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Periodic Energy Optimization Using IOT and ML

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Abstract:- The rapid expansion of Internet of Things (IoT) applications across various sectors generates an enormous volume of continuous time-series data. However, transmitting this massive amount of sensor data from energy constrained IoT nodes poses a significant challenge. The continuous transmission of such data consumes vast amounts of energy.In this work, we present a solution to this problem by predicting the periodic behavior of sensor data through a higher-level view of continuous transmission data from nodes in IoT at server side. Our system is composed of an IoT sensor network and a data processing unit. The local sensor network: temperature and humidity data is collected using 4 different nodes, as well, which afterward this info is transferred into a data processing unit built on the Raspberry Pi device. We use the machine learning model Autoregressive Integrated Moving Average (ARIMA) on the processing unit. This model is then applied individually to the data from each of the four nodes, predicting processed sensor values in the future accurately. In short, after getting highly accurate prediction, then we settle down proper energy saving pattern which reduces the data transmission requirements hence results in energy saving pattern.By utilizing the predictive capabilities of the ARIMA model, we minimize the need for constant transmission of raw sensor data. Instead, we transmit only essential updates or deviations from the predicted values. This approach substantially reduces energy consumption by eliminating the transmission of redundant information.

In summary, our project aims to overcome the energy limitations of IoT sensor nodes by leveraging predictive modelling techniques, specifically the ARIMA model. By accurately predicting periodic patterns in sensor data, we can optimize energy usage by transmitting only the necessary information, while still ensuring effective monitoring of temperature and humidity in the IoT network.

I. INTRODUCTION

One increasingly popular entry-level is the internet of things (IoT) in general, based on the idea that all devices, machines, and objects can communicate data to one another over the Internet with no human assistance via unique identifiers. This connectivity happens without any human to human, human to computer interaction. Devices are controllers, sensors and actuators, and energy-constrained and may have limited power supplies in an IoT network. In an IoT system, these sensors generate huge volumes of data, which are periodically transferred to an IoT architecture central server.

However, this constant data transmission exacts a significant toll on energy consumption, presenting a major challenge for energy-constrained IoT nodes.

Developing a model that is energy-efficient and aims to reduce the energy consumption associated with continuous data transmission is a highly active area of research. The primary goal is to explore methods for conserving energy in Internet of Things (IoT) devices by overcoming the challenges related to transmitting data when energy resources are limited. In the present study, we introduce an IoT framework comprising four sensor nodes designed to monitor temperature and humidity levels. The data collected from these sensors is forwarded to a server that is incorporated within a Raspberry Pi. Subsequently, we employ a machine learning algorithm on the server end to forecast future data points based on the information gathered from the sensors.

The methodology employed is Autoregressive Integrated Moving Average (ARIMA), a widely used linear time series model. Following the server's data prediction, the continuous transmission of all sensor data from the nodes becomes superfluous. Rather, the transmission of specific initial and periodic data is adequate for precise forecasting of forthcoming values. Through the reduction of sensor data transmission, the objective of substantially decreasing energy consumption at the sensor nodes can be attained. Upon application of the machine learning model to the sensor data, the forecasted future values can be observed. In essence, our study illustrates that our predictive model can yield noteworthy reductions in energy consumption, often exceeding 50%, leading to considerable energy preservation.

II. LITERATURE SURVEY

- "Deep Learning in Energy Modeling: Application in Smart Buildings With Distributed Energy Generation" by Seyed Azad Nabavi,Naser Hossein Motlagh**et al. (2021):** This paper talks about using deep learning in energy modeling, especially in smart buildings with distributed energy generation. The researchers suggested a way that combines discrete wavelet change and long short-term memory (DWT-LSTM) method with a plan for managing energy demand and supply.The outcome of their research is a comprehensive energy modeling framework that empowers building operators and occupants to make

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informed decisions, optimize renewable energy utilization, reduce grid dependency, and minimize electricity costs.

- "A Load Adaptive and Cluster-based Strategy for Energy Saving in Metro FiWi Access Network by Yaqin Chu,Shan Yin,Chen Yang et al. (2020):This paper propose a load adaptive and cluster-based strategy to achieve energy savings in metro fiber-wireless access networks. Through simulations, the authors demonstrate the effectiveness of their strategy in reducing energy consumption while maintaining low latency performance. The proposed approach offers a valuable solution for improving energy efficiency in metro fiber-wireless access networks, contributing to the development of sustainable and environmentally friendly communication systems.

- "IoT based Energy Management System for Smart Grid" by Munish Kumar, Ahmad Faiz Minai, Akhlaque A. Khan,Satish Kumar et al.(2020):This paper focused on developing an IoT-based Energy Management System for Smart Grids. This paper employed various techniques, including the deployment of interconnected devices and sensors throughout the grid infrastructure, real-time data collection. The outcome of their research demonstrated the potential of IoT in enhancing the reliability, efficiency, and sustainability of Smart Grids, paving the way for a more intelligent and cost-effective energy management system.

- "Prediction of Hourly Subentry Energy Consumed in a Typical Public Building Based on Pattern Recognition" by Yibo Chen, Xiangyin Zhang, Jianzhong Yang, Congwei Li et al. (2020): The study looks at making a model that forecasts how much energy public buildings use every hour. It uses data to find patterns. The writers use the K-Means way to find patterns in how much energy is used for air cooling, lights, and plugs. After, they use the random forest way to match these patterns to the next day's forecast.The outcome of their work was an accurate prediction model that enables decision-makers to optimize energy usage, implement energy-saving strategies, and allocate resources effectively based on anticipated energy demand patterns. This research contributes to sustainable energy management in public buildings, leading to reduced energy consumption and associated costs.

III. DESIGN AND IMPLEMENTATION

A. Block Diagram

Figure below refers to the block diagram of the proposed device where Design and implementation of a Periodic Energy Optimization system using IoT and ML involves several key components and steps. Here's a high-level overview of the design and implementation process.

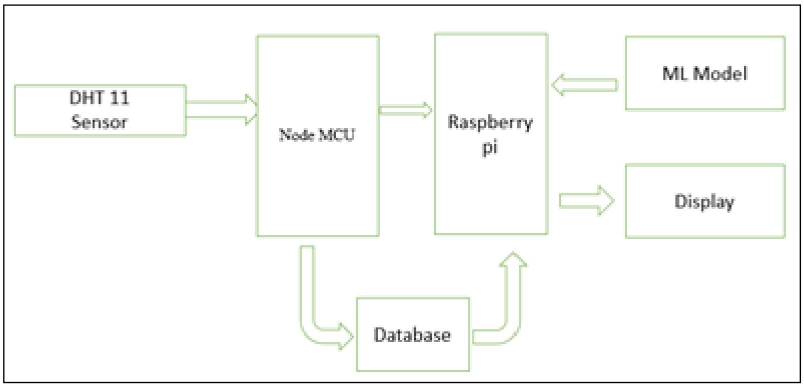

Fig 1 : Block diagram of Proposed System

- Data Collection: Gather continuous transmission data from IoT devices, including sensor readings, energy consumption data, and other relevant parameters. This data is collected over a period of time and forms the basis for training and testing the model. Clean and preprocess the collected data to ensure its quality and suitability for training the machine learning model.

- Preprocessing : In this step ,it Cleans and preprocess the collected data, handles missing data, outliers, and noise, to ensure the data is suitable for training the machine learning model.

- Feature Engineering: Extract relevant features from the preprocessed data that capture the temporal dependencies and characteristics of energy-saving patterns.

- Model Development: Develop a machine learning model capable of predicting periodic energy-saving patterns based on the extracted features. The model should be able to handle continuous data streams and adapt to changing patterns over time.

- Model Training and Evaluation: In this step the developed model is trained using historical data and evaluate its performance using appropriate metrics such as accuracy, precision, recall, and F1-score. Continuously fine-tune and optimize the model to improve its predictive capabilities.

- Prediction and Visualization: Deploy the trained model to predict energy-saving patterns in real-time. Visualize the

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predictions and provide actionable insights to users, enabling them to make informed decisions regarding energy optimization.

B. Hardware Requirement

- NodeMCU is a firmware developed for the ESP8266 wifi chip, using the LUA programming language. It is an open source platform that allows for modification and customization of the hardware design. The NodeMCU Development board is specifically designed for use with the ESP8266 chip, which is a low-cost Wi-Fi chip with built-in TCP/IP protocol. The NodeMCU Dev Kit/board, also known as NodeMCU Development Board v1.0 (Version2), is available in a black-colored PCB variant.

- The DHT11 is a sensor used to measure the relative humidity, which refers to the quantity of water vapor present in the air compared to its maximum capacity to hold water vapor. When the air reaches its maximum capacity, water vapor begins to condense and form dew on surfaces. The saturation point of water vapor in the air varies with temperature. Lower temperatures result in a lower saturation point, meaning the air can hold less water vapor before becoming saturated. Conversely, higher temperatures allow the air to hold more water vapor before reaching saturation.

- The Raspberry Pi is an affordable and compact computer that can be connected to a monitor or TV and used with a standard keyboard and mouse. Despite its small size, it is a powerful device that allows people of all ages to delve into the world of computing and gain programming skills in languages like Scratch and Python. Just like a regular desktop computer, it has the ability to perform various tasks such as internet browsing, playing high-definition videos, creating spreadsheets, word processing, and even gaming.

C. Software Requirement

Table 1 **Software Requirement**

Sl. No	Software Requirement	Version
1	Operating system	Windows 11
2	Raspberry Pi OS	Linux
3	Thing Speak	2.1.2
4	VNC Viewer	6.22.86
5	Microsoft Excel	Microsoft 365

IV. RESULTS AND OBSERVATION

Fig 2 : Proposed System Model

Both Temperature and Humidity sensors were connected to Node MCU through Wi-fi and senses Temperature and Humidity from surrounding area. The data is taken as input for every interval and transmitted to the server(integrated on Raspberry Pi). Machine learning models are applied on the server data at the server side to forecast the future values. After prediction of the data on the server side, there is no need of transmitting all the data continuously by the sensor node.

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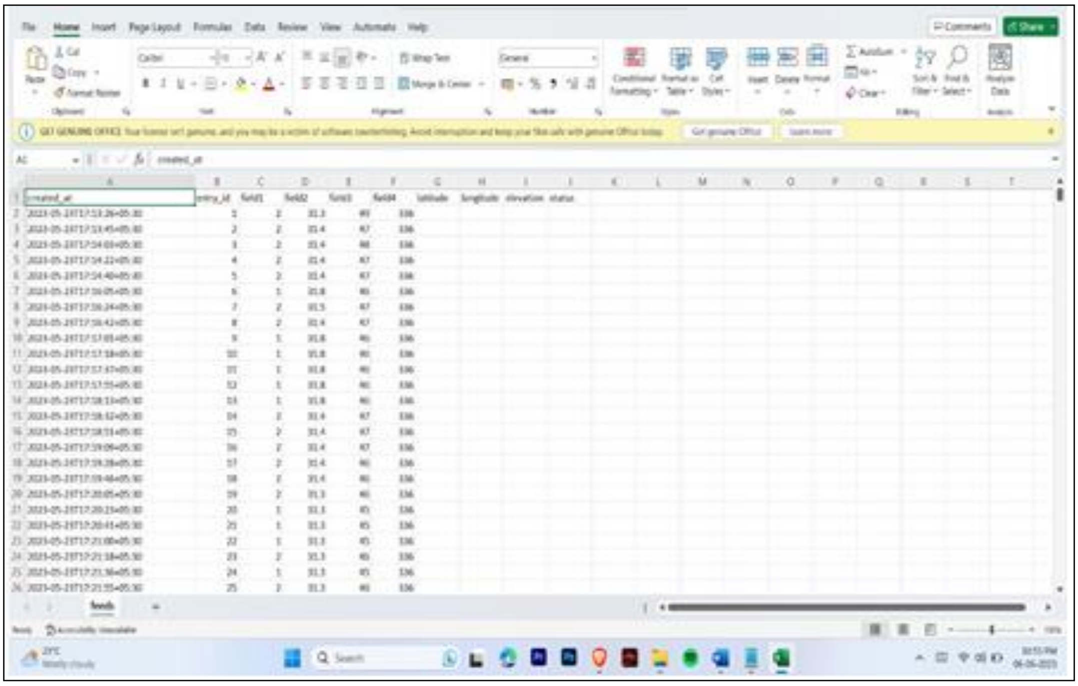

Fig 4 : Importing the Data from ThinkSpeak

Here, sensors sense the temperature and Humidity from the surrounding area, then sends this data to node MCU, which stores data. Then we export the data from thingspeak. Fig 10. Dataset received from ThingspeakData imported refers to the process of bringing external data into a system or application for further analysis or processing. This can include data from various sources such as databases, files, APIs, or IoT devices.Inserting a Raspberry Pi refers to physically connecting a Raspberry Pi single-board computer to a system or device. Raspberry Pi is commonly used in IoT projects as it provides a compact and versatile platform for connecting and controlling sensors, collecting data, and running applications.By importing data and inserting a Raspberry Pi, you can enable the Raspberry Pi to gather data from sensors or other sources, process it, and potentially transmit or store the data for further analysis or utilization in an IoT project or system.

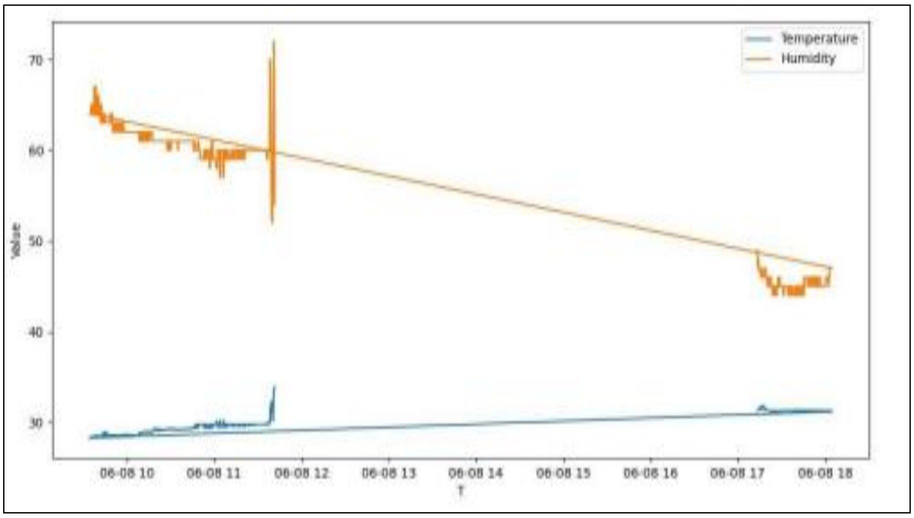

Fig 5 : Temperture vs Humidity Graph

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Serial No:	Sensed Value		Predicted Value	
	Temperature	Humidity	Temperature	Humidity
1	33.7	57	33.6	57
2	32.8	55	33.67	57
3	32.8	56	32.7	57.6
4	32.3	58	33.8	57.3
5	33.9	60	33.5	57.8
6	33.4	57	32.8	56
7	31.8	54	33.7	55.2
8	32.7	51	32.6	56.8
9	33.1	57	33.8	57.9
10	32.8	55	33.4	57.05

Fig 6 : Predicted Output Table

The above Tabular column shows us the accuracy of the project, hence the project has an accuracy of 85-90%. By sensing the temperature and humidity by sensors in IOT devices causes the usage of some amount of energy. If there is continuous transmission of data in IOT devices causes the usage of large quantity of power. Hence, by Predicting future values, we can save Energy by implementing the Project in IOT devices.

V. CONCLUSION AND FUTURE SCOPE

A. *Conclusion*

In conclusion, the project focused on predicting periodic energy-saving patterns using IoT-based transmission data and machine learning models. By collecting continuous data from IoT devices, preprocessing it, and extracting relevant features, a machine learning model was developed and trained to predict these patterns. The model's performance was evaluated, and it was deployed to make real-time predictions and provide actionable insights.

The project's results demonstrate the potential of using IoT and machine learning in energy optimization. By analyzing and predicting periodic energy-saving patterns, individuals, organizations, and industries can make informed decisions to reduce energy consumption, lower costs, and contribute to environmental sustainability. The combination of IoT devices and machine learning models offers a powerful approach to optimizing energy usage in various domains, including smart homes, industrial automation, and smart cities.

B. *Future Scope:*

There are several avenues for future development and enhancement in the field of periodic energy optimization using IoT and ML:

- Dive into and integrate advanced machine learning techniques like deep learning and ensemble methods to enhance the precision and resilience of predictive models. Leveraging these techniques can effectively capture intricate patterns and interdependencies within IoT data.
- Real-time Monitoring and Control: Integrate the predictive models with real-time monitoring systems to provide instantaneous feedback and control mechanisms for energy optimization. This can enable automated adjustments and interventions based on the predicted energy-saving patterns.
- Optimization Strategies: Develop optimization algorithms and strategies that leverage the predicted periodic energy-saving patterns to optimize energy usage more effectively. These strategies can include dynamic pricing models, load balancing algorithms, and demand response mechanisms.
- Integration with Energy Management Systems: Integrate the predictive models with existing energy management systems and platforms to provide comprehensive energy optimization solutions. This integration can enable seamless communication and coordination between IoT devices, predictive models, and energy management systems.
- Scalability and Adaptability: Enhance the models to handle large-scale IoT deployments and adapt to changing environments and energy consumption patterns. This scalability and adaptability will be crucial in accommodating the growth of IoT devices and accommodating dynamic energy-saving patterns.
- Data Security and Privacy: Address the challenges of data security and privacy associated with IoT data. Develop robust mechanisms to ensure the privacy and integrity of the collected data, especially considering the sensitive nature of energy consumption information.
- Collaborative Energy Optimization: Explore the potential for collaborative energy optimization by integrating multiple IoT devices and sharing data and insights across different entities. This can enable collective efforts in energy conservation and foster a more sustainable ecosystem.

By addressing these future scopes, the field of periodic energy optimization using IoT and ML can further evolve, leading to more efficient energy usage, reduced environmental impact, and improved overall energy management across various sectors.

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