

Advanced AI-Based Energy Monitoring and Demand Prediction with Theft Detection

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Abstract

This paper presents a study on an AI-based energy management system, which is designed for real-time monitoring of energy consumption for theft detection and energy demand prediction. Our energy management system has voltage and current sensors for energy consumption measurement and provides real-time data on voltage (V), current (mA), and energy units. We have implemented a machine learning algorithm, support vector machine (SVM), to improve the process of theft detection by identifying anomalies and classifying the status of each anomaly into either “Normal” or “Theft” on the monitoring interface. A machine learning approach based on SVMs is used to improve the identification of electricity theft and anomalous usage trends. Each detected event is classified as either “Normal” or “Theft” by the algorithm, which examines real-time consumption data to find anomalies. The results are shown on a special monitoring interface. Authorized staff are given the capacity to remotely manage the power supply using a NodeMCU microcontroller in response to suspicious activity, enabling the system to turn the power ON or OFF as a preventive and remedial action. Additionally, the NodeMCU ensures dependable data storage, retrieval, and system scalability by facilitating smooth connectivity with the cloud infrastructure. The authorized person can remotely switch ON/OFF the power supply using a NodeMCU, which further sends data to the cloud for real-time monitoring and retrieval. The long short-term memory (LSTM) algorithm is incorporated in the system to examine consumption trends in the future for predicting energy usage. The cloud infrastructure provides persistent data availability and access, thereby enabling real-time decision-making and productivity enhancement. Experimental results verify the system for energy consumption monitoring, theft prevention, and demand forecast, while further prospects are opened for energy efficiency and energy loss reduction.

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INTRODUCTION

It is now apparent that the sustainable use of energy resources is an area of growing is a global concern. With uncontrolled population growth and further industrialization, energy management has become a significant challenge. In this regard, the project intends to tackle these problems through the development of a complex system for energy monitoring, energy theft detection, and energy demand forecasting. This comprehensive plan is expected to provide information on energy use in a more accurate time frame, provide accurate timelines for energy theft or any irregularities occurring, and assist in the decisive utilization of energy by the users.

Our project highlights the need for welfare in the context of sustainable energy management, which is integral to aspects such as resource depletion and environmental pressures. This way, with the project offering to account for well-forecasted demand to produce and distribute effectively, it cuts out as much waste and damage to the environment as possible. Theft detection is integrated into it to help curb illegal energy consumption and protect revenues by providing fair access. Furthermore, the cloud-based platform will help scale and inform real-time energy-use data. Such a benefit brings data-driven decision-making for energy providers and empowers consumers to monitor and control it with full transparency. By providing solutions to these critical issues pertaining to energy conservation and management, this project is based on sustainability, resource efficiency, and accountability from all stakeholders.

The project also highlights the significance of sustainable energy management as a means of addressing pressing issues such as resource depletion and growing environmental impact. This technology helps energy suppliers better manage generation and distribution by integrating precise demand forecasting techniques. This reduces waste, greenhouse gas emissions, and energy output. Better load balancing, which improves grid stability and advances long-term sustainability objectives, is another benefit of effective forecasting. A key element of the proposed system is energy theft detection, which aims to prevent illicit energy use and provide fair access to energy sources. The system protects utility income and fosters customer justice by precisely identifying and classifying anomalous usage patterns of electricity. Furthermore, the incorporation of a cloud-based platform guarantees data availability, scalability, and safe storage of consumption data. This architecture enables real-time monitoring, historical data analysis, and smooth system expansion as demand increases.

LITERATURE REVIEW

Traditional energy monitoring systems mainly utilize analog and digital energy meters to measure electricity consumption. Although these meters provide periodic readings, they are not capable of real-time data transmission [1]. Conventional approaches to energy theft detection include loss monitoring based on power line communication (PLC) [2] and tamper-proof metering systems [3]. These PLC techniques study power loss in electrical transmission lines but suffer from very high installation costs and signal interfacing problems [4]. There are hardware means of detecting tampering, such as tamper sensors and RFID-based security [5], but these methods would be impotent against the operations of electricity theft through non-intrusive means, such as meter bypass and distortion of sensor readings [6].

Energy demand prediction has traditionally been achieved using statistical forecasting models such as auto regressive integrated moving average (ARIMA) and seasonal auto regressive integrated moving average (SARIMA) [7]. While good at picking up seasonal trends, the methods are arguably inefficient for nonlinear consumption behavior and abrupt load disturbances [8]. A few studies have experimented with machine learning models, such as decision trees and artificial neural networks (ANNs), for prediction purposes [9], but manual feature selection and a very large volume of historical data are eventually required to achieve accurate decision-making [10].

There have been many advancements in smart metering and predictive analysis [11]. However, these methods, as applied in the existing literature, rely heavily on direct readings from energy meters for monitoring and analysis [12]. Therefore, the applicability of these methods is limited to cases where real-time sensor-based measurements of energy are required. In addition, an approach to energy monitoring, theft detection, and demand forecasting underpinned by AI is often lacking in many current systems; with these areas of improvement, work will be needed to enhance efficiency and automation.

METHODOLOGY

An AI-based energy management system delivers real-time energy consumption information, theft detection, and forecasts for future demand [13]. The system consists of the optimal deployment of a voltage and current sensor network atop the power grid to gather energy-use data [14]. The sensors

monitor voltage (in volts), current (in milliamps), and energy use (in units) twenty-four seven, communicating this information to a centralized cloud platform for further processing and interpretation [15]. This provides an integrated view of the energy flow through the entire power network in real time.

A support vector machine (SVM) based algorithm was employed to combat energy theft [16]. With this algorithm, current energy consumption habits can be analyzed to search for commonly deviating patterns based on the established baseline [17]. The SVM verifies anything out of the ordinary once detection occurs; it will label it as “Normal” or “Theft,” thereby clearly mapping that something may potentially have gone wrong, as shown in Figure 1. This information is sent to a monitoring interface that enables operators to take immediate action [6].

The system integrates a NodeMCU microcontroller that allows the remote control of the power supply [7]. Based on the anomaly classification performed by the SVM, the authorized person has the power to switch the power ON/OFF from his/her remote location; thus, this renders an additional layer of protection and rapid response against suspected theft or tampering [8]. Remote control makes the operations of the system far more effective in handling energy losses and preventing the unauthorized consumption of energy.

To manage the grid properly, it is important to accurately predict energy demand. A Long Short-Term Memory (LSTM) model was used for predictions based on past consumption trends [9]. The LSTM would provide forecasts of energy demand from previous data, from which utilities would optimize electricity generation and distribution, prepare for peak demand, and improve the stability of the entire grid [10].

The decentralized infrastructure, in combination with advanced protocols, ensures the availability and accessibility of data when required [11]. Real-time data collection, analysis, and visualization enable electricity providers and consumers to monitor their usage patterns and notice any inconsistencies in energy consumption, enabling them to take constructive steps based on what they have learned [12]. This capability of the system enables better energy management, reduces the risk of theft, and improves the overall efficiency of the power grid.

In the block diagram, voltage and current sensors are connected to the power supply line, which continually measures the values of energy from Figure 2. The continuous analog measurements collected from the various measurements were converted to digital signals using an A/D converter and fed into a NodeMCU microcontroller.

NodeMCU takes on the central function of processing data before forwarding it to the cloud for detailed analysis. Meanwhile, the processed data are displayed on an LCD screen and an energy monitoring interface, both of which are made available to local and remote energy real-time users, enabling them to analyze consumption habits and identify any anomalies that are occurring.

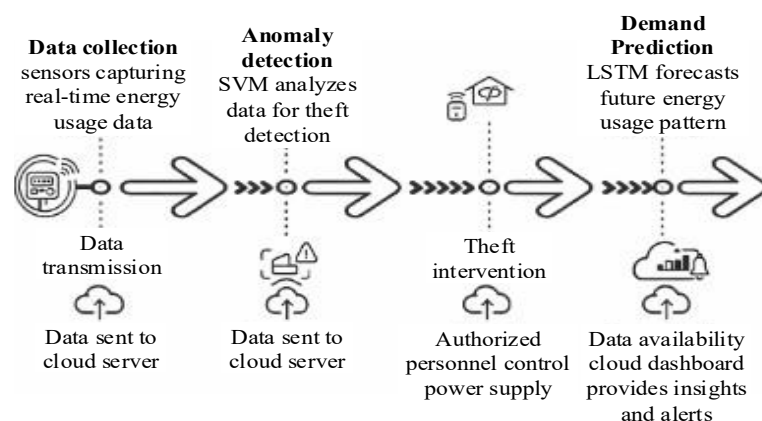


Figure 1. Flow diagram.

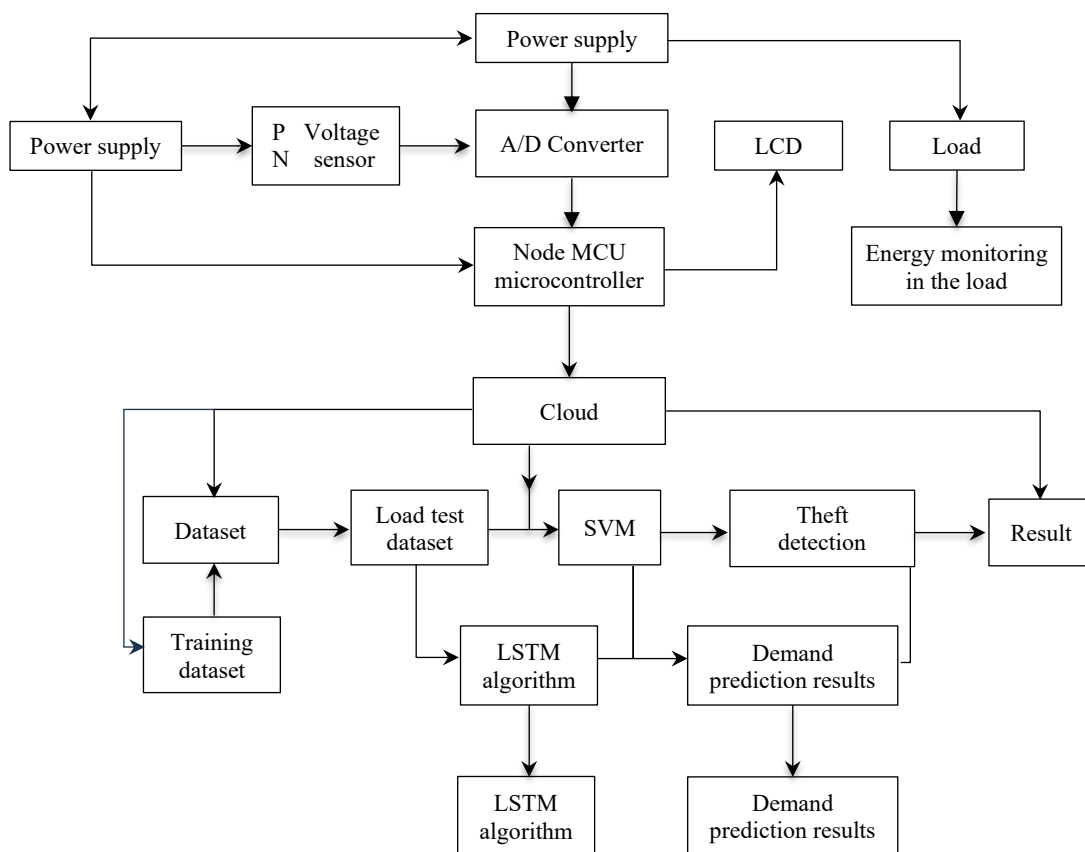


Figure 2. Block diagram.

The power of cloud functions lies in advanced analytics using two core machine learning models. To detect theft, the cloud is running a SVM algorithm.

The SVM is prepared using historical data, where it trains a special training dataset so as to be able to learn energy usage within an ordinary range. This is learned by the SVM, so that whenever real-time data are fed into it, it can classify the data, and other data that might leave it easily could mean that there is theft. Demand forecasting was performed separately using a LSTM algorithm. Trained on historical consumption data from many previous years, the LSTM model predicts future energy needs, which allows the energy provider to proactively manage energy and allocate resources. The results from theft detection using SVM and demand predictions using LSTM are displayed through an energy monitoring interface, putting those engaging with this product in a directly advantageous position in terms of efficiency and management.

RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed artificial intelligence-based energy management system, experimental studies were conducted, including real-time monitoring of energy consumption, detection of any theft occurrence, and demand forecasting, as shown in Figure 3. The system collects data from the applied voltage and current sensors with adequate power measurements at various monitoring points.

Proteus simulation creates a virtual platform to verify and validate the initial functions of the energy management system prior to implementing it in physical hardware. The simulation used an Arduino Uno to simplify the prototyping stage; however, at the final project implementation stage, the NodeMCU microcontroller was used owing to its integrated Wi-Fi capabilities, which are essential for cloud connection.



The schematic identifies some of the key circuit components, including voltage and current sensors connected to a power supply line, an LCD for local data display, and a relay controlled by microcontrollers for remote switching, as shown in Figure 4. The simulation was continually monitored for voltage and current, which mimicked the data acquisition process normally carried out by an external sensor on the physical system. When the simulation is run, developers ensure the logic behind the control algorithms, debug issues, and tweak parameters before passing the code onto the NodeMCU and placing it into a real working setup.

The virtual terminal shows an output of the serial monitor from the Arduino and knowledge of system states that could present debugging information, as shown in Figure 5. This simulated setup is crucial in the development process for easy testing and validation without constant hardware manipulation.

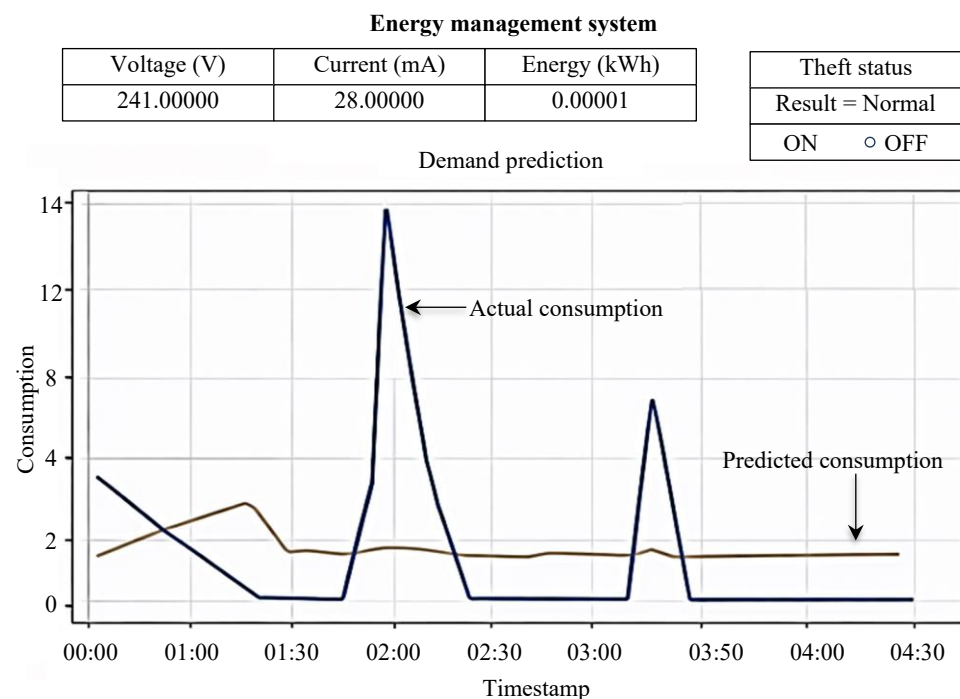


Figure 4. Webpage for monitoring, which shows theft status is normal.

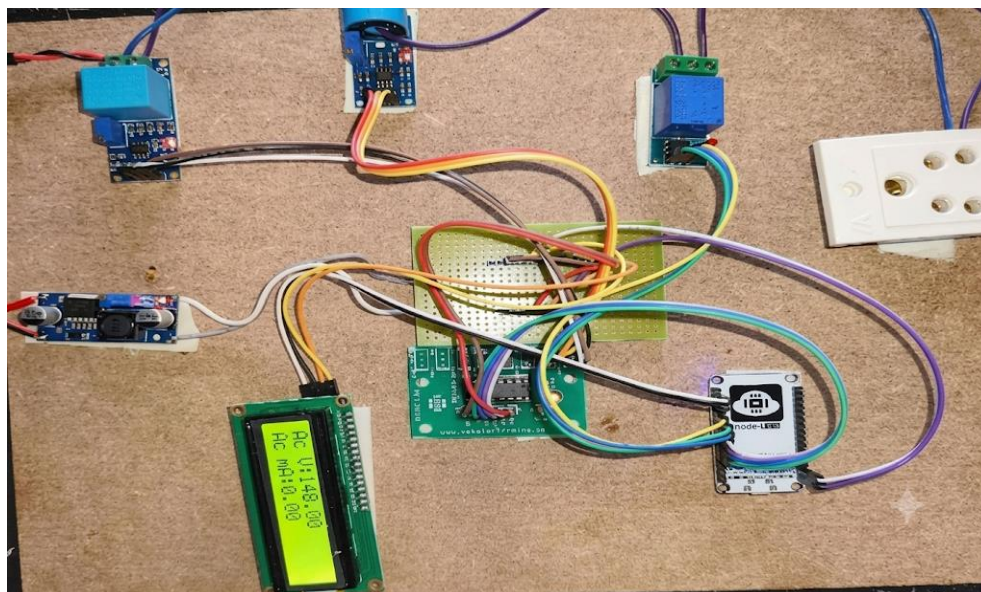


Figure 5. Hardware kit.

Anomaly detection using the SVM algorithm worked well to detect anomalies in energy consumption and classify them as normal or theft, drastically reducing energy losses. Demand forecasting was performed using the LSTM algorithm, which demonstrated good prediction abilities, accurately predicting future energy demand, and providing valuable insights into consumption trends.

This allows for better anticipation of peak demand seasons, resource allocation, and grid management. The remote control enabled by NodeMCU worked well, allowing an instant response to permit authorized personnel to switch the power supply ON/OFF remotely in case of any theft alert. The cloud infrastructure allows secure data management while being available in real time; thus, system operators can oversee energy consumption and theft alerts whenever they want. In conclusion, the system performed well in monitoring energy consumption and theft detection, which foretold the future energy demand, thus possibly enhancing energy efficiency, reducing operational costs, and providing sensible input for better decision-making.

The advanced AI-based energy monitoring system provides real-time tracking of energy consumption, voltage, and current while ensuring security through theft detection mechanisms. The system integrates demand prediction using AI models to compare actual and predicted consumption and optimize energy usage. The theft detection module analyzes anomalies in consumption patterns, identifies suspicious activities, and alerts users instantly, as shown in Figure 6. This intelligent energy management dashboard enhances efficiency, prevents unauthorized usage, and ensures a secure and sustainable power distribution system.

CONCLUSION

In conclusion, AI-based energy monitoring systems, demand estimation, and predictive analytics are based on verified theft detection. In this way, the energy consumption pattern is analyzed, improving forecast demand-related indices for loss due to theft. This establishes the optimization of energy supplies by lowering losses and allowing precise decision-making by consumers and utilities.

Timely application of data through predictive analytics assures the power distribution of effective and fast services and no loss of opportunity, and the involvement of theft lessens unauthorized access to consumption, which inspires grid security and sustainability.

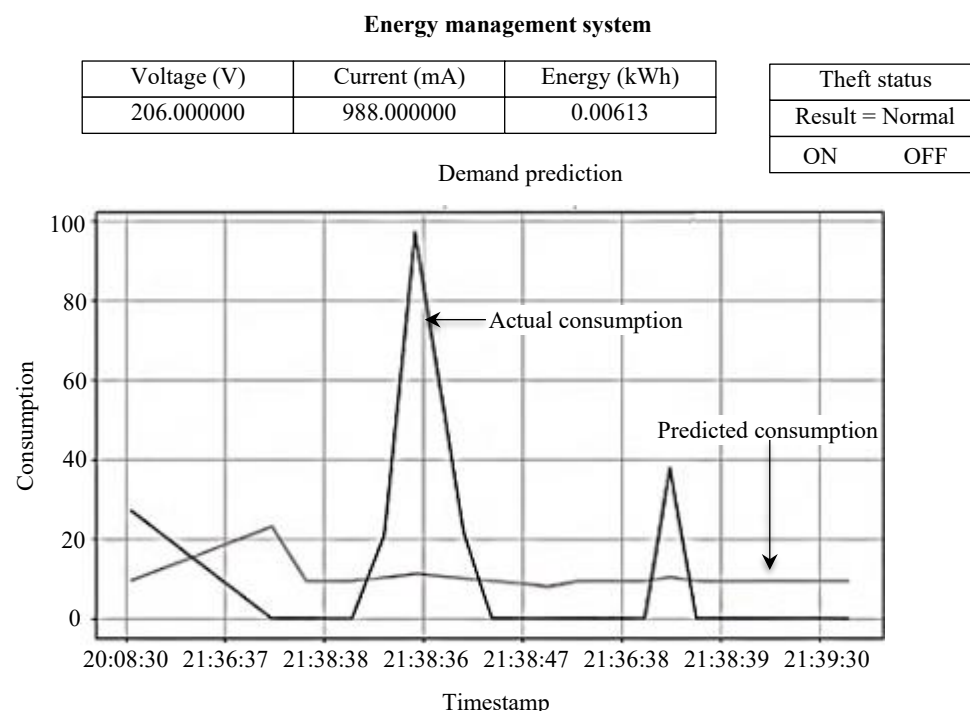


Figure 6. A webpage for monitoring that shows theft status is theft.

Other advancements include Internet of Things (IoT) smart metering, blockchain for secure transactions, and AI-controlled grid automation for improved energy distribution. This project is the first positive development toward establishing an intelligent, theft-free, and sustainable energy management platform.

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