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"An overview focusing on the assurance of load monitoring and analysis for home energy systems"

[1]Ashok Kumar Sahani, [2]Ajoy Kumar Pradhan, [2]Smruti Ranjan Nayak,
[1]Assistant Professor, [2]Professor Department of Electrical Engineering, GITAM, BBSR

Abstract
Energy monitoring is a crucial aspect of energy management, serving as a prerequisite for implementing strategies to reduce energy consumption effectively. This paper presents recent advancements in appliance energy management through Load Monitoring (LM). Various methods of Home Energy Management (HEM) employing LM have been examined and categorized to explore the latest trends in energy management research. The contributions of researchers in the field have been highlighted, along with methods for reducing building power consumption to achieve cost savings and environmental benefits. The study identifies several challenges in load management and monitoring that warrant attention, including the need for surveillance systems capable of recognizing a wide range of loads accurately. Additionally, efforts to integrate LM into appliance energy management need to be intensified. Finally, fostering a culture of energy management among electricity users in businesses, offices, and homes is deemed essential. This study aims to provide local researchers with a comprehensive understanding of the latest trends in the field.

INTRODUCTION

In India, commercial buildings account for roughly 26% of energy consumption, experiencing an annual rise in energy usage of around 2.7%, according to data from the US Energy Information Administration. Inadequate energy monitoring systems are a significant contributor to the inefficient utilization of energy in these buildings. This paper examines a suggested approach to address this issue through building energy monitoring and conducts a thorough analysis of the collected data.

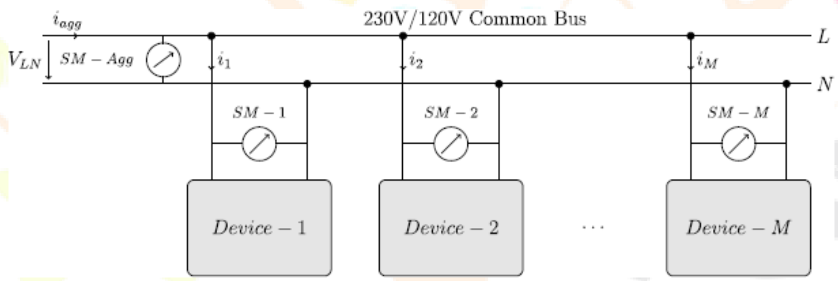
Multi-Functional Meters are employed to gather energy monitoring data, measuring diverse electrical parameters like voltage, current, and power. The study explores the various communication systems integrated with these meters to ensure efficient data collection. Initially, upon data collection, an alert message is promptly dispatched to designated personnel to avert power cable overload risks. Following this, the collected data undergoes a comprehensive analysis, emphasizing parameters such as load factor, imbalance factor, rising time, and instances of high load, extracted from the load curve. These parameters are instrumental in optimizing energy usage for commercial building managers or operators.

Moreover, to bolster meter control capabilities, there is a proposal to integrate the multifunctional meter with Arduino technology.

The price of electrical energy has gone up as a result of the decreasing supply of fossil fuels and the rising demand for electrical energy. so that the community must cultivate a culture of conserving electrical energy as a habit. On the other hand, without a controllable auxiliary system that can control how much energy is used, energy-saving behavior cannot be implemented on a large scale. Given these concerns, a strategy that encourages a culture of energy conservation must be developed. An energy-efficient culture-supporting system is proposed in this paper to facilitate active energy efficiency methods. This system combines a smart electrical panel with an electric power monitoring system. It can automatically regulate electrical loads, track power use, produce detailed data, and conduct energy analysis. It also monitors the use of electrical energy continuously. This research was carried out using the research and development approach. By using a raspberry PI 3 and a smart panel and a PZEM-004t power energy meter have been used in this research to create an electrical power control and monitoring system prototype. Electrical loads are automatically controlled by the monitoring system. Additionally, the system can provide daily, weekly, monthly, or annual data monitoring reports. The results of the tests indicate that the system can function effectively. It is anticipated that this research will aid in the development of a system that can assist the government in its efforts to conserve energy. Every day, energy consumption escalates in tandem with urbanization, especially in industries, hospitals, commercial buildings, and other settings, resulting in a disparity between supply and demand. The Indian government faces significant challenges in energy conservation and CO_2 reduction. A pivotal step toward addressing these challenges is the adoption of information and communication technology (ICT). Monitoring the energy consumption of buildings through ICT technology is imperative, given that commercial structures are major contributors to CO_2 emissions [1].

A cost-effective solution for tracking and analyzing energy consumption in commercial buildings is proposed in [2]. An advantage of this solution is that load current monitoring can be implemented without disrupting existing infrastructure—no cutting of lines, cables, or power shutdown is necessary. Furthermore, the benefits of energy tracking in commercial buildings are elucidated by demonstrating calculations for parameters such as load factor, current unbalance factor, rise time, fall time, and duration of high load.

To assess voltage imbalances in industrial buildings, the voltage unbalance factor is defined in [3], along with an explanation of the effects of imbalances on equipment voltage regulation and relay malfunction. [4] investigates the functional characteristics of top-down and bottom-up approaches to residential load curve analysis, concluding that the bottom-up strategy is the most effective. Figure 1 illustrates how load curve data can be utilized to identify peaks and troughs according to the authors' rationale [5].



. Fig. Load monitoring N devices

I.

DATASETS AND DATA ACQUISITION

To objectively assess the disaggregation architectures presented in the literature and to compare LM solutions, publicly available benchmark datasets that are measured using smart metres similar to actual circumstances have been established.

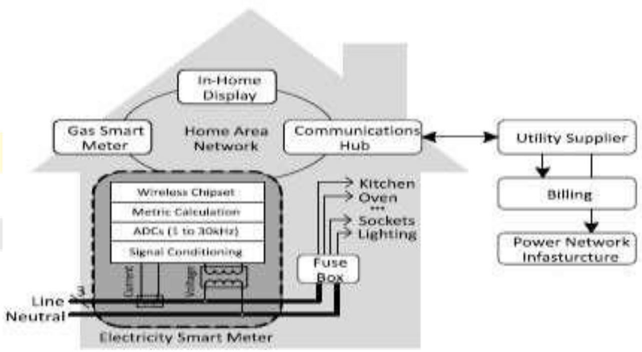


Fig .2. smart energy monitor for load scheduling

A. A Smart Meter

Household energy consumption disaggregation involves the acquisition of data at high sample rates in the range of seconds [7] in order to train and assess the disaggregation architectures depicted in fig. 2. These sorts of data are often collected by so-called smart metres. Using a communication link, a smart metre may monitor the energy usage of a building or a residence and transmit the data it collects to the customer's utility provider or other energy monitoring and management services. Simple smart metres can sample energy use once every minute, whereas more complex ones can sample up to 30 kHz [8]. Higher sample rates are typically preferable since they offer more thorough data on energy use. But these frequencies can have a side effect.

2.

Fig. 2 shows the location of the home's installation and the resulting aggregated power measurement as an example of a smart metering setup. Analogue electronics, analogue signal conditioning, and high-speed In order to compute the different properties, analogue to digital converters (ADCs) are required to measure the voltage of the mains supply and the current being pulled from it [10]. A transformer can be used to just change the mains voltage into a low voltage for the purpose of measuring voltage. Non-isolating direct voltage division is a further choice [6], [11]. To isolate current to low signal voltage conversion for current measurement, utilise a current transformer, Hall effect sensor, or Rogowski coil [6, 12]. Following ADC, the data are processed to produce assessment metrics, such as maximum energy, minimal energy, and so forth. subsequently provide them to a service provider, such as an energy company. The transmission mechanism is determined by the nation where the installation is placed. For instance, mobile cellular networks are frequently used in the UK for transmission, however ZigBee and wireless ad hoc networks are also used. Installation and use of smart metres in the United States are subject to user contracts residential settings [13]–[15]. The transmission, storage, and access to data are heavily regulated by law.

Publicly Available Datasets

The use of public datasets and the definition of standardized performance metrics are crucial in order to guarantee uniform comparison, standardization, and comparability among various LM methods [16]. In addition, the combination of public datasets and performance metrics enables cross- comparison of proposed approaches to advance the LM task, such as filtering methods, selected features, and classifiers. The monitoring of energy consumption for the purpose of creating publicly available datasets was only initiated within the last ten years, despite the growing interest in NILM techniques over the past two decades [17]. Therefore, new NILM methods can be developed and evaluated using the majority of existing datasets, which provide a good representation of existing housing structures or, less frequently, non-residential buildings. However, there have been shifts in electrical household appliances, such as the increasing prevalence of devices that are either strongly non-linear or more continuous (such as controlled air conditioning and switched power supplies) [18]. As a result, the housing structures of the coming years may not be accurately represented by the datasets that are currently available [18], which offers the most popular datasets with aggregated signal measurements and the related ground truth to give the reader an overview of the available datasets that are suitable for LM, is an updated and enlarged version [19]. The detailed summary of the year and nation in which the database was created, the number of households and target devices, the duration of the monitoring, the measuring strategy, the attributes monitored, and the sampling resolution for the target devices and aggregated data. The dataprovides a list of 29 databases with energy and power recordings from eleven different countries, as well as information about sampling frequencies, the number and types of devices, and monitoring period durations. 18 of these 29 databases (REDD [20], BLUED [21], ECO [22], UKDALE [23], Data port [24], Smart [25], RAE [26], iAWE [27], IHEPCDC
[28], REFIT [29], AMPds [30], [31], COMBED [32], DRED [33], SustDataED [34], EEUD [35], SysD
[36], LIFTED [37], and BLOND [In addition, there is a collection of six additional databases (PLAID [38], WHITED [39-40]) that contain the signatures of transient appliances. These databases can only
be used for the design of edge detectors, the creation of transient appliance models, and the extraction of features. In particular, CREAM enables the extraction of internal operation states that may be utilised to improve complicated device modelling. In addition, five of the databases—REDD, UK- DALE, BLUED, BLOND, and Sust Data ED—offer high-frequency measurements of raw current and voltage for the combined data. The databases may now be divided into high- and low-frequency groups as a result. The BLOND database is the only one, according to the authors, that offers high frequency consumption metrics (above line frequency) for each device. This makes it appropriate for testing disaggregation algorithms with varied sampling frequencies since it offers high frequency ground truth data. All databases have active power, with the exception of the BLOND database, which records voltage and current at a high sampling frequency as their primary measured feature.

II. OBJECTIVE

An employee will receive an alert email to take necessary action if a phase becomes overloaded during a specific time period. Continuous energy consumption data are required to accomplish this. Through RS485 communication, this data is obtained from the Multi Functional Meters. There are six sections in this chapter. The Multi Functional Meter is described in the first section, along with its Slave ID settings and Baud rate settings. The second section explains how to retrieve data from the meter. The third section discusses the preprocessing of the meter-collected data and the creation of the data base for its storage. Fifthly, the procedure of sending an email notification to the employee is explained. Sixth, experiments are carried out with the data that has been collected.

B. **Multi Functional Meter**

A 3-phase, 4-wire Multi-Function NOVA L&T Meter is used to measure all electrical parameters, including voltage, current, active power, energy, frequency, and power factor. As seen in the illustration, this metre contains three buttons: the choose key, the scroll UP key, and the scroll DOWN key. 2.2.1 Details Regarding the Communication Interface To obtain the meter's measured readings, RS485 connection is supported by the Multi-Function Meter. The meter's pin diagram shows that RS485 communication takes place on pins 7 and 8. To communicate with the meter, the configuration details are

- The half-duplex RS485 standard is used.
- The Baud Rate can be changed from 19200 to 4800 to 2400 to 1200. But 9600 is the default.
- Parity (None, Odd, or Even) can be selected. But even is the default.
- The MODBUS Protocol is used for the RS485 interface in RTU mode. In this case, communicating with the meter entails sending the meter commands to read and write to a specific register. From 1 to 247, a user-defined meter address (Slave ID) can be used to address the meter.

C. COMMUNICATION PARAMETERS SETTING

It is necessary to configure the meter's communication parameters, such as Baud Rate, Slave ID, and Parity, in order to communicate with it. Change the meter to programming mode to set these parameters. By holding down the Multi Functional Meter's SELECT and scroll UP keys, you can accomplish this.

The steps that need to be taken to set the Baud Rate are

1. Press and hold the scroll UP key in the Programming Menu to access "Set Port," then press the SELECT key.
2. Selecting the Baud Rate (1200 to 19200): Press the SELECT key to set the desired baud rate using the UP key.

The steps to take to set the parity are as follows: Press and hold the scroll UP key in the Programming Menu to access "Set Port," then press the SELECT key.

2. Parity(Even/Odd/None): Press the SELECT key to set the desired parity, then use the UP key to select it.

The first step in setting the Slave ID is Press and hold the scroll UP button in the Programming Menu to access "Set SL Id," and then press the SELECT key.

2. Increase the SL Id value by pressing the UP key. To go to the next digit, press the UP and SELECT keys simultaneously.
3. To set the ID, press the select key. The range of the slave id is from 1 to 247.

Data Retrieval

The first difficult task is obtaining the building's energy consumption data once the meter's communication parameters are set. [6] Provides an explanation of the problem's solution. This meter serves as a slave, collecting data from it. Because the Raspberry Pi can be mounted anywhere rather than the computer, it is used as the Master. The meter is connected to the Raspberry Pi through an FTDI-based USB to RS485 converter cable. Devices having an RS485 interface may be quickly and easily connected to USB with this connection. For RS485 connection, 5 Pins 7 and 8 are utilised. The required hardware for gathering the meter's data is listed in [38]. The connection between the metre and the FTDI-based USB to RS485 converter is shown [8]. Once the connection is complete, attach the FTDI-based USB to RS485 converter to the Raspberry Pi.

RaspberryPi uses the meter's Slave ID and communication parameters like baud rate and parity to access the meter. The registers of the meter store information about energy consumption. Some functions can access the registers that hold the necessary data by providing the register addresses and function code as input parameters as an example. To read data from the metre, use the function "read registers (R1, R2, function code)". The start and end registers are R1 and R2, and the function code identifies whether they are read-only or writable. After the data is gathered from read registers, time and date are added to make it easier to separate it from the data that was previously gathered. Since the data monitoring is ongoing, the acquired data are kept on a computer. Cloud storage can be introduced later. SSH is used by the RaspberryPi to connect to the PC. As a result, the data is transferred to a computer as a text or csv file for storage.

Data Pre process

Line by line, the data is stored in. The data, along with the date and time it was collected, are on each line of the file. In reality, the integer format is used to store the data measured by the meter. Using the function code of 4, the read registers read a total of 16 instantaneous parameters from each line. Each parameter is made up of two words, each of which is 8 bits long. 32 registers must be accessed since the parameters are kept at odd locations. where 0 represents fifty percent. as an example. Function code 04 at address 01 can access the phase 1 voltage, and function code 04 at address 03 can access the phase 2 voltage. The preprocessing procedure is divided into three steps.

III. Conclusions

The energy monitoring and data analytics component of this paper is structured into three sections. The first section focuses on alerting employees to phase-specific cable overloads, supported by a case study of a commercial IITH building. Once all meters are connected, there will be no need to frequently power off the Raspberry Pi for experimentation. Furthermore, the advantages of energy monitoring in commercial buildings are discussed by explaining the calculations of parameters like load factor, imbalance factor, rising time, and duration of high load periods. Additionally, a demonstration illustrates how to connect the meter to an Arduino, which can be upgraded to provide complete control over the meter.

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