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GSM based load monitoring system with ADL classification and smart meter design

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ABSTRACT

This paper introduces a method for the classification of activities of daily living (ADL) by utilizing smart meter and smart switch data in a synergistic approach. Through the integration of these internet of things (IoT) devices, the paper aims to enhance the application of ADL classification. Guided by recent advancements in load monitoring and energy management systems, the methodology incorporates machine learning techniques to analyze data streams from both the smart meter and smart switch. Drawing inspiration from prepaid smart meter monitoring systems, IoT-based smart energy meters for optimizing energy usage, and energy metering chips with adaptable computing engines, our design incorporates diverse perspectives. Additionally, we consider the utilization of mobile communication for prepaid meters, remote detection of malfunctioning smart meters, and an empirical investigation into the acceptance of IoT-based smart meters. We substantiate our proposed approach through experimental results, showcasing its effectiveness in accurately classifying diverse ADL scenarios. This research contributes to the field of smart home technology by offering an advanced method for ADL classification. The integration of smart meter and smart switch data provides a comprehensive understanding of energy consumption patterns, opening avenues for improved energy management and informed decision-making within smart homes.

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1. INTRODUCTION

In today's rapidly evolving energy landscape, efficient energy management is paramount for ensuring sustainable and reliable power grids. Smart energy metering systems have emerged as a key technology to optimize energy utilization, enhance grid stability, and empower consumers with actionable insights, and with that, the activity of daily living (ADL) classification in real-time can be useful for both the consumer side as well as the transmitting and generating side [1]. In this paper, an approach to smart energy metering and real-time ADL classification is presented by integrating global system for mobile communications (GSM) command-based functionality into the metering systems, and with that, a multi-class classification model was trained in order to implement the pseudo-code [2]. The ADL classification is based on the multi-class multi-label problem. Hence, the chosen algorithm was a feed-forward neural network (FFNN) as shown, and the training-testing dataset was chosen to be the UK-DALE 2015 dataset as both and showed good accuracy in a very large set of data, such as the UK-DALE dataset [2]. For the ADL classification, [1], [2] were mostly referred to, especially for choosing the correct algorithm for the classification, and as per the dataset, the appliances that were not present in [1] were considered. For this paper, the FFNN was chosen as it showed the maximum optimal accuracy. Petralia [2] proposed, a method of detecting the appliances in a time series method is proposed, which resulted in a good improvement in accuracy. The method used to classify the appliances was time series classification but was compared with other classification algorithms like K-nearest neighbor (KNN), BOSS, Rocket, ResNet, CovNet, and Inception. Wu *et al.* [3] approached that by using a group of decision trees to classify the appliances, which led to an increase in the accuracy of the classifier model. The researcher [4]-[6] showed a wider view of using the FFNN, not only in ADL classification but also in implementing the FFNN in any other integration-based technology as well.

The researcher [7]-[9] showed the ways of monitoring the intrusive and non-intrusive loads using different methods such as using generative adversarial network (GAN) instead of relying for the same on microgrids. Palacios-Navarro *et al.* [10], Sridharan *et al.* [11] showed how ADL monitoring can be useful for healthcare and monitoring over-home patients. Gambi *et al.* [12] describes the ways to recognize appliances from an IoT-based air quality sensor dataset. Ding *et al.* [13], Alkawsi *et al.* [14] show the case study of load monitoring at Excavator and Malaysia, respectively. Zungeru *et al.* [15], Irianto [16] showed a way of building a metering device and testing it. This integration of smart meter and ADL classification enables remote control and monitoring of energy consumption as well as billing options like prepaid [17] and post-paid services, offering a versatile and efficient solution for energy management in modern power grids Wu *et al.* [18], Jain and Bagree [19] as well as enabling the appliance monitoring from the provided loads only [20].

The deployment of smart energy meters has witnessed significant advancements worldwide, driven by the need to address the complexities and challenges posed by evolving energy landscapes. By incorporating GSM technology, the proposed smart energy metering system leverages the power of wireless communication to facilitate seamless connectivity and real-time data exchange, using the infrastructure of mobile communication being used for communication [21]. Although, the main idea here was to integrate the smart energy metering system with the in-built smart switch system, and ADL classifier at the server side will make the system capable enough to predict the appliances as well. Through GSM command-based functionality, users can remotely access, monitor, and control energy consumption, empowering them to make informed decisions and actively participate in energy management [22].

The integration of GSM command-based smart meters holds particular relevance in the context of developing countries, where energy management challenges are often more pronounced [23]. In countries like India, with its vast geographical expanse and diverse energy consumption patterns, the ability to remotely monitor and control energy usage becomes crucial. The wide coverage and availability of GSM networks make this approach suitable for both urban and remote areas, ensuring inclusivity and scalability [24]. The future aspects of this field are still increasing, hence a lot of technologies like theft detection [25], [26], reliability on the device [27], and easy integration with the grid monitoring system can be done [28]-[30].

2. METHOD

The proposed system is a cost-efficient, easy-to-install, easy-replacing energy measuring unit, which is based on GSM and ATMega technologies. The features to be provided by such a system are expected to provide a platform for consumers to register for their electricity meter online through a website and get a 16-digit token for the meter [31], [32]. The token is to be linked with the registered phone number on the server side of the system. This will make the server capable enough to link the registered phone number and the smart meter. This will provide the consumer the capability to switch on and off the appliances as well as monitor the power consumption of the appliance and send the data to the server.

The smart switch/meter in Figure 1 shall be able to control the flow of power binarily, that is turning on when required and turning off when not required. Hence, a microcontroller was devised with a relay control. For the whole communication purpose, instead of relying on any other technology, GSM was used, as in spite of location, we already have a well enough infrastructure for mobile communication. The device is a smart meter that can act as a combined control unit for smart switches as well. The device will send the data in the form of an array of load data, a nested array for each switch, in the following format:

$$A = [[v1, v2, v3 \ldots], \ [v1, v2, v3 \ \ldots], \ldots] \tag{1}$$

$$a = [v1, v2, v3 \ldots] \tag{2}$$

In (1), a is the representation of the array, and the values inside the nested array (v) are the values of the appliance connected to the switch after 10 seconds. The more the number of loads connected to the switch, the more values will be in the nested array. The nested array is used so that the least number of SMS' will be sent, hence optimizing the expenses. An SMS can consist of a maximum of 160 characters. So, considering the power consumption will be in the form of <x.yz>kW, where x, y, z are real numbers and a comma (,), there are 5 characters, hence 160/5=80 records for 24 hours. Hence each record at an interval of 45 minutes. A list of that many records can be directly sent to one of the phone numbers registered for the server-side communication. The other array format in (2) will be used for storing of the appliance load data.

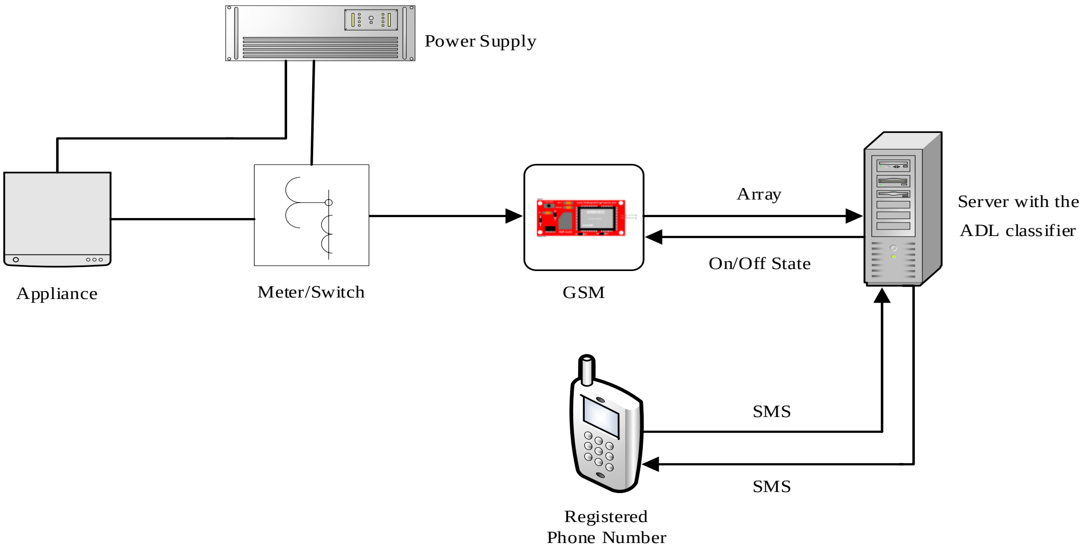


Figure 1. Flow chart of the working principle

The live server will accept the SMS which will then decode the array to create a CSV file for the consumer, which can be fetched via an SMS from the registered phone number. The ADL classifier model will be stored on the server side of the system, making the system capable enough to classify the loads into their respective appliances. The dataset will be managed on the server side only. There are two parts to the methodology, i) smart meter/switch control, and ii) ADL classifier.

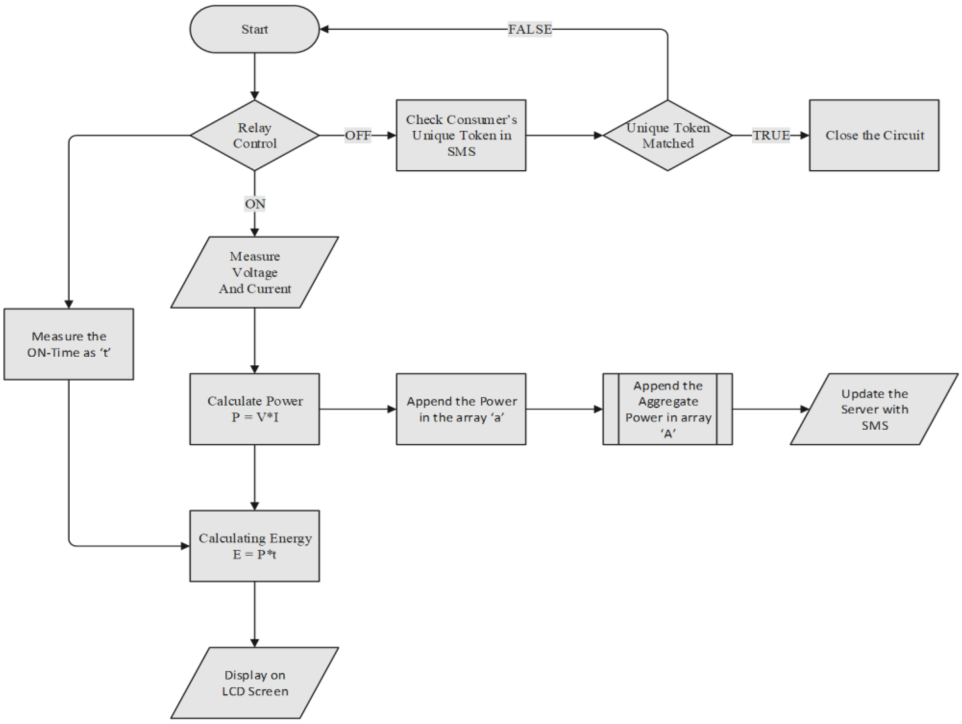
2.1. Metering device

The device has to be cheap and easily replaceable, hence ATmega328 was used as the microcontroller for the device. The voltage sensing was done by the step-down circuit and the current sensor as ACS712. The device circuits for the voltage measurement, current measurement, and display part are provided in Figure 2.

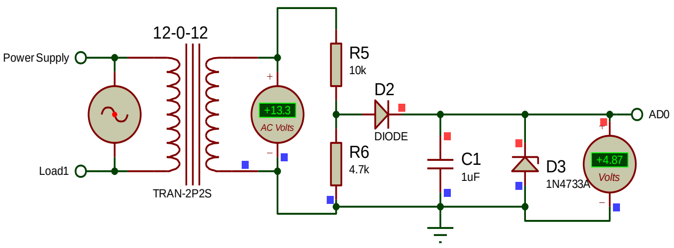
The flow chart for the metering device is provided in Figure 2(a), which also shows the calculation of power as well as energy for the SMS to be sent. The power was calculated by multiplying voltage and current. The time of activation of the meter was parallelly measured and multiplied with power to calculate energy. Figure 2(b) shows the circuit for the voltage measurement. The 12-0-12 transformer steps down the voltage and a voltage divider consisting of 10 k and 4.7 k ohm standards was placed in the circuit to convert the voltage to somewhat less than 5 V. For instance, if stepped down voltage is 13 V, then the voltage divider will convert it to 13*4.7/14.7 = 4.15 V. Further filtration will be done by the half-bridge rectifier and the capacitor. For 5 V protection, 1N5231 Zener diode has been used. The Arduino was used to take the analog measurements directly at pin number A0. In Figure 2(c), the current is being measured by the ACS712 sensor. A relay has been used to control the main supply to the load, provided the pin out is A1.

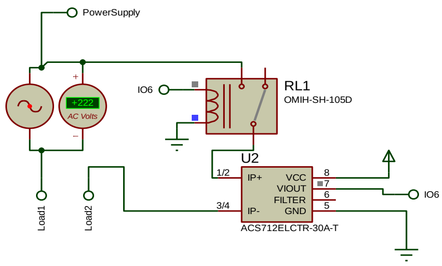
2.2. ADL classifier

Franco *et al.* [1] states better accuracy was shown by the FFNN, hence FFNN was chosen as the method for classifying the appliances. The whole FFNN was created in Python, using the platform of Google-Colab. The libraries used for the purpose include Tensorflow, Keras, Scikit-learn, Matplotlib, Seaborn, Numpy, and Pandas. Figure 3 presents a basic structure of the neural network used for the FFNN method. There are 2 hidden layers. The hidden layer 1 has 64 neurons and hidden layer 2 has 32 neurons. The chosen optimizer was Adam and the loss function was categorical cross-entropy.



(a)





(b) (c)

Figure 2. Overall workflow and schematic representation of the proposed device: (a) flow chart illustrating the device operation, (b) voltage measurement circuit, and (c) current measurement circuit

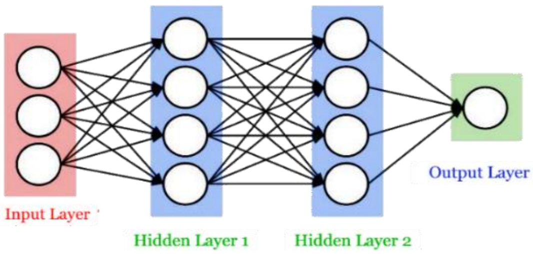


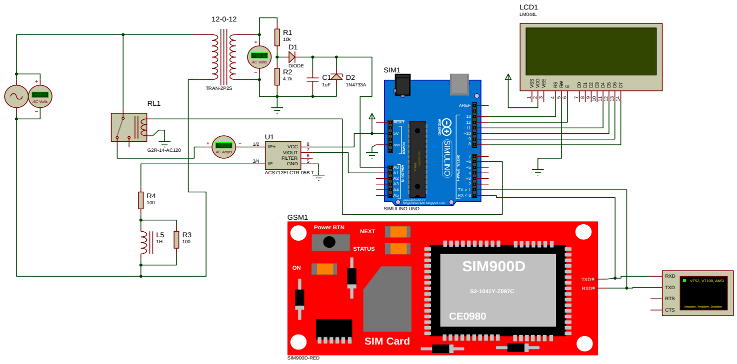
Figure 3. Structure of a general feed-forward neural network

3. PROTOTYPING AND TESTING

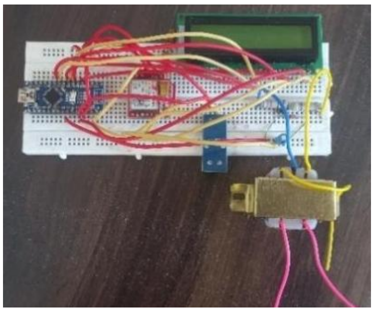
3.1. Hardware prototype using Arduino board

The proposed system from Figure 2 was tested for accuracy by building a prototype. The circuit of the device is shown in Figure 4. The circuit for the ATMega328 used, in the form of Arduino, and the prototype used for testing the load accuracy of the appliance is shown in Figure 4. Figure 4(a) shows the simulation of the overall circuit which was used to verify the workings before prototyping the device, and Figure 4(b) shows the actual prototype built for the testing. The loading error was calculated against an authorized meter shown in Figure 5(c).

The source code for the metering device is provided on GitHub. The testing took place at the University Laboratory. The basic purpose of the test was to check the error of the metering device against an authorized device. Figure 5 shows the utilities used in the testing process, including the web page created for registration in Figure 5(a), the loads used for the testing of the physical device in Figure 5(b), and the authorized meter in Figure 5(c).



(a)



(b)

Figure 4. Hardware prototype development for the proposed device: (a) simulated testing circuit and (b) physical built circuit for testing

(a)

(b)

(c)

Figure 5. Additional utilities for testing (a) website built for registration, (b) loads used for testing, and (c) authorized meter for accuracy check

3.2. Code for ADL classifier

The code combined the 4 layers and compiled the model. The model was trained with 10 life cycles with full batch size, and the output of the epochs training with their respective accuracy. The matplotlib library is used to plot the validation accuracy plot for all 10 cycles against the training accuracy. The complete code, referring to the Pseudo-code 2 is being uploaded to the GitHub Repository.

4. RESULTS AND DISCUSSION

The outcomes of the testing, including the plots and the error table are provided below in this section. The comparison of works done in the references is provided below in Table 1. This table presents a rough idea of previous works done on this topic and has been compared with the proposed work of this paper, which includes real-time implementation as well as ADL classification. The error plot tabulation is provided for the metering device in Table 2. The average error percentage was found to be 0.116%. The measured loads were rounded off to integral form for both the authorized meter as well as the testing device.

The error graph is provided in Figure 6. The error showed a decrease till 4 KW of load but then showed a small increase. Although the prototype was just for testing, it showed a possibility that such devices can work practically with less error. For the ADL classifier, accuracy plot was plotted using the Matplotlib library, using the dual matrix method. The average accuracy was found to be 99.74%. Figure 7 shows the overall performance evaluation of the proposed classifier. The plot is provided in Figure 7(a). Figure 7(b) provides a heat map for the co-relational matrix for the features and labels.

From the Figures 6 and 7, it was concluded that the proposed system could be implemented in real-time, taking the fact into consideration that the error in measurement of the device has to be decreased in order to become installment-ready on the consumer side. The classifier on the server side, according to the plot and co-relational matrix would work well on the server side.

Table 1. Tabulation for content reference

Reference	IoT architecture	Appliance recognition	Real-time implementation	ADL classification
[1]	✓	✓	×	✓
[2]	✓	✓	×	✓
[3]	✓	✓	✓	✓
[4]	✓	×	✓	×
[5]	✓	✓	✓	×
[6]	✓	×	✓	✓
[7]	✓	×	✓	✓
[8]	✓	×	✓	✓
[9]	✓	✓	✓	×
Proposed	✓	✓	✓	✓

Table 2. Tabulation for the testing

Total load used	Testing details		
	Load measured by authorized energy meter	Load measured by the designed prototype	Error in (%)
1 KW	998 W	996 W	0.20
2 KW	2001 W	1998 W	0.15
3 KW	3001 W	2997 W	0.13
4 KW	4000 W	3997 W	0.08
5 KW	5001 W	4997 W	0.08
6 KW	6002 W	5996 W	0.10
7 KW	7001 W	6995 W	0.09
8 KW	8002 W	7994 W	0.10

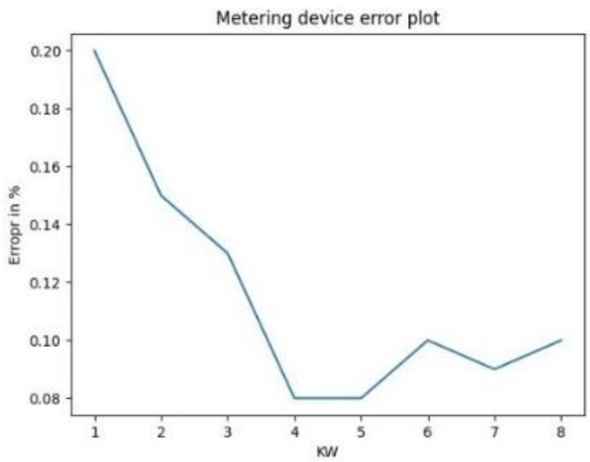
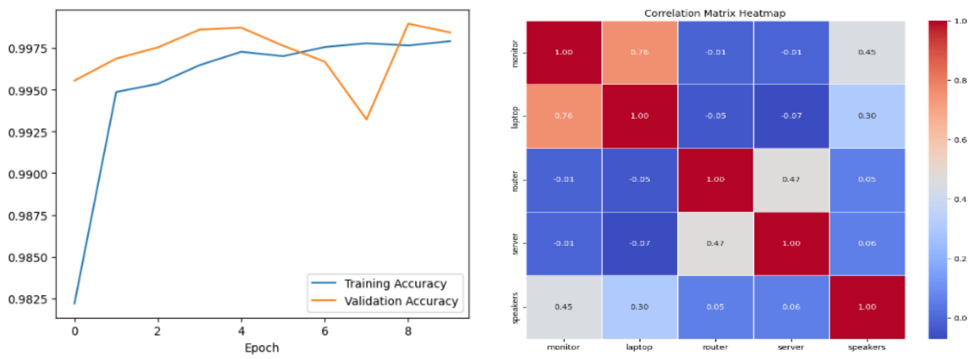


Figure 6. Error plot for the testing



(a) (b)

Figure 7. Performance evaluation of the proposed classifier: (a) training and validation accuracy plot and (b) correlation matrix highlighting feature relationships

5. CONCLUSIONS

This study presented a novel smart meter switch system that uses GSM technology to send important data to a central server. By including an ADL classifier, the system raises the bar for energy monitoring sophistication and gives users command over their energy meters. By utilizing the IoT, we create the foundation for more efficient solutions that go beyond conventional energy management. The ADL classifier's integration into the recommended smart meter device, along with its thorough testing and remarkable accuracy, demonstrate this technological innovation's enormous potential. The efficient transfer of data to the server enables real-time tracking of aggregate power consumption, giving users valuable insights into their usage patterns. This comprehensive approach not only increases user awareness but also establishes the foundation for effective energy management. The integration of the ADL classifier with the suggested smart meter device, in addition to its extensive testing and impressive accuracy, shows the great potential of this technological innovation. Real-time tracking of aggregate power consumption is made possible by the speedy transfer of data to the server, which provides users with insightful information about their usage patterns. This all-encompassing strategy not only raises user awareness but also lays the groundwork for efficient energy management.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Surender Reddy Salkuti	✓	✓		✓	✓	✓	✓		✓		✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

ETHICAL APPROVAL

This article does not contain any studies with human participants or animals performed by any of the authors.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable requests.

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