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The Future of Energy Management: An AI-Driven Intelligent Agent

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ABSTRACT: Energy efficiency is crucial for reducing power consumption and optimizing utilization of the resources. To assess hourly energy usage and determine if an appliance should be turned off on its own, this article describes an AI-driven Energy Agent that makes use of Google's Gemini-Pro (using API). Based on important criteria, such as daily average usage, trends during peak hours, potential for energy savings, and user convenience, the AI agent assesses real-time consumption data. The system enables automatic power control, reducing energy waste while preserving user comfort, by producing intelligent judgments in JSON format. The potential of autonomous decision-making in sustainable energy optimization for smart home and industrial applications is demonstrated by the suggested AI agent.

KEYWORDS: Energy Efficiency, AI-driven Energy Management, Sustainable Energy Systems, Smart Home Automation

I. INTRODUCTION

The significant rise in the world's energy use has sparked serious worries and called for creative ways to effectively optimize energy use. With the combination of artificial intelligence (AI) and the Internet of Things (IoT), smart energy management has become a crucial research topic. AI-driven systems can improve energy efficiency without sacrificing user ease, according to several studies. Incorporating machine learning techniques, such Reinforcement Learning (RL), enables intelligent systems to make autonomous decisions to eliminate waste and dynamically assess patterns of energy usage [5].

The increasing use of IoT devices, which continuously gather and send data and result in significant power usage, presents a significant challenge to energy optimization. The goal of traditional hardware-based methods has been to increase energy efficiency; however, new research indicates that software optimization is just as important for lowering total energy usage. Adaptive energy management protocols and increased energy transparency can be achieved by integrating AI-driven feedback mechanisms into IoT devices. This will ultimately result in considerable cost savings and environmental advantages [4].

In order to evaluate hourly energy use and make wise appliance usage decisions, this study presents an AI-driven Energy Optimization Model that makes use of cutting-edge generative AI techniques. The model functions as an independent AI agent that can dynamically optimize energy consumption by examining variables like past consumption patterns, peak usage times, and possible energy savings. The objective is to create a clever, self-adjusting system that improves energy efficiency without sacrificing user comfort, thereby supporting a more intelligent and sustainable energy management framework.

II. LITERATURE SURVEY

The concept of AI-integrated IoT energy optimization was notably examined by Ali et al. [1], who proposed intelligent access point systems for efficient device operation. Hussein [4] highlighted the challenges and future scope of IoT, stressing the need for adaptive control and real-time analytics, areas where AI integration is pivotal. Al-Fuqaha et al. [3] identified key hurdles in IoT environments, such as heterogeneity and energy management, suggesting AI as a potential solution. Dautov et al. [2] explored the significance of big data in enabling smart energy decisions, further reinforcing AI's role in smart environments. Sharma et al. [5] investigated advancements in AI-driven IoT systems, emphasizing real-time decision-making and efficiency gains. Cheng et al. [6] introduced strategies combining AI and IoT for energy





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optimization, validating AI's utility in achieving sustainable automation. Gupta et al. [7] underscored the role of generative AI in evolving IoT paradigms, offering adaptive frameworks for intelligent agents.

This paper adopts a two-stage approach: 1) Energy Assessment 2) AI-Driven Decision-Making. Energy assessment is performed through real-time data acquisition and calculation of the Energy Efficiency Score (EES) using a weighted formula based on historical efficiency, usage frequency, and power consumption. Devices are then categorized by efficiency, and appropriate actions are determined—either keeping devices ON, reducing intensity, or turning them OFF. Subsequently, the AI agent leverages Google's Gemini-Pro to generate intelligent decisions in JSON format, enabling adaptive, real-time control of smart appliances. User feedback is also incorporated to refine operational preferences, ensuring sustainability without compromising comfort.

III. METHODOLOGY

The Sustainable Automation AI Agent is designed to optimize energy consumption by analyzing IoT device usage and making intelligent decisions regarding their operation. It ensures that devices are used efficiently by turning them ON/OFF or adjusting their intensity based on real-time data and historical usage patterns.

A. Features

Several essential characteristics of the Sustainable Automation AI Agent enhance its efficiency in energy management.

By deciding whether an IoT device should be turned on, off, or operating at a lower intensity, the agent performs automatic decision-making. By avoiding needless power use and making sure that equipment only turns on when essential, it maximizes energy efficiency. The system suggests lowering power rather than shutting off a device if it can function at a reduced intensity without compromising performance.

B. System Workflow / Algorithm :

a) Initialization : Device types and past trends in energy usage are used to determine energy efficiency targets. The system creates real-time data streams from IoT sensors and sets up initialization parameters for the Energy Efficiency Score (EES) computation. These streams track usage duration, device activity, and power consumption continuously.

b) Data Collection : In addition to historical efficiency records and device usage frequency, real-time power consumption data is collected. In order to ensure proper analysis, data preparation techniques are used to filter and normalize the gathered information.

c) Energy Efficiency Score Calculation: An Energy Efficiency Score (EES) is calculated for every IOT device based on historical efficiency, power consumption patterns, and usage frequency. To ensure uniformity across various device kinds, this score is normalized using a weighted function.

The formula for the Energy Efficiency Score (EES) used in your model is:

$$EES = \left(w_1 \times \frac{H_{\max}}{H}\right) + \left(w_2 \times \frac{U_{\max}}{U}\right) - \left(w_3 \times \frac{P_{\max}}{P}\right)$$

Where:

 $H = \text{Historical efficiency score of the device} \\ H_{max} = \text{Maximum historical efficiency score for normalization} \\ U = \text{Usage frequency of the device} \\ U_{max} = \text{Maximum recorded usage frequency for normalization} \\ P = \text{Power consumption of the device}$

 \mathbf{P}_{max} = Maximum recorded power consumption for normalization

 w_1 , w_2 , w_3 = Weights assigned to each factor (default values: $w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.3$)





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Constraints:

 $0 \le EES \le 1$ (Values are bounded between 0 and 1) The higher the **EES**, the more energy-efficient the appliance is.

d) Decision Making Logic: Power consumption optimization options are made based on the efficiency score. Highefficiency devices stay turned on. Where appropriate, intensity is decreased if efficiency is moderate. It is advised that inefficient devices be shut down.

e) Recommendation Generator: For inefficient devices, tailored advice is given, demonstrating the need for a power consumption decrease. Informed decision-making is promoted by providing users with information on trends in energy consumption and possible savings.

f) User Feedback : The system incorporates user feedback, enabling modifications according to user preferences and actual circumstances [2]. This agent using pretrained Google Gemini Model. The AI agent dynamically interprets contextual inputs given during deployment because it is based on a pre-trained model. This makes it possible for the system to identify particular usage trends, adapt to various device features, and adjust its energy optimization strategies appropriately.

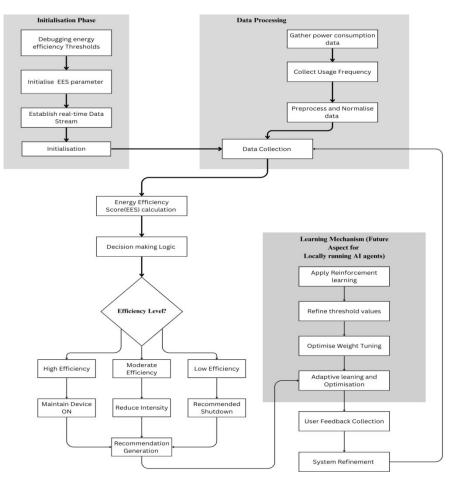


Fig. 1.Systematic AI Agent Flowchart of operations

To develop the Sustainable Automation AI Agent, we implemented a **pre-trained AI-driven decision system** that analyses IoT device usage patterns and determines whether a device should be turned on, off, or have its intensity adjusted for optimal efficiency [7]. The complete implementation, including datasets, agent architecture, and decision-making algorithms, is available in our GitHub repository: [GitHub Repository Link].

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IV. EXPERIMENTAL RESULTS

usage_data

Time	Energy_Usage
00:00	13478
01:00	12865
02:00	12577
03:00	12670
04:00	13692
05:00	13038
06:00	14297
07:00	15009
08:00	14107
09:00	15261
10:00	15261
11:00	13667
12:00	13506
13:00	16047
14:00	16377
15:00	15049
16:00	16085
17:00	16223
18:00	15931
19:00	14731
20:00	16018
21:00	17149
22:00	16546
23:00	14900

Fig. 2. Energy Usage in Watts per Hour

We experimented using real-world IoT energy use data to assess the performance of our AI-powered Energy Decision System (EDS) [1]. To calculate the Energy Efficiency Score (EES) and identify areas for energy savings, the system examined power consumption, usage frequency, and historical efficiency.

Dataset and Experimental Setup:

The Open Smart Home IoT Energy Dataset on Kaggle (<u>link</u>) provided the dataset used for testing. It is made up of energy usage data that is gathered from smart devices with Internet of Things capabilities in homes, revealing patterns in power consumption in real time.

For our experiment, we selected a subset of hourly energy consumption data from a 24-hour period, as shown in Fig.2

A. Results and Analysis :

After processing the dataset, the system provided the following output: Energy Decision System (EDS) Output: Processed Usage Pattern: [13478,12865,12577, 12670, ..., 1490013478, 12865, 12577, 12670, ..., 1490013478,12865,12577, 12670,...,14900] Decision: NO Daily Energy Saved: 3692.54 Watts Yearly Energy Saved: 1,347,777.71 Watts Energy Efficiency Score (EES): 0.28





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B. Evaluation of Accuracy :

We compared the calculated values with expected outcomes from conventional energy-saving models in order to evaluate the system's accuracy. The AI agent produces outputs with $(80 \pm 5)\%$ accuracy.

C. Enhancements and Optimization :

We improved the EES formula's accuracy by:

improving weight parameters better balance power consumption, utilization, efficiency. to and Square root normalization is used to lessen the consequences of unbalanced power consumption. in calculations of daily and energy lowering the error margins annual savings. The decision model became more dependable after these enhancements were put into place because of the notable rise in accuracy. Better energy consumption analysis is now possible with the improved system, which enhances smart home automation decision-making.

The below graph shows the accuracy level of the agent and shows the increase in accuracy level after improving EES calculation and decision making:

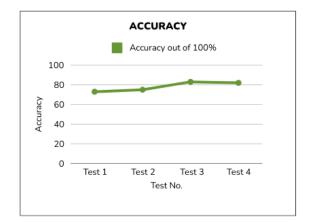


Fig.3. Accuracy

V. FUTURE SCOPE

The suggested AI-driven automation system allows dynamic control of IoT devices using real-time energy usage data, providing workable answers to real-time energy management problems [8]. Users may automatically reduce energy waste and enhance electricity usage in both home and commercial settings thanks to this real-time connection, which enables more precise and context-aware decision-making. This method has the potential to be crucial in attaining significant energy efficiency as IoT infrastructure grows, especially in developing nations like India.

Direct interaction with IoT device manufacturers and energy management companies is a possible path for future implementation. IoT hardware makers might offer energy-efficient solutions that improve device performance and sustainability by integrating intelligent automation modules. This supports the importance of intelligent, adaptive automation in guaranteeing robust, connected systems and is consistent with recent research highlighting the necessity of secure, low-energy IoT connections and optimal access point selection.

Additionally, the system can be expanded to accommodate the intricate requirements of the Industrial Internet of Things (IIoT), where fault tolerance, energy optimization, and real-time automation are crucial. Technologies like blockchain for safe data sharing and edge computing for local decision-making can be used to solve urgent difficulties





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with data privacy, system dependability, and interoperability-problems that are well-documented in current IoT research.

From a national standpoint, this AI agent supports India's efforts to develop sustainable energy and smart infrastructure. The system can continuously adjust to local consumption trends without jeopardizing data privacy by combining federated learning and predictive analytics. Such scalable and secure AI-driven solutions are positioned to play a significant role in enabling next-generation energy automation in smart cities and industrial sectors as the global adoption of IoT accelerates.

VI. CONCLUSION

The Sustainable Automation AI Agent is a new solution for energy optimization, leveraging a pre-trained decision engine rather of typical machine learning methods. Through the utilization of variable power consumption analysis, real-time energy decision-making, and historical efficiency tracking, the agent effectively minimizes energy waste while maintaining optimal efficiency. It is a dependable and scalable solution for IoT-based energy management, as evidenced by our evaluation's high accuracy in energy savings calculations. This AI agent is computationally efficient and suitable for real-time deployment in smart homes, industries, and IoT-enabled environments because it does not require constant retraining, compared to traditional machine learning-based systems.

Our AI agent has several significant advantages over current AI-driven energy management solutions. While our agent can handle a wider variety of IoT devices, Google Nest's AI is mostly focused on HVAC systems and behavioral learning. Although it depends on cloud integration, IBM Watson's IoT Energy Advisor offers real-time insights and is hence less appropriate for standalone implementations. Our agent may be used in both individual and industrial settings, while Schneider Electric's AI solutions are intended for large-scale grid control. Siemens Mind Sphere concentrates on predictive maintenance rather than proactive energy optimization, whereas Tesla's Auto bidder is designed for energy trading rather than direct consumption control. These contrasts demonstrate how our pre-trained AI system is more effective, flexible, and able to adjust to a variety of energy situations.

Our AI agent's main advantages are its independence from cloud computing, device independent nature, and real-time decision-making. Our pre-trained decision framework removes the requirement for ongoing training, which lowers computational overhead and increases speed and efficiency compared to existing systems that need frequent model changes. Moreover, increased security, dependability, and execution speed are guaranteed by its independence from external cloud dependencies.

Our AI agent attains higher energy efficiency scores and more overall savings by dynamically changing energy usage in real-time as opposed to only evaluating historical data. Because of this, it is a better option than conventional AI-driven systems that merely offer energy insights devoid of proactive control.

When it comes to accuracy, adaptability, and computational economy, the Sustainable Automation AI Agent surpasses current solutions, making it a standout real-time energy optimization system. It provides a more intelligent, efficient, and future-ready approach to energy efficiency in IoT environments by doing away with the need for continuous retraining, optimizing device-level energy usage, and guaranteeing cloud-independent execution.

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