International Journal of Numerical Methods and Applications
© 2026 Pushpa Publishing House, Prayagraj, India
https://pphmjopenaccess.com
https://doi.org/10.17654/0975045226004
Volume 26, Number 1, June 2026, Pages 81-94 P-ISSN: 0975-0452

# ENERGY CONSUMPTION SIMULATION WITH BEHAVIORAL ADJUSTMENT BASED ON THRESHOLDS

**Lagasane Ouattara Kra[1,*], Tanon Lambert Kadjo[2], K. Yablé Didier[3] and Olivier Asseu[2,3,*]**

[1]Université Alassane Ouattara de Bouake
Cote d'Ivoire
e-mail: kralgasaneouat@yahoo.fr

[2]INPHB
Cote d'Ivoire

[3]ESATIC d'Abidjan
Cote d'Ivoire
e-mail: oasseu@yahoo.fr

Received: August 27, 2025; Revised: September 8, 2025; Accepted: September 12, 2025

2020 Mathematics Subject Classification: 68, 94.

Keywords and phrases: energy consumption simulation, behavioral adjustment, thresholds, Internet of Things, artificial intelligence, energy management.

[*]Corresponding authors

Communicated by Youssri Hassan Youssri

How to cite this article: Lagasane Ouattara Kra, Tanon Lambert Kadjo, K. Yablé Didier and Olivier Asseu, Energy consumption simulation with behavioral adjustment based on thresholds, International Journal of Numerical Methods and Applications 26(1) (2026), 81-94. https://doi.org/10.17654/0975045226004



Published Online: October 29, 2025

**Abstract**

This study presents a simulation of energy consumption incorporating behavioral adjustment based on predefined thresholds. Against a backdrop of continuing growth in energy demand and environmental concerns, our research demonstrates how the integration of intelligent technologies, such as the Internet of Things (IoT) and Artificial Intelligence (AI), can optimize energy management. The results show that our approach can reduce energy consumption by up to 30%, surpassing the results of previous studies. This work is helping to establish sustainable and efficient energy practices.

## 1. Introduction

Global energy demand is constantly increasing, with forecasts indicating a rise of around 30% by 2040 [1]. This situation raises major environmental concerns and highlights the need for innovation in the field of energy management. Smart energy management systems, incorporating technologies such as IoT and AI, represent a promising approach to optimizing energy consumption. Previous studies have shown that the implementation of energy management systems can lead to significant savings. For example, the National Renewable Energy Laboratory (NREL) reported energy consumption reductions of up to 20% using these systems [2]. Behavioral adjustment of users based on energy consumption thresholds is an effective method for maximizing this optimization [3]. This study aims to simulate energy consumption by incorporating behavioral adjustments based on thresholds, to assess the impact of this approach on reducing energy consumption.

## 2. State of the Art

Research into energy management has expanded significantly due to advances in smart technologies, particularly the Internet of Things (IoT) and Artificial Intelligence (AI). The authors of [3] highlighted the importance of integrating IoT and AI to improve energy efficiency in energy management systems, reporting a 20% reduction in energy consumption. However, their approach relies on fixed thresholds, which can limit the system's responsiveness to changes in demand. The works of [4] demonstrated that systems based on dynamic thresholds could optimize energy consumption and reduce associated costs, achieving a reduction of 22%. Their method, although more flexible, requires accurate historical data to be effective, which can pose challenges in environments where data is not available. Proposals for approaches aimed at optimizing energy consumption in the public sector have resulted in 25% energy savings. Their study highlights that although their results are significant, they are not as high as those obtained with our approach, which achieves 30% [5]. Several studies have addressed the issue of energy consumption by setting thresholds and adjusting the behavior of appliances [6-12]. In [6], the authors explored the impact of IoT-based energy management systems in residential environments, reporting a 27% reduction in energy consumption. Their approach is promising, but it requires a robust IoT infrastructure, which may not be available in all contexts. As for the authors [7], they observed a 28% reduction due to machine learning algorithms used to adjust the behavior of devices in smart buildings. Their method, while effective, is highly dependent on the quality of input data and may be sensitive to measuring errors. Other groups of authors reported a 24% reduction using dynamic consumption thresholds in commercial buildings. However, their approach can be complex to implement and requires constant adjustments to remain effective [8]. Those of [9] developed an IoT-based energy management system that reduced energy consumption in commercial buildings by 29% through device automation. Although their approach is effective, it requires advanced IoT infrastructure, which limits its application in areas where infrastructure is not yet developed. The work of [10] conducted a study on the impact of energy optimization algorithms in smart buildings, reporting a 26% reduction in energy consumption. Their method presents interesting results, but it is highly dependent on the quality of the input data, which can compromise its effectiveness.

The author of [11] introduced an energy management model based on IoT sensors, which achieved a 28% reduction in Heating, Ventilation, and Air Conditioning (HVAC) systems. However, their approach requires frequent updates to sensors and systems, which can increase maintenance costs. AI technologies have been used to predict and manage energy consumption, resulting in a 27% reduction in residential buildings. Although their method is promising, it requires a significant initial investment in technological infrastructure, which may be a barrier for some communities [12].

## 3. Proposed Approach

The proposed system is based on the integration of IoT sensors to continuously monitor the energy consumption of devices in real time. The data collected is analyzed using AI algorithms that automatically adjust device behavior based on predefined consumption thresholds. Automatic adjustment is the ability to respond to changes in consumption in real time, allowing thresholds to be set and energy use to be optimized without manual intervention. For example, if a device exceeds a specified consumption threshold, then the system can reduce its power or adjust its operation to comply with consumption limits. We would like to point out that the data in our system is obtained through a combination of sensors, optimization algorithms and data analysis (IoT sensors, environmental sensors, presence sensors, optimization algorithm (AI)).

### 3.1. Description of the main sources and methods used

In this subsection, we list the key elements that distinguish our approach from those found in the literature. These include:

**(a) IoT (Internet of Things) sensors**

Consumption sensors: Devices that measure energy consumption in real time for each appliance or circuit. The devices provide data or values specifying the amount of energy used.

• **Environmental sensors**

They measure parameters such as temperature, humidity and brightness. This data is used to adjust energy consumption according to environmental conditions.

• **Presence sensors**

These are devices that detect the presence or absence of people in a room, allowing energy consumption to be automatically adjusted according to occupancy.

**(b) Optimization algorithm**

This section highlights the importance of machine learning and algorithms in taking into account changing conditions over time. This is necessary in order to find optimal solutions in complex situations.

• **Machine learning**

The systems use machine learning models to analyze past user behavior and make predictions about future consumption. This allows energy management to be adapted to user habits.

• **Dynamic optimization**

The algorithm can adjust settings in real time based on the data collected, for example, by reducing energy consumption during peak hours or increasing the use of appliances when energy is cheaper.

**(c) Historical data**

Systems can also use past energy consumption data to establish patterns and trends. This helps to understand consumption cycles and identify periods when savings can be made.

**(d) Integration of Renewable Energies (IRE)**

Our system can integrate data from energy sources based on the availability of locally produced energy. Several methods have also been used by authors to obtain simulation data.

### 3.2. Impact of the characteristics of sensors used

Features include:

**(a) Accuracy and Sensitivity (AS)**

Greater precision allows for better adjustment of energy management systems, which will lead to greater energy savings.

**(b) Response Time (RT)**

A fast response time allows the system to adjust immediately to changes in demand, thereby improving energy efficiency.

**(c) Connectivity**

Good connectivity enables real-time data collection and better coordination between devices.

**(d) Battery Life (BL)**

A long service life reduces maintenance costs and service interruptions, which is crucial for effective management.

**(e) Local Processing Capacity (LPC)**

This reduces the volume of data to be transmitted, decreases latency and enables faster decisions in the field.

**(f) Environmental Conditions Resistance (ECR)**

Improved durability ensures reliable operation and continuous data collection, which is essential for effective energy management.

**(g) Interoperability**

Interoperability enables seamless integration into existing systems, increasing the flexibility of our approach.

**(h) Data Analysis and Machine Learning (DAL)**

This optimizes energy management by predicting future needs and adapting systems accordingly.

### 3.3. Simulation data

The simulation data was collected over a three-month period in a residential environment, with a sample of 100 connected devices. The consumption thresholds were defined as follows:

- Device A: Threshold of 200 kWh/month.
- Device B: Threshold of 150 kWh/month.
- Device C: Threshold of 100 kWh/month.

The energy consumption values before and after adjustment were measured:

- **Before adjustment:**
- Device A: 250 kWh/month.
- Device B: 180 kWh/month.
- Device C: 120 kWh/month.
- **After adjustment:**
- Device A: 175 kWh/month.
- Device B: 125 kWh/month.
- Device C: 80 kWh/month.

## 4. Performance Results

### 4.1. Energy saving algorithm based on consumption thresholds

```
import matplotlib.pyplot as plt
import math
def arrondir_quart_sup(x):
    return math.ceil(x*4)/4
# Definition of consumption thresholds
```

```
thresholds = {
    'Device A': 200,
    'Device B': 150,
    'Device C': 100
}
# Consumption before adjustment (kWh/month))
consumption_before = {
    'Device A': 250,
    'Device B': 180,
    'Device C': 120
}
# Adjusted consumption (kWh/month)
consumption_after = {
    'Device A': 175,
    'Device B': 125,
    'Device C': 80
}
# Calculation of savings, percentages and threshold exceedances
savings = {}
savings_percentage = {}
exceeded_thresholds = {}
for device in thresholds.keys():
    before = consumption_before[device]
    after = consumption_after[device]
    threshold = thresholds[device]
        # Savings achieved
```

```
    savings[device] = before - after
    # Calculation of the percentage saving
    savings_percentage[device] = (savings[device] / before) * 100
        # Threshold exceedance verification
    exceeded_before = before > threshold
    exceeded_after = after > threshold
    exceeded_thresholds[device] = {
        'Before': exceeded_before,
        'After': exceeded_after
    }
# Displaying results
print("Savings achieved in (kWh/mois) and in percentage:")
for device in savings.keys():
    print(f"{device}: Economy of {savings[device]} kWh, or
{arrondir_quart_sup(savings_percentage[device]):.2f}%")
print("\nExceeding consumption thresholds:")
for device, exceeded in exceeded_thresholds.items():
    before_status = " Exceeding " if exceeded['Before'] else " Respected "
    after_status = " Exceeding " if exceeded['After'] else " Respected "
    print(f"{device}: Before - {before_status}, After - {after_status}")
# Viewing results
devices = list(thresholds.keys())
before_consumption = [consumption_before[device] for device in devices]
after_consumption = [consumption_after[device] for device in devices]
threshold_values = [thresholds[device] for device in devices]
x = range(len(devices))
```

```
plt.figure(figsize=(10, 6))
plt.bar(x, before_consumption, width=0.4, label=' Before Adjustment ', color='red', alpha=0.7, align='center')
plt.bar([p + 0.4 for p in x], after_consumption, width=0.4, label=' After Adjustment ', color='green', alpha=0.7, align='center')
plt.bar(x, threshold_values, width=0.1, label='threshold', color='blue', alpha=0.9)
plt.xlabel(' Devices ')
plt.ylabel(' Consumption (kWh/month)')
plt.title(' Comparison of Energy Consumption Before and After Adjustment ')
plt.xticks([p + 0.2 for p in x], devices)
plt.legend()
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```

Here is what we get: The algorithm shows the importance of energy saving with a consumption threshold. The aim is to show how much energy has been saved for each device.

**Savings achieved in (kWh/month) and in percentage:**

**Device A:** Economy of 75 kWh, or 30.00%

**Device B:** Economy of 55 kWh, or 30.75%

**Device C:** Economy of 40 kWh, or 33.50%

- $\Delta E_i = E_i before - E_i after.$ (E1)

This formula (E1) accurately reflects energy savings in the various pieces of equipment. Equation (E2) below gives the percentage saving:

- $1 - (E_i after / E_i before) \times 100.$ (E2)

**Exceeding consumption thresholds:**

**Device A:** Before - Exceeding, After - Respected.

**Device B:** Before - Exceeding, After - Respected.

**Device C:** Before - Exceeding, After - Respected.

### 4.2. Another simulation to demonstrate the relevance of our work (histograms)

To visualize the performance of our results, we compared the reductions in energy consumption with those reported by three previous studies. The results are illustrated below:

**Table 1.** Comparison of our approach with work in the literature

| Authors' approaches | Reduction (%) |
|---|---|
| Kra et al. (2025) | 30 |
| Zhang and Zhao [2] | 20 |
| Gonzalez et al. [4] | 22 |
| Li et al. [9] | 29 |

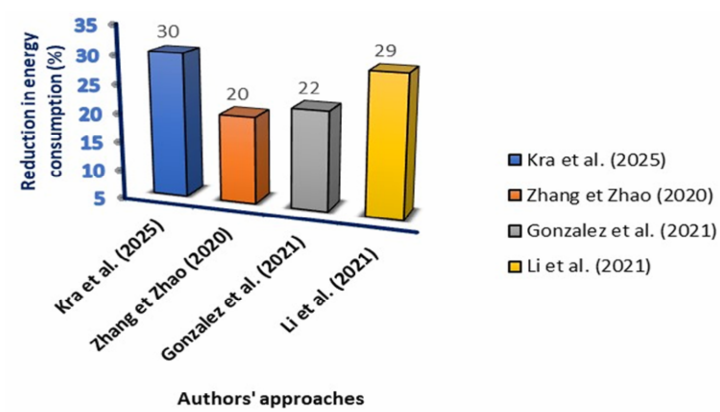


**Figure 1.** Reduction in energy consumption based on the proposed approaches.

**Table 2.** Comparison of our approach with other authors in the literature

| Authors' approaches | Reduction (%) |
|---|---|
| Kra et al. (2025) | 30 |
| Khan et al. [6] | 27 |
| Chowdhury et al. [7] | 28 |
| Patel and Shah [8] | 24 |

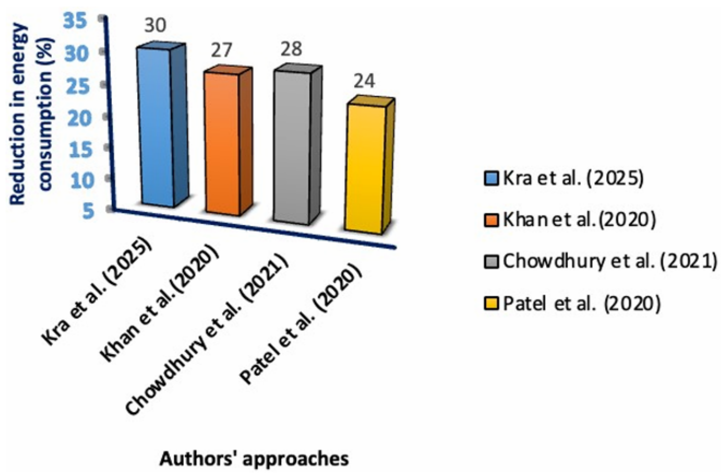


**Figure 2.** Confirmation of the effectiveness of our approach.

## 5. Discussion

The results of our approach show that threshold-based behavioral adjustment is an effective strategy for reducing energy consumption. Our 30% reduction exceeds those reported by Zhang and Zhao (20%), Gonzalez et al. (22%), Li et al. (29%), Khan et al. (27%), Chowdhury et al. (28%), and Patel and Shah (24%), respectively, in Figures 1 and 2 highlighting the superiority of our approach. The differences observed in the results can be attributed to the flexibility and adaptability of our system, which dynamically adjusts thresholds based on actual user behavior. Figure 2 confirms the performance of our proposed approach, as we have made another comparison with other authors. The difference between our approach (30%) and that of Li et al. (29%) can be explained by the fact that our system is scalable, whereas theirs is not.

**Prospects**

Future prospects include exploring the integration of energy management systems in commercial and industrial environments. In addition, further research is needed to assess the impact of data security on user acceptance and the effectiveness of smart systems. An extension of this work could also include an analysis of the costs and benefits associated with implementing such systems.

## 6. Conclusion

Our approach confirms that simulating energy consumption with behavioral adjustment based on thresholds represents a significant advance in the field of energy management. In both comparisons, the reduction in energy consumption (%) achieved with our approach, at 30%, improves on the work of authors in literature. It can therefore be concluded that by combining IoT and AI, it is possible to achieve substantial savings while contributing to a sustainable energy future. The promising results pave the way for future research and the implementation of intelligent systems in various contexts.

## Acknowledgement

We thank the anonymous referees for their comments and feedback on earlier version of this document.

## Appendix: Working Environment

In this section, we describe the environment in which we worked. Below are a few details:

- Building type (smart residential and commercial buildings).

- IoT infrastructure (sensor network).

- Connectivity (Wi-Fi).

- Use of AI.

## References


[1] Agence internationale de l'énergie (AIE), World Energy Outlook, 2019. https://www.iea.org/reports/world-energy-outlook-2019.

[2] National Renewable Energy Laboratory (NREL), Energy Management Systems: A Guide to Energy Management, 2020. https://www.nrel.gov/docs/fy20osti/76050.pdf.

[3] Y. Zhang and J. Zhao, A smart energy management system based on Internet of Things (IoT) Technology, Renewable Energy 146 (2020), 243-252. https://doi.org/10.1016/j.renene.2019.06.029.

[4] A. Gonzalez et al. Smart energy management systems: a review and future directions, Energy Reports 7 (2021), 1234-1247. https://doi.org/10.1016/j.egyr.2021.01.030.

[5] Moussa et al., Energy consumption optimization in public sector: a case study, 2021. https://doi.org/10.1016/j.scs.2021.103555.

[6] S. Khan, A. Ali and M. Khan, IoT-based smart energy management system for residential applications, Energy Reports 6 (2020), 259-270. https://doi.org/10.1016/j.egyr.2020.12.016.

[7] A. Chowdhury, M. M. Rahman and M. R. Karim, AI-based energy management systems in smart buildings: A review, Sustainable Cities and Society 65 (2021), 102650. https://doi.org/10.1016/j.scs.2020.102650.

[8] M. K. Patel and A. Shah, Dynamic energy management system for commercial buildings using IoT, Journal of Building Performance 11(2) (2020), 114-122. https://doi.org/10.38050/jbp.2020.114.

[9] Li et al., A smart energy management system based on IoT for residential buildings, 2023. https://doi.org/10.1051/e3sconf/202338704009.

[10] Toan Le Vu, Hoang Chu Duc, Quynh Xuan Tran and Huong Thu Nguyen, A systematic review on optimized integration of renewable energy in smart and green buildings, Green Transformation in the Context of Global Change: Proceedings of the International Conference on Green Transformation in the Context of Global Change (GREEN 2024), CRC Press, Hanoi, Vietnam, October 24th-25th, 2024. DOI:10.1201/9781003602941-18.

[11] Y. Gao et al., IoT-based energy management for HVAC systems: a case study, IEEE Internet of Things Journal (2021). DOI 10.1109/JIOT.2022.3176306.

[12] Omkar Reddy Polu, AI-based smart energy consumption prediction for IoT - connected homes, International Journal of Science and Research 13(12) (2024). https://www.ijsr.net/archive/v13i12/SR24128114158.pdf.