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Non-Intrusive Electrical Load Monitoring and Identification: Approaches, Tools and a Case Study

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Abstract: Efficient energy consumption has always been of significant interest to decision-makers in many countries. Awareness, knowledge and a real understanding of proper use of energy patterns is a key element in improving consumption behaviour. Despite the amount of available knowledge on how to save energy, many consumers still fail to take noticeable steps to enhance energy efficiency and conservation. Many significant and innovative studies have been conducted, yet there is still room for more sophisticated approaches to persuade users to optimize energy consumption. Therefore, integrating the Internet-of-Things (IoT) devices such as smart meters and mobile applications in a coherent framework would be one solution to achieving the desired changes in energy consumption behaviour. The present paper investigates current work in progress for optimizing energy use with IoT devices to provide sufficient feedback for users. This paper adopts a non-intrusive load monitoring algorithm (NILM) to assist in generating a recommender system based on smart meter data. The NILM identifies appliances and patterns of user consumption behaviour and disaggregates consumption of individual appliances from a single-point smart meter data. The results benefits not only household consumers but also energy providers and top decision-makers.

Keywords: Energy optimization, IoT, NILM, Smart meter.

1 Introduction

Currently, electricity is essential for economic growth and industrial development. It has allowed us to accomplish more and improve the quality of life using technological advances. Nevertheless, inefficient energy consumption poses a huge challenge to electricity providers, especially with the increasing demand for energy worldwide. Energy-efficiency analysts and researchers have become increasingly concerned about the growing rate of household energy consumption. Statistics show increased consumption of 30% in some countries in Europe and the US [1,2]. Malaysia, in particular shows a large increase in energy demand, especially with the rapid development of both the industry and the economy. In 2012, it was reported that household energy consumption was growing at an annual rate of 6.9%, compared to GDP and population at only 5.4% and 2.2%, respectively [3]. Thus, household energy caused serious environmental problems. For example, in the UK, almost 26% of carbon emissions result from the energy use of households [4].

To alleviate the environmental risks caused by household energy use, much research and analysis have been conducted over recent decades [5]. Improving the efficiency of energy use [6,7,8] and reducing demand [9, 10,11] are among the most promising ways to mitigate pressure on the environment and climate change [12]. Although the use of advanced technology and implementing regulations to promote energy conservation and improve efficiency are important [12], it is increasingly recognized that behavioural factors are of great significance in achieving energy conservation [13, 14,15,16].

The patterns of household energy consumption vary because of many factors that affect the decision making of individual users. These factors include but are not limited to income, age, lifestyle, house type, and user's enthusiasm towards saving. The efficient use of energy

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can be achieved with a deep understanding of these factors which contribute positively to changing the consumption behaviour of users. Studies show that a potential saving can be achieved (i.e. up to 27% of households' energy) with wise and efficient use [17]. A case study [18] focusing on EU countries that individual households can save up to 1300 kWh per annum through behavioral-and technology-based changes. Therefore, it is obvious that improving energy efficiency can be achieved through an effective change in household consumption behaviour [8].

Two main approaches to conserving energy are improving efficiency and reducing consumption [3]. The former involves one-time action such as upgrading to more energy-efficient appliances, that are normally costlier. The latter requires willing participation by the consumer to practice good energy consumption habits, such as switching off an appliance each time after use [2]. However, many are still not aware of effective ways to save energy or the real benefits that could be gained from it. Moreover, adjusting to a new habit and disciplining oneself to persistently use energy wisely is often hard. Therefore, this study reviews various behavioural related approaches that deploys IoT devices for improving users' energy consumption habits. We propose a solution that takes as input users consumption profiles, and activity profiles to produce a set of optimal recommendations. We believe that the paper can provide an insight to researchers dealing with energy consumption on how user behaviour can contribute to electricity consumption.

2 Related work

One key element to improve the energy consumption behaviour of users is to understand their energy use patterns. This can be achieved by analysing their usage data. The related approaches that make use of smart meters, behavioural changes, and NILM are discussed in the following subsections.

2.1 Smart Meters

Smart grid technology provides an advanced power system with integrated communication infrastructure to enable a two-way flow of energy and consumption information [19,20]. The involvement of smart meters and IoT appliances in the smart grid increases the accuracy of real-time profiling of energy consumption patterns, opening the door for data science tools to analyse, process, and furnish optimal recommendations. However, the potential of these tools is not yet fully explored or exploited. Current treatment of the subject focuses only on individual aspects of possible improvements,e.g. behavioural understanding, information-based intervention, or limited load scheduling. Analysing smart meter data gives insights into how user behaviour affects the amount of electricity consumed. Most of the methods of analysis utilize artificial intelligence-based applications such as NILM and/or other machine learning techniques.

Analysing the data collected from smart meter and other acquisition terminals on a daily or monthly basis reveals electricity consumption patterns. This can help users to reduce their consumption by increasing their awareness via IoT devices [15]. Through real-time interaction with the power company, consumers can adjust and optimize their behaviours, thus reducing their energy costs [8]. For power companies, more timely, flexible and personalized marketing strategies or demand-side management measures can be developed [21]. However, the literature indicates that the smart meter concept is still in its infancy [22]. Although the devices have been used for several years, challenges such as effective feedback, technology awareness, and privacy are yet to be addressed [23,24,25].

Related work on the impact of the smart meter is presented by Collotta and Pau [26], who stated that smart meters would have a full impact only when the integration of smart grids and smart homes takes place. They suggest that low-powered linked network segments are connected to a central management controller in the household. Nevertheless, the effects of smart meters on consumer saving behaviour have been examined in several studies [27,28,29,30,31]. The findings confirming the effect of the information provided by smart meters on consumption reduction are presented in Table 1. These studies conclude that the type of information introduced to consumers plays an essential role in motivating them to save energy.

Smart meter feedback such as real-time reading and pricing has not been effective. Asensio and Delmas [30] found that the tailored messages about the environmental and health implications of consumption can be salient and lead to more lasting behavioural effects. Similarly, Schleich et al. [28] examined the effects of providing written feedback in addition to smart metering devices on households' consumption and found persistent effects from written feedback over time. Delmas and Lessem [27] proposed a public rating system that presents consumption as being above or below average energy conservers. They found that public information can motivate both those who are and those who are not ideologically green [27]. In summary, the utilization of smart meter data to provide effective feedback will increase the electricity-saving rate.

2.2 Behavioural Change Approach

Behavioural changes can be just as effective as technological changes [21]. The vast increase in smart meters deployment in houses has encouraged researchers to focus on effect behavioural changes on the energy consumption [32]. Barbato et al. [33] and Rottandi et al.

[34] studied certain energy-saving applications used in consumers' everyday activities using consumption feedback and gamified social interactions to encourage consumers to reduce consumption. This kind of feedback and interaction has shown different levels of success and clarity for the users [8], by breaking down the consumption (e.g. type of consumption, by events, or per appliance) that will facilitate long-term sustainable behaviour, and build consumption feedback effectively [33, 34].

Many energy-behaviour researchers have focused on influencing behaviour determinants (e.g. beliefs, attitudes and behavioural control) without positioning the interventions in the behavioural change process [35]. However, there is growing awareness that interventions and incentives need to be provided based on the behavioural change process, that is a one-size-fits-all approach does not work. Models such as the transtheoretical model for behavioural change applied to energy consumption show how a change in energy behaviour occurs through different phases [36, 37], from becoming aware of the need to change behaviour, to understanding concrete actions to save energy, to performing them and ultimately developing new behavioural habits.

Zhou and Yang [5] agree that the energy consumption behaviour of consumers is an important way to improve energy efficiency and to seek effective energy conservation. Behavioural and psychological factors underly individuals' energy consumption behaviour and are affected by both objective and subjective factors. Objective factors do not depend on the subjective sense of individuals, such as income levels, housing characteristics, family size, as well as energy prices, climatic conditions, and energy policies. Subjective factors are those related to individuals' intention and awareness. The effects of subjective factors on household energy consumption behaviour are important research questions.

2.3 Non-intrusive Load Monitoring (NILM)

Non-intrusive load monitoring (NILM) is a process of obtaining and identifying appliance-specific information in a premise [37]. The total power data is collected at the main input, and load activities are then disaggregated to extract important information [38]. Numerous NILM frameworks and algorithms to resolve various types of problems have been proposed in the literature. For instance, in [39], the authors incorporated step-change information to define the electrical signature for each device instead of just the steady-state signals. Meanwhile, [40] proposed a NILM algorithm based on features of the V–I trajectory and found that it has higher accuracy than the other load features. To address the issue of supply voltage variability, [37] proposed a Real-Time Non-Intrusive Load Monitoring (RT-NILM) solution by assembling voltage-specific appliance signatures. In another advanced study considering solar panels-installed residential building, [41] developed a subspace component power level matching algorithm to simultaneously identifies the amount of solar power influx as well as the turned ON appliances, their operating modes, and power consumption levels. The study [42], even attempted to take NILM application a step further to detect faulty appliance's anomalous behaviour, which will enable early detection and corrective measures to avoid energy wastage.

3 The Proposed Solution: Methodology and Simulation

The proposed recommendation system involves elements from three areas: smart grid, consumer behavioural change, and energy consumption optimization. This involves smart meter data collection, algorithm implementation, and mobile application development. The first stage of this study is the smart meter data collection (input stage). Data was collected at a separate location from the recommender workstation, requiring it to be stored offline and handed over to the recommender workstation. Hence, the recommender is limited in processing the smart meter data in real-time. In the data processing stage. The smart meter data, which consists of a power draw parameter with its timestamp, is forwarded to the recommender workstation for analysis using the NILM algorithm. The final stage is to devise a simple and Effective method to disseminate the outcome of the processing stage. The integration of these methods introduces the recommender system, which generates personalized recommendations for users through their mobile applications, as described in Figure 1.

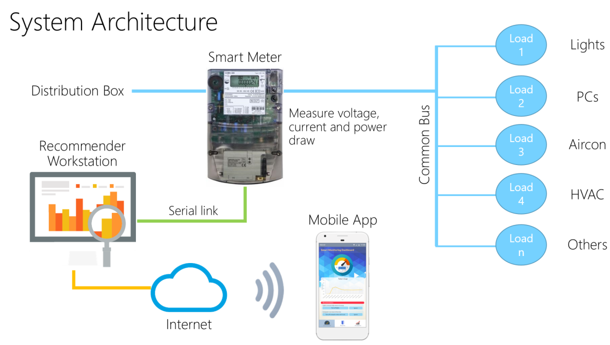

Fig. 1: System architecture of the proposed solution.

Table 1: Smart meters on energy consumption & reduction.

Study	Summary	Type of information	Result (%)
[27]	Experiment: Smart meters installed in 66 residence hall rooms on the UCLA campus for one year	Private Information: Real-time information over their usage by source (heating and cooling, lights and plug load), and historical and social usage comparisons Public Information: Public rating system that presents consumption as being above or below average energy conservers.	20% reduction in electricity consumption
[28]	Experiment: Observation of electricity consumption via smart meters for 1,525 households in Austria, the data collected in 11 months.	Data on real-time & written feedback..	5% reduction
[29]	Experiment: Electricity data from 215 households were recorded remotely at 5-min intervals in one year	Electronic feedback via consumption indicator on electric cookers	15% reduction
[30]	Experiment: A randomized controlled trial was conducted to observe electricity consumption for 118 households over 9 months in Los Angeles	Health-based frame messages Saving-based frame messages	8-10% energy saving
[31]	Experiment: Smart meter trail data from 5,000 installed meters in Ireland in one year	Data on real-time and historic usage	0-14% demand reductions

3.1 Input: Smart Meter Data Collection

The data was collected by the smart meter in a commercial building (the High Voltage Power Laboratory, Universiti Kebangsaan Malaysia (UKM) Bangi, Selangor) over several weeks and saved as a dataset for testing the recommender system. As the lab power supply is connected Separately to the smart meter from another area, the data stream collected from the smart meter is discrete from the lab power consumption. This laboratory consists of high voltage equipment, instrumentation, computers, lights, air conditioners, and other items.

The consumption data from up to four controllable appliances was collected over 24 hours in daily cycles for two months. Besides the normal set of appliances for the research, other electricity consumption was estimated including outdoor connected load, networking appliances, lab equipment, and instrumentation, known as the baseload. Baseload is calculated as the minimum level of electricity demand on the individual supply system over 24 hours.

A smart meter is used to collect and measure the total load at a time interval of 30 seconds. When an appliance is toggled ON and OFF, power samples change and a new steady power level is established. This is portrayed by a difference in real and reactive power. Appliance detection can be made by an algorithm and matched to the electrical consumption of each appliance whose characteristics are recorded in the database [13]. In addition to the real power measurement, smart meters usually offer other metrics, such as reactive power, power factor, and frequency, each of which could be used as supplementary features conditional on the group of appliances to be disaggregated [2]. The collected data is input to a power profiling algorithm in NILM that conveys the appliance power consumption variation with the mode or state of the appliance.

Fig. 2: High Voltage Power Laboratory in Universiti Kebangsaan Malaysia (UKM) Bangi, Selangor.

3.2 Data Processing and Analysis: using the NILM Algorithm & Recommender System

The collected data from smart meters consists of a power-draw parameter with its timestamp. In the data processing stages, the data proceeds to the recommender workstation for analysis using the NILM algorithm. The recommender then generates a personalized recommendation for the user.

a) Data Preparation: To initiate the energy disaggregation process, the system was trained on individual electrical Device signals by toggling ON/OFF appliance switches for a length of time. It was also given identified appliance change-points in the total electrical signal. The training is essential for the NILM system to have accurate appliance detection. The study focuses on controllable appliances and excludes permanent continuous devices; for instance, the lights, computers and climate control appliances are switched on and off discretely and in combination over time, as illustrated in Table 2.

b) Recommender System: Recommender systems allow users to link their activities to their electricity consumption [5]. They help the consumer to understand why a given amount of energy is consumed [43]. Data collected from smart meters were supplied as input to a power profiling algorithm in NILM that conveys the appliance power consumption variation with the mode or state of the appliance as calculated in Table 3.
The recommender system for appliance load identification and recommendation algorithm was designed to disaggregate all appliances in the building. It has essential features to give a better understanding of how electricity usage is connected to the daily routine. Some of the features included are providing daily energy consumption, total operation period, usage frequency, cost of appliances' energy consumption and weekly usage trend of the individual appliances.

c) Input and Output Module: Smart meter power parameter is loaded on to the input column at 30-minute intervals. While none of the controllable appliances is active, it is offset to zero to exclude permanent continuous load in the analysis. The assumption is made to find the minimum power draw during a no-load condition by detecting at least two minimum points. After this, the appliances are identified using the appliance identification module.

d) Appliance Identification Module: In this module, the appliance power profile, which was introduced earlier at the data preparation stage, is compared with the normalized real power entries. Multiple tests with different combinations of appliances are conducted until the set tolerance range of the tested load consumption is reached. Through numerous tweakings, the set tolerance value to obtain the correct appliance identification eventually settles according to the (1) where x represents the success of the identified appliance.

$$\begin{cases} x = 1, \; x_{min} > -0.037 \text{ and } x_{min} < 0.01 \\ x = 0, \; x_{max} > -0.02 \;\text{ and } x_{max} < 0.03 \end{cases} \tag{1}$$

e) Appliance Energy Consumption, Active Hours and Costing Module: In this module, each appliance's energy consumption and active hours are determined based on the number of times the appliance is active in every 30 minutes.
Energy consumption is calculated with the average appliance power profile with the number of active periods. Since the smart meter data is sampled at half-hour intervals, the active hours are half the number of active periods as shown at (2).

$$EnergyCoumption = \frac{1}{2}\sum_{1}^{k} P_{rms} \tag{2}$$

where P represents the normalized power, k represents the number of appliances, and active hours can be calculated by dividing the triggered points by (2) as in (3).

$$ActiveHours = \frac{(Trg\ pts)}{2} \tag{3}$$

The daily electricity cost of each individual appliance is gauged by the total energy consumption and the assumed cost of electricity, RM 0.34; however, it does not integrate the increase in tariff as the total power consumption escalates. The power consumption and active duration of each appliance is sorted from highest to lowest to be used to provide energy reduction recommendations of high consuming appliances.

Table 2: Controllable appliances active in each period with power consumption logged for NILM algorithm training.

Time	Appliance Power Profile	Power (kW)
14.50	Baseload	0.998
14.53	Lights	2.319
15.09	1 Computer (1PC)	1.103
15.18	2 Computers (2PCs)	1.120
15.33	Air conditioning (A/C)	2.184
16.00	Lights and A/C	3.446
16.13	Lights, A/C, and 2PCs	3.662
16.36	Lights, A/C, 2PCs, and HVAC	7.556
16.56	Lights, A/C, and HVAC	7.442
17.03	HVAC	5.000
17.08	End	-

f) Output: Generation of recommendations: To provide energy-saving recommendations that would benefit targeted consumers, the data needs further analysis to identify which appliance:
–Consumes the most energy daily.
–Is used for the longest time.
–Is the most frequently used.

Table 3: Appliances Power Profile.

Power Profile	State/Units	Min (kW)	Max (kW)	Average (kW)
Base Power				0.260
Lights		1.331	1.354	1.343
PC	1	0.070	0.120	0.095
	2	0.110	0.132	0.121
A/C		1.103	1.160	1.132
HVAC	Lo	1.101	1.173	1.137
	Hi	3.992	4.032	4.012

Based on the results, the recommender system will suggest energy conservation guidelines for the high-consumption Appliance, by notifying the user in real-time through their mobile application.

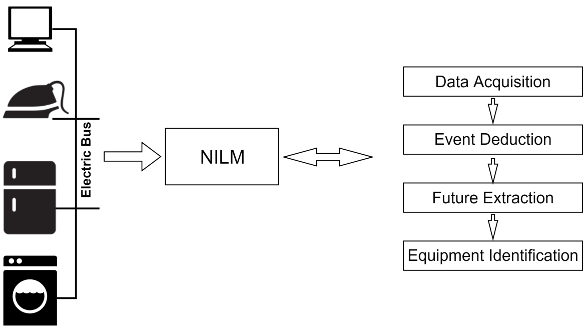

Fig. 3: Processes of Non-intrusive Load Monitoring (NILM).

4 Results and Discussion

4.1 Energy Consumption Profile

Figures 4 and 5 show the energy consumption and the length of use of four unidentified appliances. Some appliances are indistinguishable through their association with small appliances running. As discussed above, these are referred to as baseloads. These loads are calculated as the minimum level of electricity demand on the supply system over 24 hours, including outdoor connected loads, networking appliances, and other small lab devices.

4.2 Energy Consumption Analysis

The power consumption and active duration of each appliance are sorted from highest to lowest, as illustrated in Table 6. This result is used to generate energy reduction recommendations for high-consumption appliances.

Table 5 shows each appliance's energy consumption, active hours, and costing based on the number of times the appliance is active in every 30 minutes.

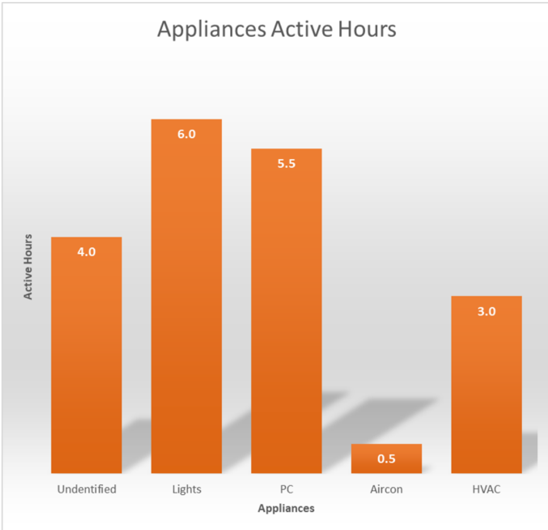

Fig. 4: Results of the active hours of consumption in the laboratory.

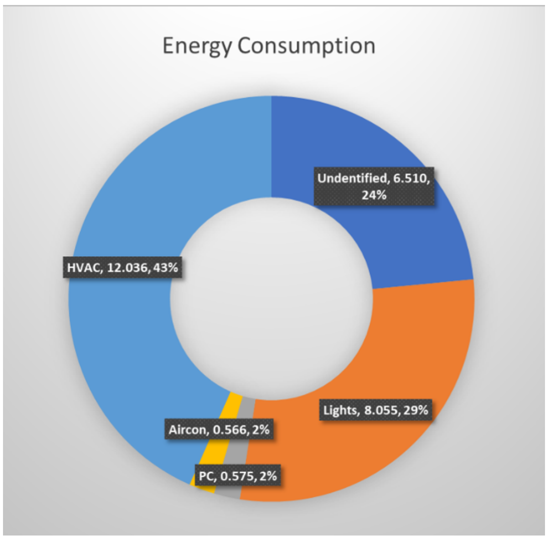

Fig. 5: Daily rate of appliances energy consumption.

4.3 Energy Saving Recommendations

The system creates a recommendation based on the excessive total energy consumption and lengthy appliance

Table 4: The results of the appliance identification module in Table 4 are based on the NILM algorithm. Appliance identification results.

Test	Min	Max	Found?		Active load			
			TRUE		No load			
Active Load	State	Count	Trigger	Selected state	Min	Selected	Max	Selected
No		000000	26					
Base Power		TRUE	8	-				
Lights		0	12	-				
PC	1	0	7	1	0.070	0.070	0.120	0.120
	2		4	1	0.070		0.132	
A/C		0	1	-				
HVAC	HI	0	0	1	3.992	3.992	4.032	4.032
	Lo	0	3	Hi	1.101		1.173	

Table 5: Appliance energy consumption, active hours and costing results.

Appliance	State	Energy Consumption (kWh)		Active Hours		Cost (RM/Day)
Unidentified		6.510	6.510	4.0	4.0	2.21
Lights		8.055	8.055	6.0	6.0	2.74
PC	1	0.333	0.575	3.5	5.5	0.11
	2	0.242		2.0		0.08
A/C		0.566	0.566	0.5	0.5	0.19
HVAC	HI	12.036	12.036	3.0	3.0	4.09
	Lo	0.000		0.0		0.00
Total		27.741				9.43

Table 6: Appliances sorting results.

No	Appliance	Energy	Appliance	Hours
1	HVAC	12.036	Lights	6.0
2	Lights	8.055	PC	5.5
3	Unidentified	6.510	Unidentified	4.0
4	PC	0.575	HVAC	3.0
5	A/C	0.566	A/C	0.5

Table 7: High consumption appliances.

Priority	Finding
1	HVAC appliance consumes the most amount of energy
2	Lights consume the greatest amount of energy
3	Lights are ON most of the time
4	PCs are ON most of the time

operation by comparing appliances consumption results with the assumed standard values, which often indicate energy wastage. A sample of the daily power consumption trend at UKM High Voltage Laboratory, as shown in Table 7, will Be used to identify appliance operating trends as illustrated in Figure 6.

Based on the power trend, higher-consumption appliances can be detected, as shown in Table 6; the respective recommendations are then sent to consumers. Based on these findings, the recommender system will notify the consumer's smartphone periodically in push mode.

The mobile application consists of the Dashboard page, which displays power consumption gauge, daily usage graph, and energy-saving recommendation. The rooms tab presents the appliance operation state, energy consumption, and duration of the active state and the weekly usage trend of each appliance.

5 Future Works

Challenges remain in identifying appliance activity, concerning appliances with similar power draw, appliances with multiple settings, and parallel appliances activity. Further research should, therefore, consider the use of available open smart meter data, and using multi-objective optimization techniques to reconcile user preferences and energy-efficiency goals.

Although NILM is the most cost-effective in terms of implementation and maintenance, it has some drawbacks. However, these shortcomings can be solved by applying harmonic current signatures. They can be measured by using a high-sampling smart meter which is capable of sampling in kHz or MHz range [44]. Harmonic currents created by the appliance can be used as a signature to identify the appliance, integrating transient current analysis. Harmonic current signatures might be useful in identifying certain appliances that are too similar to be distinguished by their real and reactive power signature.

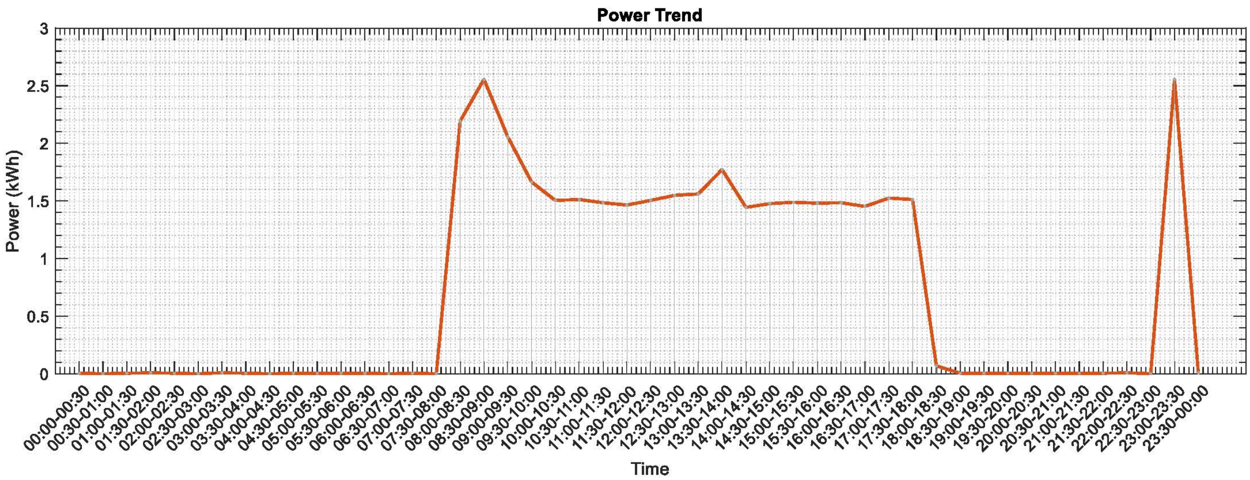

Fig. 6: Power consumption trend on one day of the data collection period.

Fig. 7: Smart meter application dashboard.

6 Conclusions

This study reviewed several techniques used for energy consumption with respect to behavioural changes. From all discussed approaches, it is vital that energy providers as well as users can achieved greater saving with the deployment of advanced technologies such as smart meters along with the latest IoT related apps. The relationship between users' daily routine and the household energy consumption is crucial for improving home energy management. This means that creating a system for collecting consumer power consumption data and analysing these data can be a key to improve and optimize energy consumption.

In this study, a mobile application and a smart grid domain are integrated to develop a demand-side personalized recommender system, based on the implementation of the NILM algorithm for identifying significant energy consumption events. It can enable the generation of tailor-made recommendations to consumers through smartphones. The results of this study confirm the feasibility of the proposed system and establishes a baseline for future development of the system.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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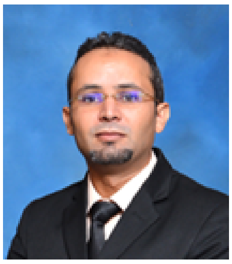

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