

Non-Intrusive Estimation of Household Behavioral Lifestyle Using Smart Meter Time-Interval Aggregation Algorithms

Youhee Choi
Energy ICT Research Section
ETRI
Daejeon, Korea
yhchoi@etri.re.kr

Tai Yeon Ku
Energy ICT Research Section
ETRI
Daejeon, Korea
kutai@etri.re.kr

Wan-Ki Park
Energy ICT Research Section
ETRI
Daejeon, Korea
wkpark@etri.re.kr

Abstract—The growing demand for personalized energy management and smart city services has highlighted the importance of accurately understanding household behavioral patterns through non-intrusive methods. This study proposes a time-interval aggregation algorithm that infers sleep and wake time patterns from multi-source smart meter data, including electricity, cold water, and hot water usage. The method addresses challenges such as baseline consumption noise and irregular usage behaviors by applying threshold-based filtering, interval merging, and temporal frequency analysis. It consists of six structured steps: identifying active usage hours, constructing continuous intervals, selecting frequently recurring intervals, integrating multi-source data, inferring sleep–wake times using behavioral heuristics, and classifying weekday versus holiday patterns. Validation using real-world residential datasets demonstrates the algorithm’s effectiveness in consistently estimating circadian behavior without requiring wearable sensors or intrusive monitoring. The results show potential for enhancing energy efficiency services, carbon reduction strategies, and personalized lifestyle analytics within smart grid environments.

Keywords—multi-source, non-intrusive, behavioral lifestyle

I. INTRODUCTION

In recent years, the demand for non-intrusive methods to monitor residents' daily activity rhythms has increased, especially in smart residential systems. Among such patterns, sleep and wake intervals are closely linked to personal health, energy efficiency, and responsive welfare services. Traditional approaches often rely on wearable devices or dedicated sensors, which present limitations in terms of user acceptance, installation costs, and privacy concerns. Electricity consumption data from smart meters has been proposed as a potential data for inferring resident activity states. However, electrical usage alone does not capture the full spectrum of daily life, particularly due to background loads such as refrigerators or routers that remain active even during sleep. In contrast, water and hot water usage patterns exhibit clearer on/off dynamics and thus offer stronger signals for behavioral transitions like sleep onset and morning routines. This study proposes a novel algorithm that integrates hourly electricity, water, and hot water usage logs to estimate the sleep and wake intervals of individual households in multi-unit residential complexes. By analyzing deviations from household-specific baselines and incorporating utility-specific thresholds, the method achieves personalized, accurate, and non-intrusive inference of rest-activity cycles. The algorithm is validated using real-world datasets and compared against electricity-only models to demonstrate performance gains.

II. RELATED RESEARCHES

Prior research on smart meter-based behavior inference has largely focused on electricity-only data, applying rule-based or statistical models to identify activity zones[1,2]. High-resolution disaggregation of electricity usage has been used to detect appliance-level events, but this approach requires fine-grained data and computational overhead[3,4]. Water and hot water usage data remain underutilized in the context of behavioral inference, despite their potential to reflect human interactions with hygiene and cooking activities. In the healthcare domain, sleep estimation has traditionally relied on physiological sensors, such as actigraphy or polysomnography, which are accurate but impractical for large-scale deployment. Recently, ambient intelligence approaches have gained traction, exploring smart home data for passive health monitoring. However, integrating multiple utility data sources to infer behavioral patterns is still an emerging area. A comparison with prior work highlights key distinctions of our method. For instance, Lee et al. (2020) used hourly electricity data and moving average thresholds, but their approach could not differentiate passive loads from active behavior[5]. Zhang et al. (2021) employed smart plug-level data and clustering methods to detect behavioral states, yet required high-resolution data and raised privacy concerns due to device-level monitoring[6]. Kim et al. (2022) utilized 15-minute interval electricity readings with statistical smoothing, but their approach suffered from ambiguity during periods when residents used electricity passively, such as kitchen or bathroom lights during nighttime[7]. In contrast, our study introduces a tri-modal approach combining electricity, water, and hot water usage data, enabling more accurate state inference. By applying utility-specific thresholds and household-personalized baselines, our method avoids the pitfalls of electricity-only logic, offers interpretable results, and does not require intrusive sensors or device-level disaggregation. To our knowledge, this is the first large-scale non-intrusive method that fuses multiple utility sources to infer sleep-wake behavior in urban apartments.

III. ALGORITHM FOR INFERRING SLEEP AND WAKE TIMES USING HOURLY MULTI-SOURCE ENERGY DATA

This study proposes a data-driven, non-intrusive algorithm to infer daily sleep and wake-up times for individual households based on hourly usage patterns from electricity, hot water, and cold water sources. The algorithm is designed to process real-world smart meter data in a multi-step pipeline that captures behavioral cues without requiring sensors or user intervention. The procedure comprises six core stages:

A. Step 1: Identification of Active Hours Based on Usage Thresholds

For each energy type (electricity, hot water, cold water), hourly usage is compared against the daily average usage of the corresponding household. Hours with usage exceeding the daily mean are retained as active hours, representing meaningful interactions with household systems beyond baseline consumption (e.g., appliance standby load).

B. Step 2: Construction of Continuous Usage Intervals

Consecutive active hours are merged to form usage intervals, each characterized by a start time, end time, and duration. These intervals are assumed to represent discrete user activities or energy events (e.g., showering, cooking).

C. Step 3: Frequent Interval Selection Based on Temporal Repetition

For each household, the frequency of each unique time interval (e.g., 07:00 – 08:00) is calculated over the entire observation period. Intervals that appear on $\geq 50\%$ of the total observed days are retained as representative patterns. If the number of qualified intervals falls short of a predefined minimum, the most frequently occurring intervals are added to supplement the set.

D. Step 4: Merging of Intervals Across Energy Sources

All usage intervals from the three sources are merged by time. Overlapping or identical time ranges across sources are consolidated into unified records, and the associated energy types are aggregated (e.g., "Electricity, Hot Water"). This step creates a single daily timeline of household activity.

E. Step 5: Inference of Sleep and Wake Times

Using the merged multi-source timeline, the algorithm infers sleep and wake-up times based on behavioral heuristics:

- **Sleep Time:** The most recent energy usage ending between 00:00–04:00, or between 18:00–23:00 of the previous day, is considered the likely sleep onset. Priority is given to intervals involving hot or cold water usage, reflecting typical pre-sleep hygiene routines.
- **Wake-Up Time:** The earliest energy usage starting between 05:00–12:00 of the current day is considered the wake-up time. Again, water-based activities (e.g., morning shower or cooking) are prioritized over electricity alone.

F. Step 6: Classifying Weekday/Holiday Sleep-Wake Time Patterns

To summarize long-term behavioral tendencies, the algorithm computes the mode (most frequent value) of the inferred sleep and wake times separately for weekdays and holidays. Along with the mode values, the algorithm records the frequency of occurrence and the number of valid days. This output enables statistical characterization of household-level lifestyle patterns and supports comparative or cluster-based analysis in subsequent applications.

IV. CASE STUDY

The dataset utilized in this study was collected from smart meters installed across multiple households within a high-density urban residential complex in South Korea. The smart meters recorded hourly consumption data for three energy types—electricity (kWh), hot water (liters), and cold water

(liters). Each data record includes a household identifier (meter_id), the corresponding date (str_date), start and end times (start_time, end_time) indicating the period of consumption activity, a calculated duration of use (duration), and an energy-type label (used_energy) identifying whether the consumption pertained to electricity (e), hot water (hw), or cold water (cw). The raw datasets were initially stored separately for each energy type and later unified through interval merging procedures, as described in Section III. The final integrated dataset encompasses 467 households, comprising approximately 381,168 hourly energy usage records collected over a 34-day observation period from May 18, 2023, to June 20, 2023. The data are fully anonymized to protect the privacy of individual households, and no personally identifiable information is retained. All data processing and analysis were conducted in compliance with ethical standards and institutional data usage policies. This section presents the step-by-step application of the proposed algorithm to the real-world dataset, illustrating how each stage contributes to the inference of sleep and wake times from multi-source hourly energy data.

A. Step 1: Identification of Active Hours Based on Usage Thresholds

For each household and energy type (electricity, cold water, hot water), the hourly usage on a given day is compared to the average usage at the same hour computed across all days. Hours with above-average usage are marked as active. Fig. 1, Fig. 2, and Fig. 3 illustrate the hourly energy usage of a randomly selected household on May 19, 2023, for electricity, cold water, and hot water respectively.

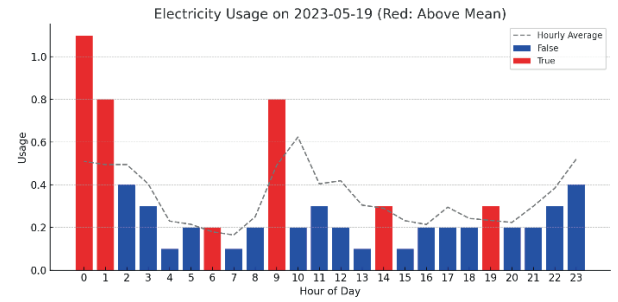


Fig. 1. Hourly energy usage of a randomly selected household for electricity

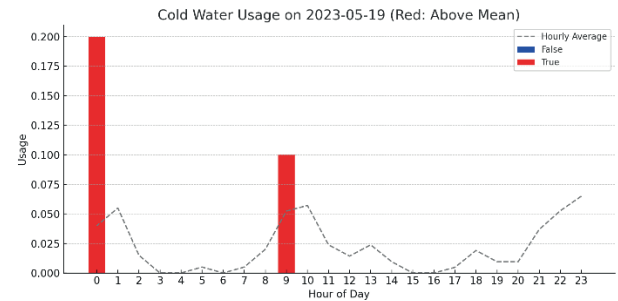


Fig. 2. Hourly energy usage of a randomly selected household for cold water

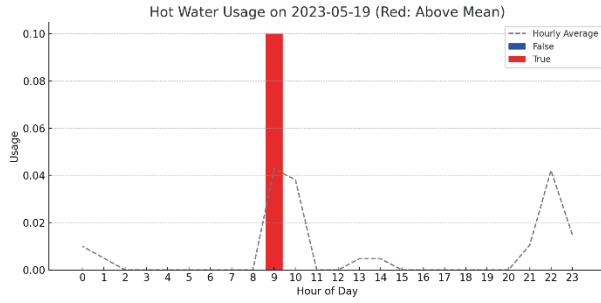


Fig. 3. Hourly energy usage of a randomly selected household for hot water

In each subfigure, red bars represent hours in which the energy consumption exceeded the corresponding hourly average across all observed days, while blue bars indicate hours with below-average usage. The gray dashed line reflects the mean hourly usage computed for each energy type over the entire observation period. These visualizations enable temporal anomaly detection and facilitate behavioral interpretation by comparing actual consumption on a given day to the normative hourly patterns established across the dataset.

B. Step 2: Construction of Continuous Usage Intervals

Consecutive active hours are merged to form usage intervals, each characterized by a start time, end time, and duration. These intervals are assumed to represent discrete user activities or energy events (e.g., showering, cooking). Fig. 4, Fig. 5, and Fig. 6 illustrates the constructed time ranges during which energy usage continuously exceeded the corresponding hourly average, across multiple days, for a randomly selected household. The visualizations capture the temporal dynamics of energy consumption for three energy types—electricity, cold water, and hot water. Each horizontal bar represents a contiguous time interval on a given date during which the usage for that specific energy type remained above the mean for the same hour calculated across the entire observation period. The Y-axis represents the date, and the X-axis corresponds to the hour of the day. The annotated time ranges within each bar (e.g., “9–11”) indicate the start and end hour of active usage periods. This visualization enables the identification of temporal usage patterns that persist or fluctuate day by day. For example, sustained usage during late evening hours (e.g., 21:00–23:00) or consistent morning consumption (e.g., 6:00–9:00) may indicate routine behavior or anomalies depending on the expected baseline.

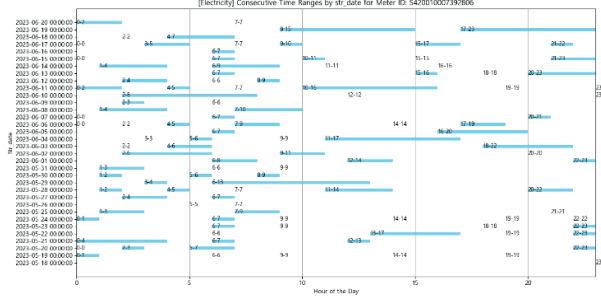


Fig. 4. The constructed time ranges during which electricity usage continuously exceeded the corresponding hourly average, across multiple days, for a randomly selected household

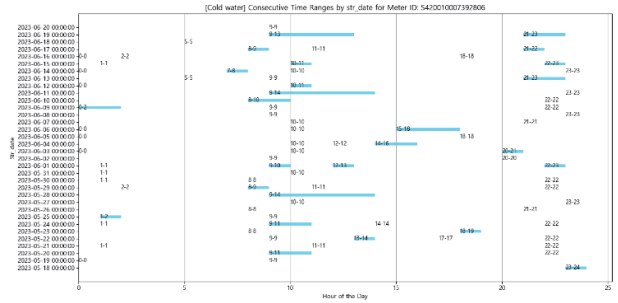


Fig. 5. The constructed time ranges during which cold water usage continuously exceeded the corresponding hourly average, across multiple days, for a randomly selected household

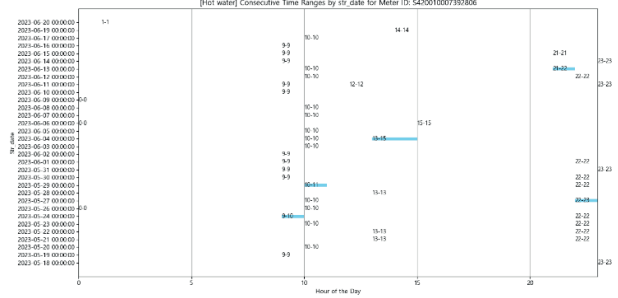


Fig. 6. The constructed time ranges during which hot water usage continuously exceeded the corresponding hourly average, across multiple days, for a randomly selected household

C. Step 3: Frequent Interval Selection Based on Temporal Repetition

Step 3 identifies frequent usage intervals by examining recurring time segments across days. Fig. 7, Fig. 8, and Fig. 9 presents daily active usage intervals of a randomly selected household for electricity, cold water, and hot water. For example, electricity is frequently used from 21:00 to 23:00, while, cold water and hot water usage is concentrated around 9:00 and 22:00. These recurring intervals are candidates for defining typical behavioral routines.

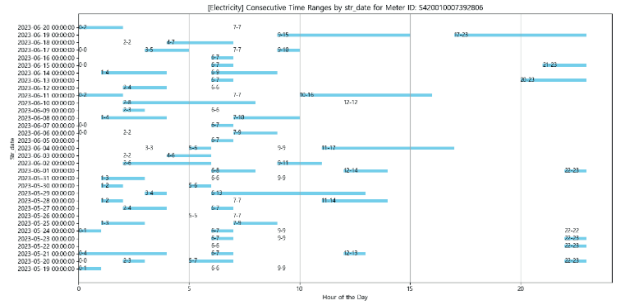


Fig. 7. Daily active usage intervals of a randomly selected household for electricity

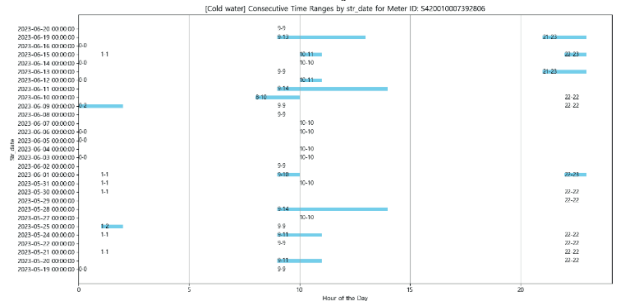


Fig. 8. Daily active usage intervals of a randomly selected household for cold water

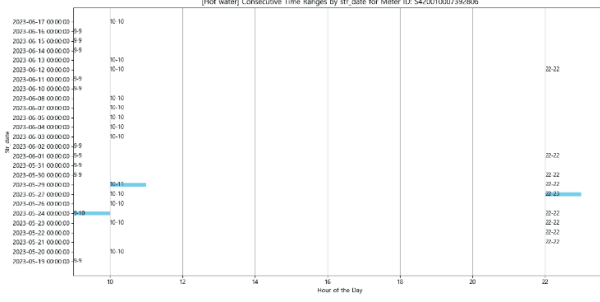


Fig. 9. Daily active usage intervals of a randomly selected household for hot water

D. Step 4: Merging of Intervals Across Energy Sources

In this step, the goal is to identify overlapping or temporally adjacent usage windows across different energy sources. By aligning the intervals from electricity, cold water, and hot water usage, it becomes possible to infer behaviorally meaningful activity segments, such as morning routines or evening household activities. Fig. 10 demonstrates how merging intervals provides a holistic view of daily energy behaviors. For example, certain time blocks (e.g., 6–9 AM or 20–23 PM) show consistent usage across multiple energy types, which may correspond to regular household routines.

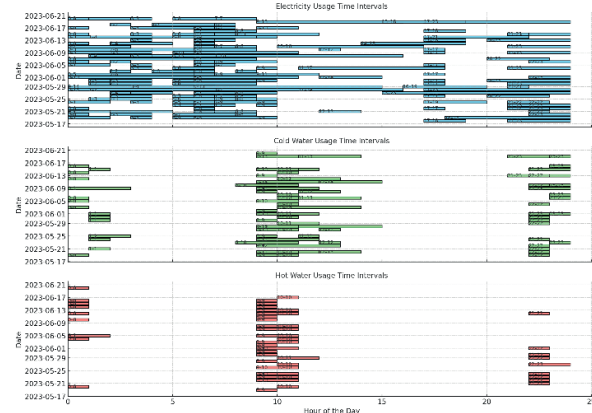


Fig. 10. The energy usage intervals for electricity, cold water, and hot water across multiple days, focusing on a single household

E. Step 5: Inference of Sleep and Wake Times

Table 1 illustrates the results of inferring sleep and wake-up times for a representative household, identified as meter ID S420010007392806. For each date, the algorithm estimated the household's sleep time and wake-up time based on multi-source energy usage data. Sleep time was determined by identifying the latest recorded end time of energy usage occurring either between 18:00–23:00 on the previous day or between 00:00–04:00 on the same day. Wake-up time was inferred from the earliest recorded start time of energy usage within the morning window of 05:00–12:00 on the same date. Along with the time values, the table records the type of energy source—electricity, cold water, or hot water—that was associated with the detected sleep and wake-up events. The holiday column distinguishes weekdays from holidays, enabling further lifestyle pattern comparisons.

TABLE I. SLEEP AND WAKE-UP TIMES FOR A REPRESENTATIVE HOUSEHOLD

	meter_id	date	sleep_date	sleep_time	sleep_time_energy	wake_time	wake_time_energy	holiday
0	S420010007392806	2023-05-19	2023-05-19	0	cw	9	cw,e,hw	0
1	S420010007392806	2023-05-20	2023-05-20	3	e	9	cw	1
2	S420010007392806	2023-05-21	2023-05-21	1	cw	6	e	1
3	S420010007392806	2023-05-22	2023-05-21	22	cw,hw	9	cw	0
4	S420010007392806	2023-05-23	2023-05-22	22	cw,hw	10	hw	0
5	S420010007392806	2023-05-24	2023-05-24	1	cw	9	hw	0
6	S420010007392806	2023-05-25	2023-05-25	2	cw	9	cw	0
7	S420010007392806	2023-05-27	2023-05-27	4	e	10	cw,hw	1
8	S420010007392806	2023-05-28	2023-05-28	2	e	9	cw	1
9	S420010007392806	2023-05-29	2023-05-29	4	e	10	hw	1
10	S420010007392806	2023-05-30	2023-05-30	1	cw	9	hw	0
11	S420010007392806	2023-05-31	2023-05-31	1	cw	9	e,hw	0
12	S420010007392806	2023-06-01	2023-06-01	1	cw	9	hw	0
13	S420010007392806	2023-06-02	2023-06-01	23	cw,e	9	cw,hw	0
14	S420010007392806	2023-06-03	2023-06-03	0	cw	10	cw,hw	1
15	S420010007392806	2023-06-04	2023-06-04	3	e	10	cw,hw	1
16	S420010007392806	2023-06-05	2023-06-05	0	cw	10	hw	0
17	S420010007392806	2023-06-06	2023-06-06	0	cw,e	10	cw	1
18	S420010007392806	2023-06-07	2023-06-07	0	e	10	cw,hw	0
19	S420010007392806	2023-06-08	2023-06-08	4	e	9	cw	0
20	S420010007392806	2023-06-09	2023-06-09	2	cw	9	cw	0
21	S420010007392806	2023-06-10	2023-06-09	22	cw	8	cw	1
22	S420010007392806	2023-06-11	2023-06-11	2	e	9	hw	1
23	S420010007392806	2023-06-12	2023-06-12	0	cw	10	hw	0
24	S420010007392806	2023-06-13	2023-06-12	22	hw	9	cw	0
25	S420010007392806	2023-06-14	2023-06-14	0	cw	9	hw	0
26	S420010007392806	2023-06-15	2023-06-15	1	cw	9	hw	0
27	S420010007392806	2023-06-16	2023-06-16	0	cw	9	hw	0
28	S420010007392806	2023-06-17	2023-06-17	0	e	10	hw	1
29	S420010007392806	2023-06-20	2023-06-20	2	e	9	cw	0

F. Step 6: Classifying Weekday/Holiday Sleep-Wake Time Patterns

Fig. 11 presents the classified sleep and wake-up time patterns for a representative household (meter ID S420010007392806), differentiated between weekdays and holidays. The x-axis denotes the calendar date, explicitly labeled with "(W)" for weekdays and "(H)" for holidays to provide immediate visual distinction. By analyzing the distribution of points, it becomes evident that this household maintains relatively stable wake-up times across both weekdays and holidays, predominantly between 8:00 and 10:00. In contrast, sleep times show greater variability, particularly on holidays, where later sleep time is observed more frequently.

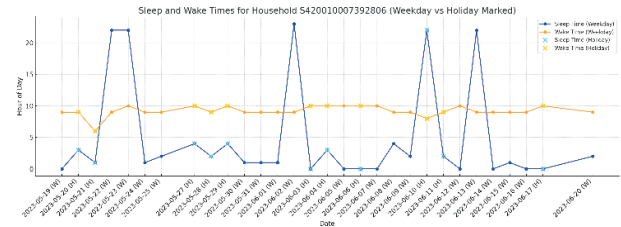


Fig. 11. The classified sleep and wake-up time patterns for a representative household

V. CONCLUSIONS

This study presented a non-intrusive method for estimating household behavioral lifestyle by leveraging multi-source smart meter data, specifically electricity, hot water, and cold water usage logs. By designing a structured time-interval aggregation algorithm consisting of six core steps—including active hour identification, interval construction, temporal frequency filtering, cross-source interval merging, sleep-wake time inference, and weekday/holiday pattern classification—the proposed framework enables interpretable and scalable behavioral profiling without requiring any direct

sensor installation or user intervention. In the future, we will evaluate the proposed method's substantiality and reliability by validating the inferred patterns against ground-truth survey or sensor-based data to further confirm the reliability and generalizability of the method.

ACKNOWLEDGMENT

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) and the Ministry of Science and ICT(MSIT) of the Republic of Korea (No. 202502217507)

REFERENCES

- [1] J. Chen, S. Barker, A. Subbaswamy, D. Irwin, and P. Shenoy, "Non-intrusive occupancy monitoring using smart meters," *Proceedings of the 2nd ACM SIGKDD International Workshop on Urban Computing*, pp. 1–8, Aug. 2013.
- [2] R. Gravina, P. Ma, G. Fortino, and H. Liu, "Multi-Occupancy Household Activity Recognition Using Electricity Consumption Data," *Sensors*, vol. 21, no. 23, p. 8036, Nov. 2021.
- [3] J. Kelly and W. Knottenbelt, "Neural NILM: Deep Neural Networks Applied to Energy Disaggregation," *Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments (BuildSys)*, pp. 55–64, 2015.
- [4] H. Batra et al., "Nilmk: An open source toolkit for non-intrusive load monitoring," *Proceedings of the 5th ACM International Conference on Future Energy Systems*, pp. 265–276, 2014.
- [5] J. Lee, H. Park, and S. Kim, "Daily Routine Estimation from Smart Meter Data in Urban Homes," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 3320–3330, Apr. 2020.
- [6] Y. Zhang, L. Chen, and D. Xu, "Inferring Household Activities Using Smart Plug Data: A Clustering Approach," *Sensors*, vol. 21, no. 2, 2021.
- [7] M. Kim, J. Kwon, and H. Choi, "Statistical Detection of Sleep-Wake Transitions Using Residential Electricity Patterns," *Energy and Buildings*, vol. 255, Jan. 2022.