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Home Energy Management System

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Abstract: The paper introduces a broad and general optimization framework on Home Energy Management System (HEMS). The twenty-first century is now an age in which everything operates primarily on electricity. In recent pandemic circumstances, the regular routine saw the higher electricity consumption. A predictive model sets out the steps to keep track of whether excess electricity is being used. The Home Energy Management System is used to estimate the power consumption of the home at the device level. Within the web application, users can find predicted data. For this a unique key generated for login credentials which gives login access requests. In different stages of preprocessing data, all backend processing will be performed by splitting into training with existing dataset. Further the testing with real-time data is integrated with an algorithm (RNN-LSTM) which would provide estimated results that suit for better understanding in the analysis of graphs and table values.

With a smaller degree of granularity for the household level, all the predicted values will be more effective, because more integrated data would be handled and the predicted values would be much better. The LSTM algorithm has been used for data size processing since initially data will be weekly and monthly recorded smaller in size but gradually increased as it reaches yearly and leads to computes large amounts of data simultaneously.

Keywords: RNN-LSTM, HEMS

I. INTRODUCTION

With population growth and better standards of human life, houses would be becoming one of dominant sectors of energy use. Electricity is one of the primary forms of energy which houses absorb. A substantial proportion of primary energy globally accounts for this energy consumption. In most developing nations, households account for up to 40 per cent of the final consumption of electricity. The refrigerators, ovens and air-conditioning systems in a household often take up more than 50% of home energy resources. These systems, though, are typically found in practice at large, leading to higher costs and more energy use.

There is an overwhelming need for electricity anytime a power outage arises. In power plants, there is greed when the electricity supply cannot be reached. Accidents involving power failure often result in massive economic losses to the social system. Thus, forecasting energy consumption is quite significant. Though numerous studies on the prediction of household electricity usage have been implemented, there is a lack of spatial analysis in predictive analysis, especially at the level of single appliances. Precise prediction of household energy consumption has therefore become a central factor and a reliable statistical model for optimization needs to be developed to reduce energy costs and improve the environment. Using deep learning algorithms, the project is planned for implementation. Deep learning algorithms help us process huge amounts of data and give us the highest yield, i.e., maximum precision in our case, without overlooking critical observations or incorrectly tuning the model. The model also determines whether, from its own neural network architecture, our forecast is better or worse. We have therefore made an assumption that if prediction is first analyzed from prediction data at the individual appliance level, the performance of household consumption prediction would be increased and improved. Using the HEMS, the forecast of an appliance's electricity consumption could significantly boost the efficiency of household energy consumption.

II. REVIEW OF LITERATURE

The authors from some of the reviewed papers stated how to implement individual statistical models for each household. As temperatures and weather can have a big impact on how much energy you use they checked at a few of the applications that had been developed, such as temperature and moisture detection and a smart doorbell. Under various conditions, the model controller plots graphs of the power used in various devices, which could help in lowering the electricity payment and peak demand. Overall power predictions were seen, as well as individual appliance level consumption predictions for a particular region was studied. At the granularity level, the researchers did not address the device that leads to high power consumption in a home. Meter Data Management software was provided access to information about power usage. They suggest using a Smart Meter at the household level to build a Smart Grid. The authors were unable to determine which household in a block consumes the most electricity. Few papers referred using the CNN-LSTM approach to equate the efficiency of Machine Learning with Linear Regression. The goal was to create a power consumption scheduling process that would reduce electricity bills and improve the peak-to-average ratio while also considering the comfort of the residents.

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III. METHODOLOGY

Check if the Arduino configuration is finished. We could use and attach to the Arduino board using CT sensors. Since data collection is supplied by the sensor. Data is collected periodically with a timestamp and stored in the Arduino memory until the upload command is scheduled. When the upload command is activated, all the Arduino memory data will be stored in the HEMS in a text file format.

The user must login to the website and register to generate a unique key-id for login credentials via the web page once setup is finished. Then the user enters details including login-id and password. To see previous reports generated (maximum last three reports), users can then access the web platform if any and even request for estimation of future reports that could be generated. If a user requests for prediction of data then the RNN-LSTM algorithm is applied.

We follow certain steps to construct a prediction model. We would import the required libraries first. The version of the cleaned-up dataset is stored as a new file. We would initially map all characteristics in separate timestamps. For each year, we will review or explore Active power consumption and plot graphs based on the distribution of power consumption. The next step would be to prepare a dataset for testing and build an LSTM model. Subsequently, the research dataset and LSTM model test are required to be prepared. Since this is a regression problem, evaluating the model using the mean square error criterion.

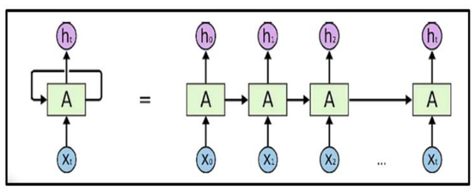
In all cases of weekly and monthly unit resolutions (kilowatts) with 4 parameters involved within the dataset, the model could then forecast electric energy consumption. The outcomes are displayed in graphical form across the platform.

IV. SYSTEM ALGORITHMS

A. Recurrent Neural Network (RNN)

Recurrent neural networks are the most advanced algorithm for sequential data (RNN). It's the first algorithm to have an internal memory that understands its input, making it ideal for machine learning problems with sequential data. When past results have an effect on the current outcome, the RNN network is used to identify trends. The time-series functions, for example, are an RNN application in which the data order is critical. The neuron in this network architecture receives not only its normal input (the previous layer output), but also its previous state as input.

Fig 3.2.1 RNN

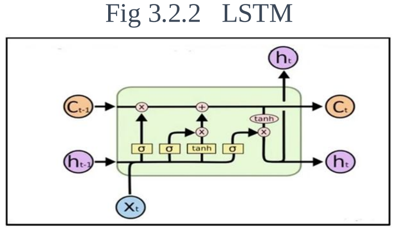


In the diagram, the neuron state is denoted by the symbol H. As a result, when in state H_1, the neuron uses the parameters X_1 and H_0 as input (its previous state). The biggest drawback in this model is that it suffers from memory loss. The older states of the network are easily forgotten. RNNs struggle to recall in sequences where we need to remember beyond the immediate past.

B. Long-Short Term Memory (LSTM)

Long-Short Term Memory unit (LSTM) is a form of recurrent neural network that was designed to overcome the limitations of a recurrent neural network (RNN). Long time series data sets can be a time-consuming operation, which can slow down RNN architecture training time. We could reduce the data volume, but this would result in information loss. In any time-series data collection, it is important to consider previous patterns and the seasonality of data in order to make accurate predictions.

Fig 3.2.2 LSTM



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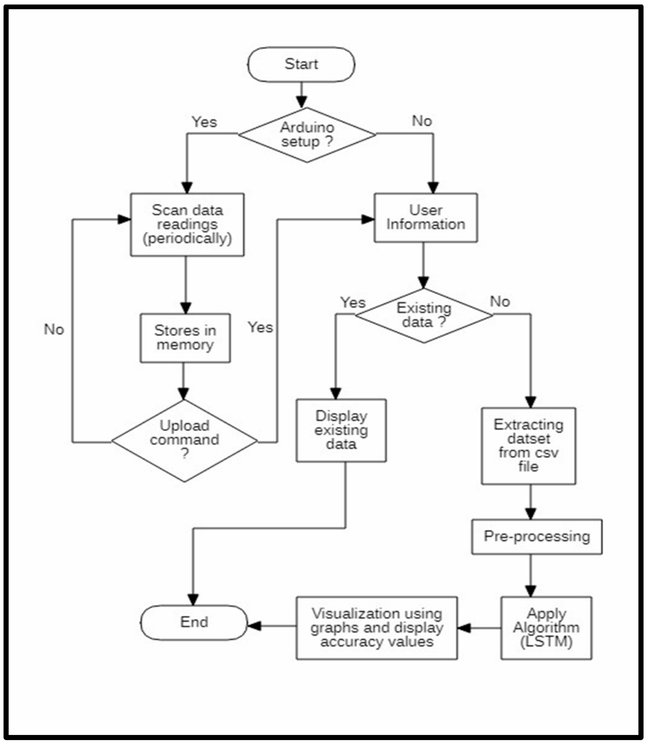
On the left-hand side of the diagram, Ct-1 represents the previous cell state, ht-1 represents the previous cell's output, and Xt represents the current cell's input. The cell's outputs are Ct and ht, which correspond to the current cell's cell state and output. The forget gate layer (f) of an LSTM is where we decide what we're going to forget from the previous cell state. This usually takes the inputs ht-1 and Xt and performs a linear transformation with weights and bias terms before passing it to the sigmoid function. As sigmoid function's value is always between 0 and 1, so its output is always between 0 and 1. Here, 0 will represent forgetting it and 1 will represent keeping it.

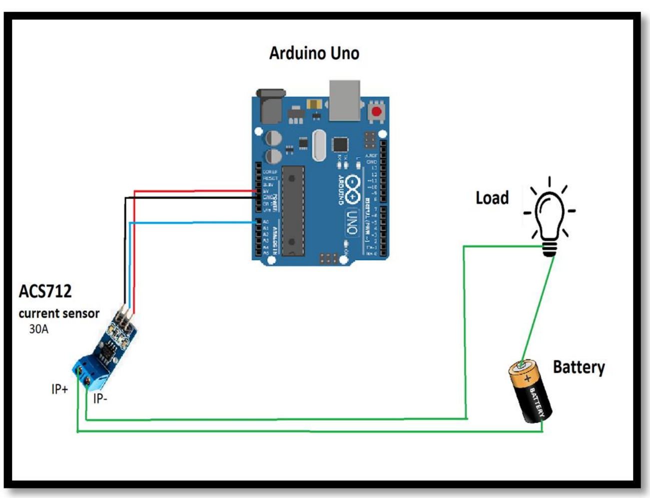
V. PROJECT DESIGN

Fig 3.3.:Flowchart



VI. CIRCUIT DESIGN

Fig 3.4 Circuit Diagram



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A. Hardware Requirements

1) *ACS712 Current Sensor:* Allegro MicroSystems' ACS712 Current Sensor is used to precisely calculate both AC and DC currents. Since the sensor relies on the Hall Effect, the IC requires a Hall Effect device. The ACS712 Sensor available in three different versions, each with a varying sensing range. +/-5A, +/-20A, and +/-30A are the optimal levels. The model has an internal ACS712 8 pin IC, as shown in the diagram Figure 3.4.1.

Fig 3.4.1 ACS712 IC pin diagram

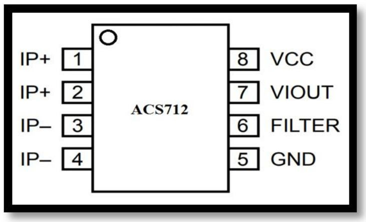
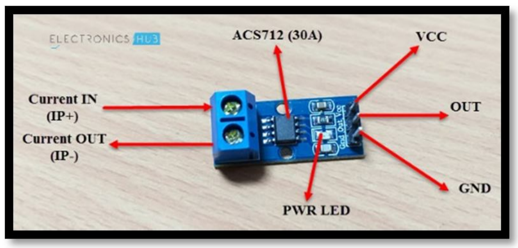
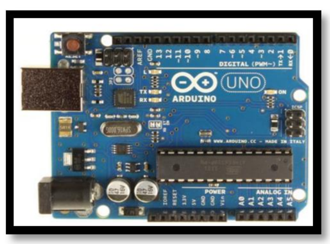


Fig 3.4.2 ACS712 current sensor



2) *Arduino UNO:* The Arduino Uno is a microcontroller board which is open-source. Arduino boards can read inputs such as light from a sensor, a finger on a bell, or the turning on of an LED. The board comes with a number of optical and analogue input/output (I/O) pins that would be used to connect to other expansion boards and circuits. A USB cable or an AC-to-DC adapter may be used to link them to a device.

Fig 3.4.3 Arduino UNO



The board's chip attaches directly to the USB port and function as a simulated serial port on the device. The advantage of this configuration is that serial connectivity is a basic and time-tested protocol, and USB allows for fast and comfortable connecting with modern computers. It's an open software design, and one of the benefits of being open source is that it attracts a large group of people.

VII. CONCLUSION

There's massive population growth and development in the level of human residency, so households turn out to be one of the dominant sectors of energy consumption. Electricity has been one of the major sources of power that houses use. In most developed countries, households account as the very last use of energy. However, the fact that the appliances which are usually found oversized in practice, could lead to higher cost and more energy consumption.

The demand for power is enormous when a power failure occurs. In power plants, there is greed because the production of energy could not be fulfilled. Though a number of studies have been conducted to forecast household electricity use, there is a lack of spatial analysis in performance forecasting, especially at the level of individual devices. Therefore, we concluded that if the prediction is first aggregated from the prediction data at the level of each device, the performance of the household consumption forecast would be enhanced and increased, resulting in high granularity of the data for accurate outcome and better performance.

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In our project refrigerators, ovens and air-conditioning systems in a home are considered for energy consumption among home energy devices. The HEMS has two objectives, the first being to design a framework for energy consumption prediction. For users, it will be useful to understand the optimal use of power and thus reduce the power havoc frequently seen these days. We aim to help the customer obtain a better experience of predicting and working using the Home Energy Management System according to the action plan during crises such as over power consumption or power outage. The second vision is to use a user interface tool to function on real-time data. As it is accessed by login credentials, the system's user interface needs to be efficient and user friendly. Web-platform visualization tools could be provided to make it more convenient for users to efficiently understand the information that requires to be predicted using backend code outputs. Users will be able to estimate energy consumption at the granularity level, i.e. appliance, using HEMS,thus it will be cost-effective and help minimize the waste of electricity. In the HEMS, with all the data that would be given to consumers of this device, the estimation of the electricity usage of an appliance could significantly improve the performance of household energy consumption. This proposed system will therefore assist in the efficient use of the system for a better and brighter future.

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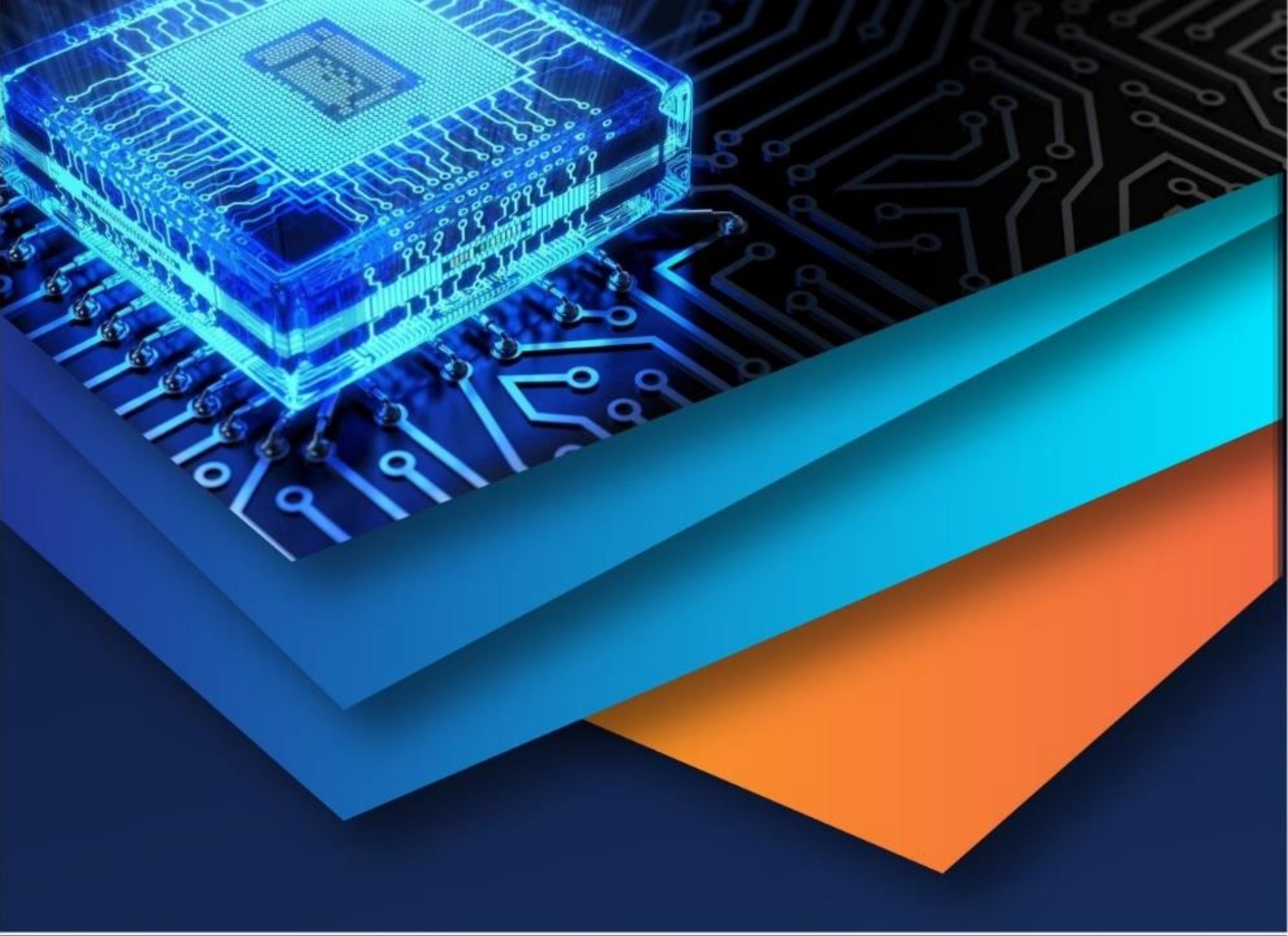

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