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HEMS using Machine Learning and IoT in Energy Management

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Abstract

The smart grid is a significant component of our modern networks and society. Smart metres are essential. A smart metre offers user engagement, automated information gathering, energy control, and instantaneous monitoring of dependable status. Additionally, it offers two ways for information to move between suppliers and customers, improving efficiency and control. In addition, it offers power management and real-time usage information. As long as the customer's maximum load demand exceeds the maximum Value, the electricity supply to customers will be separated with the help of implementation of IOT based system for HEMS. In an ideal environment with normal workload conditions, the smart meter has a service life of 5 to 6 years. In this paper the use of the smart meter with IOT Technology is introduced. Many methods are recommended, such as the Energy Monitoring and Prediction System, which is an effective way to keep an eye on the gadgets that are used in homes or businesses. In this research, we have focused on estimating the electric energy consumption of household appliances in a low-energy consumption flat using a machine learning technique. In order to enable demand-side management and allow any legitimate consumer to view their individual consumption rate remotely, this paper focused on a smart system that wirelessly profiles energy consumption by calculating the facility consumed by each individual consumer. The calculated rate is then transmitted to a cloud web server.

Keywords: *Energy Meter, Intelligent Prediction Model, Internet of Things. Energy Management.*

1. Introduction

Accurate prediction within the domain of Home Energy Management Systems (HEMS) is of paramount importance for the effective orchestration of Demand Response (DR) in smart homes, with the objective of improving residents' comfort levels while keeping electricity expenses reasonable. This investigation undertook a comprehensive scrutiny of the application of Machine Learning (ML) forecasting algorithms in diverse aspects of HEMS. The examination demonstrates that reliable load prediction can effectively support the balance between energy supply and demand in HEMS. Furthermore, precise forecasting of residential energy usage significantly impacts the management of peak demand, ensuring a stable power requirement crucial for resource sustainability. Additionally, precise prediction of Photovoltaic (PV) energy plays a crucial role in guiding the control of the Smart Microgrid, mitigating uncertainties and fluctuations. In contrast, price forecasting acts as a tool for achieving cost savings in energy consumption. Moreover, an enhanced HEMS model, anchored on the most accurate ML prediction algorithms, has been presented. This model is devised to efficiently manage energy demand and provide suggestions to users based on anticipated data, thereby enriching residents' financial well-being and quality of life. Consequently, the model is scheduled for prototype development using advanced methodologies and a simulation of a multi-agent system. Its precision will be evaluated against similar models to determine its operational efficiency and cost-effectiveness in the near future [1-3].

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1.1. Objectives

Various instances of Home Area Network (HAN) implementations can be identified in the existing literature, with a predominant focus on energy management through task scheduling and demand side management techniques [4]. The attention given to the actual hardware implementation and associated costs, crucial for widespread adoption of Home Energy Management Systems (HEMS), is notably limited. Nonetheless, alternative architectures for home area networks have been put forth, emphasizing that the selection of an architecture model significantly influences the success of smart grid deployment. Two main architectural paradigms, centralized and distributed, play a pivotal role in smart grid deployment scenarios. In a centralized architecture, a smart meter governs device operations, whereas a distributed architecture delegates control to a home gateway. The distributed model is favored for its scalability, flexibility, and enhanced demand response capabilities, mirroring the architecture choice we advocate. Literature also delves into software development for HEMS, exemplified by the energy management system Green Home Service (GHS) employing a task scheduling strategy. Despite limited commercial endeavors in HEMS, a surge in research initiatives and projects has been observed. While some studies concentrate on system architectures, others center on strategies to curtail energy consumption and electricity expenses, often incorporating considerations for user comfort. Nevertheless, the definition of comfort tends to be narrow, lacking differentiation across various comfort levels. Recognizing distinct comfort levels is paramount, as consumers may accept lower comfort levels in specific circumstances. A tangible metric for comfort is essential for evaluating diverse decisions and comprehending their implications. Our proposition involves a policy-driven HEMS designed to minimize electricity costs while upholding comfort levels as stipulated in a comfort specification [5].

1.2. Existing System

A small one-bedroom flat shown in Figure 1 is selected for the proposed method. For efficient energy management, each Smart Home Energy Control System (SHECS) requires both a central controller and separate room controllers. The room controller uses instructions from the central controller to control the gadgets. The local storage is refilled with the help of On the other hand, in the event that there is a lack of local storage, the customer is assured an uninterrupted power supply. The SHECS central controller makes use of four different status parameters [6].

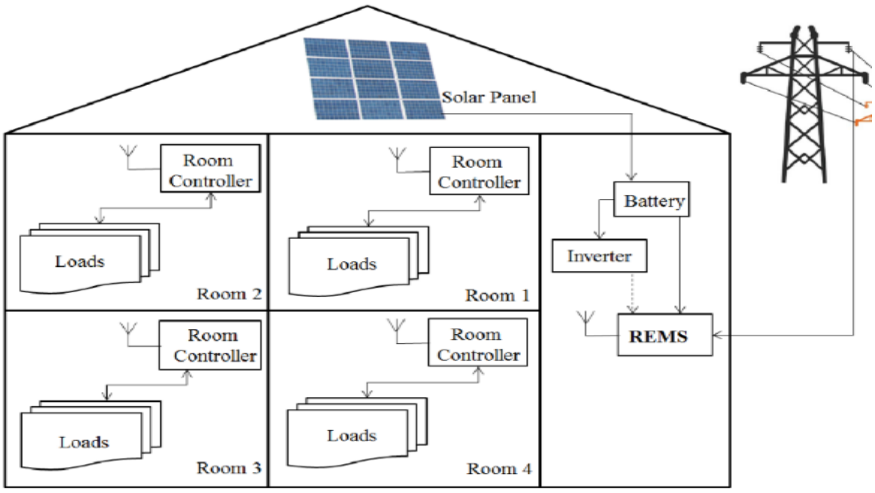

Figure 1 Block Diagram of Conventional Method

The grid availability parameter empowers the controller to monitor the Battery State of Charge (SOC) facilitating a potential switch between the loads. The Day/Night parameter allows proposing actions concerning the battery's charge-discharge operations [7-9]. The devices in the user's premises

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are sorted into four groups depending on their power usage, with insufficient charge in the local storage triggering battery safeguarding. Decision 4 is vital as both the fluctuate. Every trend, together with its corresponding decision, signifies the condition and the relevant step to be executed on the premises,

Table 1 Example Table

Decision	Description
1	Maintain the same state
2	Redirect to battery
3	Redirect to grid
4	Message to consumer

Table 1 An example table that shows the data trends and the decisions that led to Smart Energy Control. This is demonstrated when there is a discernible decrease in grid energy use as a result of the installation of many of these devices in residential areas.

Case a:
In the absence of the grid, light loads in the consumer premises are causing the battery to discharge. Since it's daylight, there's a greater chance that the battery will charge, therefore there's no need to act right now.

Case b:
The present active medium loads are supplied with electricity via both the grid and the battery energy storage system. When the battery's state of charge (SOC) falls between 75% and 99%, it is considered appropriate for powering the loads during the day. The best course of action is to direct the power supply through the battery, which will reduce the demand for electricity on the public grid.

Case c:
In this scenario, both the battery and the grid are contributing to powering heavy loads, with the battery SOC ranging from 75% to 90%. This leads to a rapid discharge exacerbated by the inability to recharge during the nighttime. Consequently, the preferred course of action is to reroute the power supply through the grid, ensuring uninterrupted power delivery to the consumer.

Case d:
During nighttime when both the grid and battery are not available, and a heavy load is active in the consumer's premises, the appropriate action is to alert the consumer through a transmitted message. Subsequently, once the data patterns and corresponding decisions are established, the Renewable Energy Management System (REMS) should be automated utilizing a suitable algorithm that emulates human reasoning and experiential capabilities.

1.3. Existing Result and Discussion

1.3.1. Artificial Neural Network Algorithm

The most popular choice for algorithms that mimic human speech is the Artificial Neural Network (ANN). REMS belong to the category of supervised learning algorithms as they already know the target vectors. Many classification applications have discovered that the back propagation approach is an appropriate supervised learning algorithm. To do 4-fold cross validation, a control table with 80 possibilities is created and divided into four groups. Four models are trained with various combinations of input patterns by merging these groups. Eighty percent of the whole data set is used for training, while the remaining twenty percent is used for testing.

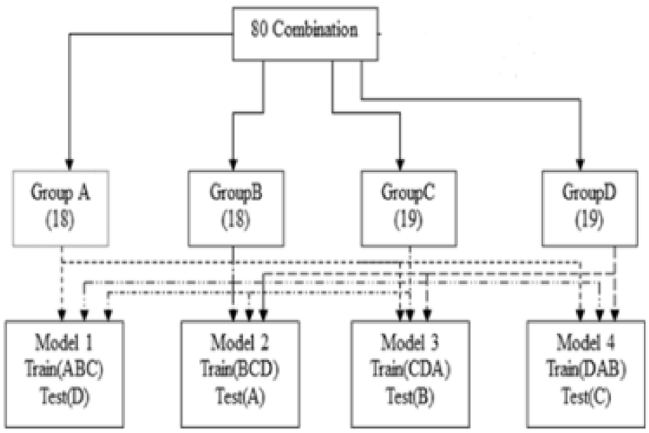

Figure 2 Formation of Groups of Training Data

With a convergence parameter of 0.25, the models are trained using the NN Toolbox, which is a feature of MATLAB. To achieve the highest level of accuracy, the number of neurons to be employed in the hidden layer is determined by a trial-and-error process. As shown in Figure 2, each model with a variable number of hidden layer neurons produces an array of accuracies. It is clear that the model that was trained using data from the CDA group and evaluated with data from group B produced an 83.3% classification accuracy, correctly identifying 16 of the total 18 patterns.

1.3.2. Support Vector Machine Algorithm

Since the primary goal of IEMS is to lessen the load on the grid based on the availability of local storage, accuracy in recommending actions to be taken based on the state of the home premises is important. SVM, an optimised method based on statistical learning theory, is used instead of increasing accuracy. Using LIBSVM integrated in MATLAB, models are generated with the four sets of data used for ANN training. Binary classification is carried out using SVMf for both linear and non-linear data. The non-linear data are categorised linearly using kernel functions. For the non-linear REMS, the Radial Basis Function (RBF) kernel is employed since it maps the input space to an infinite-dimensional feature space where the data are binaryly categorised. In SVM, there are two parameters, specifically: The trade-off between minimising training error and model complexity is defined by penalty parameter C, while the nonlinear mapping between the input space and feature space is defined by kernel parameter γ.

2. Method

2.1. Proposed System

This proposal proposes a home energy management system based on predictive analysis. The control and monitoring system is pic microcontroller based. Current and voltage sensors are used to calculate the energy consumption by load. The microprocessor computes and reads the various load voltages. The controller, which updates the webserver with the reading of the household energy use, is interfaced with the Internet of Things module. For the IOT module, we utilised esp8266 in this instance. With the help of this module, the user may attach the IoT server to our controller kit by providing a user name and password.Estimating the cost analysis of the electricity utilised is the second step. When load consumption above predetermined thresholds, the GSM transmits a notification to the user. Furthermore, the node mcu is utilised for controlling the specific load to be reduced. Our project's whole development is shown on an LCD panel. In all economic sectors, there is a pressing need to optimise energy use, particularly with regard to electric energy. Enforcing the usage of renewable energy is often the goal from the perspective of the electrical source. From an economic perspective, however, the goal is to lower the related expenditure because energy expenses account for a significant portion of the overall expenditures of industrial operations. In order to optimise expenses, this study proposes an IOT-based machine learning system that supports a new intelligent system for energy management within a certain time frame. Under certain situations, its operation is predicated on the analysis and decision-making of real-time data on energy generation and consumption.

2.2. Internet of Things

The confluence of many technologies, real-time analytics, machine learning, commodity sensors, and embedded systems has led to the evolution of the Internet of Things. The Internet of Things is made possible by the traditional domains of embedded systems, wireless sensor networks, control systems, automation (including automation of homes and buildings), and others. IoT technology is most commonly associated with consumer goods that go under the umbrella of the "smart home," which includes cameras, lighting fixtures, thermostats, security systems, and other appliances that are part of a shared ecosystem.

2.3. Steps in IoT Web Page Creation

2.3.1. Collect Data in a New Channel

Creating a new channel to gather and analyse data is demonstrated in this example. You import data into your new channel by reading it from the public ThingSpeak channel 12397 - Weather Station. See Write Data to Channel and the API Reference to find out how to send data from devices to a channel (Figure 3).

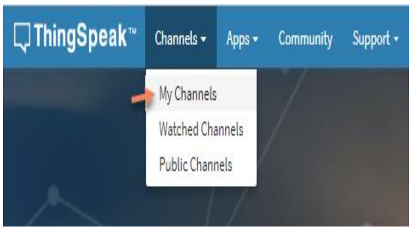

Figure 3 API Reference

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2.3.2. Create a Channel

- Sign In to ThingSpeak™ using your MathWorks® Account, or create a new MathWorks account (Figure 4).
- Click **Channels** > **MyChannels**.
- On the Channels page, click New Channel.
- Check the boxes next to Fields 1–3. Enter these channel setting values:

  Name: Dew Point Measurement
  Field 1: Temperature (F)
  Field 2: Humidity
- Click Save Channel at the bottom of the settings.
- You now see these tabs:

  Private View: This tab displays information about your channel that only you can see.
  Public View: If you choose to make your channel publicly available, use this tab to display selected fields and channel visualizations.
  Channel Settings: This tab shows all the channel options you set at creation. You can edit, clear, or delete the channel from this tab.

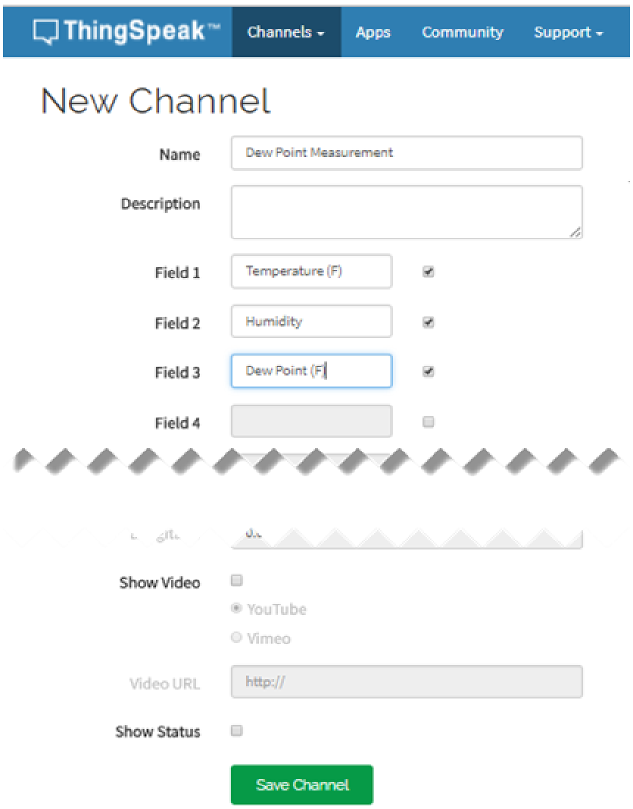

Figure 4 IoT Channel Creation

Sharing: This tab shows channel sharing options. You can set a channel as private, shared with everyone (public), or shared with specific users.
API Keys: This tab displays your channel API keys. Use the keys to read from and write to your channel.
Data Import/Export: This tab enables you to import and export channel data.

Next Steps

In the next example, Analyzer Data, you use the current and voltage data from the public Home Station channel to calculate the dew point data. Then you can write the current, voltage, and calculated dew point data to Fields 1, 2 and 3, respectively, of your Dew Point Measurement channel. For advanced energy management analysis with MATLAB® and Thing Speak.

3. Results and Discussion

3.1. Result

Predicting future energy consumption is the goal of energy forecasting, which leads to efficient energy management. The suggested system includes a forecasting model that makes use of a decision tree classifier to anticipate energy usage based on the consumer's limited historical data as well as other characteristics. Holidays (to differentiate between working days and holidays), historical energy usage, humidity, and the current day's temperature are the factors considered in forecasting. Users are able to plan resources more effectively by using forecasting to estimate their future use. Because they provide precise and trustworthy information, new technologies like the Internet of Things (IoT) have the potential to significantly transform the utilities industry and enable effective energy management.

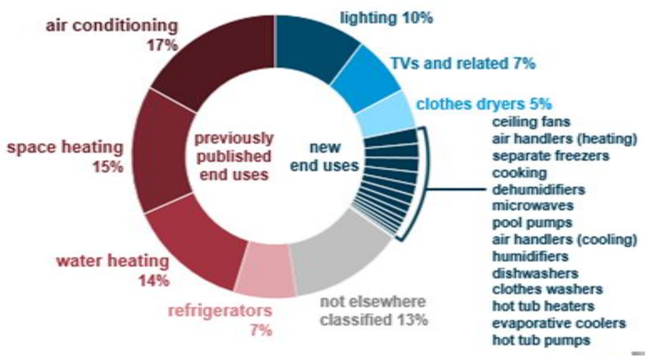

Figure 5 Residential Loads Consumption Percentage

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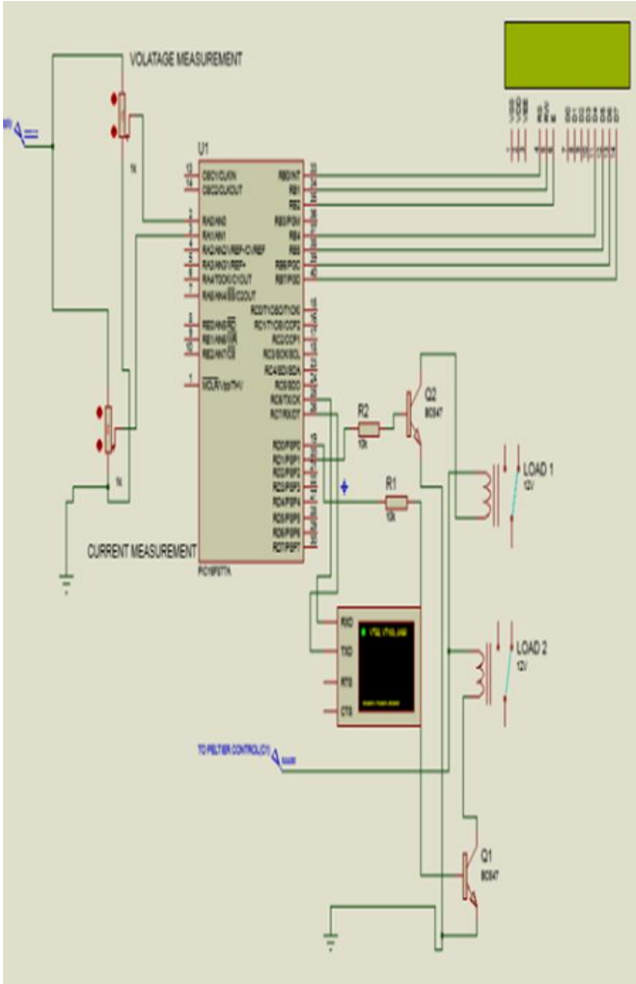

Figure 6 **Overall Simulation Output**

As per the simulation results the above figure 5 & 6 shows that the residential loads consumption percentage is analyzed.

3.2. Discussion

Machine learning approach is crucial for developing efficient home energy management systems (HEMS) to reduce energy consumption in residential buildings. Research has shown that machine learning methods, such as reinforcement learning and deep learning, play a significant role in predicting and managing energy consumption in smart homes [1] [2]. Non-intrusive load monitoring (NILM) techniques, combined with artificial neural networks (ANNs) and particle swarm optimization (PSO), have been proposed to accurately identify and manage energy consumption of individual appliances, enhancing the effectiveness of HEMS [3]. Additionally, the integration of NILM with graph reinforcement learning (GRL) enables intelligent decision-making in HEMS by efficiently identifying user behavior and optimizing energy management strategies based on real-time data [4]. Implementing these machine learning-based approaches in home automation systems utilizing the Internet of Things (IoT) allows for remote monitoring and control of household appliances, contributing to sustainable energy practices in residential buildings [5].

Conclusion

The conclusion of the study emphasizes the importance of precise forecasting in Home Energy Management Systems (HEMS) to effectively handle Demand Response (DR) in smart homes, ensuring residents' comfort while keeping electricity costs manageable. The research conducted a comprehensive analysis of Machine Learning (ML) prediction algorithms applied in various areas within the HEMS domain. Findings indicate that dependable load prediction plays a crucial role in balancing energy demand and supply in HEMS. Moreover, accurate forecasting of household energy consumption significantly influences peak demand scheduling, crucial for maintaining stable power demand and resource sustainability. Additionally, precise prediction of Photovoltaic (PV) energy impacts the overall control of Smart Microgrids (MG) by addressing uncertainties and fluctuations. Price prediction, on the other hand, contributes to energy cost reduction. The study also introduced an optimized HEMS model based on the most precise ML prediction algorithms, aimed at effectively managing energy demand and providing personalized recommendations to users based on predicted data, ultimately enhancing residents' economic well-being and lifestyle. Future plans involve prototyping the model using advanced techniques and a multi-agent system simulation, with a comparative analysis against similar models to assess its functionality and cost-effectiveness.

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