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Usage Behavior Analysis of Household Appliances Based on a Panel Study in Shenzhen, China#

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ABSTRACT

The temporal mismatch between renewable energy generation and energy consumption in residential buildings is highly dependent on user behavior, which is crucial for future home energy management and demand-side response solutions aimed at increasing renewable energy consumption. This study leveraged a custom-developed personal energy tracking app to conduct both a questionnaire survey on social attributes and a self-monitoring tracking survey of residents in Guangdong, China. 373 data on their 24-hour energy usage behaviors were collected and utilized clustering algorithms to extract typical usage times and patterns for various appliances. Additionally, the study examined the significance and importance of social characteristics affecting residents' usage behaviors. The findings provide valuable insights for further investigation into residents' willingness to participate in flexible energy regulation, the formulation of incentive policies, and the design of home energy management strategies.

Keywords: energy usage behavior, home energy management, app development, panel study, k-means clustering, random forest

1. INTRODUCTION

With the continuous growth of global energy demand and increasing environmental protection pressures, the development of renewable energy and optimization of energy management have become key strategies for achieving sustainable development. Photovoltaic (PV) power generation, as a crucial component of clean energy technologies, plays a vital role in this process. PV power generation is widely regarded as an effective means to address climate change and energy security challenges due to its renewable and pollution-free characteristics[1]. However, the immediacy and non-storability of electricity necessitate that the power system maintains a constant supply-demand balance to avoid grid overloads or power shortages. The intermittency and volatility of PV power generation also pose new challenges to the stability of the power system[2].

To address the supply-demand fluctuations caused by PV power generation, demand response has emerged as an important strategy for optimizing power system operations. Demand response uses economic incentives and price signals to guide users in adjusting their electricity consumption behavior during peak demand periods, thereby achieving supply-demand balance and improving the stability and efficiency of the power system. The participation of residents is a key factor in the success of demand response. By studying residents' electricity consumption behavior, policymakers and energy service providers can design more precise and effective incentive mechanisms to encourage residents' active participation in demand response, thereby enhancing overall energy efficiency and system reliability.

Most existing studies on residents' energy usage behavior rely on questionnaire surveys, which are subjective self-reports based on memory. These methods often lead to discrepancies between recalled and actual usage due to the vagueness of inquiries. With technological advancements, researchers have started exploring the use of smart devices and sensor technology for more accurate behavior monitoring. For example, cameras can monitor and analyze residents' energy usage behavior in real-time, but privacy issues hinder widespread adoption[3]. Smart meters require household installation and individual sockets, facing challenges of privacy and comprehensive data collection[4]. The low penetration rate and diversity of smart appliances also pose difficulties in standardization. Despite the potential of these technologies to better capture behavior, privacy concerns and household equipment configurations prevent large-scale application in ordinary households in China, making it

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difficult to conduct large-scale surveys on energy usage behavior. Furthermore, existing studies often focus on detailed analysis of single appliances, such as air conditioners, without extracting and comparing typical usage patterns across multiple appliances[5].

Therefore, this study develops a home energy consumption tracking application to conduct precise 24-hour self-reported tracking surveys of users.

2. METHOD

2.1 *Panel study*

The self-monitoring tracking survey method was chosen as the primary data collection approach for this study due to its balance between privacy protection and data accuracy. The panel study method, which involves repeatedly collecting data from the same group over an extended period, allows researchers to observe changes in individual behavior over time and analyze energy consumption patterns across different periods. To achieve precise tracking of residents' energy consumption behavior, this study developed a home energy consumption tracking application(Fig. 1).

The first phase of this study involved collecting basic social attribute information through the user information input interface, encompassing residents with diverse social attributes from Guangdong Province. In the second phase, users needed to select the appliances they owned in the living room, bedroom and study, dining room and kitchen, bathroom and balcony, and non-fixed usage scenarios. The third phase involved 24-hour spatiotemporal electricity usage tracking, requiring participants to log their electricity usage behavior on both weekdays and weekends. Researchers synchronized detailed data in real-time, including "user"-"appliance"-"usage room"-"start time"-"end time"-"power usage"-"current activity type." Activity types preset for usage included working, studying, eating, cooking, doing housework, washing up, bathing, entertainment, resting, sleeping, and going out, with users selecting the appropriate options. This method balanced privacy protection and data accuracy.

2.2 *K-means Clustering, Random Forest,* T-tests and Chi-Square Test

This study employed the K-means clustering algorithm and the Random Forest classification algorithm to analyze data, aiming to understand energy usage patterns of different appliances and the feature importance of social attributes among clusters. T-tests and Chi-Square test were also used to analyze the significance difference of various options of social attributes within important features regarding appliance usage behaviors.

Fig. 1 Energy-Tracker APP User Interface

3. ANALYSIS

3.1 *Demographic and appliance characteristics*

373 data of residents from Guangdong Province was collected using *Energy-Tracker APP*.

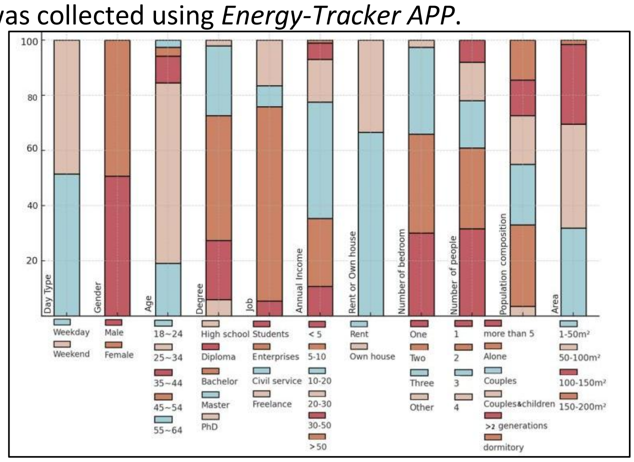

Fig. 2 User attributes statistics

In residential buildings, different types of electrical loads exhibit specific operating patterns and usage characteristics, which determine their potential application in demand-side management[6]. This study categorizes them based on their flexibility impact on user behavior into five types to identify similarities: Power Adjustable Loads can be adjusted according to demand without altering usage time; Time Adjustable Loads can be advanced or delayed without significantly affecting the user's life; Rigid Loads meet user needs without delay or power adjustment; Memory Loads experience gradual power changes after user control; and Battery Loads rely on battery power, providing some energy storage capability.

There are 15 appliances selected from 44 user-owned appliances for in-depth analysis(*Table.1*):

Space Type	Appliance Name	Load Type
Living Room	Living Room Light	Power Shiftable
	Living Room AC	Memory
Bedroom or Study	Bedroom Light	Power Shiftable
	Bedroom AC	Memory
Kitchen or Dining	Dining Kitchen Light	Power Shiftable
	Rice Cooker	Time Shiftable
	Induction Cooker	Time Shiftable
Bathroom or Balcony	Bathroom Light	Power Shiftable
	Water Heater	Time Shiftable
	Washing Machine	Time Shiftable
Others	Electric Vehicle	Battery
	Laptop	Battery
	Desktop Computer	Rigid
	Fan	Rigid

Table.1 Characteristics of different appliances

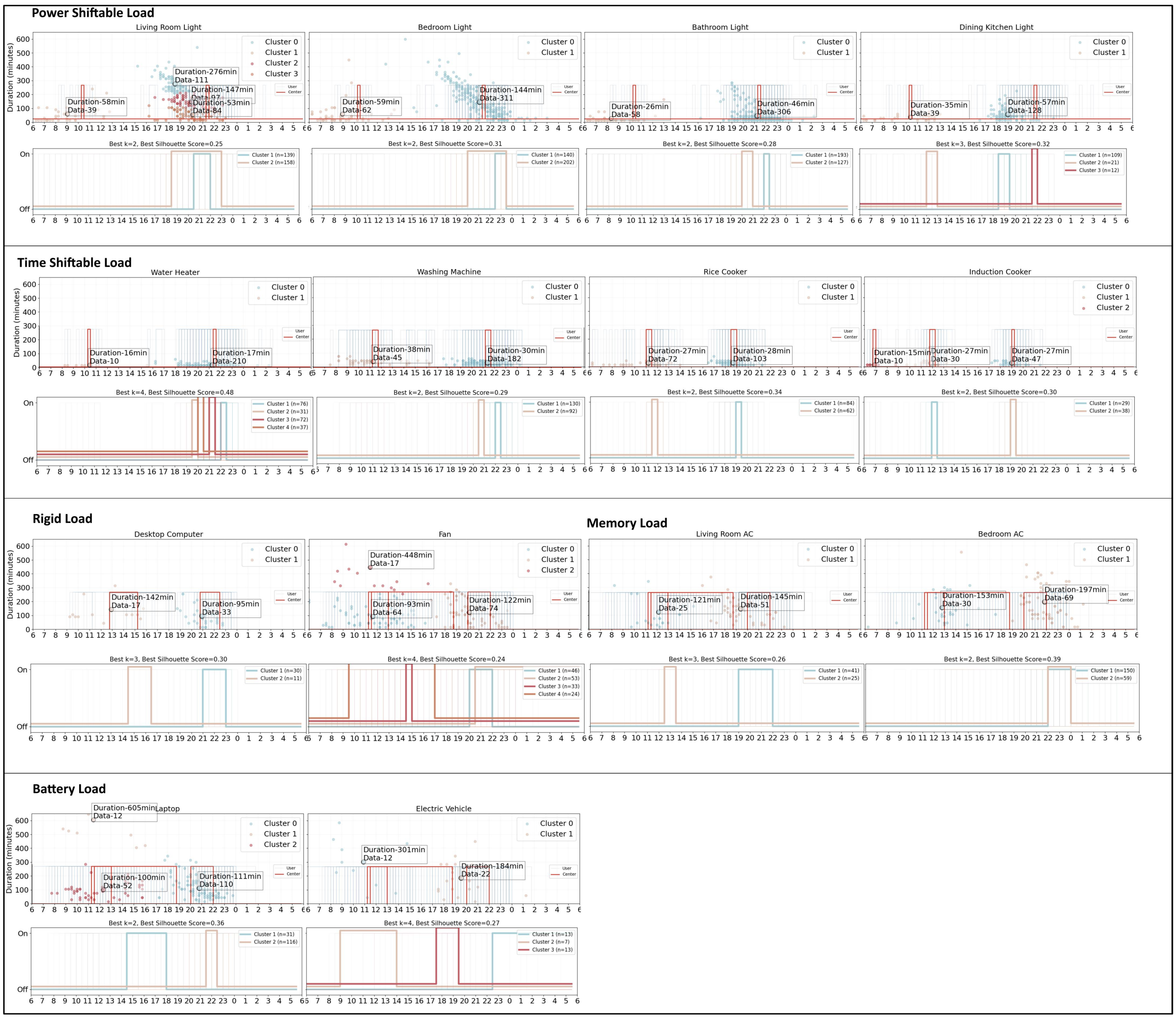

Fig. 3 Clustering results and trajectories of each appliance by defined categories

3.2 *Appliance usage time duration and usage pattern*

The K-means algorithm grouped energy usage behavior data according to appliance usage time and patterns separately, using distinct features to reflect residents' home energy usage behaviors[7].

In the first clustering, aimed at analyzing appliance usage time characteristics, clustering features were constructed from the start time, end time, and duration of single use for each appliance within the effective usage period (the 1st row of each type in Fig. 3).

In the second clustering, focused on analyzing 24-hour usage patterns of each appliance, Conv1D was used to convolve the input time series to extract local features, while more abstract features were gradually extracted through multi-layer convolution and pooling operations. The K-means algorithm, with an initial cluster number range of 2 to 4, then generated cluster center loci from binary digit data using Hamming distance (the 2nd row of each type in Fig. 3).

Power Shiftable Loads have clear peak periods with longer usage times in the evening; Time Shiftable Loads are tied to specific daily activities with distinct usage times; Rigid Loads are used as needed throughout the day; Memory Loads have consistent usage at specific times with a delay between different appliances; Battery Loads have varied but generally long usage times. These differences highlight the unique usage patterns and flexibility of each appliance type.

3.3 *Important features and significant difference*

Analyzing the importance of appliance usage features helps identify key factors influencing usage patterns, reflecting the impact of users' social backgrounds, family situations, and lifestyle habits. After the 1st clustering, the Random Forest algorithm is employed to analyze feature importance. The feature importance analysis reveals how different social attributes influence usage behavior [8](Fig. 4). For most appliances, "weekday or weekend" and "area" are the most significant features affecting usage.

Random Forest help identify important features, while significant differences in the sample average of usage duration between different groups across various time slots were identified using a T-test. For example, notable difference of Washing Machine exists between age groups, especially in the morning (Fig. 5).

Simultaneously, using the user attributes as feature and the second cluster labels as target, another Random Forest classification model is trained to predict 24-hour usage patterns. The Random Forest model demonstrated high predictive performance, with 3 appliances (Desktop Computer, Dining Kitchen Light and Laptop) achieving prediction accuracy of over 72%. Additionally, the accuracy of 6 appliances(Livingroom Light, Bedroom Light, Bathroom Light, Livingroom AC, Bedroom AC, Washing Machine, Rice Cooker, Gas Stove) ranges from 65% to 69%. However, only 2 appliances(Water Heater and Fan) exhibited lower accuracy due to limited data samples.

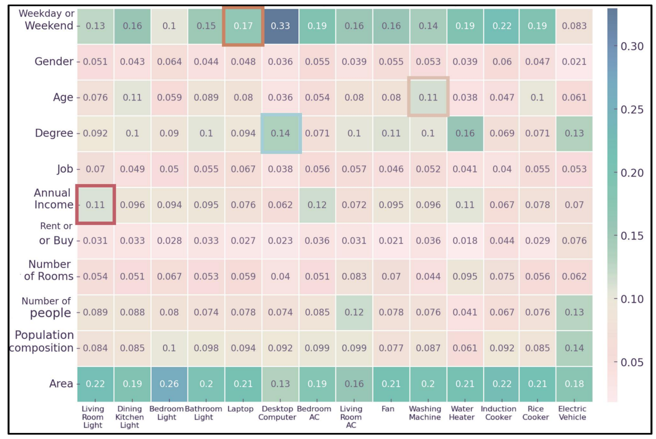

Fig. 4 Feature importance heatmap of Random Forest based on appliance usage time characteristics

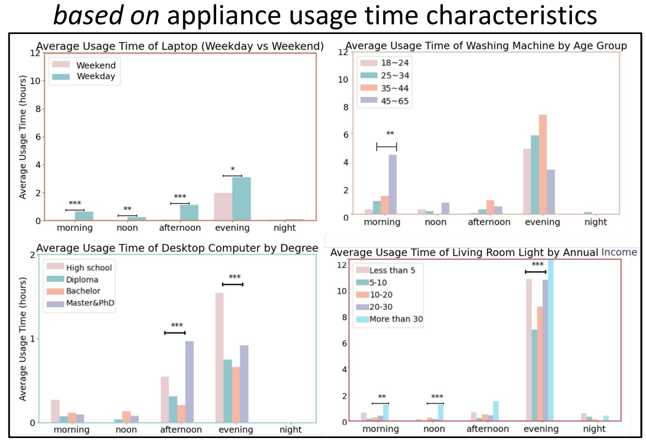

*Fig. 5 Significance difference of selected appliance(**** for p-values <0.001, ** for p <0.01, and * for p<0.05*)*

The feature importance heatmap of Random Forest based on 24-hour usage patterns shows the "area" is still the most important feature influncing the usage pattern prediction except “weather”(Fig. 6). Use the Chi-Square test for independence between classified variables (clusters) and calculate the proportion of each group in the user attributes (Fig. 7). For example, weekdays (67%) contribute to cluster 1 of Desktop Computer, while weekdays (91%) contribute the most to cluster 2.

This analysis provides valuable insights into how various social and demographic factors influence appliance usage patterns, informing the development of targeted energy management strategies and policies.

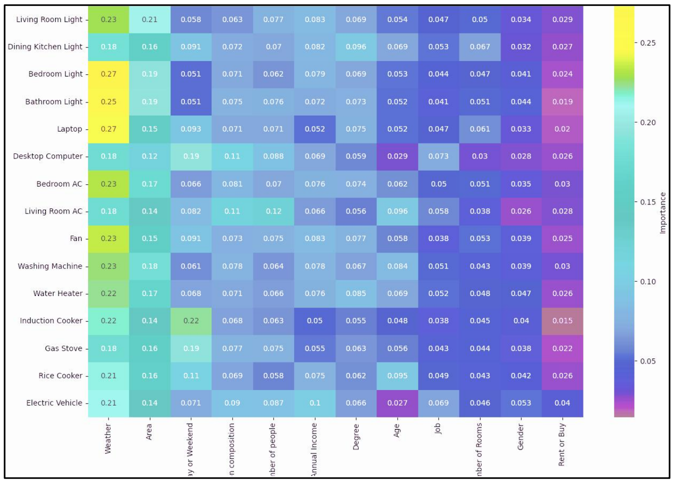

Fig. 6 Feature importance heatmap of Random Forest based on 24-hour usage patterns

appliance usage time and patterns from 373 24-hour usage data. Key conclusions include:

1. Typical appliance usage times and patterns: Appliance usage trajectories of cluster centers revealed their typical usage frequency and duration throughout the day. For example, significant peaks in usage were observed in the mornings and evenings, reflecting daily routines. Regarding different appliance categories, Power Shiftable Loads were primarily used in the evenings; Memory Loads around noon and evening; Time Shiftable Loads at fixed times; and Rigid and Battery Loads in dispersed patterns.

2. Impact of social attributes on predicting appliance usage patterns: A Random Forest model was trained to predict appliance clusters based on social

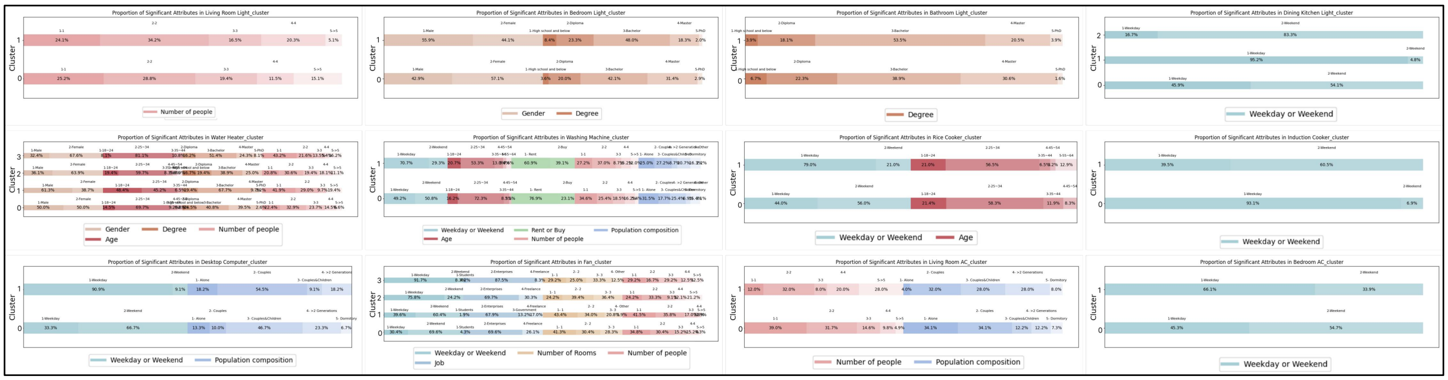

*Fig.7 User attributes proportion of 24-hour patterns clusters with significance difference(*p-value<0.05*)*

attributes. Attributes such as day-type, area, education, income, and age were found to significantly impact usage patterns, as indicated by the feature importance analysis.

3. Significance of day-type on usage duration: For example, weekend usage was longer during the day compared to weekdays.

These findings can help formulate policies and incentives to encourage participation in demand response, optimizing power resource allocation. Future research could investigate how appliance usage patterns change over long time or respond to external influences like energy-saving policies or smart home technologies. Incorporating machine learning models for continuous monitoring and prediction of consumption behaviors may further optimize the balance between user satisfaction and energy efficiency. This study sets the foundation for advanced energy management systems that accommodate diverse behaviors while promoting a more sustainable and adaptable power grid.

4. DISCUSSION

This study identifies patterns and factors influencing residential energy usage for various appliances but has limitations: The sample from Guangdong Province is relatively small and may not represent nationwide behaviors; The data still rely on self-reporting, which introduces an acceptable level of bias[9]; The application's usability may affect data accuracy, particularly for elderly users. Future research should expand the sample size for improved generalizability. Integrating more smart devices and addressing privacy concerns could enable long-term tracking of energy consumption behaviors.

5. CONCLUSIONS

This study analyzes residential energy consumption using a tracking application and panel study method. K-means, Random Forest, T-test, and Chi-Square tests were applied to analyze the regularity and diversity of

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