# Intelligent-of-things multiagent system for smart home energy monitoring

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**ABSTRACT**

The proliferation of IoT devices has ushered in a new era of smart homes, where efficient energy management is a paramount concern. Multiagent artificial intelligence-of-things (MAIoT) has emerged as a promising approach to address the complex challenges of smart home energy management. This research study examines MAIoT's components, functioning, benefits, and drawbacks. MAIoT systems improve energy efficiency and user comfort by combining multiagent systems and IoT devices. However, privacy, security, interoperability, scalability, and user acceptability must be addressed. As technology advances, MAIoT in smart home energy management will offer more sophisticated and adaptable solutions to cut energy consumption and promote sustainability. This article describes how energy status and internal pricing signals affect group intelligent decision making and the interaction dynamics between consumers or decision makers. In a multiagent configuration based on the new concept of artificial intelligence-of-things, this intelligent home energy management challenge is simulated and illustrated using software and hardware. Based on sufficient experimental simulations, this paper suggested that residential clients can significantly improve their economic benefit and decision-making efficiency.



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## 1. INTRODUCTION

The advent of the internet of things (IoT) has revolutionized the way we interact with and manage our living spaces. In the contemporary era, the concept of a "smart home" has become increasingly prevalent. Smart homes are equipped with a multitude of interconnected devices, ranging from thermostats and lighting systems to appliances and security systems, all designed to enhance user comfort and energy efficiency. The integration of these devices, combined with the need for effective energy management, presents both opportunities and challenges [1], [2]. Optimizing energy consumption in smart homes is not a straightforward task, as it requires real-time monitoring and control of a diverse array of devices, all while considering user preferences and external factors such as weather conditions and fluctuating energy prices. To address these complexities and achieve the desired outcomes, multiagent artificial intelligence-of-things (MAIoT) systems have emerged as a promising solution. MAIoT combines the power of multiagent systems with the capabilities of IoT devices, providing a framework for intelligent energy management and automation [3]–[5]. This research paper aims to delve into the concept of MAIoT for smart home energy management, examining its key components, operational mechanisms, advantages, and the challenges it faces. It also explores the future prospects of MAIoT in the context of smart homes. By the end of this paper, readers will gain a comprehensive understanding of how MAIoT can be leveraged to create more energy-efficient and user-friendly smart homes, offering benefits to both homeowners and the environment [6], [7].

A multitude of distributed energy communities, shared energy projects, and microgrids across various regions are currently engaged in active investigation of novel demand-side energy interaction and transaction paradigms [8]. The brooklyn microgrid project, olympic peninsula tradable energy project, sonnen community local energy trading project in germany, and powerpeers shared energy project in the Netherlands are examples. Though distributed energy trading has advanced over the past decade, resource allocation and pricing in the electricity market are still largely governed by the hierarchical top-down framework of power system management [9]. Prosumers remain passive participants in local energy trading. This leads to higher transaction costs, lower efficiency, and slower regulatory responses [10]. However, sending wholesale pricing signals to retail is difficult. This affects downstream energy end-users' consumption patterns to meet system operating needs [11], [12]. Thus, some studies propose transactive energy or transactive control [13] to link the pricing mechanism to the energy status of adaptable distributed resources, enabling nuanced device or customer energy flow adjustments [14]. This notion might help the local energy infrastructure adjust to uncertain small consumer behavior and irregular renewable energy generation. Deregulated, open energy markets would also boost energy community and distributed energy resources collective resilience.

In the realm of energy management for distributed resources, the prevailing approach in current research is to utilize model-based control paradigms. Game-theoretic solutions, model predictive control, lagrange relaxation, and optimization algorithms are these paradigms [15]–[21]. However, creating an accurate physical model and controlling distribution network demand-side resources are difficult. Additionally, these methods will increase computing complexity and lower intelligence. In addition to model-based control, several academics are using advanced AI technologies to solve energy management problems [22]. Data-driven and model-free control frameworks like reinforcement learning (RL) or deep reinforcement learning (DRL) learn from the environment to build optimum control techniques without prior knowledge.

## 2. MULTIAGENT ARTIFICIAL INTELLIGENCE-OF-THINGS (MAIoT)

MAIoT represents a novel approach that combines the principles of multiagent systems with the capabilities of the IoT to optimize energy management within smart homes. This integrated framework offers a sophisticated solution for addressing the dynamic challenges associated with smart home environments. The foundation of MAIoT comprises a vast array of IoT devices strategically positioned within a smart home. These devices encompass sensors, actuators, and controllers. They are responsible for collecting data related to energy consumption, environmental conditions, and user behavior. Examples of IoT devices include smart thermostats, motion sensors, lighting controllers, and smart appliances. The core of the MAIoT framework is a multiagent system. Within this system, software agents operate independently to perform various tasks, such as data analysis, decision-making, and control. Each agent is equipped with specific functionalities and is capable of collaborating with other agents to collectively achieve predefined goals. Orchestrating the entire MAIoT ecosystem is a centralized controller. This controller serves as the hub for data processing and decision execution. It receives data from IoT devices and communicates with relevant agents within the multiagent system to make informed decisions regarding energy consumption and home automation [23], [24].

### 2.1. Operation of MAIoT

MAIoT operates in a synchronized manner to facilitate efficient energy management within smart homes: i) IoT devices continuously collect data related to energy consumption and environmental conditions, such as temperature, occupancy, and lighting levels. ii) The collected data is transmitted to the centralized controller and shared with relevant agents within the multiagent system. iii) Agents analyze the incoming data and make real-time decisions to optimize energy consumption. For instance, an agent might decide to adjust the thermostat settings based on user preferences and the current temperature. iv) Agents communicate with one another to coordinate actions. For example, a lighting agent may dim the lights if the heating, ventilation and air conditioning (HVAC) agent determines that the room temperature needs adjustment for energy savings. v) The centralized controller then implements the actions based on agent decisions, ensuring that energy consumption is optimized while user comfort and convenience are maintained. This seamless coordination between IoT devices, agents, and the centralized controller allows the MAIoT system to adapt to changing conditions, make intelligent energy management decisions, and enhance the overall user experience within the smart home. MAIoT is a holistic framework that integrates the capabilities of IoT devices with multiagent systems to optimize energy management in smart homes. By promoting data-driven, adaptive, and user-centric approaches to energy consumption, MAIoT offers significant advantages in terms of energy efficiency and user comfort. However, the deployment of MAIoT systems also presents challenges related to privacy, security, interoperability, scalability, and user acceptance, which must be addressed to ensure successful implementation in real-world smart homes [25].

### 2.2. MAIoT for smart home energy management

The system architecture outlined in this article employs AI and IoT technologies, or a combination of the two, to manage the prosumer's energy status. The prosumer functions as an agent within this architecture. The IoT control terminal governs the electric device's state in accordance with the prevailing electricity market price and the physical limitations of the devices at hand. The millisecond-level broadcasting latency of the information interaction link between the community energy management system agent, and IoT terminal is disregarded in this study but remains amenable to further investigation. Simultaneously, when power remains constant, it is presumed that the pertinent conditions of diverse loads remain unchanged over the 15-minute time scale specified by the user. The application of MAIoT in smart home energy management presents numerous advantages, ranging from enhanced energy efficiency to improved user comfort and convenience. Below are the key advantages of employing MAIoT systems in the context of smart homes: MAIoT systems are designed to continually monitor and analyze energy consumption patterns within a smart home. By processing real-time data from IoT devices and employing advanced algorithms, these systems can make data-driven decisions to optimize energy use. This results in substantial energy savings over time, reducing electricity bills and environmental impact. One of the primary objectives of MAIoT is to enhance user comfort and convenience. The system considers user preferences, habits, and schedules when making energy management decisions. For example, it can adjust lighting, heating, or cooling systems to align with user preferences, ensuring that residents experience a comfortable living environment while also conserving energy.

MAIoT systems are highly adaptive. They can respond to changing circumstances in real-time. For instance, if weather conditions change or energy prices fluctuate, the system can promptly adjust heating, cooling, and lighting settings to ensure optimal energy use. This adaptability ensures that the smart home remains energy-efficient under varying conditions. Multiagent systems are inherently decentralized, with multiple agents operating independently but coordinating their actions as needed. This decentralized nature ensures fault tolerance, meaning that the failure of one agent or device does not disrupt the entire system. Even if a component malfunctions, other agents can compensate, maintaining the overall functionality of the system. MAIoT systems reduce the need for manual intervention in managing smart home devices. They can automate routine tasks like adjusting thermostats, controlling lighting, and managing appliances based on pre-defined user preferences. This automation not only enhances energy efficiency but also simplifies daily living for homeowners. MAIoT systems rely on data collected from IoT devices to make informed decisions. By analyzing this data, the system can identify patterns, anomalies, and energy-saving opportunities. This data-driven approach allows for more precise and efficient energy management.

The real-time data processing capabilities of MAIoT systems enable instantaneous control over various devices. This means that changes in energy consumption can be addressed promptly, minimizing energy wastage and ensuring that the smart home operates in an energy-efficient manner. The integration of MAIoT in smart home energy management offers numerous advantages, including improved energy efficiency, enhanced user comfort, adaptability to changing conditions, fault tolerance, automation, data-driven decision-making, and real-time control. These benefits collectively contribute to the vision of energy-efficient, comfortable, and convenient smart homes, benefiting both homeowners and the environment [26]–[32]. This article presents an intelligent home energy management framework that encompasses several components, including the grid company, community energy management system (CEMS), multiple residential customers, and IoT control terminals. The system framework is depicted in Figure 1. Residential consumers own internal electric loads that encompass adaptable resources capable of regulation, such as air conditioners (AC), electric water heaters (EWH), electric vehicles (EV), and distributed energy storage. Certain users also possess the capability to utilize distributed photovoltaic (PV) systems. The domestic client might be classified as a prosumer due to their significant capacity for power generation. The article presents a proposed system architecture that employs AI technology and IoT technology, collectively referred to as AIoT, to effectively control the energy status of the prosumer. In this design, the prosumer is considered as an agent. The control terminal of the IoT is responsible for regulating the operational states of electric devices. This regulation is determined by considering two factors: the market electricity price and the physical limitations imposed by the available devices [33]–[36].

### 2.3. Multiagent framework

The difficulty of making intelligent decisions for managing household energy in a single prosumer setting can be effectively resolved. This study examines a multiagent system that comprises many prosumers, as depicted in Figure 2. Based on the previously indicated system framework, distinct energy management strategies are implemented for various prosumers. It is important to acknowledge that the depicted schematic in Figure 2, illustrating the multiagent framework and energy management strategies for various prosumers, serves as a conceptual representation. It is crucial to recognize that the framework can be further extended to accommodate the intricacies and real-world circumstances.

### 2.4. Challenges and future prospects

While MAIoT offers substantial advantages for smart home energy management, it also presents a set of challenges that must be addressed. Additionally, exploring the future prospects of MAIoT reveals potential developments that can further enhance its effectiveness and adoption. As MAIoT systems collect and process vast amounts of data from IoT devices, privacy and security concerns arise. Protecting the sensitive information gathered from smart homes is essential to ensure user trust. Future developments must focus on robust encryption, authentication, and access control mechanisms to safeguard data against unauthorized access or breaches.

The current landscape of IoT devices is characterized by a lack of standardized communication protocols and interfaces. Interoperability challenges hinder the seamless integration of various devices into MAIoT systems. Future prospects involve the development of widely accepted standards that promote interoperability, allowing different devices to work together more effectively. The increasing number of IoT devices within smart homes poses scalability challenges for MAIoT systems. As homes become more connected, the MAIoT infrastructure needs to accommodate the growing device ecosystem. Future developments should focus on scalable architectures and efficient resource management to ensure MAIoT systems can adapt to the increasing device count. User acceptance is critical for the successful implementation of MAIoT systems. Many users may be unfamiliar with the complex workings of MAIoT and may be hesitant to trust these systems with energy management decisions. Future prospects include user education and the design of intuitive user interfaces to improve user acceptance and engagement.

While MAIoT aims to reduce energy consumption, it should also consider the sources of the energy being consumed. A future challenge is to optimize not only energy usage within a smart home but also to integrate renewable energy sources and consider broader environmental implications. MAIoT systems could become more proactive in maximizing the use of green energy sources.

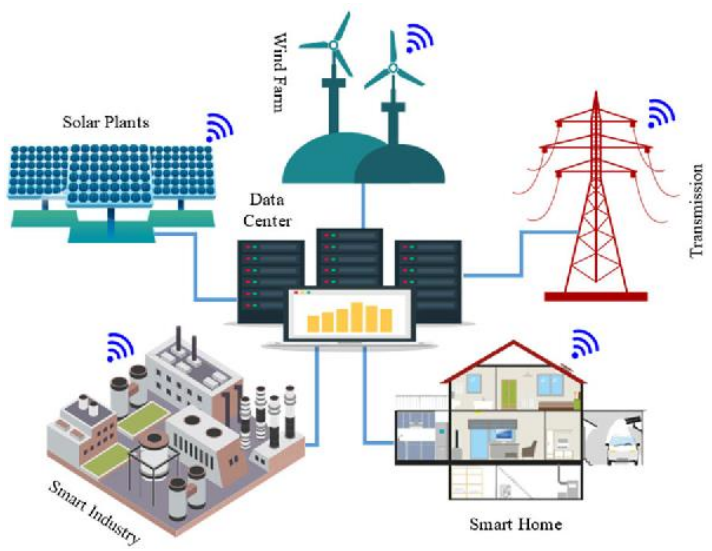


Figure 1. The AIoT-based framework of a smart home energy management system

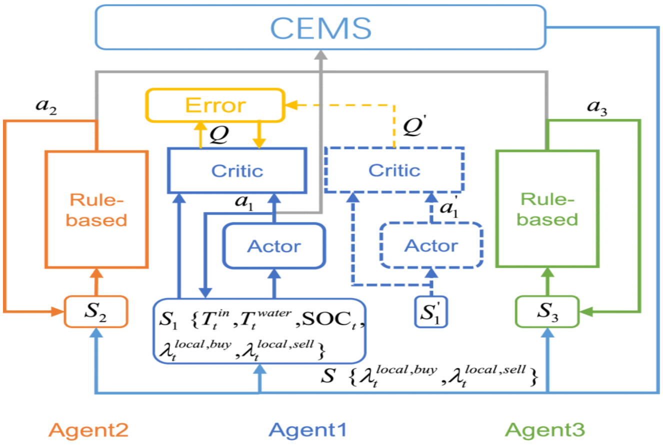


Figure 2. Multiagent framework for simulation

### 2.5. Machine learning and AI advancements

The field of machine learning and artificial intelligence continues to evolve rapidly. Future prospects for MAIoT systems involve leveraging advanced AI techniques, such as reinforcement learning and deep learning, to make more informed, nuanced decisions regarding energy management. This will further enhance energy efficiency and user comfort. Edge computing, which enables data processing and decision-making to occur closer to the IoT devices, can reduce latency and improve the real-time control capabilities of MAIoT systems. Future developments in edge computing will enhance the responsiveness and efficiency of MAIoT. Future MAIoT systems could provide users with more comprehensive customization options, allowing them to fine-tune their energy management preferences, which may include energy-saving goals, comfort levels, and even energy pricing preferences. Integrating MAIoT systems with smart grids can facilitate two-way communication between the home and the grid. This will enable demand-response programs and further optimization of energy usage based on grid conditions. The challenges associated with MAIoT, such as privacy, security, interoperability, scalability, and user acceptance, should be addressed to ensure the successful adoption of these systems in smart homes. Future prospects for MAIoT include advancements in AI, edge computing, customization, and integration with smart grids, all of which will further enhance energy management and contribute to more sustainable, efficient, and user-friendly smart homes.

## 3. RESULTS AND DISCUSSION

The case study presented in this article has a horizontal timeline of 58 hours and employs a time step of 15 minutes. Consequently, the model is trained over a total of 202 time intervals during each iteration. The case study incorporates data derived from actual settings, encompassing fixed load characteristics, outdoor temperature, and photovoltaic (PV) production. The remaining data, which encompasses the hourly water use and the electricity consumption associated with commuting using electric vehicles (EVs), is derived using data simulations.

Nevertheless, due to the model's independence and the agent's structure, the aforementioned framework was not implemented. Instead, we created our own environment code with OpenAI Gym as a foundation. During the training phase, the model's reliability is enhanced by subjecting the PV generation data and outdoor temperature data to a 6% disturbance shift in each training iteration. It is important to acknowledge that the limits established in this article are not obligatory in nature. During the initial phase of training, it is expected that the state space will surpass the constraints' limit. However, the training process will persist until completion. In order to enhance the intricacy of the model and validate the scalability of the proposed multiagent architecture, two additional agents are incorporated in this scenario, both of which employ the control strategy based.

### 3.1. Training process

At present, there exist RL environment frameworks, one of which is CityLearn [37]. Nevertheless, due to the model's autonomy and the agent's structure, the aforementioned framework was not implemented. Instead, we devised our own environment code with OpenAI Gym as a foundation. During the training phase, a 5% disturbance change is applied to the PV generation data and outdoor temperature data in order to improve the robustness of the model. It is important to acknowledge that the limits established in this article are not obligatory in nature. During the initial phase of training, it is expected that the state space will surpass the constraints' limit. However, the training process will persist until completion.

Figure 3 illustrates the alterations in the reward value curves of the three agents employing distinct regulation methodologies. Control approaches that are rule-based do not necessitate training. Once the agent has undergone a substantial number of training sessions, the reward value curve starts to converge, hence highlighting the benefits in comparison to rule-based regulatory approaches. The utilization of an intelligent energy management technique by a single trained agent (referred to as Agent 1) presents several notable advantages. Nevertheless, the decision made by the neural network model for an individual time node may not necessarily be the optimal choice. To optimize the performance of Agent 1, it is recommended to employ ensemble learning, which involves training numerous actor network models and combining their outputs into a unified prediction. Therefore, the issue of inadequate regulation impact resulting from a singular temporal node, which may be attributed to a solitary neural network model, has been resolved. In its entirety, this particular amalgamation yields a more favorable outcome. The aforementioned logic is depicted in Figure 4.

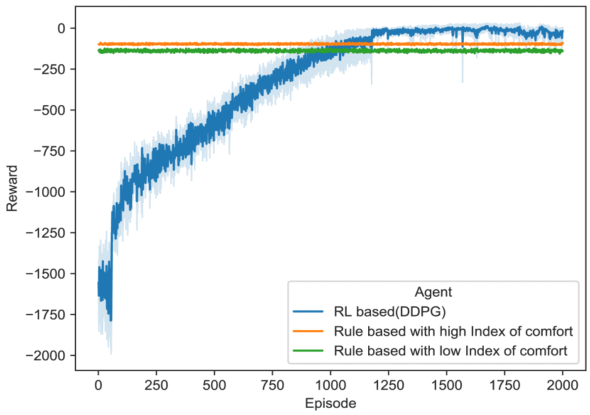


Figure 3. Reward value curves for different agents

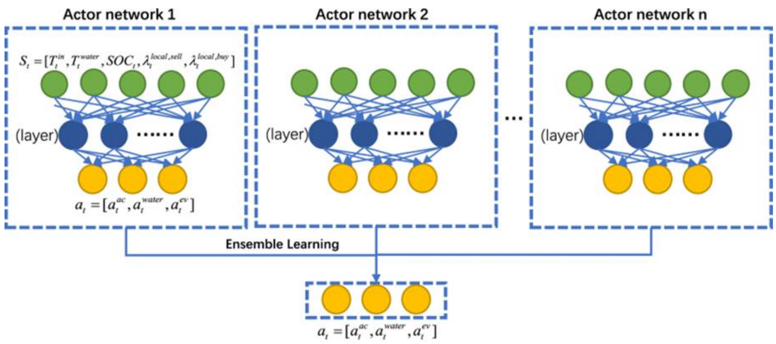


Figure 4. Aggregate multiple actor networks

The assessment of energy management solutions only based on electricity cost is deemed unsuitable due to the varying comfort requirements of individual users. In exceptional circumstances, in the absence of any comfort-related prerequisites, the user's electrical expenditure will be considerably less throughout this period. Therefore, an economic index is built for each of the three aforementioned sorts of electrical devices. The aforementioned economic index is not solely based on power cost, but rather incorporates the comfort index to assess the associated economic implications.

The initial component of the equation pertains to the conversion of the reward function into an economic index, while the subsequent component accounts for the electrical expenses associated with different devices. The comfort range differs across various users. The coefficient k is employed to represent the varying requirements of diverse consumers in terms of comfort. In real-world scenarios, users have the ability to customize the coefficient ω in the previously described reward function to align with their own requirements, hence personalizing the training process. Figure 5 displays the economic index of the control method and the rule-based control approach across different categories of electrical products.

### 3.2. Extension of multiagent framework

To enhance the intricacy of the model and assess the scalability of the proposed multiagent framework, two additional agents are introduced. These agents employ a control strategy as their operational approach. In the preceding study, we acquired three distinct datasets to facilitate the training of agents.

In the preceding study, we acquired three distinct datasets for the purpose of training agents. This study examines the datasets utilized by individual agents and the corresponding outcome data. In a manner akin to the training framework employed by three agents, the reward curve associated with the energy management method exhibits convergence and demonstrates a notable superiority over the rule-based strategy subsequent to undergoing 2000 training iterations. The increase in the complexity of models results in variations in the trajectory of the training curve. Due to the agent's limited capacity to directly perceive the actions and states of other agents, the involvement of additional agents results in a reduction of the influence exerted by the agent's own actions. The data pertaining to the related load and internal price can be observed in Figure 6. The internal price undergoes modification when there is an excess of energy inside the community, and it remains constrained between the range of the feed-in tariff price and the retail price offered by the Grid Company consistently.

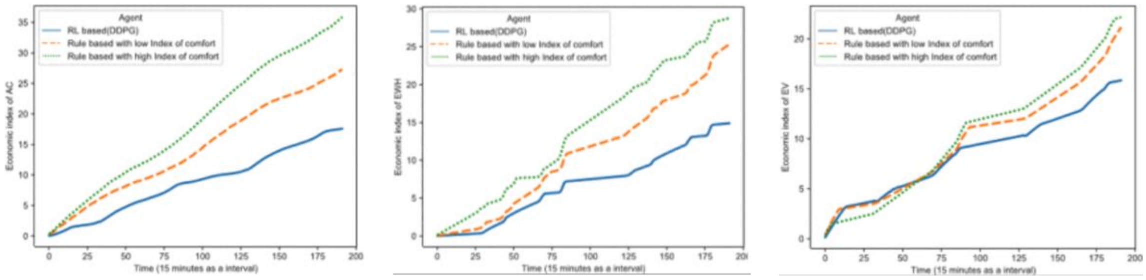


Figure 5. Economic indexes of various types of electrical devices

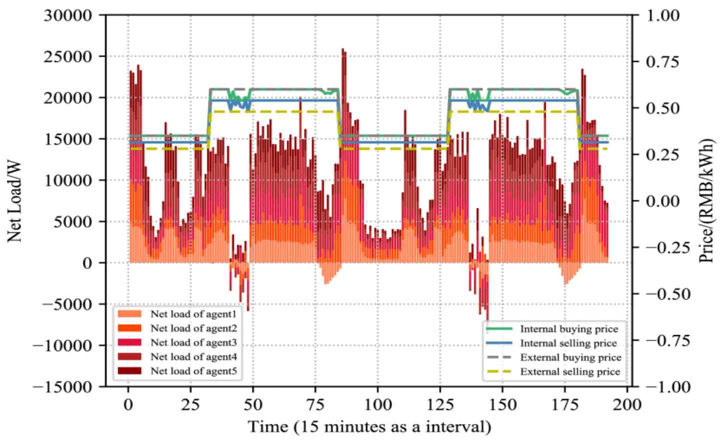


Figure 6. Load and internal price for different agent

## 4. CONCLUSION

MAIoT represents a groundbreaking approach to smart home energy management by combining the capabilities of the IoT with intelligent multiagent systems. This research paper has examined the core components, operation, advantages, challenges, and future prospects of MAIoT in the context of smart homes. MAIoT offers a multitude of benefits, including enhanced energy efficiency, improved user comfort, adaptability to changing conditions, fault tolerance, automation, and data-driven decision-making and real-time control. These advantages collectively contribute to the vision of energy-efficient, comfortable, and convenient smart homes, which benefit both homeowners and the environment. However, challenges such as privacy and security, interoperability, scalability, and user acceptance must be addressed to ensure the successful implementation of MAIoT systems. Using self-adaptive capabilities, the proposed energy management strategy is capable of intelligently regulating a variety of electric devices. While maintaining user convenience, the automated decision-making procedure may result in electricity cost savings for the user. These challenges require ongoing research and innovation to create systems that are trustworthy, user-friendly, and seamlessly integrated into smart home environments. Looking to the future, several promising developments are on the horizon for MAIoT. These include advancements in machine learning and AI, which will enable more sophisticated decision-making, edge computing to enhance real-time control and responsiveness, and the integration of smart grids for more comprehensive energy management. User-centric customization and the consideration of energy sources and environmental impact are additional aspects that can be further refined.

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