Towards Novel Forecasting Methods that Utilize Smart Home and Activity Tracking Data to Improve Energy Literacy and Lifestyles

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As energy consumption rises globally, finding sustainable solutions to meet these energy demands is essential. This need has created opportunities for various energy monitoring solutions aimed that inform users about their consumption to help achieve individual and community-oriented energy goals. However, making improvements and changing behaviors can be a laborious, expensive, and complicated process that often fails to account for the habits, preferences, and social practices that define building occupants' energy lifestyles. In this workshop paper, we presented recent literature and several user-centric use cases that envision supporting by leveraging energy monitoring systems, IoT devices, and personal activity data to produce novel human-building interactions.

CCS Concepts: • **Human-centered computing** → **Human computer interaction (HCI);** ***Wearable and Ubiquitous computing systems and tools***; • **Social and professional topics** → Sustainability.

Additional Key Words and Phrases: sustainability, health, ubiquitous computing, wearable devices, energy, smart home

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1 INTRODUCTION

As global energy consumption continues to increase, finding sustainable solutions to meet these rising demands becomes crucial. A promising trend in recent years is countries worldwide increasingly adopting policies and promoting devices to meet demand more efficiently, reducing overall consumption even in places with rising incomes and populations [11]. In 2022, for example, the residential and commercial sectors made up 38% of the total energy consumption in the United States [1]. With continued innovations and efforts expected, some reports suggest that energy consumption from these sectors could approach 25% by 2050 (e.g., [5]). This increase in energy demand creates opportunities for Internet of Things (IoT) devices to help us meet a crucial goal and continue to transform how we manage energy consumption within residential, multi-occupancy, and commercial buildings. Smart meters, smart homes (e.g., thermostats, plugs, lighting, assistants), wearable technologies (e.g., smart watches), and other devices (e.g., smartphones) collect a massive amount of data on power consumption, building systems, and human activity creating a rich technological environment for precise monitoring as well as resource and schedule optimization [2]. However, improving energy efficiency is often a complex and costly process that overlooks the habits, preferences, and social practices that define building occupants' energy lifestyles. In this workshop paper, we presented recent literature and user-centric use cases that leverage energy monitoring systems, IoT devices, and personal activity data to create novel human-building interactions that support sustainable energy practices.

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2 RELATED WORKS

Our work currently focuses on understanding energy consumption related to numerous lifestyle habits that might be missed in current modeling and forecasting approaches. For example, Ding et al. (2019) introduced an occupancy-based model for predicting a building's electricity consumption that moves beyond traditional area-based metrics, which have become less effective due to rising per capita space and energy demand [3]. The occupancy-based model distinguishing between 'basic' and 'variable' consumption influenced by occupancy and utilized probability functions and Markov models for greater accuracy in reflecting energy usage dynamics [3]. Other studies have looked at whole home factors. For example, Jin et al. (2021) analyzed household energy consumption patterns using a clustering method and identified items like outdoor temperature as a crucial factor that affects energy usage during peak summer months [6]. Such studies highlight that many factors influence the forecasting and modeling of energy demand.

Given the myriad factors influencing energy demand, determining policy and pricing can be difficult. For example, demand response programs incentivize customers to shift their energy usage through TOU pricing, direct load control, and critical peak pricing. Energy providers also create demand response programs to incentivize their customers to use less energy during peak hours, taking advantage of lower demand periods and offering electricity at lower rates [4]. According to Walawalkar (2010), financial incentives, regulatory mandates, and education/outreach efforts are being used to support these programs [12]. Implementing demand response programs and policies can contribute to a more reliable and sustainable energy system. However, responding to these changes in pricing may put additional stress on residential consumers with limited flexibility in their schedules (e.g., families [10]).

The complexity of energy consumption in residential and multi-occupancy settings can be addressed by improving data collection to predict and influence energy use patterns. Recent work by Kapp et al. (2023) contributes to energy forecasting with a new machine-learning model based on extensive data from manufacturing plants that rely on linear regression and specific quantitative factors that might not fully encapsulate industrial energy use's dynamic and multifaceted nature, with less quantifiable influences like human behavior [7]. HEMS-IoT- which is a combination of Home Energy Management Systems (HEMS) and the Internet of Things (IoT), employs big data and machine learning, specifically the J48 algorithm and Weka API, for optimizing energy use, comfort, and safety and adapts to user behaviors and preferences using RuleML and Apache Mahout, effectively reducing energy consumption while ensuring homeowner comfort and safety [8]. Further, a recent study on occupants in intelligent or quantified buildings that focused on occupants' perceptions, concerns, and values regarding the collection and use of data within these environments emphasized the importance of prioritizing occupant privacy and engagement while leveraging technology to enhance living and working spaces and the need for integrating occupant feedback into the design process [9].

Much of the work here indicates that understanding various factors influencing energy consumption is critical. Responsive smart buildings offer solutions to meet user needs and expectations for energy consumption but should also be ethical and user-centered. Next, we describe several use case scenarios illustrating a novel approach expected to enhance the ability to forecast energy consumption while providing more effective and personalized energy-saving interventions.

3 USE CASES

3.1 Residential Energy

We can see in the Figure 1 scenario a family living in a suburban home where the father works from home during the day, the mother works outside the house, and the children are in school.

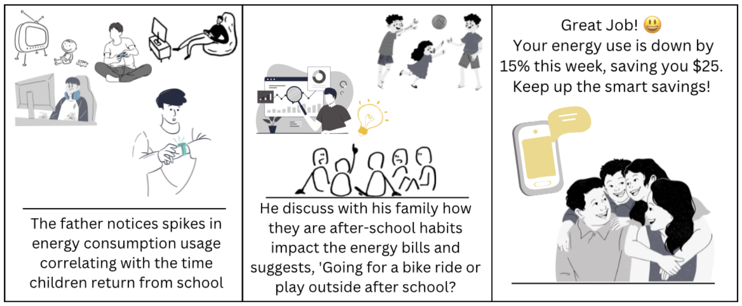

Fig. 1. Smart Home Energy Insights : A Family-Friendly Approach to Monitoring.

Problem: The father has been receiving alerts on his smartwatch lately that their energy consumption is higher than usual during the afternoons. The father does not know how to reduce this consumption and wants to learn more about the source of the problem and mitigation strategies.

Solution: By constantly monitoring energy usage patterns and activity data, we can detect unusual activity and offer helpful tips to optimize energy consumption habits. For instance, an intervention system may strongly recommend using daylight hours for outdoor activities to reduce energy consumption. It can also suggest discussing better energy consumption habits with the children and encouraging them to turn off lights and electronic devices when not in use.

Benefit: The system helps users understand energy expenses, promotes energy consciousness through smartwatch integration, and offers data-driven insights and suggestions for improving household efficiency beyond saving money.

3.2 Energy Policy for Residents with Inflexible Schedules in Multi-Occupancy Buildings

The building manager seeks to optimize energy usage without unfairly impacting residents who, due to rigid work schedules or other constraints, cannot adjust their energy consumption habits. As shown in Figure 2

Problem: The building manager recognizes that residents with fixed schedules, such as night-shift workers or those who work from home, are often disadvantaged by traditional energy policies and face higher energy costs during peak hours when they need to use energy the most.

Solution: The forecasting model can accommodate these residents' unique activity patterns, ensuring that heating, cooling, and major appliances are optimized around their presence and peak activity periods, thereby avoiding disruptions during their at-home hours.

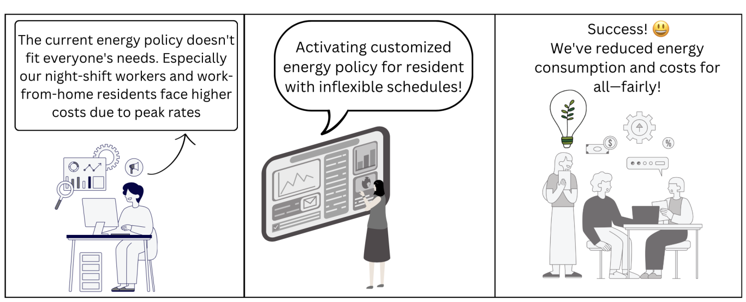

Fig. 2. Customized Energy Policy Implementation for Residents with Inflexible Schedules in Multi-Occupancy Environments.

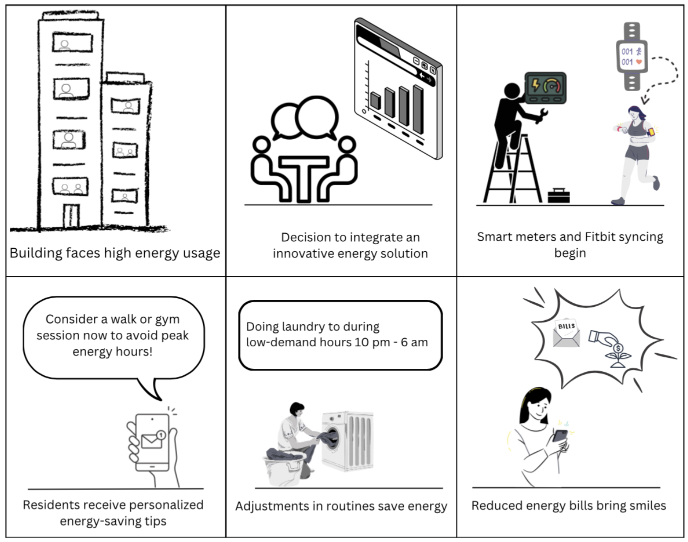

Fig. 3. Dynamic Energy Management in Multi-Occupancy Buildings with Mixed-Use Spaces (Left-Right).

Benefit: Our customized approach reduces the overall energy footprint of the building while minimizing the impact on residents who cannot shift their energy use to off-peak times. It promotes fairness by adjusting energy savings measures to the lifestyle constraints of each resident, ensuring that all benefit while maintaining a comfortable living environment.

3.3 Cooperative Energy Management in Mixed-use Development Zones

The diversity of occupancy patterns and the building's operational needs require a dynamic approach to energy management that houses residential units alongside retail and office spaces. As we describe the scenario in Figure 3.

Problem: Traditional energy management systems struggle to meet the fluctuating demands of mixed-use buildings, where peak energy usage, influenced by residential and commercial activities, drives up costs and consumption.

Solution: Future systems could accurately forecast energy usage using occupancy data, provide customized energy-saving advice, optimize lighting and HVAC settings during low-occupancy periods, and encourage shifting energy-intensive tasks to off-peak hours. Additionally, the systems could dispatch tailored notifications to guide residents and commercial tenants on adjusting their activities to contribute to energy savings goals.

Benefit: This system reduces energy demand, fosters community, promotes sustainability, boosts efficiency, and encourages healthy lifestyles. It creates a culture of eco-conscious living and working spaces for all occupants.

4 CONCLUSIONS

Our work aims to develop a solution for managing energy consumption in residential, multi-occupancy, and other community buildings using data from intelligent energy and activity-tracking devices. The expected contributions of our work include (i) new forecasting models and intervention methods, (ii) deployment studies investigating how such systems might improve demand response and pro-environmental behaviors, and behavioral models to understand energy consumption. We aim to discuss these use cases and other questions at the workshop. For example, how might sharing data from smart buildings with various stakeholders effectively help negotiate changes to energy policy while respecting occupants' privacy?

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