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Predicting Human Activity and Energy Management in smart Home through Artificial Intelligence: A Review

Amel Bouacida[1*], Abderrezak Guenounou[2], Fathia Chekired[3], Okba Rahmani[1].

[1*] *LTSM Laboratory Faculty of technology, University of Blida1* Blida,Algeria, [2]*dept. of Renewable Energies Faculty of technology, University of Blida1* Blida,Algeria, [3]*Unité de développement des equippements solaires, UDES. Centre de developpement des Energies Renouvelables, CDER.* Tipaza, 42004, Algeria

*Corresponding author *Email: bouacida_amel@univ-blida.dz*

Abstract

Human activity prediction plays a crucial role in energy management within smart homes. By understanding and anticipating residents' daily behaviors, energy management systems can optimize resource usage by adjusting lighting, heating, or appliance consumption based on actual needs. This approach helps reduce energy consumption, minimize costs, and maximize energy efficiency. In this paper we provide a comprehensive review of human activity recognition and prediction methods, focusing on machine learning techniques. It also explores associated energy management methods, highlighting how these techniques, when combined with activity predictions, enable smarter and more autonomous energy management systems in connected homes.

Keywords: *Human Activity Prediction, Energy management, Smart Homes, Artificial intelligence, Machine Learning, Renewable Energy.*

1. Introduction

Our homes have evolved into increasingly sophisticated and interconnected environments, driven by advances in technology. At the core of this technological revolution lie human activity prediction, intelligent energy management, and the Internet of Things (IoT), all working together to shape the concept of the smart home [1].

Modern residential technology now extends far beyond automating daily tasks. It promises to transform how we live, interact with our surroundings, and utilize energy resources, offering unprecedented benefits in comfort, security, and sustainability[2]. Intelligent energy management and human activity prediction play pivotal roles in this transformation[3]. By anticipating the behaviors and preferences of residents, smart home systems can autonomously adapt lighting, heating, and cooling, ensuring personalized and efficient energy use[4]. The ability to forecast occupant needs not only enhances living comfort but also enables highly optimized resource utilization[5]. Through these advanced capabilities, smart homes significantly reduce energy waste[6], contribute to environmental sustainability, and lower energy costs for occupants, marking a profound shift in residential living.

The paper is organized into several clearly defined sections to ensure ease of understanding and navigation. Section 2 explores the human activity detection process, from data collection to prediction. Section 3 examines various techniques for effective energy management. Section 4 offers a comprehensive review of previous studies, highlighting the methods, algorithms, results, and limitations of energy management in smart homes, with a particular focus on energy optimization techniques and intelligent control systems. In conclusion, we summarize the key findings, emphasize the critical role of activity prediction and energy optimization in the context of smart homes, and propose directions for future research

2. Human activity prediction

A. The process of human activity prediction

The process of human activity prediction is a crucial component in the development of intelligent systems, especially in the context of smart homes[7]. It leverages data from various sensors and machine learning algorithms to anticipate the actions and behaviors of individuals within a given environment[8]. The process of human activity prediction typically involves several key steps summarizing in Figure1.

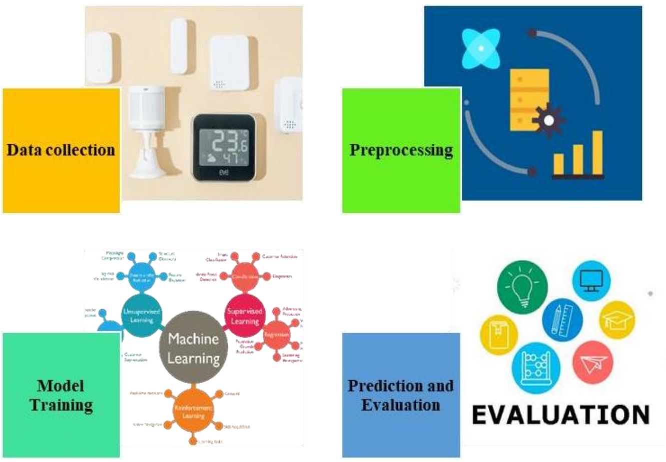

Figure 1: Human Activity Prediction Process

- Data Collection: This stage involves gathering data from various sensors, such as motion sensors, wearables, or environmental sensors, which track activities and behaviors over time.
- Preprocessing: The raw data is cleaned and processed to remove noise, handle missing values, and transform it into a suitable format for analysis. This step may include normalization or feature extraction.
- Model Training: Machine learning algorithms, such as decision trees, neural networks, or hidden Markov models[3], are trained using historical data to learn the patterns associated with different activities.
- Prediction: Once the model is trained, it can predict future activities based on real-time data input. The model assesses the current sensor data and classifies the corresponding human activity.

- Evaluation: The model's performance is evaluated using metrics such as accuracy, precision, and recall, to assess its effectiveness in predicting human activities accurately.

3. Home energy management system

Human activity prediction plays a pivotal role in advanced energy management by enabling the proactive optimization of energy consumption. By accurately forecasting daily behaviors, such as appliance use and environmental control, energy systems can dynamically adjust to demand, reducing inefficiencies and enhancing resource allocation[9, 10]. This integration of activity recognition with energy management facilitates real-time adjustments, supports demand-response strategies, and contributes to more sustainable, cost-effective energy consumption in smart environments[11].

A. Techniques of energy management systems

Home Energy management systems (HEMS) are crucial for controlling a home's electrical consumption, especially during Demand Response (DR) events[12]. DR events are moments when companies require customers to reduce their electrical consumption during times of high demand or to minimize the strain on the grid[13]. Following in Figure 2 are some techniques that HEMS can employ to schedule appliances throughout DR events.

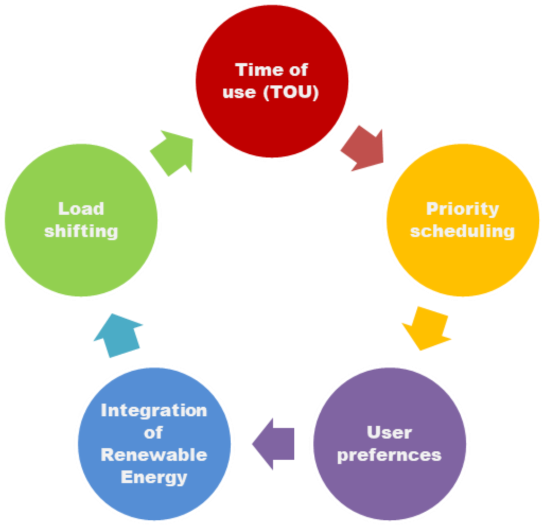

Figure 2: Different DR techniques for HEMS system

- Time-of-Use Scheduling: HEMS can schedule the operation of appliances based on the time-of-use pricing offered by the utility. Appliances may be programmed to run during off-peak hours when electricity rates are lower[10].
- Load Shifting: HEMS can shift the operation of certain appliances to times when overall energy demand is lower. For example, a dishwasher or washing machine could be scheduled to run during the early morning or late evening hours to avoid peak demand times[14].
- Priority Scheduling: HEMS can prioritize the operation of appliances based on factors such as energy efficiency, user preferences, and immediate needs. For example, it may prioritize running the refrigerator or heating system over other appliances during peak demand periods[14].
- Integration with Renewable Energy Sources: HEMS can optimize appliance scheduling to take advantage of periods when renewable energy sources, such as solar or wind power, are generating electricity.

Appliances can be scheduled to run when renewable energy production is high, thereby reducing reliance on grid electricity[15].

4. Review of hems techniques

In this section, we will present the state of the art of techniques used for energy management, outlining the approaches, results achieved, and their limitations. We will examine existing methods, highlighting their performance in various application contexts, and analyze the challenges these technologies face, to better understand their potential and constraints in the field of energy consumption optimization.

A. Litterature Review

The proposed method of Lima, et al. [16] utilizes machine learning techniques to automatically recognize the user's activities, and then a ranking algorithm is applied to relate activities and existing home appliances to save up to 35% of electricity in a smart home.

Rashid, et al. [17]presents a power management algorithm (PMA) for HEMS that integrates renewable energy sources (RESs) and energy storage systems (ESS) to optimize energy usage and reduce costs, achieving savings of up to 34% in energy and 45% in costs.

Ramalingam and Shanmugam [18] presents a day-ahead scheduling strategy for battery energy storage in smart homes, integrating RESs. It utilizes antlion optimization and salp swarm optimization algorithms to minimize electricity costs while managing battery charging and discharging constraints effectively.

Jing, et al. [19] presents a HEMS that optimizes smart appliance operation, integrating rooftop photovoltaic systems to enhance cost-effectiveness. It employs a novel scheduling method based on time-of-use pricing, comparing Gurobi optimizer with particle swarm optimization for effectiveness

Mehrabani, et al. [20] presents a home energy management system for a smart home utilizing RESs, including photovoltaic and wind systems, alongside battery storage and electric vehicles, optimizing energy management through various demand-side management programs and scenario simulations.

Baliyan, et al. [21] proposes an intelligent EMS for smart homes that integrates solar energy and battery storage, optimizing power flow and enabling users to sell excess energy, thus enhancing economic efficiency and reducing reliance on the power grid.

The paper of Mohammad, et al. [22] presents a HEMS that integrates RESs and ESS to optimize energy usage, reduce costs by 45.80%, and enhance efficiency through home-to- grid (H2G) power flow functionality.

Sharda, et al. [23] presents an IoT-based automated HEMS that integrates photovoltaic power, utilizing a stochastic real- time scheduling algorithm to minimize electricity costs while maintaining consumer comfort through smart plugs and cloud computing for efficient energy management, achieving average cost savings of 40%, 45%, and 48% under different pricing schemes..

Tammam Ajami and Jamaludin [24] presents a HEMS that optimizes energy costs, utilizes excess energy by selling it to the grid, manages battery state of charge, and enhances user comfort through load shifting without user scheduling, achieving an 83.66% cost reduction..

Wei, et al. [25] proposes a real-time energy management algorithm using deep reinforcement learning for smart homes with rooftop photovoltaics and energy storage. It aims to minimize energy costs while ensuring user comfort through effective scheduling based on various influencing factors.

Anguraj, et al. [26] proposes a precise energy consumption algorithm (PECA) for smart homes utilizing hybrid renewable energy. It employs smart plugs, gateways, and a mobile app to analyze and optimize energy usage, enhancing efficiency and maximizing renewable energy utilization.

Rashid, et al. [27] presents a load scheduling system using a Genetic Algorithm in a Smart Grid, integrating renewable energy to reduce electricity costs and Peak-to-Average Ratio (PAR) while adapting to real-time pricing, enhancing efficiency in home energy management.

In this paper, Masrani, et al. [28] proposed a real-time monitoring system for smart living, which allows the user to have greater control of their energy usage, all while automating things like adjusting devices based on weather conditions, turning on or off appliances based on occupancy of the room, etc.

Gorle and Farhan [29] proposes a unique architecture for a HEMS that optimally schedules household appliances using a particle swarm optimization algorithm, integrating rooftop solar and wind energies to enhance energy efficiency and reduce costs for residential consumers.

Abd-Elsalam, et al. [30] presents a HEMS that optimizes RESs and schedules appliances to minimize costs and Peak- to-Average-Ratio (PAR), utilizing a genetic algorithm for multi-objective optimization, enhancing user comfort and energy efficiency.

The proposed HEMS in the work of Sayed, et al. [31] incorporates rooftop PV units and electric vehicles, utilizing a load shifting technique for demand-side management. It optimizes energy use, reduces peak load demand, and enhances sustainability in smart grid environments.

Huy, et al. [32] presents a mixed integer linear programming (MILP) model for home energy management, integrating RESs like solar PV, ESS, and DR strategies to optimize energy scheduling and reduce electricity costs in smart homes.

Ghanavati, et al. [33] presents a HEMS model that optimizes energy consumption in smart homes, focusing on scheduling appliances and Electric Vehicle charging, which can be enhanced by integrating RESs for improved efficiency and cost savings.

Kanakadhurga and Prabaharan [34] proposes a HEMS, utilizing real-time pricing-based DR, integrating RESs like wind and solar, and employing the Binary Particle Swarm Optimization algorithm for efficient scheduling of smart appliances and electric vehicle operations.

B. Discussions

In the context of HEMS, various techniques have been explored to optimize consumption and enhance energy efficiency. Among these approaches, the integration RESs emerges as the optimal solution. RES, such as solar and wind energy, not only provide a sustainable power source but also help reduce reliance on fossil fuels, thereby lowering the carbon footprint of homes.

The following table summarizes the techniques discussed in each article, highlighting the superiority of using renewable energy for a more environmentally friendly and efficient energy management system.

Table I: Energy Management Techniques in Smart Homes

References	**Techniques Used**			
	Time of Use Price	Load scheduling	Load shifting	RE Integration
[17]				✓
[18]				✓
[19]	✓			✓
[20]				✓
[21]				✓
[22]				✓
[23]	✓			✓
[24]			✓	✓
[25]		✓		✓
[26]				✓
[27]	✓	✓		✓
[28]	✓			
[29]		✓		✓
[30]		✓		✓
[31]			✓	✓
[32]		✓		✓
[33]		✓		✓
[34]	✓	✓		✓

C. Challenges of HEMS

In home energy management systems, each technique comes with specific challenges that make effective energy optimization complex[35]:

a) **Time-of-Use Pricing**: This pricing model, which encourages energy use during off-peak hours, can be hard to implement as it requires consumers to be aware of pricing changes and willing to adjust their routines. Advanced smart meters and user-friendly interfaces are often needed to make ToU effective.

b) **Load Scheduling**: Automating energy use during low-demand times helps save energy but can be inconvenient if schedules don't align with user preferences. Limited compatibility across devices also makes efficient scheduling harder to achieve.

c) **Load Shifting**: Moving energy use away from peak hours sounds simple but can actually lead to mini-peaks at new times if many people shift at once. This requires careful coordination and predictive models to avoid new demand spikes.

d) **Renewable Energy Integration**: Bringing solar or wind power into homes is promising but complicated by the fact that these energy sources aren't always available. Effective integration requires costly storage solutions and advanced systems that balance supply and demand seamlessly.

4. Conclusion

Home Energy Management Systems in smart homes represent a promising solution for optimizing energy consumption by monitoring and controlling appliances in real time. These systems aim to achieve an efficient balance between energy usage, cost reduction, and user comfort, often incorporating renewable energy sources like solar panels to further improve sustainability.

The effectiveness of HEMS lies in the application of diverse computational techniques and algorithms. Rule-based systems, for example, provide structured control by following predefined guidelines for energy usage. However, more advanced optimization methods—such as genetic algorithms, particle swarm optimization, and linear programming—allow HEMS to dynamically adjust to changing conditions, such as energy prices or grid demand. Machine learning approaches, particularly classification and reinforcement learning algorithms, play an essential role in understanding and predicting user behaviors and daily activity patterns, enabling the system to adapt in real time. Reinforcement learning, in particular, is valuable as it continuously learns from environmental interactions, making it highly suitable for complex, real-time decision-making tasks within smart homes.

Despite these advancements, several critical challenges must be addressed to fully realize the potential of HEMS. One of the main issues is the variability and unpredictability of human behavior, which makes it challenging for predictive models to accurately anticipate usage patterns. Additionally, privacy concerns arise as HEMS require data on household habits, preferences, and schedules, demanding strong security measures to protect personal information. Technical challenges also include compatibility issues among diverse appliances and devices, often using different communication protocols, making seamless integration complex. Moreover, the high initial costs of HEMS installation and ongoing maintenance can deter widespread adoption, especially in lower-income households or regions without subsidies or incentives.

Ultimately, while HEMS technology holds tremendous promise for transforming energy management in smart homes, advancing this field requires focused innovation to address technical, privacy, and economic challenges. Successful implementation would lead to energy-efficient homes that are both environmentally sustainable and aligned with users' lifestyles, contributing significantly to broader energy-saving goals and climate change mitigation efforts.

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