Design and Implementation of IOT-enabled Meter for Predictive Energy Management using Machine Learning

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Abstract: In the era of digital transformation, internet of things (IoT)-based smart metering systems represent a pivotal advancement in energy management and monitoring. This paper introduces an innovative smart metering system leveraging machine learning models to predict yearly energy demand and cost. By integrating IoT sensors with advanced data analytics, the system offers real-time monitoring and predictive capabilities, optimizing energy consumption for both consumers and utility providers. Through the analysis of historical usage patterns and environmental factors, such as weather conditions and population dynamics, the machine learning models accurately predict future energy demand, empowering consumers to make informed decisions and proactively address energy challenges. The fusion of IoT and machine learning holds the promise of revolutionizing energy management, with new technologies fostering a greener, more resilient planet for generations to come.

Keywords: IoT, smart metering, machine learning, energy demand, real-time monitoring, energy management

Introduction

The marriage of IoT and machine learning is particularly potent in the realm of predictive analysis. The inherent capabilities of IoT devices to collect real-time data provide a rich source for training machine learning models. Accordingly, IoT devices, equipped with sensors, continuously gather data on various parameters, such as temperature, humidity, location, and usage patterns. This data is thereafter transmitted to centralized systems for processing. Since machine learning models require clean and relevant data for effective analysis, IoT-generated data often undergoes preprocessing steps to handle outliers, and missing values, and ensure consistency. Machine learning algorithms are thus trained using historical IoT data to recognize patterns, correlations, and anomalies. This phase involves selecting the appropriate model, feeding it with labeled data, and adjusting parameters for optimal performance. Once trained, the machine learning model can make predictions based on real-time data from IoT devices. For example, in a smart manufacturing environment, the model could predict equipment failures or maintenance needs by analyzing sensor data. One of the biggest benefits is the capacity for predictive energy consumption. Leveraging historical data, real-time measurements, and various influencing factors, this study empowers a proactive approach to managing energy resources. This predictive capability enables stakeholders to anticipate and respond to fluctuations in energy demand effectively. The IoT-enabled smart meter for predictive analysis using machine learning has been the subject of numerous topics in recent times.

Work done by Nelson et al., (2023) addressed the challenges related to energy consumption and management in households. The authors highlight India's increasing energy demand and the need for accurate monitoring and billing systems. They propose an IoT-enabled smart energy meter system that utilizes machine learning techniques for efficient energy management. The system described in the paper consists of various components and features. It includes a data collection unit with power and IR sensors for measuring energy consumption and monitoring human presence in different rooms. The collected data is transmitted to a server using NodeMCU, and an alerting system is implemented to notify users when consumption exceeds certain thresholds. The authors also introduced a home automation feature that automates appliance operation to maintain consumption below a predefined threshold. The system operates in manual mode or autonomous mode, depending on user preferences and the presence of individuals in rooms. Furthermore, the paper discusses an energy forecasting system that utilizes a decision tree classifier to predict future energy consumption based on historical data and other variables such as holidays and weather conditions. This forecasting capability helps users plan their resources effectively. An Android application is developed as a user interface to display consumption patterns, and billing details, and provide control over appliances. The application facilitates two-way communication between users and the system. The study concluded that by leveraging IoT and machine learning technologies, smart energy meter systems can contribute to efficient resource utilization, accurate billing, and better energy management. The implementation of such systems can lead to energy conservation, which is a crucial need in the current scenario. Overall, the paper presents a comprehensive framework for an IoT-based smart energy meter system that combines data collection, analysis, forecasting, and user interaction to improve energy efficiency and conservation in households.

In contrast, work done by Shapi et al., (2021) developed a predictive model for energy consumption in smart buildings, specifically in Malaysia. The study addresses the problem of low prediction accuracy in energy consumption prediction, which is a crucial aspect of Building Energy Management Systems (BEMS) aimed at reducing energy wastage. The authors proposed three methodologies for the predictive model: Support Vector Machine, Artificial Neural Network, and k-nearest Neighbour. These machine learning algorithms are implemented using the Microsoft Azure cloud-based machine learning platform. The performance of each method is evaluated using metrics such as Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), and Mean Absolute Percentage Error (MAPE). The results showed that differing energy consumption exhibits different distribution characteristics. The study emphasizes the importance of energy consumption prediction in smart buildings for energy efficiency and reducing wastage. By using machine learning techniques, the researchers improved the accuracy of energy consumption prediction and enable effective energy management in buildings. Ezhilarasi et al., (2023) investigated the challenges and costs associated with the deployment of smart meters in developing and underdeveloped nations. The study highlighted the need for cost-effective solutions and proposed a low-cost Smart Network Meter (SNM) that upgrades existing meter infrastructure without the need for complete replacement. The paper describes the architecture and functionality of the SNM and presents simulation results that validate its viability and cost-effectiveness. Seyedzadeh et al., (2018) investigated the application of various data-driven methods for predicting electricity consumption in buildings. The study aims to assess the performance and suitability of different algorithms in online energy predictions using large-scale data extracted from various types of buildings. The paper addresses the characteristics of building electricity use and data reliability through preprocessing steps such as visualization, cleaning, parsing, and filtering. It compares and summarizes mathematical algorithms used in previous studies, focusing on four data-driven methods: Artificial Neural Network (ANN), Gaussian Process Regression (GPR), Support Vector Machine (SVM), and Multivariate Linear Regression (MLR). The result obtained from the study showed that the complexity of the method does not necessarily correlate with the highest accuracy. While ANN is the most complex method, it does not always yield the highest accuracy. On the other hand, GPR, which is the fastest computation method, tends to have lower accuracy results. SVM and MLR methods generally perform better in the studied scenarios. All the prediction accuracies meet the requirements proposed by ASHRAE, with RMSE (Root Mean Square Error) less than 30% and NMBE (Normalized Mean Bias Error) less than 10%. The computation time varies from less than 1 second to 22 seconds per prediction. The study concludes that the proposed methods work well for buildings with stable energy use patterns. However, for buildings with complex and unstable occupancy schedules and energy use patterns, MLR and SVM methods are capable of achieving high accuracy with fast computation speed. Rochd et al., (2021) focused on the design and implementation of a smart Home Energy Management System (HEMS) that integrates renewable energy and improves energy efficiency in residential buildings. The system was implemented as part of a pilot project in Benguerir, Morocco. The HEMS framework is based on two control strategies: Supply-Side Management and Demand-Side Management. Supply-Side Management involves scheduling and controlling power dispatch among generation, consumption, and storage agents, while Demand-Side Management focuses on scheduling and controlling flexible appliances for optimal load profile modulation. The management of energy flows takes into account grid electricity price, forecasting data (such as PV generation and weather conditions), and user preferences. To optimize the system, an AI-based multi-objective optimization algorithm is used. This algorithm aims to minimize costs and maximize comfort levels simultaneously. The results of the study validated the effectiveness of the proposed algorithm, showing increased penetration of PV energy for self-consumption, reduced electricity costs, and a balance between monetary spending and comfort level. The implementation of such systems on a larger scale is seen as a way to decarbonize the residential energy sector by integrating more renewable energy sources and improving energy efficiency in buildings. Park and Son, (2017) considered the implementation of an advanced metering infrastructure (AMI) in Korea and explores the cost analysis of a hybrid AMI system. AMI is a crucial component of a smart grid environment and enables two-way communication between electricity consumers and suppliers. The studied highlighted that the choice of communication technology for AMI depends on the application environment and utility preferences. Two main communication methods are considered: power line communication (PLC) and wireless communication. PLC utilizes existing power line infrastructure, while wireless communication offers high data throughput and flexible network configurations. The authors emphasized that using a single communication technology may result in adverse effects in certain areas. For instance, PLC technology can lead to increased installation costs in low-density areas like farming and fishing regions, while wireless communication may face interference issues in downtown underground distribution line sections. To address these challenges, the study proposed a hybrid AMI system that combines both wired and wireless communication technologies. A simulation-based cost analysis is conducted, comparing the hybrid AMI method with the PLC-only AMI method. The results demonstrated that the hybrid AMI system achieves a 10% reduction in communications network costs compared to the PLC-only method. Furthermore, depending on the installation method, the hybrid AMI can lead to a maximum 19% cost reduction in communications network installation. The authors further argued that a hybrid AMI system is technically and financially advantageous, as it allows for the configuration of a flexible network. They emphasized the importance of considering the density of the installation environment when determining the most suitable communication technology.

Work done in Olu-Ajayi et al., (2023) provided a comprehensive review of data-driven tools used for predicting building energy consumption. The authors emphasized the importance of selecting the appropriate tool for energy prediction based on specific conditions. The review focuses on evaluating the performance of data-driven tools concerning data properties, the type of energy considered, and the type of buildings explored. The study reviewed 63 research articles and compares the performance of various data-driven tools, including Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), Linear Regression (LR), and Autoregressive Integrated Moving Average (ARIMA). Based on the reviewed studies, SVM consistently demonstrated better performance than other tools in the majority of cases. ANN and RF also showed favorable performance in several studies compared to statistical tools such as LR and ARIMA. The authors highlighted that no single tool emerged as the best choice for all conditions. Each tool has its strengths and weaknesses, and they tend to yield different results depending on the specific conditions. Therefore, the study provides a proposed guideline for selecting the appropriate tool based on their strengths and weaknesses in different situations. The paper identifies research gaps and suggests future directions for data-driven building energy consumption prediction. It emphasizes the need for studies that identify relevant features for model development and evaluate the performance of data-driven tools under different conditions. The paper concludes by providing a framework for tool selection and encourages further research in this field.

Naji et al., (2016) proposed a novel method to estimate building energy consumption using the Extreme Learning Machine (ELM) method. The study focused on improving the energy efficiency of buildings by estimating their operational energy usage during the design phase. The authors emphasized that the current energy requirements of buildings contribute significantly to global energy consumption. They argued that addressing energy efficiency and the choice of construction materials is crucial for a sustainable future. By estimating energy consumption early in the design phase, architects and engineers can create more sustainable structures. To estimate building energy consumption, the ELM method is applied to building material thicknesses and their thermal insulation capability. The EnergyPlus software application is used to simulate various scenarios with different material thicknesses and insulation properties. The accuracy of the ELM model's estimation and prediction is compared with genetic programming (GP) and artificial neural network (ANN) models, showing that the ELM approach outperforms the other two methods. The study highlighted the importance of energy usage estimation in achieving energy efficiency in buildings. It also emphasized the significance of insulation in reducing energy costs and ensuring thermal comfort. The research focuses on materials and systems prevalent in Eastern Europe and Turkey, where energy demands have been increasing.

Almalaq and Zhang, (2019) introduced a novel approach, termed "Evolutionary Deep Learning-Based Energy Consumption Prediction for Buildings," which was designed to enhance the accuracy of energy consumption predictions in buildings. Motivated by the imperative to reduce energy usage and the necessity for precise energy forecasts to enable efficient energy management, the authors proposed a hybrid methodology. This approach combines evolutionary deep learning techniques, integrating genetic algorithms with long short-term memory (LSTM) networks, to optimize predictive models. Unlike conventional methods reliant on manual hyper-parameter adjustments, the proposed approach dynamically adjusts time window lags and hidden neurons within the network through genetic algorithms to enhance predictive accuracy. Accurately predicting building energy consumption poses challenges due to various influential factors such as weather conditions, geographical location, building structure, and occupancy. While prior research explored physical, statistical, and machine learning techniques like artificial neural networks (ANN), support vector machines (SVM), decision trees, and k-nearest neighbors (kNN), deep learning methods, particularly LSTM, have shown promise. The study discusses the effectiveness of convolutional neural networks (CNN) and recurrent neural networks (RNN) in energy consumption prediction, highlighting their superiority over traditional models. Additionally, the authors underscore the utility of evolutionary computation techniques such as genetic algorithms in refining predictive models. The proposed hybrid approach, integrating GA optimization with LSTM, offers improved prediction accuracy, as demonstrated through experiments on residential and commercial building datasets, thereby showcasing the potential of evolutionary deep learning in energy consumption forecasting. Ahmad et al., (2018) explored the application of supervised machine learning models to predict energy consumption across various temporal scales in different building settings. Using power consumption data obtained from a power transmission and distribution network organization, the authors categorized the data into monthly, seasonal, and yearly intervals to facilitate short-term, medium-term, and long-term energy forecasting. Four supervised machine learning models, including Binary Decision Tree, Compact Regression Gaussian Process, Stepwise Gaussian process regression, and Generalized Linear Regression Model, were employed for energy prediction. These models utilized input variables such as day-type/hour-type, net energy consumption of different load types, and limited external environmental data, aiming to predict total energy demand. Evaluation metrics like mean absolute percentage error (MAPE) revealed varying model accuracy across seasons and prediction timeframes, with the Binary Decision Tree model exhibiting the best performance in autumn for both seasonal and yearly forecasting, achieving MAPE values of 0.809% and 0.989% respectively. Furthermore, the study compared these models against actual energy consumption and an artificial neural network model, revealing promising results in terms of prediction accuracy, with MAPE and coefficient of variation values found to be 2.416% and 3.290% respectively for yearly prediction. The study underscored the significance of precise energy forecasting for efficient planning and development of power systems. By incorporating limited energy usage and environmental data as input variables, the study demonstrates the potential of supervised machine learning models in accurately predicting short-, medium--, and long-term energy demand in diverse building environments, thus aiding in effective energy management and infrastructure planning.

Xu et al., (2019) presented a novel method for predicting energy use in multiple buildings by combining social network analysis (SNA) with artificial neural networks (ANN). The study addressed the challenge of defining reference buildings and predicting energy use in a multi-building context using limited building data and reducing the complexity of prediction models. The proposed method involves establishing a building network (BN) using SNA to identify reference buildings and determine correlations between reference and non-reference buildings. The ANN technique is then used to learn these correlations and historical building energy use, enabling the prediction of multi-building energy use. To validate the SNA-ANN method, the study focuses on 17 buildings in the Southeast University campus in Nanjing, China. These buildings are categorized into four types: office, educational, laboratory, and residential. The results demonstrate that the integrated SNA-ANN method achieves high prediction accuracies for each building group, ranging from 83.32% to 92.34%. The paper emphasizes the importance of predicting multi-building energy use at a campus or city district scale, as it provides insights into large-scale energy use patterns and opportunities for energy savings. By considering the interrelationships between building groups, the proposed method contributes to advancing interdisciplinary research on multi-building energy use prediction.

Liu et al., (2019) provided an in-depth review of the application of machine learning techniques in predicting building energy consumption. The paper addresses the challenge of determining the predictive structure with the best performance in this field. The authors conducted accuracy analyses based on different types of buildings, temporal granularity, input/output variables, and historical data collections. They compared the performance of artificial neural networks (ANN) and support vector machines (SVM) in terms of prediction complexity, accuracy, data requirements, and the number of inputs. The strengths and weaknesses of hybrid and single machine learning methods were also outlined and compared. The paper emphasizes the importance of achieving accurate and reliable predictions of building energy consumption. It highlights that machine learning methods have the potential to improve accuracy and reliability in this field. The authors suggest that machine learning methods should receive more attention from researchers due to their development potential. Overall, this paper provides insights into the application of machine learning in building energy consumption prediction, including model comparison, analysis of accuracy factors, and identification of research directions.

Pham et al., (2020) considered the development of a prediction model based on Random Forests (RF) for short-term energy consumption forecasting in multiple buildings. The goal of the study is to improve energy efficiency and sustainability in the building sector. The authors highlighted the significance of energy-efficient and sustainable buildings due to their substantial contribution to global energy consumption and greenhouse gas emissions. Predicting energy consumption patterns in buildings is crucial for utility companies, users, and facility managers to enhance energy efficiency. The paper proposes the RF model as an effective prediction tool and compares its performance with other machine learning models such as M5P and Random Tree (RT). In summary, the paper focuses on the development and evaluation of a Random Forest-based prediction model for short-term energy consumption forecasting in multiple buildings. It highlights the significance of energy efficiency and sustainability in the building sector and demonstrates the effectiveness of the RF model in improving energy performance and aiding decision-making processes for building owners and facility managers.

Biswas et al., (2016) considered the challenges and importance of predicting energy consumption in residential buildings. The authors emphasize that although the residential sector accounts for a significant portion of energy demand, it has received less attention compared to other sectors. They highlight the need for optimal and robust solutions in modeling residential building energy consumption. The study focuses on the application of artificial neural networks (ANNs) as a method to address the nonlinearity of building energy data and handle large and dynamic datasets. The authors present the development and validation of ANN models using data from the TxAIRE Research houses, which serve as realistic test facilities for new technologies. The input variables used in the models include the number of days, outdoor temperature, and solar radiation, while the output variables are house and heat pump energy consumption. Two algorithms, namely Levenberg-Marquardt and OWO-Newton, are employed in the model development, and promising results are obtained with coefficients of determination ranging from 0.87 to 0.91, which are comparable to prior literature. The authors acknowledge the impact of weather conditions on energy consumption and demonstrate the ability of their models to capture this influence. Overall, the paper contributed to the development of a robust model for predicting residential building energy consumption using neural network approaches. It underscores the relevance of this research area in achieving energy conservation and emissions reduction goals.

Ezhilarasi et al., (2023) considered a cost-effective approach to smart metering for the deployment of affordable smart grid systems. The authors highlight the importance of smart meters in modernizing the power grid and mention the challenges faced in their widespread adoption, particularly in developing and underdeveloped nations. The authors proposed a low-cost Smart Network Meter (SNM) that upgrades existing meter infrastructure without requiring complete replacement. The SNM utilizes an add-on device to extract consumption details and communicate wirelessly with a central system. The paper includes a simulation of the SNM to validate its viability and assess its efficacy. A consumer opinion survey is conducted to gather evidence supporting the adoption of the proposed low-cost smart metering solution. The authors emphasize the need for cost-effectiveness in the design of smart meters and deployment strategies. They discuss the challenges associated with smart meter implementation, including lack of standardization, interoperability issues, and cost considerations. The paper also includes a literature review on the costs associated with smart meter design, highlighting previous research on cost-effective smart meter solutions. Overall, this paper presents a cost-effective approach to smart metering and provides insights into its potential benefits and acceptance among consumers.

In contrast to existing results, this study aims to explore the integration of machine learning and IoT technologies in the context of energy management, with a focus on real-time data analysis, predictive maintenance, and improved operational efficiency. The goal is to accurately forecast energy demands, promote intelligent resource usage, optimize energy consumption, and achieve significant cost savings. Additionally, the study aims to investigate the potential impact of IoT capabilities in enhancing energy management and conservation, as well as the role of artificial intelligence (AI) in smart metering systems for accurate energy monitoring, anomaly detection, load management, and improved efficiency.

The objectives of this study are summarized as follows

System Hardware Design and Implementation

The hardware system would be capable of capturing and transmitting energy consumption data from various sources within the household or facility. It would also entail the selection of appropriate sensors and components for accurate measurement and data collection, considering factors such as voltage, current, and frequency. Measures for energy efficiency and reliability to ensure continuous operation and minimal maintenance requirements with the integration of security protocols to safeguard sensitive data and prevent unauthorized access or tampering. The hardware system would be tested thoroughly to validate its performance under different operating conditions and ensure compatibility with the chosen software framework.

Software Design and Development

A machine learning algorithm would be developed, one capable of predicting year-on-year energy demand and cost based on historical data and relevant external factors such as weather patterns, occupancy, and time of day. For data visualization and analysis, a user-friendly interface would be designed allowing users to monitor their energy consumption patterns, set preferences, and receive recommendations for optimizing usage.

Adoption of data preprocessing techniques to clean and preprocess raw data collected from the hardware sensors, ensuring accuracy and consistency for machine learning model training. Utilization of machine learning libraries and frameworks to train predictive models, considering factors such as regression techniques, feature selection, and model evaluation metrics. Model retraining and adaptation mechanisms to accommodate changing usage patterns and environmental conditions over time, implementation of data storage and retrieval mechanisms to efficiently manage large volumes of historical data for analysis and model training purposes.

Create an Interface Between the Software and Hardware

This entails the implementation of real-time data streaming mechanisms to transmit energy data from the hardware to the software for analysis and visualization. Compatibility and interoperability between the software and hardware components must be seamless, considering factors such as data formats, transmission protocols, and latency requirements.

Methodology

The software development methodology used in this study can be described as a mix of the incremental development model and the Evolutionary Prototyping approach. The study was broken into small chunks and for each chunk, the objectives and constraints were determined. They were then developed, tested, and, where needed, refined. Then, the next iteration was planned. Using the Evolutionary Prototyping approach, the system is continually improved and built upon. As an example of the development method, the following paragraph describes the process of creating the command-control functions. A simple command-control function on the Application was built.

Analysis of the proposed system

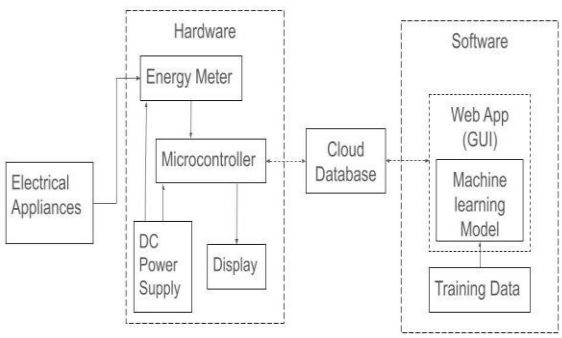

Fig 1: Proposed Block diagram

This system is broken down into four major stages and three segments, hardware design and implementation, data acquisition and preprocessing, machine learning model development, IoT and cloud services lastly the deployment stage. These stages are outlined below;

The Hardware design and implementation phase involves meticulous selection of microcontrollers and sensors tailored to accurately measure energy consumption. This selection process considers factors such as precision, power efficiency, and compatibility with the intended application. The hardware consists of a microcontroller, OLED, Current Transformer, Voltage sensor, Digital Humidity and Temperature sensor (DHT). The microcontroller to be used is ESP8266.

The data acquisition and preprocessing phase is crucial for gathering and preparing energy data for analysis. Energy consumption data is collected from sensors installed in smart meters, capturing information such as current, voltage, and temperature readings. Preprocessing techniques are then applied to the collected data to handle missing values, normalize the dataset, and clean it of any anomalies or outliers. This prepares the data for further analysis and ensures its quality and consistency.

Machine learning model development phase to enable predictive energy analysis. Engineers select relevant features and machine learning algorithms suited to the task of forecasting energy demand and cost. Historical energy consumption data serves as the training dataset for these models, which are then trained and validated using techniques such as cross-validation. Model performance is evaluated, and parameters are fine-tuned to optimize accuracy and predictive capabilities.

The IoT and cloud services phase constitutes the fourth step, enabling seamless communication and data management capabilities. Connectivity protocols for IoT communication, such as MQTT or HTTP, are established to facilitate communication between smart meters and cloud platforms. Smart meters are integrated with cloud services for data storage, analytics, and remote monitoring. To ensure the security and integrity of data transmission and storage, robust security measures, including encryption and authentication mechanisms, are implemented.

The deployment phase involves planning and executing the deployment of smart meters in real-world environments. Deployment strategies are carefully planned, taking into account factors such as geographical location, network connectivity, and user requirements. Field testing is conducted to validate the performance and predictive capabilities of the deployed smart meters. Ongoing monitoring and maintenance activities are then carried out to ensure the optimal operation of the system and address any issues that may arise over time. This comprehensive approach to deployment ensures the successful implementation and operation of IoT-enabled smart meters for predictive energy management.

Microcontroller

The microcontroller to be used is ESP8266 a versatile and cost-effective Wi-Fi microcontroller module that has gained widespread popularity in the field of IoT (Internet of Things) and embedded systems. Its relevance in smart meter hardware systems lies in its ability to provide connectivity to Wi-Fi networks, enabling seamless communication with cloud services, remote monitoring platforms, and other IoT devices. With its integrated Wi-Fi capabilities, the ESP8266 facilitates real-time data transmission and remote access, essential for smart metering applications. This allows smart meters to transmit energy consumption data to cloud servers for storage, analysis, and visualization. Additionally, it enables remote monitoring and control of smart meters, offering users the flexibility to manage energy usage and monitor performance from anywhere with internet access. Moreover, the ESP8266's compact size, low power consumption, and ease of integration make it an ideal choice for smart meter hardware designs. It can be easily integrated into existing metering systems or incorporated into new designs without significantly increasing the overall size or power requirements of the device. Its affordability also makes it accessible to a wide range of developers and manufacturers, contributing to the widespread adoption of smart metering solutions.

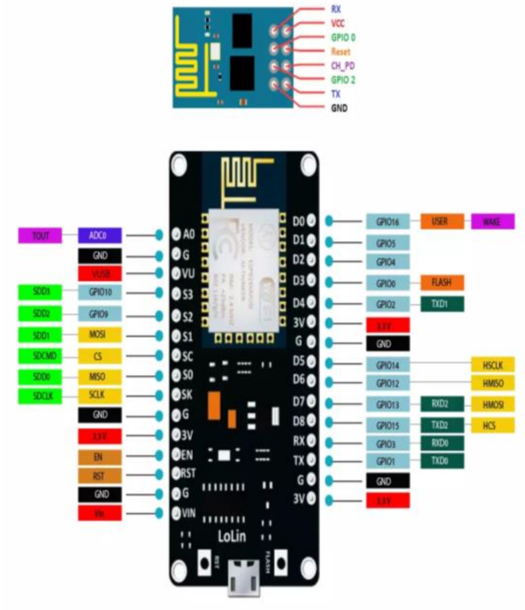

Fig. 2: ESP 8266 NodeMCU
\Source:https://www.theengineeringprojects.com/2018/08/esp8266-pinout-datasheet-features-applications.html

Cloud Database

Among the options available, Amazon DynamoDB stands out as a robust choice for its scalability, flexibility, and integration with other AWS services, which can streamline the development and deployment process. Amazon DynamoDB is a fully managed NoSQL database service offered by Amazon Web Services (AWS). It provides high availability and seamless scalability, making it well-suited for applications with variable workloads and large datasets, such as those encountered in smart metering systems. DynamoDB offers features like automatic scaling, built-in security controls, and low-latency performance, ensuring reliable and efficient data storage and retrieval. Additionally, DynamoDB integrates seamlessly with other AWS services commonly used in IoT applications, such as AWS IoT Core for device communication and AWS Lambda for serverless computing. This integration enables developers to build end-to-end solutions within the AWS ecosystem, simplifying development and reducing time-to-market. Furthermore, DynamoDB's flexible data model allows for the storage of structured and semi-structured data, making it suitable for storing sensor data collected by smart meters. Its query capabilities and indexing features enable efficient retrieval and analysis of historical energy consumption data, essential for predictive analytics and reporting.

C++ Programming Language

The NodeMCU board is programmed using the C++ programming language

Arduino Software (IDE)

The Arduino Software (IDE) is an open-source software which is used to program the Arduino boards and is an integrated development environment, developed by Arduino which allows users to write and upload code to Arduino boards, and it consist of several libraries. Figure 3 shows a typical Arduino IDE.

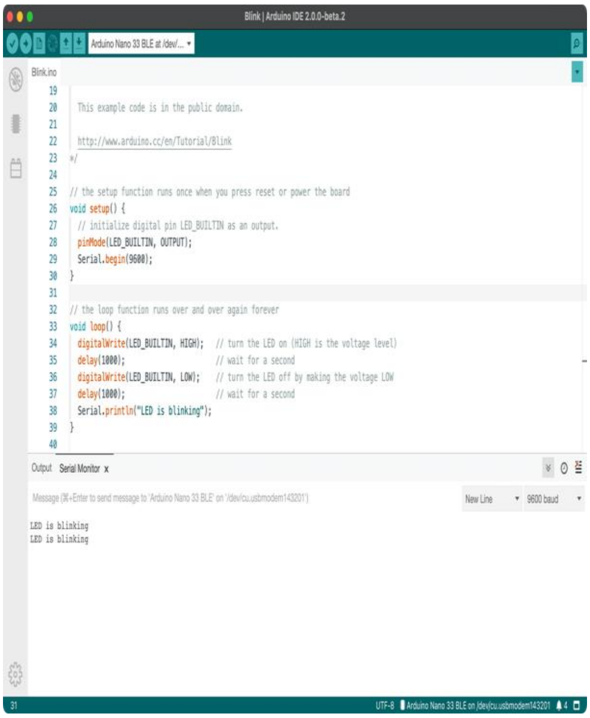

Fig. 3: Arduino IDE
Source: https://www.arduino.cc/pro/software-arduino-pro-ide/

System Design

This phase describes how different components of this study are assembled from the least components/devices to the major components. It contains all the necessary diagrams and flowcharts for the design process. The major purpose of the system design process is to provide sufficient detailed information about the study design, construction, and implementation. The procedure for connecting the devices is given in the following steps:

Step 1: Connect the ESP 8266 to the relay board and connect the switch mode power supply (SMPS).

Step 2: Connect the HV side of the relay board in NC type and to the power supply socket.

Step 3: Program the ESP 8266 to connect to Wi-Fi by providing an SSID and password.

Step 4: Write basic Python and JavaScript code providing the user interface to control the appliances and store data from the IoT

Step 5: Setup a backend API service using Firebase

Step 6: On the WebApp, write functions to send updates to the API service.

Step 7: Configure the ESP 8266 program to listen to updates from the API service

Step 8: launch and log on to the web app to have access control and upon validation, the IoT device can now be controlled.

The flow chart for the proposed system design is shown in Figure 4.

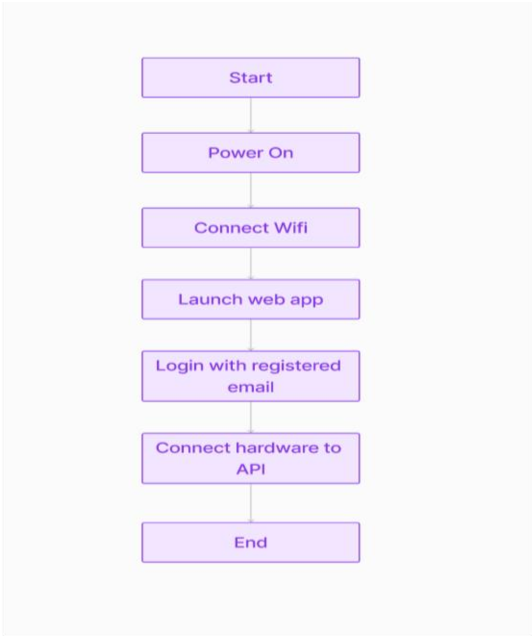

Fig. 4: Flowchart of ESP 8266 working

System Architecture

The core of the proposed IoT-based smart meter consists of two main hardware components: the mobile/web interface, and the Arduino microcontroller board which is compact, inexpensive, and offers a variety of digital and analog inputs, serial interface, and digital outputs. The circuit design for the smart meter is shown in Figure 5.

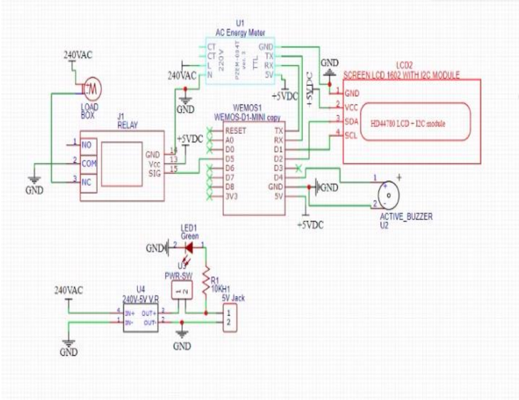

Fig. 5: Circuit design of smart meter

Result

Figure 6 below shows the front end of the web app, where users can view their consumptions in real-time. Parameters such as voltage, energy cost, power, cumulative energy use, and daily predictive cost, and data are displayed.

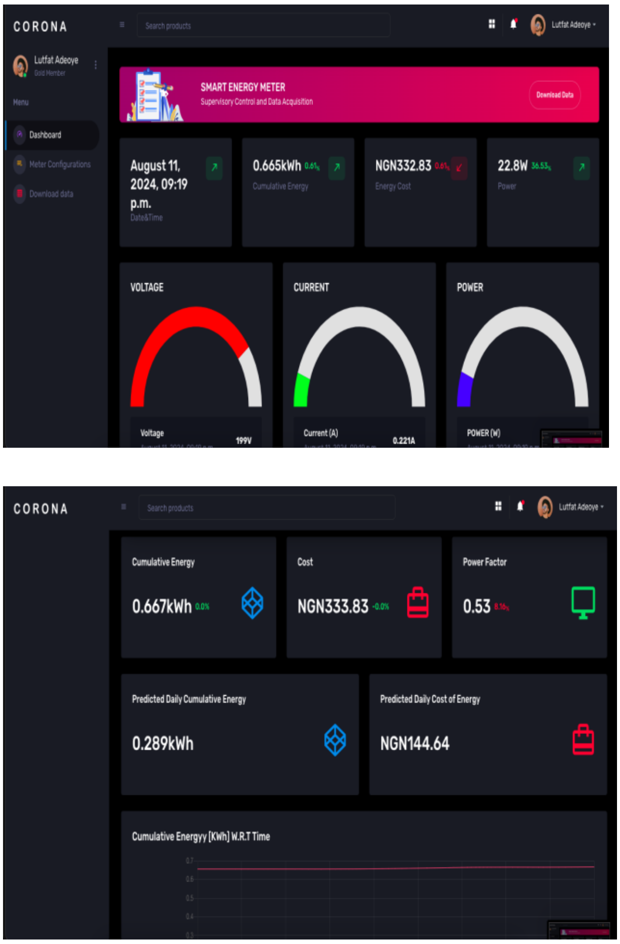

Fig. 6: Smart meter Web app

Conclusion

This study presents the design and implementation of an IoT-enabled meter system for predictive energy management using machine learning techniques. The study represents an innovative approach to addressing energy challenges by integrating IoT sensors and advanced data analytics. The system leverages machine learning models to analyze historical usage patterns, and data to accurately predict future energy demand. This enables both consumers and utility providers to make more informed decisions and proactively manage energy consumption.

For future improvements, enhancing the system's connectivity and interoperability by exploring the use of emerging communication technologies, such as 5G or IoT protocols, to enable seamless data exchange and integration with other smart grid or smart city initiatives is recommended.

Overall, the study showcases a promising approach to leveraging IoT and machine learning for predictive energy management, with ample opportunities for future enhancements and wider deployment to address the growing energy challenges facing both consumers, and utility providers.

Reference

Ahmad, T., *et al.*, "Supervised based machine learning models for short, medium and long-term energy prediction in distinct building environment", *Energy*, vol. 158, pp. 17–32, 2018, doi: 10.1016/j.energy.2018.05.169.

Almalaq, A., and Zhang, J. J. "Evolutionary Deep Learning-Based Energy Consumption Prediction for Buildings", *IEEE Access*, vol. 7, pp. 1520–1531, 2019, doi: 10.1109/ACCESS.2018.2887023.

Biswas, M. A. R., Robinson, M. D., and Fumo, N. "Prediction of residential building energy consumption: A neural network approach", *Energy*, vol. 117, pp. 84–92, Dec. 2016, doi: 10.1016/j.energy.2016.10.066.

Ezhilarasi, P., Ramesh, L., Sanjeevikumar, P., and Khan, B. "A cost-effective smart metering approach towards affordable deployment strategy", *Scientific Reports*, 13(1), p. 19452, 2023, doi: 10.1038/s41598-023-44149-9.

Kumar, V. D. A., Mlathi, S., Balas, V. E., Favorskaja, M. N., and Perumal, T. "*Smart intelligent computing and communication technology*", in Advances in parallel computing, no. volume 38. Amsterdam: IOS Press, 2021.

Liu, Z., *et al.*, "Accuracy analyses and model comparison of machine learning adopted in building energy consumption prediction", *Energy Exploration & Exploitation*, 37(4), pp. 1426–1451, 2019, doi: 10.1177/0144598718822400.

Nelson, I., Annadurai, C., Ramya, E., Shivani, R., Mathusathana, V. "IoT Based Smart Energy Meter System Using Machine Learning', 38: pp.358-362, 2021. doi: 10.3233/APC210066.

Olu-Ajayi, R., Alaka, H., Owolabi, H., Akanbi, L., and Ganiyu, S. "Data-Driven Tools for Building Energy Consumption Prediction: A Review", *Energies*, 16(6), pp. 2574, 2023, doi: 10.3390/en16062574.

Park, S-W., and Son, S-Y. "Cost Analysis for a Hybrid Advanced Metering Infrastructure in Korea", *Energies*, 10(9), pp. 1308, 2017. doi: 10.3390/en10091308.

Pham, A-D., Ngo, N-T., Truong, T. T., Huynh, N.-T., and Truong, N-S. "Predicting energy consumption in multiple buildings using machine learning for improving energy efficiency and sustainability", *Journal of Cleaner Production*, vol. 260, p. 121082, Jul. 2020, doi: 10.1016/j.jclepro.2020.121082.

Rochd, A. *et al.*, 'Design and implementation of an AI-based & IoT-enabled Home Energy Management System: A case study in Benguerir — Morocco', *Energy Reports*, vol. 7, pp. 699–719, Nov. 2021, doi: 10.1016/j.egyr.2021.07.084.

Shapi, M. K. M., Ramli, N. A., and Awalin, L. J. "Energy consumption prediction by using machine learning for smart building: A case study in Malaysia", *Dev. Built Environ.*, vol. 5, p. 100037, 2021. doi: 10.1016/j.dibe.2020.100037.

Seyedzadeh, S., Rahimian, F. P., Glesk, I., and Roper, M. "Machine learning for estimation of building energy consumption and performance: a review", *Vis. in Eng.*, 6(1): pp. 5, 2018, doi: 10.1186/s40327-018-0064-7.

Xu, X., Wang, W., Hong, T., and Chen, J. "Incorporating machine learning with building network analysis to predict multi-building energy use", *Energy and Buildings*, vol. 186, pp. 80–97, Mar. 2019, doi: 10.1016/j.enbuild.2019.01.002.