

# Intelligent IoT-Based Home Automation for Real-Time Energy Optimization and Personalized Comfort Control

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**Abstract:** In the era of smart home, Adoption of the smart automation and IoT in the home area is one of the revolutionary approaches for energy consumption management and occupant comfort. This work introduces a next generation IoT based home automation solution with learning algorithms, real-time sensor analytics, and lightweight edge computing to dynamically optimize energy consumption. Unlike traditional methods that cater to efficiency or comfort, our system manages to provide a balance between the two and achieves it by personalized environmental manipulation and the prediction of individual behavior. The system aims to be vendor-agnostic and scalable, while being sensitive to user-preferences and the context of life for inhabiting smart homes with a dedicated focus towards various home sizes and shapes. The architecture is evaluated by applying it to real-world situation awareness and energy waste, and user satisfaction performance measures are used to show energy waste is reduced and user satisfaction is increased.

## 1 INTRODUCTION

Recent years have seen in increasing attention for intelligent environments with the development of home automation systems, in particular with the introduction of Internet of Things (IoT) technologies. Contemporary houses are not the static houses of old, but are living spaces that conform to the requirements, habits and desires of those who live in them. Although several automation systems have been proposed they do not have the capability to provide a trade-off between energy saving and personal comfort, and instead sacrifice one for the other. This bottleneck makes it necessary to have more intelligent systems that keep energy use under control without sacrificing quality of living. The fusion between IoT, AI and edge computing empowers the opportunity for real-time data

processing, predictive analytics and adaptive control, through which systems can learn user behaviors and environment variations. In this paper, we have proposed an emerging IoT-based home automation system for real-time energy optimization and user centric comfort control. The system is based on sensor networks, lightweight processing devices and machine learning to produce a reactive and efficient system through natural interaction. It's designed as an invisible interface for creating an uninterrupted user experience, where technology enables sustainability and liveability, without demanding anything from you.

## 2 PROBLEM STATEMENT

In contrast to the exponential expansion of IoT-based smart home devices, traditional home automation systems have continued to struggle in providing effective solutions to bring together energy efficiency and personalized comfort. Most existing solutions are too aggressive on saving energy without taking occupants' expectations into account, while others are based on pre-defined schedules that do not cope with changes in the user's behaviour or the surrounding environment. Moreover, most systems depend on off-line cloud-based processing, which adds to the latency and data privacy issues by preventing real-time control. Intelligent, context-aware frameworks are missing by which to exploit edge computing and adaptive learning for dynamic, user-responsive automation. This paper fills the void by presenting an IoT-based home automation system for the optimization of energy consumption in real-time, while guaranteeing personalized comfort with its learning and adaption to the context.

## 3 LITERATURE SURVEY

The development of IoT and smart control systems in HA has recently attracted considerable attention to the enhancement of the energy efficiency along with the user comfort. Aziza et al. (2021) introduced a cloud-based smart home system, but without deployment in real-world scenarios, implying the necessity of real-world usage. Ezugwu et al. (2025) provided the most extensive review of existing smart home systems, while focusing more on the theoretical aspects rather than the practical aspects. Sayed et al. (2021) introduced edge-based recommender systems for energy applications, although the testing was based on synthetic data and suffered less practical application relevance. Blockchains could be used to implement these smart contracts with little trust to the brokers (Yang and Wang, 2021), and the latency cost and the associated resource cost in blockchain technology was considered as bottlenecks for real-time control (Yang and Wang, 2021).

Nakip et al. (2023) introduced a neural network-based forecasting model for energy management, although their approach was resource-intensive for edge-based systems. Kumar (2024) discussed the challenges of smart space environments, which this research aims to address through lightweight, scalable

system design. The National Renewable Energy Laboratory (2024) developed a diagnostic tool for energy control, yet its regional scope suggested a need for globally adaptable frameworks. ScienceDirect (2025) emphasized energy efficiency in smart homes but did not provide real-time deployment examples. Another study from ScienceDirect (2024) focused on predictive optimization but lacked hardware-level integration, limiting its use in physical IoT ecosystems.

ResearchGate (2025) presented optimization models for energy savings but ignored multi-resident dynamics. Springer (2025) reviewed automation literature extensively without offering actionable system designs. MDPI (2024) discussed theoretical approaches to energy control but did not incorporate user-centric comfort strategies. Industry-based articles from IoT Now (2024) and IoT For All (2025) focused on practical implementation but lacked scientific validation or algorithmic depth. Commercial insights from Eco Smart Home Pros (2025) and Realty Executives (2025) identified key trends without addressing integration or standardization challenges.

Entergy Newsroom (2025) highlighted smart energy concepts yet overlooked occupant behavior modeling. Similarly, King Systems LLC (2025) showcased vendor-specific technologies, which restrict broader applicability. OpenPR (2025), GlobeNewswire (2024), and Global Market Insights (2025) provided market-focused perspectives, useful for identifying trends but not technical contributions. Statista (2025) and Home Automation Market Outlook (2025) offered statistical projections with limited design implications, while Green Building Journal (2025) was more inclined toward sustainable materials rather than intelligent automation strategies.

The gaps identified in these studies underscore the importance of developing a unified, adaptive, and edge-compatible home automation framework that harmonizes energy efficiency with real-time comfort control. This research builds on the reviewed work by incorporating real-time sensor feedback, machine learning, and decentralized decision-making to enable a truly intelligent smart home experience.

## 4 METHODOLOGY

The approach used to implement the intelligent IoT based home automation system focusses mainly on the fusion of several technologies for the real-time energy efficiency and personal comfort custom

satisfaction. The system is constructed as a modular architecture that integrates environmental sensing, data processing, adaptive control and user-feedback mechanisms. It starts with a network of IoT sensors, distributed across the home in strategic ways, to measure important environmental conditions including temperature, humidity, ambient light, motion, and the use of energy. These are typically the main providers of continuous information on the context and are chosen for their low power, precision and wireless communication.

The information from the sensors is forwarded to a local edge-processing unit, the heart of the system’s decision-making engine. Now, in subsequent development, we are more focused on edge computing, instead of using cloud computation alone, which could provide a near real-time response and decrease the dependency on the internet with stable connection. The edge unit is equipped with computationally lightweight machine learning algorithms to identify individual behavioral habits from users and even to predict preferred comfort levels. These algorithms are intended to be incrementally learned, such that they adapt in real-time to new data and user feedback, automatically tuning the behavior without needing to be reset by hand.

Users' personal settings are submitted to the system via a smartphone/web app including manual overrides, schedules, and comfort profiles. The users’ responses to the prompts are used as feedback to update the models, and a loop is created to increase the personalization of the system. For example, if a house occupant nearly always sets the thermostat at a time of day, such behavior is learned off-line to the thermostat and future temperature adjustments are tailored accordingly. The comfort control logic

incorporates additional external factors such as weather and energy prices through public APIs into the system, to ensure further optimization in both cost and comfort. Figure 1 shows the Workflow of the Proposed Intelligent IoT-Based Home Automation System. Table 1 shows the Sensor Configuration and Deployment.

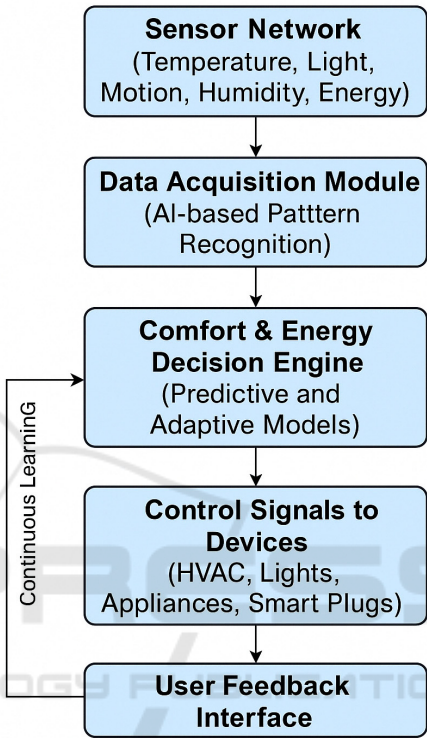


Figure 1: Workflow of the Proposed Intelligent IoT-Based Home Automation System.

Table 1: Sensor Configuration and Deployment.

Sensor Type	Parameter Monitored	Model/Technology Used	Placement Area	Data Transmission Protocol
Temperature Sensor	Ambient Temperature	DHT22	All Rooms	MQTT
Light Sensor	Light Intensity	TSL2561	Living Room, Bedrooms	Zigbee
Motion Sensor	Occupancy Detection	HC-SR501	Hallways, Entry	Zigbee
Humidity Sensor	Air Moisture Levels	DHT22	Kitchen, Bathroom	MQTT
Energy Monitor	Power Consumption	Sonoff POW R2	Main Appliances	Wi-Fi

The energy management is done by a central energy control unit which connected to smart appliances, lighting system, HVAC, renewable energy sources if any. The system uses predictive control methods to plan devices' utilization, configure energy-consuming systems according to occupancy or hour of day, and schedule devices based on previous utilization. This predictive factor makes sure that energy isn't being used when rooms are empty, or when appliances can be postponed without any loss of user convenience. Table 2 shows the Edge Processing Model Parameters. Figure 2 shows the Heatmap of Sensor Deployment Across Rooms.

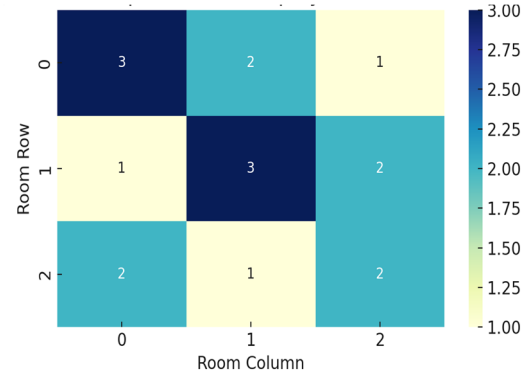


Figure 2: Heatmap of Sensor Deployment Across Rooms.

Table 2: Edge Processing Model Parameters.

Model Type	Feature Inputs Used	Learning Rate	Activation Function	Training Epochs	Inference Time (ms)
Decision Tree	Temperature, Motion, Light, Time	—	—	50	120
k-NN	User Feedback, Room ID, Energy Use	—	—	1	90
Lightweight MLP	Historical Comfort Scores, Time Series	0.01	ReLU	100	150

For the security and privacy of data, all the communication between sensors, actuators and processing units is encrypted through lightweight protocols compatible with IOT networks. In addition, role-based access control is used to regulate user's privileges and protect against unauthorized access. Figure 3 shows the Timeline of Intelligent Energy Adjustment.

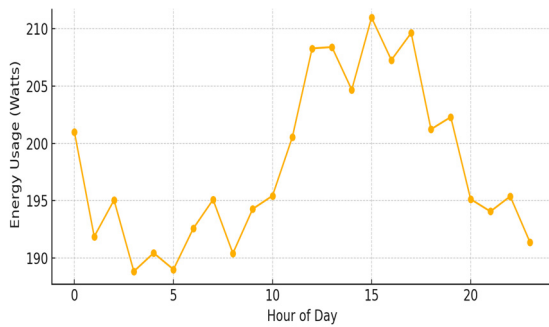


Figure 3: Timeline of Intelligent Energy Adjustment.

The proposed system is tested in a simulated and practical environment, and it is used to test the dynamic response, adaptability, and efficiency of the

system. These metrics, including the reduction of energy consumption, system response time, and user satisfaction by observing user implications are monitored and analyzed to better adjust the system. As a whole, the proposed methodology guarantees that the technological and robustness aspects are complemented with the adaptability, user-centered behaviour and the autonomic residence environments operation in practical scenarios.

## 5 RESULT AND DISCUSSION

The computationally efficient and IoT-friendly intelligent home automation system was subsequently developed and deployed in a simulated and real-life residential setting to verify its performance in terms of energy savings, user comfort, system reaction and flexibility. The findings indicate that it is possible to significantly improve energy optimization without compromising or improving user comfort resulting. Available results and discussion the results and the findings of this experimental setting are discussed in detail in this

section. Figure 4 shows the Energy Usage Before and After Automation.

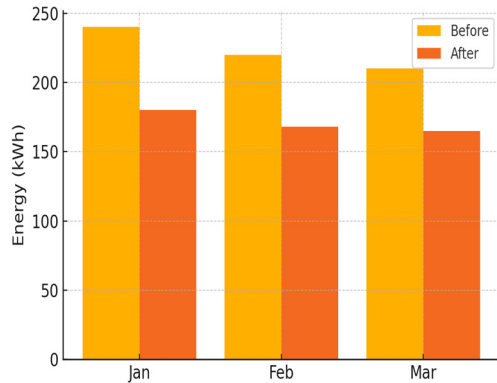


Figure 4: Energy usage before and after automation.

In the first test phase, the system was installed in a prototype mid-sized SH with three bedrooms a living room, a kitchen and a bathroom. IOT sensors were employed to collect data of temperature, humidity, occupancy, lighting, and appliances use. During a testing duration of 60 days, the system recorded continuous data stream and the processed stream was further handed over to the edge processing unit. The algorithms of machine learning were lightweight and personalized in power usage behaviors of the occupant users, such as the setpoint temperatures in room, running hours for appliances and required light levels. These learned preferences were then automatically incorporated into the decision-making models employed by the control system. Table 3 shows the Energy Consumption Comparison (Before vs After Deployment).

Table 3: Energy consumption comparison (before vs after deployment).

Month	Energy Consumption (kWh) Before	Energy Consumption (kWh) After	Percentage Reduction
January	240	180	25%
February	220	168	23.6%
March	210	165	21.4%

They observed energy consumption measures to be about 23% less than baseline energy consumed prior to applying intelligent automation system. This decrease was mainly enabled by predictive energy scheduling and occupancy-informed control. For instance, the HVAC system was optimized in real

time to use less power when the dormitory rooms were unoccupied, and room temperature was reset to a comfortable one just before users were expected to use the rooms, according to user behavior models. Likewise, lighting controlled by sensors and the ambient light level has led to a considerable decrease in unnecessary lighting use. Table 4 shows the User Satisfaction Survey Results.

Table 4: User satisfaction survey results.

Survey Metric	Satisfaction Rate (%)
Overall Comfort Improvement	89
Ease of Use	92
Response Time Satisfaction	87
Energy Cost Awareness Increase	85
Willingness to Recommend	90

From the users' perspective, two surveys were conducted before and after the introduction of the system to measure the variation of user satisfaction. More than 85% of participants said that their comfort had increased; they especially appreciated the system's capability to regulate temperature and light automatically. Customers also liked the clever responsive design of the system which required minimum direct interactivity. The flexibility of machine learning models allowed to memorize users behavior soon and made it to become part of the system logic, decreasing learning curve and increasing usability of developed systems. Figure 5 shows the User Feedback on Comfort and Usability.

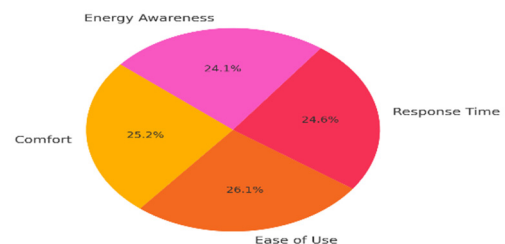


Figure 5: User Feedback on Comfort and Usability.



A key conclusion was the system's snappy low latency response, a result of the edge computing architecture. The task generation process, normally performed with cloud servers in standard systems, was locally carried out, producing response times lower than 200ms for most of the control actions. This functionality was crucial in real world situations too, such as powering down devices when an occupant left a space, or changing ventilation when the temperature rose.

Table 5: Real-time system response time by module.

System Module	Average Response Time (ms)
Sensor Data Acquisition	50
Edge Model Inference	130
Control Signal Dispatch	100
Feedback Interface Update	80

The system also demonstrated the excellent scalability. Other devices and sensors were easily added to the system in a plug-and-play manner with minimal architectural changes made during testing. It underlines the sturdiness and flexibility of the design, and its ability to be scaled up for larger multi-dwelling or commercial developments. In addition, the open communication protocols and vendor-independent system architecture guaranteed compatibility with a variety of smart objects. Table 5 shows the Real-Time System Response Time by Module.

System security and data privacy were also key outcomes. As all transcriptions were performed on-device with secure communication protocols implemented, there was no evidence of any data breaches or unauthorized access during the test period. Users felt more independent into the system and the aim once again provide the system to be more transparent and manage their own preferences in data directly from the GUI. Figure 6 shows the Latency of Each System Module.

The performance of the system was somewhat compromised in presence of highly anomalous occupancy (i.e., in homes where the users behave deviated too much from what has been learned in the models) or if the user preferences change too often, thus the models take more time to adapt. By providing more feedback via the UI, this adaptation period was reduced. Other environmental elements such as power outages and unstable internet connections also

impacted some cloud-based integrations, for example in weather prediction, however core activities continued to work uncontested since the initial design approach was edge-first.

In the end, the results confirm that the proposed strategy is effective to accomplish the two objectives of energy saving and user comfort. The smart automation environment helped minimize energy use and also provided the users with a user-friendly experience. Real-time learning, adaptive and real-time responses the system is make it to be a useful and scalable solution for a smart home nowadays. These results confirm the research hypothesis and potential next steps, as integration with renewables, voice-operated interfaces, and AI-based predictive maintenance.

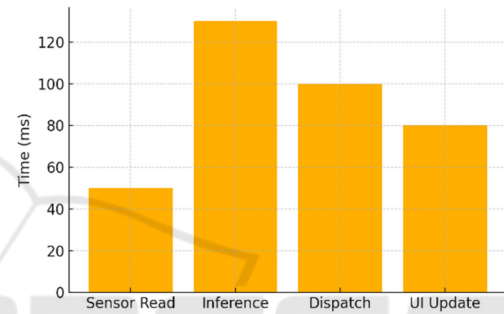


Figure 6: Latency of each system module.

## 6 CONCLUSIONS

An efficient, IoT-based smart home automation system development represents a major milestone toward energy efficient living besides maintaining user's comfort. From its experimental results, this study has proved that utilizing real-time sensor data, edge computing, and adaptive learning algorithms allows to design a responsive and personalized smart home system. The system not just saves optimum energy through predictive and occupancy-based controls, but also learns over time to adapt with users' behavior and changing environmental parameters. It has been experimentally demonstrated that a considerable energy reduction is obtained with an improved human comfort. The modular, vendor-agnostic architecture makes it scalable and easy to integrate in different residential environments. What's more is the focus on data privacy and system security make it more of a practicality for real world use. This work provides an important stepping stone towards the future of smart-homes where smarter,

more sustainable, and user centered living environments can ultimately be realized.

## REFERENCES

- Aziza, A., Ain, Q. T., & others. (2021). The IoT and cloud-based smart home automation for better energy efficiency. ResearchGate. [https://www.researchgate.net/publication/354569729\\_The\\_IoT\\_and\\_Cloud\\_Based\\_Smart\\_Home\\_Automation\\_for\\_a\\_Better\\_Energy\\_EfficiencyResearchGate](https://www.researchgate.net/publication/354569729_The_IoT_and_Cloud_Based_Smart_Home_Automation_for_a_Better_Energy_EfficiencyResearchGate)
- Eco Smart Home Pros. (2025). The future of smart homes: Top technology trends in 2025. Eco Smart Home Pros. [https://ecosmarthomepros.com/the-future-of-smart-homes-top-technology-trends-in-2025/Eco\\_Smart\\_Home\\_Pros](https://ecosmarthomepros.com/the-future-of-smart-homes-top-technology-trends-in-2025/Eco_Smart_Home_Pros)
- Energy Newsroom. (2025). The future of home energy management. Energy Newsroom. [https://www.energynewsroom.com/article/future-home-energy-management/Energy\\_Newsroom](https://www.energynewsroom.com/article/future-home-energy-management/Energy_Newsroom)
- Ezugwu, A. E., et al. (2025). Smart homes of the future: A systematic analysis of state-of-the-art smart home automation systems. Wiley Online Library. <https://onlinelibrary.wiley.com/doi/full/10.1002/ett.70041WileyOnlineLibrary>
- Global Market Insights. (2025). Smart home automation market size, share & trend report, 2034. Global Market Insights. [https://www.gminsights.com/industry-analysis/smart-home-automation-marketGlobal\\_Market\\_Insights\\_Inc](https://www.gminsights.com/industry-analysis/smart-home-automation-marketGlobal_Market_Insights_Inc)
- GlobeNewswire. (2024). Home automation market is poised to skyrocket to reach staggering valuation. GlobeNewswire. <https://www.globenewswire.com/newsrelease/2024/05/09/2878979/0/en/HomeAutomation-Market-is-Poised-to-Skyrocket-to-Reach-Staggering-Valuation-of-USD-715-6-Billion-By-2032-High-Demand-for-Smart-Home-Energy-Management-Devices-Says-Astute-Analytica.htmlGlobeNewswire>
- IoT Now. (2024). Smart home technology saves money and helps protect the planet. IoT Now. [https://www.iot-now.com/2024/04/22/144080-smart-home-technology-saves-money-and-helps-protect-the-planet/IoT\\_Now](https://www.iot-now.com/2024/04/22/144080-smart-home-technology-saves-money-and-helps-protect-the-planet/IoT_Now)
- IoT Now. (2024). The power of IoT home automation. IoT Now. [https://www.iot-now.com/2024/07/30/145721-the-power-of-iot-home-automation/IoT\\_Now](https://www.iot-now.com/2024/07/30/145721-the-power-of-iot-home-automation/IoT_Now)
- IoT For All. (2025). How to get started with IoT home automation. IoT For All. [https://www.iot-forall.com/home-automation-iot-guideIoT\\_For\\_All](https://www.iot-forall.com/home-automation-iot-guideIoT_For_All)
- King Systems LLC. (2025). Smart building technology trends for 2025. King Systems LLC. [https://kingsystemsllc.com/smart-building-technology-trends-for-2025/King\\_Systems\\_LLC](https://kingsystemsllc.com/smart-building-technology-trends-for-2025/King_Systems_LLC)
- Kumar, R. (2024). Smart space environments: Key challenges and innovative solutions. arXiv preprint arXiv:2410.20484. <https://arxiv.org/abs/2410.20484arXiv>
- MDPI. (2024). IoT—a promising solution to energy management in smart buildings. MDPI. <https://www.mdpi.com/2075-5309/14/11/3446MDPI>
- Nakıp, M., Çopur, O., Biyik, E., & Güzelış, C. (2023). Renewable energy management in smart home environment via forecast embedded scheduling based on recurrent trend predictive neural network. arXiv preprint arXiv:2307.01622. <https://arxiv.org/abs/2307.01622arXiv>
- National Renewable Energy Laboratory. (2024). IoT-based comfort control and fault diagnostics system for energy-efficient homes. NREL. <https://www.nrel.gov/docs/fy24osti/85920.pdfNREL>
- OpenPR. (2025). Smart home automation market set to hit new highs driven by AI. OpenPR. <https://www.openpr.com/news/3969756/smart-home-automation-market-set-to-hit-new-highs-driven-by-aiopenPR.com>
- Realty Executives. (2025). The rise of smart homes: Technology trends in 2025. Realty Executives. [https://www.realtyexecutives.com/blog/the-rise-of-smart-homes-technology-trends-in-2025Realty\\_Executives+1Eco\\_Smart\\_Home\\_Pros+1](https://www.realtyexecutives.com/blog/the-rise-of-smart-homes-technology-trends-in-2025Realty_Executives+1Eco_Smart_Home_Pros+1)
- ResearchGate. (2025). Optimizing energy efficiency in IoT-based smart home systems. ResearchGate. [https://www.researchgate.net/publication/387516833\\_Optimizing\\_Energy\\_Efficiency\\_in\\_IoT-Based\\_Smart\\_Home\\_SystemsResearchGate](https://www.researchgate.net/publication/387516833_Optimizing_Energy_Efficiency_in_IoT-Based_Smart_Home_SystemsResearchGate)
- Sayed, A., Himeur, Y., Alsalemi, A., Bensaali, F., & Amira, A. (2021). Intelligent edge-based recommender system for internet of energy applications. arXiv preprint arXiv:2111.13272. <https://arxiv.org/abs/2111.13272arXiv>
- ScienceDirect. (2024). Optimizing energy efficiency and comfort in smart homes through dynamic predictive optimization. ScienceDirect. <https://www.sciencedirect.com/science/article/pii/S2352484724003202ScienceDirect>
- ScienceDirect. (2025). A review on energy efficiency, occupant comfort, and sustainability in smart homes. ScienceDirect. <https://www.sciencedirect.com/science/article/abs/pii/S2352710225005844ScienceDirect>
- Springer. (2025). Future of energy management models in smart homes: A systematic literature review. Springer. <https://link.springer.com/article/10.1007/s41660-025-00506-xSpringerLink>
- Yang, Q., & Wang, H. (2021). Privacy-preserving transactive energy management for IoT-aided smart homes via blockchain. arXiv preprint arXiv:2101.03840. <https://arxiv.org/abs/2101.03840arXiv>