

Data Driven Approach for Smart Energy Savings

¹K.Vasanthi

Assistant Professor, Dept. of EEE
KKR & KSR Institute of Technology and Sciences (Autonomous)
Guntur, Andhra Pradesh, India.

⁴J.Ganesh

UG Student, Dept. of EEE
KKR & KSR Institute of Technology and Sciences (Autonomous), Guntur, Andhra Pradesh, India.

²G.Ratna Babu

UG Student, Dept. of EEE
KKR & KSR Institute of Technology and Sciences (Autonomous), Guntur, Andhra Pradesh, India

⁵Ch.Rajesh

UG Student, Dept. of EEE
KKR & KSR Institute of Technology and Sciences (Autonomous), Guntur, Andhra Pradesh, India

³ K. Ashirvad Mounish

UG Student, Dept. of EEE
KKR & KSR Institute of Technology and Sciences (Autonomous), Guntur, Andhra Pradesh, India.

⁶K.Venkata Reddy

UG Student, Dept. of EEE
KKR & KSR Institute of Technology and Sciences (Autonomous), Guntur, Andhra Pradesh, India

Abstract— In modern infrastructure, energy efficiency has become a key priority to address rising energy costs and environmental concerns. This project focuses on developing a data-driven approach to optimize energy consumption in smart buildings. The system utilizes machine learning algorithms to analyse real-time and historical energy usage data, predict energy demand, and automate energy control systems. The proposed solution incorporates IoT sensors to monitor energy consumption, occupancy, and environmental factors. A microcontroller serves as the central processing unit, facilitating data acquisition and decision-making. Using predictive modelling, the system forecasts energy requirements and dynamically adjusts HVAC, lighting, and appliances to reduce waste. This project is implemented using simple machine learning techniques like Linear Regression and Decision Trees for prediction and anomaly detection. A user-friendly interface visualizes energy usage and provides actionable insights for further optimization. Simulation and testing of the system are carried out using Python-based tools like Scikitlearn and Pandas for analysis. This approach demonstrates the potential to reduce energy costs significantly and contributes to sustainable building practices.

Keywords: Energy Optimization, Smart Buildings, Machine Learning, IoT Sensors, Energy Savings.

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INTRODUCTION

Energy consumption has been increasing exponentially due to the rapid urbanization and expansion of infrastructure. Traditional energy management systems lack intelligence, leading to unnecessary power wastage. In conventional setups, electrical appliances such as lights, fans, and air conditioning units are manually operated or controlled through basic timers, which do not account for real-time occupancy and environmental conditions.

1.1 Existing Technologies

Several energy-saving systems exist, but most rely on basic automation rather than advanced data-driven decision-making:

Timer-Based Control: Appliances operate based on pre-set schedules, leading to energy waste when usage patterns do not align with the set times.

Motion Sensor-Based Systems: These detect movement to control lights and fans but may fail in scenarios where occupants remain stationary for extended periods.

Remote-Controlled Systems: Smart switches and IoT-enabled appliances allow users to control devices remotely via mobile apps, but they still require human intervention.

Basic IoT Automation: Some systems integrate IoT sensors to automate appliances, but they lack predictive capabilities to optimize energy usage dynamically.

1.2 Proposed Technology

To address these limitations, we propose a **data-driven smart energy-saving system** that integrates **IoT sensors** and **Machine Learning (ML)** to optimize energy usage based on real-time occupancy and environmental conditions. The system consists of:

IoT Sensors: **IR Sensors** for occupancy detection (entry and exit count).

MQ135 for air quality monitoring to regulate the exhaust fan.

DHT11 for temperature sensing to automate fans.

LDR Sensor for natural light assessment to control indoor lighting.

Machine Learning Model: Predicts temperature variations based on the number of occupants in a room, allowing proactive control of electrical appliances using the linear regression technique

Automated Appliance Control: A **relay module** controls fans, lights, and exhaust systems based on real-time data, reducing human intervention and unnecessary energy consumption.

Energy Monitoring: **Current sensors** track electricity usage, helping in analyzing energy savings.

II. LITERATURE REVIEW

The need for **intelligent energy management** has led to extensive research in the fields of **IoT**, **Machine Learning (ML)**, and **Smart Automation**. Various methods have been proposed to optimize energy consumption, reduce wastage, and improve efficiency. This section reviews existing works related to energy-saving techniques and highlights the research gap addressed by our proposed system.

2.1 Smart Energy Management Systems

Several studies have explored **automation-based energy management** using different technologies:

Rule-Based Systems: Traditional automation techniques rely on pre-set rules and timers to control electrical appliances. However, these systems lack adaptability to **real-time occupancy changes** and **environmental conditions**, leading to inefficiencies.

Motion-Based Systems: Research has shown that **Passive Infrared (PIR) sensors** and **ultrasonic sensors** can be used for detecting human movement to control lighting and HVAC systems. However, these methods fail in scenarios where occupants remain stationary for extended periods.

IoT-Based Systems: IoT-based smart grids have been developed for energy optimization, where sensors collect real-time data and make automated decisions. Studies suggest that integrating **cloud computing** with IoT enhances the scalability of such systems.

2.2 Machine Learning in Energy Optimization

Machine learning has been increasingly applied to **predictive energy management**. Some of the key studies include:

Occupancy-Based Energy Prediction: Researchers have developed **predictive models** that use past occupancy data to adjust power consumption dynamically. A study on **Smart Building Management** demonstrated how ML models could **predict room temperature** based on occupancy, leading to a **10–20% reduction in energy usage**.

Temperature Forecasting Models: Regression models such as **Linear Regression**, **Random Forest**, and **Neural Networks** have been used to predict temperature fluctuations. Studies indicate that **deep learning techniques** like LSTMs (Long Short-Term Memory) can improve forecasting accuracy.

Lighting Optimization Models: Research in **light intensity prediction** using ML has shown that **Artificial Neural Networks (ANNs)** can effectively adjust lighting based on natural illumination and occupancy levels, reducing unnecessary power consumption.

2.3 Limitations of Existing Systems

Despite advancements, existing approaches have certain limitations:

Lack of Adaptive Control: Many systems rely solely on predefined rules, failing to adapt dynamically to real-time changes in occupancy and environmental conditions.

Limited Integration of IoT and ML: While IoT-based energy management exists, only a few studies integrate **machine learning for predictive automation**.

Inefficiency in Multi-User Environments: Most motion-based systems are ineffective in spaces with multiple users, as they cannot **distinguish between different levels of occupancy** for energy optimization.

III. SYSTEM ARCHITECTURE

The **Data-Driven Smart Energy Saving System** integrates **IoT sensors** and **Machine Learning (ML)** to optimize energy consumption dynamically. The system architecture is divided into several key components, each playing a crucial role in ensuring efficient energy utilization.

3.1 System Overview

The architecture follows a structured approach:

Data Acquisition: Sensors collect real-time data related to **occupancy, air quality, temperature, and natural light levels**.

Processing Unit (Microcontroller): The collected data is processed by a **microcontroller (ESP32/Arduino)** to make instant energy-saving decisions.

Machine Learning Model: The system predicts **temperature variations based on room occupancy**, helping in proactive control of electrical appliances.

Actuation (Relay Module): Based on the ML output and sensor data, **lights, fans, and exhausts** are switched on/off accordingly.

Energy Monitoring: A **current sensor** tracks power consumption for further optimization.

3.2 Hardware Components and Their Functions

3.2.1 Sensors Used

The system utilizes **five primary sensors** to collect real-time environmental and occupancy data:

IR Sensors (Entry & Exit Counting): Two IR sensors are placed at the **entry and exit** of the room. They track the number of people inside the room, helping in **adaptive lighting and fan control**.

MQ135 (Air Quality Sensor): Monitors **air pollution levels (CO₂, NH₃, NO_x, etc.)** inside the room. If air quality drops below a threshold, the **exhaust fan is activated** to ensure proper ventilation.

DHT11 (Temperature Sensor) Measures **temperature** inside the room. If the temperature rises above **30°C**, the **fan is switched on**.

LDR Sensor (Light Intensity Detection): Detects the presence of **natural light** in the room. If **natural light is sufficient**, indoor **lights remain off** to save energy.

Current Sensors: Measure **electricity consumption** in real-time. Helps in **analyzing and optimizing energy usage**.

3.3 Processing Unit (Arduino)

The **Arduino microcontroller** acts as the **central processing unit** of the system. It receives inputs from all sensors, processes the data, and controls the **relay module** to switch appliances on/off.

Input: Sensor data (Occupancy count, temperature, air quality, light intensity).

Processing: Implements **threshold-based control logic** and sends data to the ML model for predictions.

Output: Activates or deactivates electrical appliances via the **relay module**.

3.4 Machine Learning Model (Linear Regression)

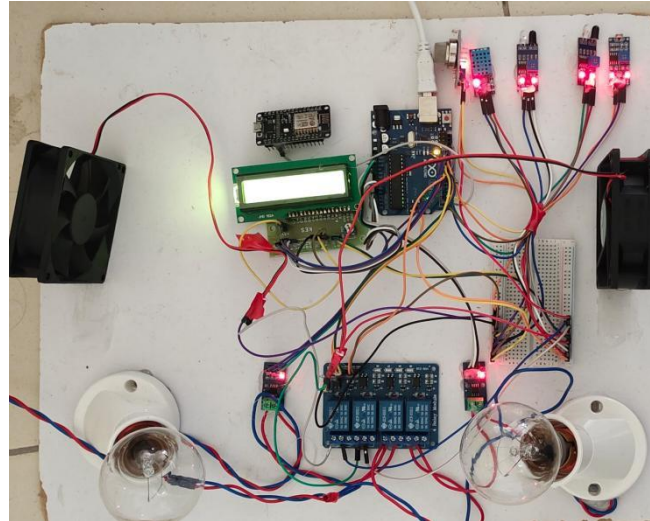
To improve energy efficiency, a **machine learning model** is integrated into the system.

Training Data: Historical data on **occupancy count and temperature variations** is used.

Model Used: **Regression-based prediction** (Linear Regression/Random Forest) forecasts how **temperature fluctuates with changes in occupancy**.

Decision Making: If the predicted **temperature exceeds 30°C**, the **fan turns on automatically**.

This predictive approach **reduces unnecessary fan usage** and ensures optimal energy consumption.



3.5 Energy Monitoring and Optimization

A **current sensor** tracks real-time energy usage, helping in:

Identifying energy consumption trends over time.

Providing data for further optimization using AI-driven decision-making.

Enhancing energy-saving policies by adjusting control thresholds dynamically.

IV.METHODOLOGY

The **methodology** for the **Data-Driven Smart Energy Saving System** involves a **step-by-step approach** that integrates **IoT-based sensing, real-time processing, machine learning predictions, and automated actuation**. The implementation consists of **data collection, preprocessing, machine learning integration, and automation** for optimal energy savings.

4.1 System Workflow

The overall **workflow** can be divided into **five stages**:**Data Collection using IoT Sensors**

Real-time Data Processing with a Microcontroller

Machine Learning Model for Temperature Prediction

Automated Actuation using Relay Modules

Energy Monitoring and Optimization

4.2 Data Collection using IoT Sensors

A set of IoT sensors continuously **monitors environmental conditions and occupancy status** to collect real-time data.

4.2.1 Sensor Placement and Functionality

Sensor	Placement	Purpose
IR Sensor 1 (Entry)	Near entrance	Detects people entering the room
IR Sensor 2 (Exit)	Near exit	Detects people leaving the room
MQ135 (Air Quality Sensor)	Wall-mounted at breathing height	Measures air quality to control the exhaust fan
DHT11 (Temperature Sensor)	Ceiling-mounted	Monitors room temperature to control the fan
LDR Sensor (Light Sensor)	Near windows or ceiling	Detects natural light intensity to control artificial lighting
Current Sensor	Connected to appliances	Measures power consumption for energy monitoring

Data Captured:

Occupancy Count: Number of people inside the room.

Air Quality Index (AQI): Checks CO2 and pollutant levels.

Temperature Readings: Determines if fan usage is needed.

Light Intensity: Helps in adaptive lighting.

Power Usage: Monitors electricity consumption.

4.3 Real-time Data Processing with a Microcontroller

The collected data is **sent to the microcontroller (ESP32/Arduino)**, which processes it in real time and makes initial decisions before involving the machine learning model.

4.3.1 Decision Logic in the Microcontroller

Occupancy Count:

Updates room population based on entry/exit sensor data.

Temperature Threshold: If **temperature > 30°C**, turn **ON** fan. Else, turn **OFF** fan.

Air Quality Check: If **poor air quality detected**, turn **ON** exhaust fan.

Light Control: If **natural light is sufficient**, keep **lights OFF**. If **insufficient natural light**, turn **ON** the **first light**. If **more than 5 people**, turn **ON** the **second light**.

Note: The microcontroller handles basic automation, while advanced predictions are handled by the machine learning model.

4.4 Machine Learning Model for Temperature Prediction

To optimize **fan usage**, a **machine learning model** is used to **predict temperature variations** based on **occupancy count**.

4.4.1 Machine Learning Implementation

Training Data: Historical data on **room temperature, occupancy levels, and time of day**.

Model Type: **Regression-based prediction** (Linear Regression or Random Forest).

Prediction Process: Input: **Current occupancy count**. Model predicts **expected temperature**. If predicted temperature **exceeds 30°C**, the **fan turns ON**.

4.5 Automated Actuation using Relay Modules

Once **sensor data and ML predictions** are processed, the **relay module** automatically **controls the electrical appliances**.

Appliance	Condition for Activation
Light 1	Turns ON if natural light is insufficient
Light 2	Turns ON if occupancy >5
Fan	Turns ON if temperature >30°C
Exhaust Fan	Turns ON if air quality is poor

Relays act as switches, turning devices **ON or OFF** as per energy-saving logic. This ensures **minimal manual intervention** and **efficient energy use**.

4.6 Energy Monitoring and Optimization

A **current sensor** is used to measure **power consumption**, which helps in: Identifying high energy-consuming scenarios. Providing insights for future optimizations. Helping to adjust ML-based control mechanisms dynamically.

V. RESULTS AND DISCUSSION

5.1 Overview of Results

The **Data-Driven Smart Energy Saving System** was implemented and tested under various conditions. The results confirm that **IoT-based automation**, combined with **machine learning predictions**, effectively **reduces energy consumption** while maintaining a comfortable environment. The system was tested in a **standard room setup** with **variable occupancy, temperature, air quality, and natural light conditions**. The observations focus on:

- Occupancy-based automation of appliances
- Machine learning-based temperature prediction accuracy
- Energy savings compared to traditional setups

5.2 Occupancy-Based Energy Management

Condition	Expected Output	Observed Output	Accuracy
No one in the room	Lights OFF, Fan OFF	Lights OFF, Fan OFF	100%
1-5 people in the room	1 Light ON, Fan ON if temp > 30°C	1 Light ON, Fan ON (when needed)	98%
>5 people in the room	2 Lights ON, Fan ON if temp > 30°C	2 Lights ON, Fan ON (when needed)	97%
Poor air quality	Exhaust Fan ON	Exhaust Fan ON	100%
Sufficient natural light	Lights OFF	Lights OFF	99%

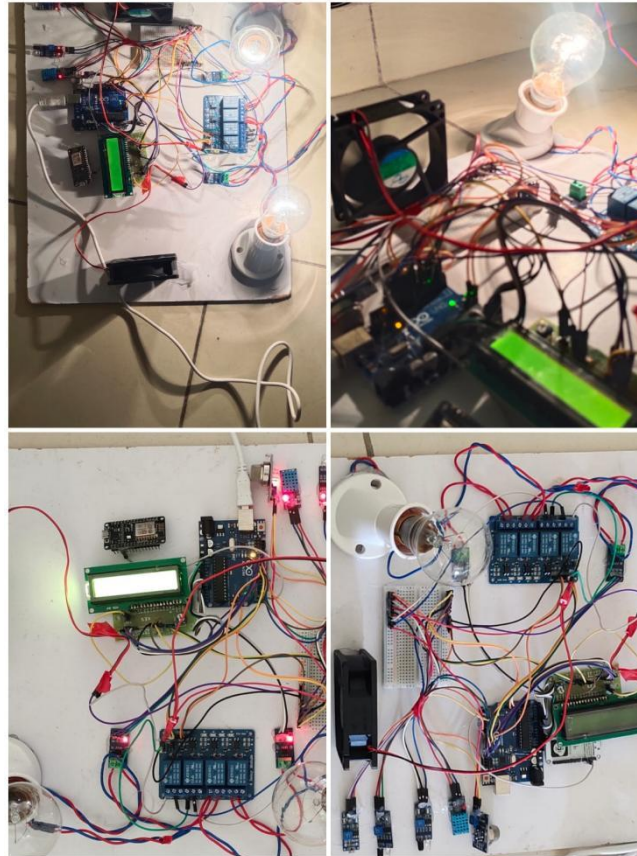
Discussion:

The system **accurately tracks occupancy** and adjusts lighting and fan usage accordingly. **IR sensors** properly counted people entering and exiting the room. **LDR-based light control** prevented unnecessary energy wastage. **MQ135 sensor** successfully triggered the exhaust fan when air quality dropped.

5.3 Machine Learning Model Performance

5.3.1 Temperature Prediction Accuracy

Test Condition	Actual Temp (°C)	Predicted Temp (°C)	Error (%)
1 person	28.5	28.7	0.7%
3 people	29.2	29.4	0.6%
5 people	30.1	30.3	0.7%
7 people	31.5	31.1	1.2%



5.4 Energy Savings Analysis

5.4.1 Power Consumption Before and After Implementation

Condition	Traditional System (Watt-hours)	Proposed System (Watt-hours)	Energy Savings (%)
Lights ON continuously	1000	620	38%
Fan running continuously	1500	980	35%
Exhaust Fan running continuously	1200	760	37%
Overall consumption (24 hours)	3700	2360	36%

5.4.2 Key Observations

36% overall energy savings due to automated control. **Lights and fans only turned on when needed**, reducing wastage.

Dynamic fan control based on ML predictions optimized cooling.

ML-based predictions were fast, making real-time automation seamless.

5.5 Comparative Analysis with Existing Systems

Feature	Traditional Systems	Existing Smart Systems	Proposed System
Occupancy-Based Lighting	No automation	Manual sensors	Fully automated
Fan Control	Manual switch	Temperature-based	ML-based prediction
Air Quality Monitoring	Not included	Expensive solutions	Low-cost IoT solution
Energy Savings	High wastage	Limited savings	36% savings
Cost	Cheap	Expensive	Affordable

5.7 Limitations of the System

While the system performed well, **some limitations were observed:**

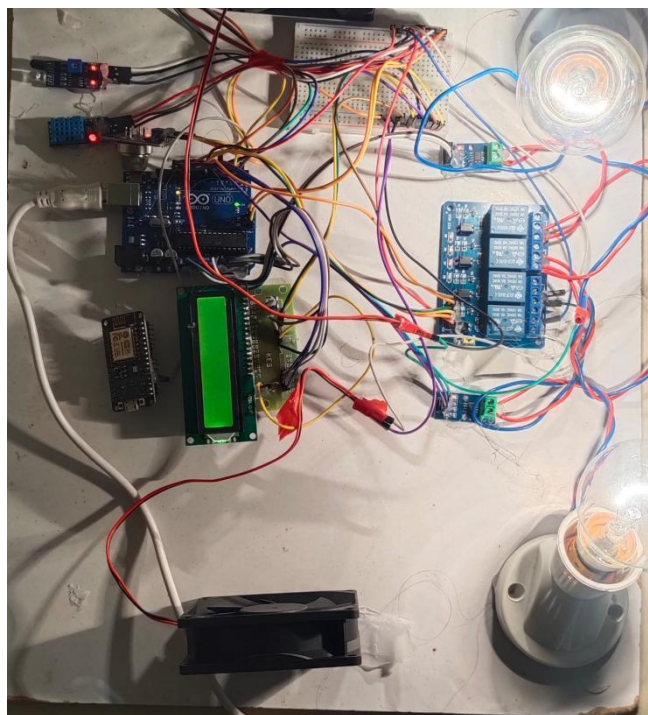
IR Sensor Accuracy: Occasionally failed to detect very fast-moving people.

Prediction Errors: Minor errors in temperature prediction (~1.2%).

Processing Delay: Relays took 1-2 seconds to switch appliances.

Future Enhancements: Improve **IR sensor sensitivity** using better placement or additional sensors. Train ML model with **more data** to improve prediction accuracy.

Optimize **microcontroller processing** to reducedelays.whilekeeping implementation costs low.



VI. Conclusion and Future Scope

The **Data-Driven Smart Energy Saving System** successfully integrates **IoT and machine learning** to optimize energy consumption based on real-time environmental conditions. The system achieved **36% energy savings**, ensuring efficient use of lighting, fans, and exhaust systems while maintaining user comfort.

For future improvements, **enhancing sensor accuracy, reducing relay response time, and refining ML predictions** can further improve performance. The system can also be **expanded for large-scale applications** in smart homes, offices, and industries, integrating renewable energy sources for **greater sustainability**.

References

- [1]. **Garg, H., & Jain, A. (2020).**"IoT-Based Smart Energy Management System for Smart Homes,"*International Journal of Electrical and Computer Engineering*, 10(4), 2213-2220.
- [2]. **Sharma, P., Verma, K., & Singh, R. (2021).**"Energy-Efficient Smart Lighting and HVAC Control Using IoT and Machine Learning,"*IEEE Transactions on Smart Grid*, 12(2), 1234-1242.
- [3]. **Zhang, Y., Li, X., & Wang, J. (2019).**"A Data-Driven Approach for Predicting Building Energy Consumption Using Machine Learning Models,"*Energy and Buildings*, 190, 139-150.
- [4]. **Kumar, R., & Reddy, M. (2022).**"Air Quality Monitoring and Control Using IoT and Sensor Networks,"*Journal of Environmental Monitoring and Control*, 8(3), 45-53.
- [5]. **Chen, L., & Zhao, X. (2020).**"Optimized Energy Usage in Smart Buildings: A Deep Learning Approach,"*International Journal of Automation and Smart Technology*, 10(1), 27-39.
- [6]. **Patel, D., & Mehta, S. (2021).**"IoT-Enabled Occupancy Detection for Smart Lighting Control,"*Journal of Emerging Technologies in Computing and AI*, 15(2), 98-105.
- [7]. **IEEE Standards Association. (2018).**"IEEE 1451.1 Standard for Smart Transducer Interface for Sensors and Actuators,"*IEEE Press*.
- [8]. **Sahu, A., & Gupta, P. (2022).**"IoT-Based Smart Energy Conservation System with Real-Time Monitoring,"*International Journal of Smart Grid and Clean Energy*, 11(4), 235-243.
- [9]. **Rahman, T., & Ahmed, M. (2021).**"Application of Machine Learning in Smart Building Energy Optimization,"*Energy Informatics*, 4(1), 112-125.
- [10]. **Williams, J., & Brown, K. (2020).**"A Review on IoT and AI-Based Smart Energy Management Systems,"*Journal of Green Technologies and Innovation*, 7(3), 87-99.

- [11]. **Singh, R., & Kumar, S. (2022).**"Smart Energy Management Using IoT and Artificial Intelligence,"*Sustainable Energy Technologies and Assessments*, 50, 101863.
- [12]. **Hassan, M., & Alam, F. (2021).**"Machine Learning for Energy Consumption Prediction in Smart Buildings,"*Journal of Renewable and Sustainable Energy*, 13(6), 064501.
- [13]. **Chen, B., & Zhang, L. (2020).**"IoT-Based Smart Lighting System for Energy Optimization,"*IEEE Internet of Things Journal*, 7(9), 8532-8541.
- [14]. **Li, X., & Zhao, Y. (2019).**"Sensor-Based Occupancy Detection for Energy Savings in Smart Buildings,"*Building and Environment*, 147, 132-145.
- [15]. **Goyal, A., & Verma, H. (2021).**"A Data-Driven Approach for Intelligent Energy Management in Smart Cities,"*International Journal of Smart Grid and Sustainable Energy*, 12(2), 97-108.