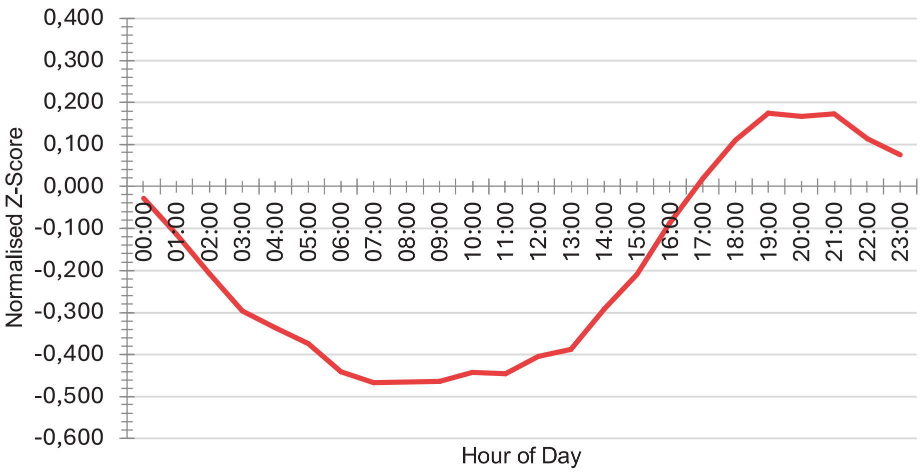

Fig. 2. Mean 24-hour normalized diurnal profile for Cluster 0 (Z-score). Values above 0 indicate above-daily-mean consumption; values below 0 indicate suppression. Peak at 19:00–21:00; trough at 07:00–09:00.

Cluster 3 (n = 599) presents the structural mirror image of Cluster 2: an elevated night-time plateau (00:00–07:00, mean 1.540 kWh/h) declining through business hours to a minimum of 0.952 kWh/h at 16:00, then recovering through a sharp reactivation step at 17:00–18:00 (+14.8 % in a single hour) before ascending toward the overnight peak. The night-to-daytime trough ratio of 1.596, meaning these businesses consume 60 % more at night than in the afternoon, is the defining diagnostic feature of this archetype, characteristic of process-driven night-shift operations in sectors such as cleaning, baking, and logistics [15].

Cluster 0's diurnal profile was captured in the normalized Z-score domain, as this cluster was characterised using the shape-normalized output rather than raw kWh/h. Figure 2 presents the 24-hour Z-score profile, which expresses each hour's mean consumption relative to each client's own daily mean, eliminating absolute scale while preserving shape [16].

The Cluster 0 profile reveals a morning suppression of consumption lasting from 07:00 to approximately 16:00 (Z-score consistently negative, trough −0.467 at 07:00), followed by a crossover to above-daily-mean consumption at 17:00 and a sustained evening peak at 19:00–21:00 (Z-score +0.174). The diurnal excursion amplitude of 0.641 Z-score units, combined with the shift from deep morning suppression to above-mean evening activity, defines the evening-entertainment archetype of this cluster, a pattern closely aligned with the evening load profiles documented for hospitality and leisure sector consumers [17]. Higher standard deviations during evening hours (SD 0.63–0.67) compared to morning hours (SD 0.38–0.43) indicate greater between-client and between-day heterogeneity during the peak window, consistent with the variable operating intensities typical of hospitality and entertainment businesses on different days [18].

3.3 Day-of-Week Load Patterns

Figure 3 presents the mean daily load (kWh/h) for all four clusters across the seven days of the week. The plot reveals dramatically different weekly seasonality structures across the four archetypes, with particularly notable differences in peak-day identity and weekend-to-weekday orientation. Weekly variation is a well-established dimension of commercial electricity demand, with different business sectors exhibiting structurally distinct day-of-week profiles [19].

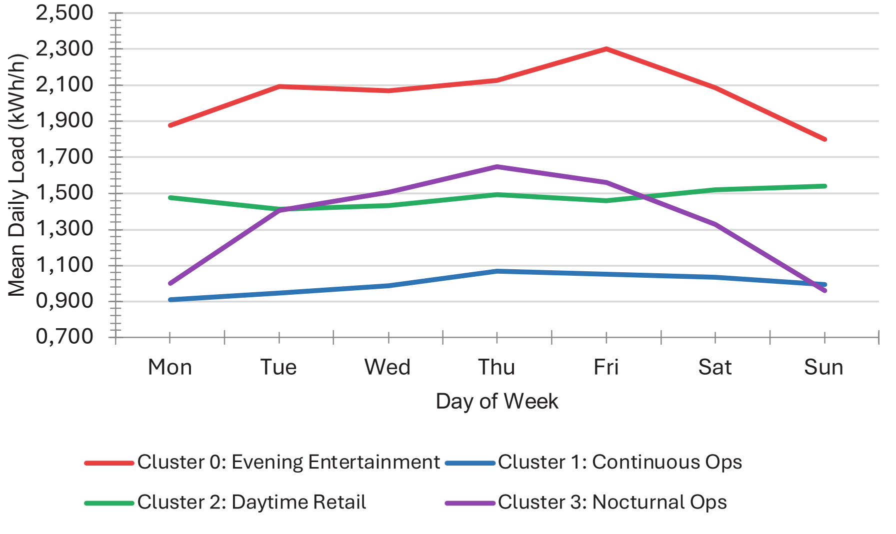

Fig. 3. Mean daily load by day of the week for all four clusters (kWh/h). Note the diverging weekend profiles: Clusters 2 and 1 rise at the weekend, while Clusters 0 and 3 decline.

Four structurally distinct weekly patterns emerge. Cluster 0 shows a pronounced Friday peak (2.303 kWh/h) with Monday (1.875 kWh/h) and Sunday (1.799 kWh/h) as the low-demand bookends, a pattern consistent with the end-of-week intensification of evening-entertainment activity [20]. Cluster 1 presents the flattest weekly profile, oscillating between 0.909 kWh/h on Monday and 1.067 kWh/h on Thursday (a Thursday/Monday ratio of 1.173), with weekends marginally exceeding weekdays (ratio 1.019) [13].

Cluster 2 exhibits a systematic weekend elevation, with Sunday as the peak day (1.541 kWh/h) and the weekend-to-weekday ratio of 1.052 the highest of the four clusters, consistent with consumer-facing retail and leisure businesses that peak on Sunday afternoons [14]. Cluster 3 shows the strongest day-of-week contrast of any cluster, with a Thursday peak (1.649 kWh/h) and Sunday minimum (0.961 kWh/h) producing a Max/Min ratio of 1.716 – a pattern consistent with commercial operations that cease entirely on Sundays [15].

Figure 4 presents the hourly load profiles for all four clusters on Thursday: the peak day for Clusters 1 and 3. For Cluster 0, the profile is expressed as approximate kWh/h derived from the normalized Z-score profile scaled to the cluster's mean load level [21].

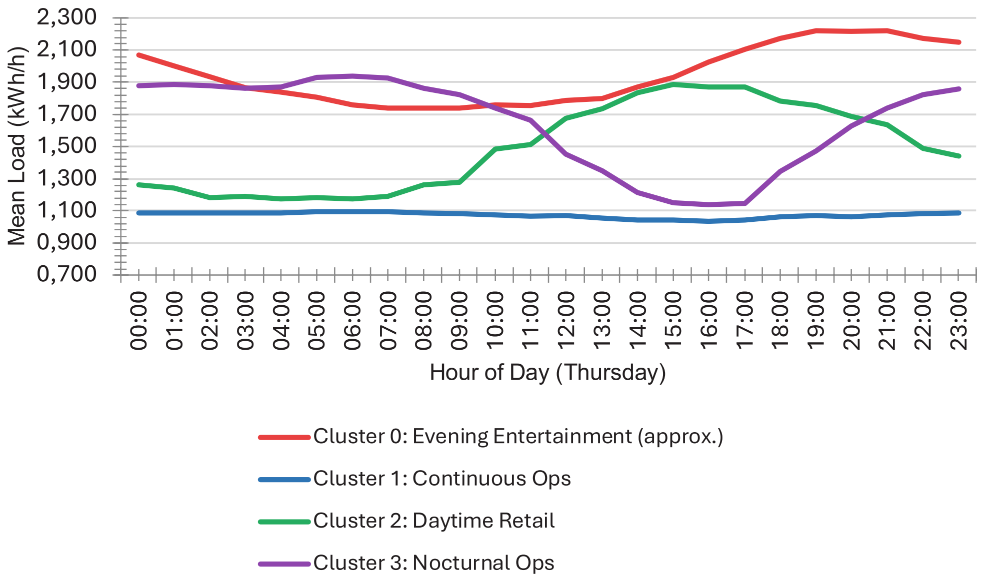

Fig. 4. Hourly load profiles for all four clusters on Thursday. Cluster 0 is an approximation derived from normalised Z-score data. The four curves occupy completely distinct hour-of-day peak windows, validating the discriminative power of the k-means segmentation.

Figure 4 provides the most visually striking confirmation of the four archetypes' distinctiveness. The four load curves occupy non-overlapping peak windows across the 24-hour cycle: Cluster 3 peaks in the early morning (06:00 on Thursday, 1.938 kWh/h) and troughs in the mid-afternoon; Cluster 1 remains essentially flat; Cluster 2 peaks at 15:00 (1.888 kWh/h); and Cluster 0 peaks in the evening (19:00–21:00 window). The four peak times: 01:00–06:00, flat, 15:00, 19:00–21:00, are separated by approximately equal time intervals across the 24-hour dial, creating a remarkably even temporal distribution of SME demand [22].

The grouped bar chart in Fig. 5 confirms the weekly peak-day diversity. Monday is characterised by suppressed Cluster 0 and Cluster 3 loads. Thursday represents the convergent peak for both Clusters 1 and 3, driven by entirely different operational mechanisms. Sunday provides the sharpest contrast: Cluster 2 reaches its weekly maximum (1.541 kWh/h), while Cluster 3 reaches its weekly minimum (0.961 kWh/h), yielding a Sunday Cluster 2/Cluster 3 ratio of 1.604 [11].

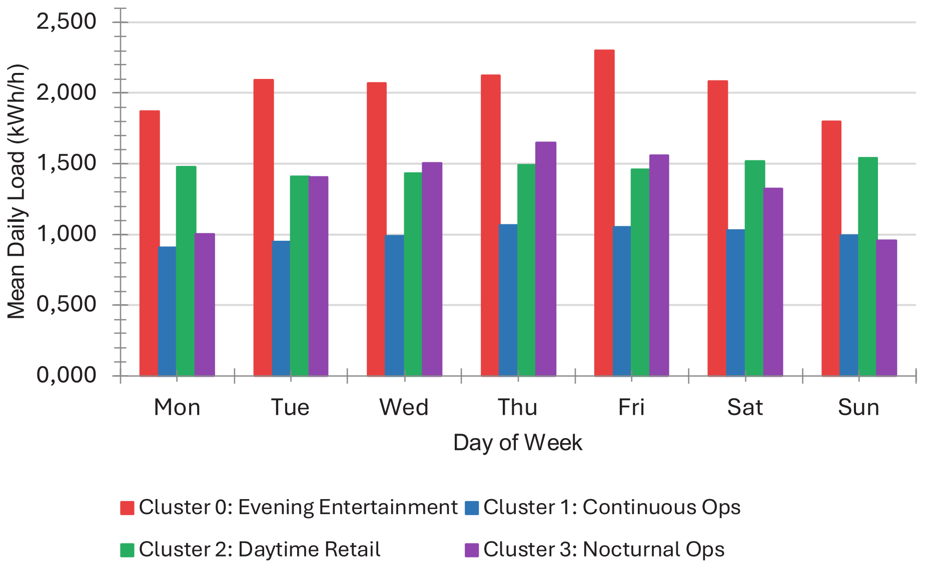

Fig. 5. Day-of-week load distribution across all four clusters (grouped bar chart). Each group of bars represents one day; cluster colour coding is consistent throughout.

3.4 Diurnal Variability and Weekend Orientation

The diurnal coefficient of variation (CV) provides a single-number summary of how structured and temporally concentrated each cluster's daily demand pattern is. Figure 6 presents this comparison across the four clusters [12].

Cluster 1 stands apart with a diurnal CV of only 1.56 %, approaching the theoretical minimum for a real-world consumption series. This near-zero CV is consistent with continuously-operating equipment loads (refrigeration, server infrastructure, HVAC systems in 24-hour facilities) that are largely invariant to the time of day [13]. Clusters 2 and 3 share similar CV values (17.21 % and 16.22 %, respectively), reflecting comparably structured but opposing diurnal patterns. Cluster 0's CV of 22.5 % (in Z-score terms) reflects the deepest morning suppression and strongest evening peak of any cluster [17].

The weekend-to-weekday mean load

ratio spans a range of 0.249 units (from 0.803 to 1.052), reflecting fundamentally different operational week structures. Cluster 2 (ratio 1.052) and Cluster 1 (ratio 1.019) are weekend-elevated, with Cluster 2's consumer-facing Sunday retail peak driving its above-unity ratio. Cluster 0 (ratio 0.928) is weekday-oriented, while Cluster 3 (ratio 0.803) exhibits the strongest weekday concentration of any cluster, consistent with strictly commercial five-day operational schedules [20], [15].

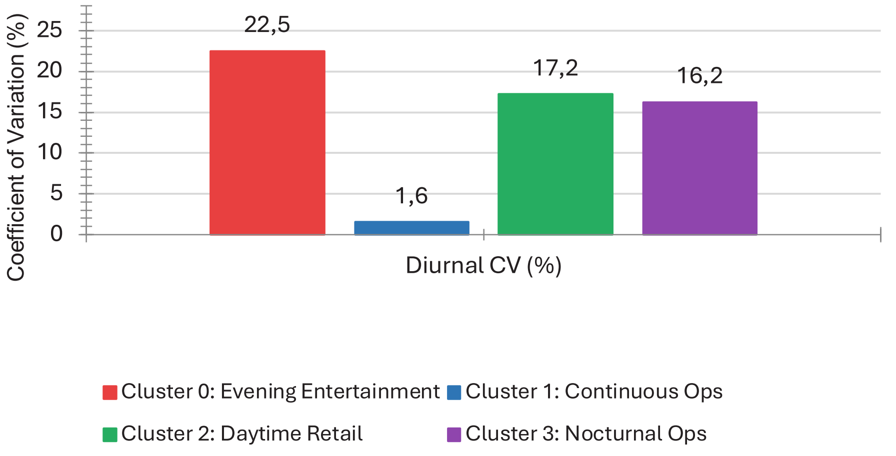

Fig. 6. Diurnal coefficient of variation (%) by cluster. A higher CV indicates a more structured, peaked daily profile. Cluster 1's near-zero CV reflects its flat baseload character.

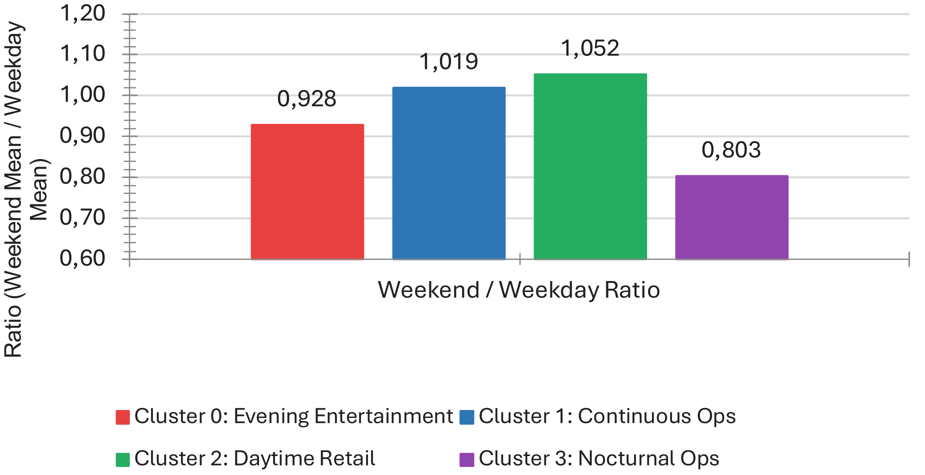

Fig. 7. Weekend-to-weekday mean load ratio by cluster. Ratios above 1.0 indicate weekend-dominant clusters; below 1.0 indicate weekday-dominant. The dashed line at 1.0 represents a flat weekly profile.

3.5 Cross-Cluster Statistical Comparison

Table 2 provides a detailed numerical comparison of key statistical metrics for each cluster across 15 structural parameters, serving as a reference summary for the full four-cluster typology [23].

Table 2. Detailed Numerical Comparison of the Four Clusters across 15 Statistical and Structural Parameters

Parameter	Cluster 0 Evening	Cluster 1 Continuous	Cluster 2 Retail	Cluster 3 Nocturnal
Members (n)	382	1,712	323	599
Overall mean (kWh/h)	~2.09 (raw)	0.999	1.477	1.344
Peak hour	19:00–21:00	09:00 (flat)	15:00	01:00–02:00
Trough hour	07:00–09:00	15:00 (flat)	06:00	16:00
Diurnal amplitude	0.641 (Z)	0.055 kWh/h	0.714 kWh/h	0.615 kWh/h
Diurnal CV	22.5 %	1.56 %	17.21 %	16.22 %
Peak day	Friday	Thursday	Sunday	Thursday
Lowest day	Sunday	Monday	Tuesday	Sunday
Max/Min day ratio	1.228	1.173	1.091	1.716
Weekend/Weekday ratio	0.928	1.019	1.052	0.803
Night baseload vs. day	Below mean	≈ Equal	Deep trough	60 % above the day
Evening step (h17 – h18)	+0.141 Z	Flat	+0.027 kWh/h	+0.141 kWh/h
Thursday night (h00–07)	n/a	~1.088 kWh/h	~1.263 kWh/h	1.897 kWh/h
Sunday profile	Suppressed flat	Near-mean flat	Peak day (15:00)	Dormant flat

3.6 Four-Archetype Typology: A Unified Framework

The four clusters together define a coherent and mutually complementary typology of SME electricity consumption behaviour. Each archetype occupies a distinct and non-overlapping position in a two-dimensional space defined by peak hour and weekly orientation. Table 3 summarises this typology framework [24].

Table 3. Unified Four-Archetype Typology of SME Electricity Consumption Patterns
Note: Each cluster occupies a distinct non-overlapping position in the temporal consumption space.

Cluster	Archetype Name	Temporal Position	Weekly Orientation	Likely Sector Composition
0	Evening Entertainment	Evening peak 19:00–21:00; morning suppression	Weekday-oriented; Friday peak; subdued Sunday	Bars, restaurants, night-clubs, event venues, late-night F&B
1	Continuous Operations	Flat 24-hour profile; CV 1.56%	Continuous; slight Thursday–Friday elevation	Food retail, logistics, data centres, hotels, care facilities
2	Daytime Retail	Afternoon peak 15:00; deep night trough	Weekend-dominant; Sunday peak; Tuesday trough	Shopping centres, personal services, leisure, cafes/ bistros
3	Nocturnal Operations	Night peak 01:00–02:00; afternoon trough 16:00	Weekday-dominant; Thursday peak; Sunday dormant	Cleaning services, bakeries, night-shift production, logistics depots

The typology is notable for its internal coherence and the structural symmetry between opposing pairs of clusters. Clusters 2 and 3 are temporal mirror images of each other: both have comparable diurnal CVs (~17 %) and amplitudes (~0.65 kWh/h), but their peaks and troughs are offset by approximately 13–15 hours. Similarly, Cluster 0 (evening social commerce) and Cluster 3 (nocturnal service operations) both operate predominantly outside standard business hours, but in different segments of the after-dark window. Cluster 1 occupies the low-variability centre of the space, serving as the background continuous load against which the time-structured behaviour of the other three clusters is superimposed [25].

3.7 Demand-Side Management and Forecasting Implications

The four-cluster typology has direct actionable implications for tariff design and demand-response programme construction. Time-of-use (TOU) pricing is most effective when the tariff structure creates a meaningful incentive for load shifting relative to the consumer's natural load shape [26].

Cluster 3 (nocturnal) is the most naturally aligned with overnight off-peak pricing, consuming its peak load during hours when wholesale electricity prices are typically lowest. These businesses are natural candidates for fixed-rate overnight contracts and wind energy procurement schemes in the Baltic markets where nocturnal wind generation tends to be highest [27]. Cluster 2 (daytime retail) presents the largest TOU incentive opportunity: a 48.3 % diurnal amplitude and a deep overnight trough offer substantial scope for shifting thermal preconditioning, refrigeration pre-cooling, and battery charging to the off-peak window [14].

Cluster 1 (continuous) has limited TOU responsiveness due to its near-flat profile. Engagement strategies for this cluster should focus on absolute consumption reduction, efficiency investment, and renewable energy procurement contracts rather than temporal shifting [28]. At the system level, the even distribution of cluster peak times across the 24-hour cycle provides a partial natural diversity benefit, reducing the coincidence factor of simultaneous peak demand events [29]. However, the dominance of Cluster 1 (56.8 % of metering points) means that the background continuous load is substantial and largely invariant to time-of-day demand management interventions [30].

Regarding short-term load forecasting, for Cluster 1 the dominant predictive signal is day-of-week rather than hour-of-day; for Cluster 2, hour-of-day is dominant with a secondary weekend-elevation correction [31]. For Cluster 3, the hour-of-day by day-of-week interaction is critical – the peak hour varies by day – requiring a model that captures this interaction through a tree-based structure such as LightGBM [32]. Temperature sensitivity is expected to be highest for Cluster 2 (HVAC in retail environments) and lowest for Cluster 3 (process-driven nocturnal operations) [33], [34].

4. CONCLUSIONS

This paper has presented a comparative structural assessment of four SME electricity consumption archetypes derived from k-means clustering of hourly smart-meter data from 3,016 metering points in Latvia. The following conclusions have been drawn:

- The four k-means clusters exhibit non-overlapping dominant peak-hour positions within the 24-hour cycle, evening-oriented (Cluster 0), flat/near-invariant (Cluster 1), afternoon-oriented (Cluster 2), and nocturnal-oriented (Cluster 3) – confirming the discriminative validity of the segmentation and demonstrating that the applied daily-mean shape Z-score normalization effectively preserves structural load-shape differences while removing scale bias.
- Each cluster demonstrates a unique weekday–weekend orientation: Cluster 0 peaks on Friday, Cluster 1 exhibits a continuous profile with moderate Thursday elevation, Cluster 2 peaks on Sunday, and Cluster 3 peaks on Thursday with pronounced Sunday dormancy; the Thursday/Sunday ratio of 1.716 in Cluster 3 represents the widest day-of-week dispersion observed, confirming that weekly structure acts as an independent discriminative dimension alongside diurnal variation.
- Quantitatively, 56.8 % of SMEs exhibit near-invariant baseload behaviour (Cluster 1, CV = 1.56 %), while the remaining three clusters display time-structured demand patterns (CV = 16–23 %); this asymmetry has direct implications for load predictability and flexibility potential estimation, as baseload-dominant SMEs require fundamentally different demand-side management instruments than temporally structured SMEs.
- The four-archetype typology provides an actionable segmentation framework for demand-response programme design, distribution network planning, and cluster-specific short-term load forecasting; future research should validate cluster membership against official SME sector classification data, perform seasonal sub-period clustering, and assess cluster stability across geographic regions to establish EU-level comparability.

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