Final Report:
Small-Scale Home/Office Energy Management

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Executive Summary

Sustainable energy use requires optimal energy utilization in smart grid systems. It is possible by empowering the Internet of Things (IoT) based wireless connectivity through real-time energy monitoring and power consumption patterns analysis. IoT-based networks can collect data from appliances and devices in the home or office, thus helping us understand individuals' power consumption patterns and guiding users for smart energy usage. In this project, three objectives are proposed, including 1) building Low-cost flexible wireless architectures and networks at homes/offices to collect power consumption data; 2) labeling the power consumption data from smart plugs and analyzing usage patterns, and 3) developing a framework based on behavior analysis to guide users to smart energy consumption.

We aim to use wireless IoT technology coupled with smart plugs/smart meters to connect low-cost small-scale office work-spaces for personal power consumption management, including real-time monitoring of energy consumption, analyzing power usage patterns, recognizing the resident's electricity consumption behaviors and so on. Machine Learning Models are trained for real-time energy disaggregation in the local home server. Simultaneously, the local data is regularly uploaded to the cloud server for usage patterns analysis. After combining other information (e.g., electricity price and personal information), the system enables to provide more intelligent services (e.g., recommendations) for end-users.

The research goal is to address the challenge of one-to-one mapping of energy disaggregation in device-sharing environments by multi-users, aiming to accurately match the energy consumption of electrical appliances with specific users. It differs from existing studies on power consumption analysis for the whole household. The significance includes helping reduce individual power consumption in the small-scale IoT network (e.g., homes and offices) and benefit the large-scale IoT network (e.g., buildings, communities and widespread regions) in the total energy saving.

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1 Project Overview

1.1 Background and Problem Statement

The sustainable use of energy is one of the biggest challenges that our society is facing today [29]. As the demand for energy (e.g., electricity) continues growing, it would be significant if we could use and manage energy in a smarter way (i.e., smart energy management).

How to achieve smart energy management? The priority is to figure out how the energy is consumed? Statistically, the electricity power use can be mainly divided into commercial use (e.g., in the office or factory) and residential use (e.g., at home). Alternatively, it can be simply classified as lighting and using devices if considering the use intention. Since a considerable portion of the power consumption is closely related to people's indoor activities, such as cooking with a microwave or oven in the kitchen, using a computer/laptop or printer at work, watching T, listening to music, heating, cooling, and so on, monitoring the energy consumption, analyzing power usage patterns and recognizing the residents electricity-consumption behaviors will help better energy management. Moreover, smart energy management is conducive to the sustainable development of energy. In the short term, it will help to reduce individual power consumption in the small-scale IoT network (e.g., homes and offices); in the long term, it will also benefit the large-scale IoT network (e.g., buildings, communities and widespread regions) in terms of total energy saving.

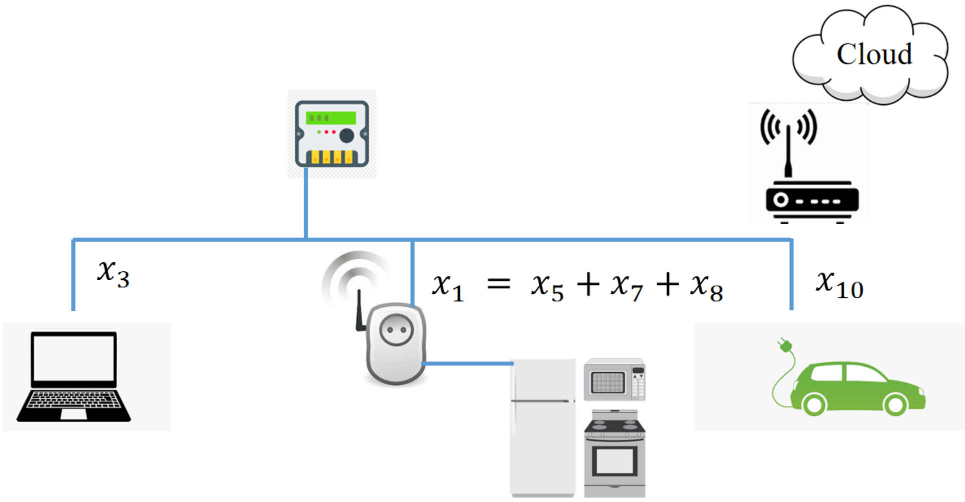
To effectively analyze power usage patterns for optimal energy utilization, the premise is that the power consumption of each device can be accurately obtained. The Internet-of-Things (IoT) is to connect devices and sensors through the Internet, and there are a number of successful IoT applications such as smart cities, smart factories, and so on [6]. To support wireless connectivity for things (i.e., devices and sensors), various technologies can be considered with short-range and long-range connectivity, such as Bluetooth, ZigBee, Wifi and LoRa [14]. In most IoT applications, while sensors and devices are expected to transmit their measurements (e.g., thermometer sensors send their temperature readings), they can also be used to send power consumption data (e.g., smart plugs). Thus, IoT networks become capable of supporting smart energy management through data analytics [34]. In particular, the energy disaggregation used in individual homes or offices can be performed simultaneously on a large-scale in tens or hundreds of homes or offices via IoT networks, which raises the possibility of large-scale smart energy management, e.g., over neighborhoods, or suburbs.

To monitor energy consumption, the most direct way is deploying measurement equipment (e.g., smart plugs) to connect to dedicated devices (e.g., personal computers). Then data acquisition for associated individuals is conducted to enable fine-grained energy monitoring. However, there is also office equipment shared by multiple individuals (e.g., kettles, copy machines). Thus, one-to-one mapping between measurement equipment and an individual is impossible, i.e., data from smart plugs becomes unlabeled data. Besides, the power consumption varies widely due to the different numbers and types of electrical appliances used in the house. Other uncertainties include the different models of the same type of appliances, the different working modes of appliances, the overlapping operation of multiple appliances, and the background noise. For the above reasons, energy disaggregation is a complex problem. Also, a new method of energy disaggregation based on power consumption data analysis needs to be developed.

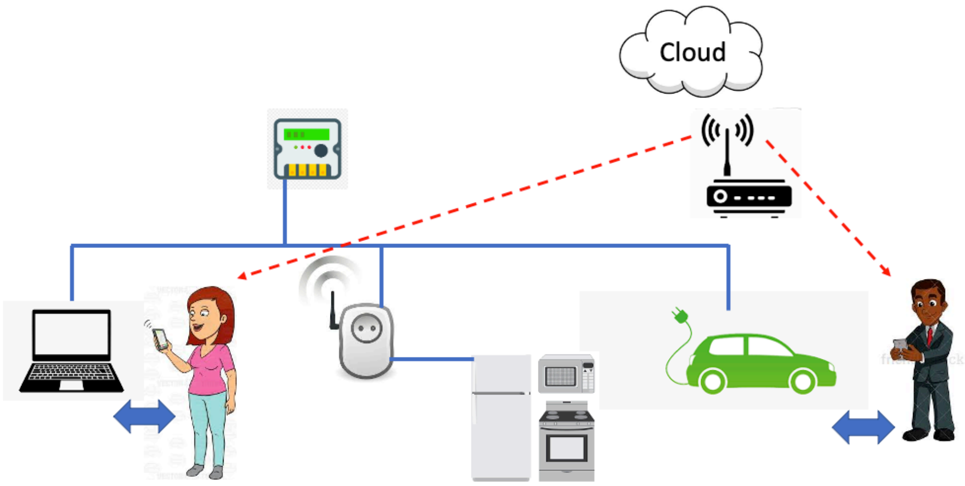
1.2 Project Scope and Objectives

The Internet-of-Things (IoT) is to connect devices and sensors via the network. IoT-based networks can collect data from appliances and devices at homes or offices, thus helping us to understand power consumption patterns by individuals and guide users for smart energy usage.

As shown in Fig. 1, we assume that an IoT network is deployed at a home. A number of appliances and devices are connected to a local home server (directly or indirectly through smart plugs), which can collect real-time power consumption data. For example, the laptop and car are connected to their own power measurement equipment separately, so their electricity consumption can be obtained directly, indicated as $x3$ and $x10$ shown in Fig. 1 (a). Besides, the refrigerator, washing machine and oven are connected to the gateway via a small IoT network, and the total energy consumption can be obtained, marked as $x1 = x5 + x7 + x8$, where $x5$ represents the power consumption of the refrigerator, $x7$ represents the power consumption of the washing machine, and $x8$ represents the power consumption of the oven. A small-



(a) Energy Disaggregation



(b) Usage Pattern Analysis

Figure 1: An illustration of IoT network for smart energy management.

scale IoT network composed of the above devices can upload the total electricity power consumption to the cloud server, and end users can remotely view or monitor the energy usage through their mobile phones, shown in Fig. 1 (b). Although the total electricity power consumption of the entire network can be obtained by smart meters, individual appliances, such as $x5$ and $x7$, still cannot get a one-to-one power consumption corresponding accurately.

In this project, we aim to use wireless IoT technology coupled with smart plugs/smart meters to connect low-cost small-scale office workspaces for personal power consumption management, including monitoring the energy consumption in real-time, analyzing power usage patterns, recognizing the resident's electricity consumption behaviors and so on. Specifically, Machine Learning Models can be trained and used for energy disaggregation in the local home server. Simultaneously, local data is uploaded to the cloud server database with a fixed frequency, and usage patterns can be analysed to understand power consumption patterns. After combining other information (e.g., electricity price and personal information), the system enables to provide end-users with more intelligent services (e.g., recommendation).

This project has three objectives that correspond to different challenging tasks:

- Objective 1:
  Building a Low-cost flexible wireless architecture and network at homes/offices to collect power consumption data.
- Objective 2:
  Labeling power consumption data from smart plugs and Analyzing usage patterns.
- Objective 3:
  Developing a framework based on behavior analysis to guide users to smart energy consumption.

Note that, the roles of the local home server for smart energy management are as follows:

i. Collecting real-time power consumption data from appliances and devices

ii. Training machine learning (ML) models to perform power disaggregation and user detection

iii. Recommending smart energy usage for end-users

For the third role, with known energy cost at a given time and duration, the local home server can provide a recommendation to individuals to lower the energy cost. If all the appliances and devices are directly connected with wireless transceivers to the local home server, their real-time power consumption information can be known by the local home server. However, there might be some appliances without wireless transceivers. Thus, we can consider the use of smart plugs (or a smart meter) that can provide the power consumption information for any connected appliances and devices. Since a smart plug (or a smart meter) may collect the aggregated power consumption, the local home server needs to perform energy disaggregation, which will be explained in the following section.

1.3 Research Contribution

In this project, we propose a new method/perspective based on individual energy usage pattern analysis for accurately matching the energy consumption of electrical appliances with specific users. In particular, we firstly adopt high-performing machine learning models for real-time energy/power disaggregation on the local server (i.e., small-scale home/office) to ensure that comparable or better performance with state-of-the-art disaggregation algorithms can be achieved. Next, energy usage patterns and individual power consumption data are analyzed comprehensively to match overall energy consumption and label datasets by events. The effectiveness of the proposed method is verified by using simulated datasets in a motivation scenario.

A unique contribution of this project is to propose that it is not just energy use of appliances that can be determined from energy consumption data but also the energy use of particular individuals (or his/her appliances). While this has implications for power savings, billing, and accountability for homes, e.g., in shared household contexts, it also has use for shared office space contexts (where there might be different users of the same shared space with different devices, possibly at different times), and even for commercial office space rentals (in the Airbnb-style), e.g., where billing includes energy use per person.

2 Project Milestones and Timeline

The project mainly included three milestones, corresponding to three objectives, as shown in Table 1. The detailed tasks for algorithm development and data analysis are shown in Table 2.

No.	Milestone	Duration
Phase 1	Building a prototype test-bed with installing smart plugs to collect datasets	3 months
Phase 2	Developing algorithms at local and cloud servers	6 months
Phase 3	Revising and improving algorithms/wireless systems and developing the framework for smart energy management.	3 months

Table 1: Project Milestones

No.	Tasks	Date for completion
1	Literature review on the energy disaggregation algorithms	March, 2022
2	Data analysis for public datasets and testbed datasets	March, 2022
3	Design use case scenarios and experiments	April, 2022
4	Collecting/Simulating energy consumption data for different devices (testbed)	April, 2022
5	Collecting/Simulating energy aggregated data of selected devices (testbed)	April, 2022
6	Developing algorithms for the energy disaggregation	April, 2022
7	Analysis of usage patterns for different appliances/users	April, 2022
8	Testing algorithms in different time windowns	May, 2022
9	Compare with the state-of-the-art methods	May, 2022
10	Experiments results and performance evaluation	May, 2022
11	Final Report and future plans	June-July, 2022

Table 2: The detailed tasks for algorithm development and data analysis.

3 Related Work

3.1 Energy Disaggregation Algorithms

The early NILM technology mainly aims to estimate major appliances' on/off status in the total load [19], which usually needs high-frequency data (e.g., current and voltage waveform) support. Later studies started focusing on estimating the amount of energy consumption for different appliances by training the disaggregation models. [36]. The most well-known NILM algorithm is the Hidden Markov Model [15], such as Factorial Hidden Markov Models (FHMMs) and its variants like Additive Factorial Hidden Markov Models (AFHMMs). These HMM-based approaches work in a supervised or unsupervised setting, and their learning processes often rely on the expectation-maximization algorithm to achieve the local-optima solutions. So, the accuracy of such algorithms is not high.

Other algorithms are Sparse Coding [16], Graph signal processing (GSP) [42], Integer Programming and so on. As mentioned earlier, energy disaggreagtion is a special case of blind source separation, sparse coding has been proven effective for such problems where an additional constraint of sparse activations is introduced [24]. In particular, GSP utilizes the regularization of graph signals with the assumption that the signal is piecewise-smooth. Under this assumption and consideration, the total graph variation is generally not significant and can be used for a variety of applications including energy disaggregation. GSP has been proven effective over other algorithms because of its trainning efficiency, reliability in dealing with noisy data, ability to deal with different sampling rate, etc [21]. GSP-based approaches need more investigation related to the robustness of the algorithm, capability of dealing with incomplete training set, and real-time performance improvement.

Due to the Neural Network's remarkable success in computer vision, researchers began to apply NN to energy disaggregation. In many studies, ML-based solutions have shown promising outcomes. In 2015, Kelly and Knottenbelt [26] tested three deep neural networks, including Recurrent Neural Network (RNN) with long short-term memory units, i.e., LSTM, Denoising Autoencoder and Convolutional Neural Network (CNN). The experiments show that deep learning-based methods outperform the traditional methods (e.g., Combinational Optimization and FHMM). Besides, supervised LSTM models are proved to be highly efficient classifiers in time-series analysis for energy disaggregation [35], although training the model is time-consuming.

Deep neural networks are promising algorithms for the energy disaggregation problem. For example, the WaveNet model has been used for energy disaggregation in [18] [24], which shows better performance compared with other HMM-based algorithms and is promising for data from multiple sources, e.g., combined consumption and weather data. In addition, the waveNet model is much faster than the traditional RNNs [39] due to no recurrent connections. In [25], a multi-channel Recurrent CNN architecture is proposed to capture energy signal inter-dependencies, and the new model outperforms counterpart approaches with higher accuracy and faster convergence time.

There are other studies focusing on real-time energy disaggregation. Chen et al. [11] used a convolutional sequence to sequence model for disaggregation. Zhang et al. [44] propose a Sequence-to-Point (Seq2Point) method based on a deep convolutional network to infer energy consumption at a point. However, these methods are not really practical because a set of historical data is needed as the input, e.g., the time window includes 1 hour of aggregated data. In [31], a sliding window approach based on RNN is proposed for near real-time energy disaggregation, which adopts 10-20 minutes of data as the input window. The experiments show that the Seq2Point learning paradigm takes less time to train Neural Network models, which means that the Seq2Point method is an effective real-time energy diaggregation method. In [41], Seq2Point learning is introduced to an improved Long Short Term Memory (LSTM) network for load identification, and experiments on three public datasets (i.e., UK-DALE dataset, REDD dataset and REFIT dataset) demonstrate that the combined method can significantly improve the accuracy and generalization. That is, 15%∼18% improved on mean absolute error (MAE) and 21%∼30% improved on normalized signal aggregate error (SAE).

3.2 Energy Usage Pattern Analysis

The purpose of the energy usage pattern analysis is to give occupants a clear insight to understand their daily behavior in consuming electricity by identifying the usage patterns of various appliances, which can enhance their awareness of power-saving and lead them to a sustainable and healthier lifestyle [3].

Event detection is an effective way for analyzing the energy-consumption pattern for household appliances, as people's indoor activities and the use of electrical appliances are closely related [23]. Another and more straightforward way is to detect the switch status of these devices, namely, on and off. For most appliances, there is a fixed power value for start and operation, i.e., on-power threshold. An appliance is recognized as starting working only when its output power reaches the threshold. Since different appliances have different on-power threshold, identifying and classification for various appliances can be achieved based on this point. For example, the on-power threshold of a kettle is about 2000 watts, while a washing machine only needs 20 watts. Such problems can be implemented using regression-based learning methods and classification-based learning methods [24].

3.3 Comparative Discussion

This project aims to address the challenges of small-scale IoT systems (e.g., home/office) in energy management and data analysis using cutting-edge technologies, such as machine learning, artificial intelligence and the internet of things. We aim to develop smart energy management systems using wireless technology and smart plugs. Then we break down each user's energy consumption and usage patterns by data-driven machine learning algorithms, which is different from existing studies on power consumption analysis for the whole household.

Based on the literature review, most energy disaggregation solutions are based on smart meters, which record the total amount of electricity used in households. Existing energy disaggregation algorithms are used to estimate the power consumption of the main appliances in the total load (e.g., 80% of the total consumption). Thus, users can learn about the power consumption pattern of the whole family [36]. However, the existing smart meter solution usually gathers data at a very low sampling frequency (e.g., 15 $\sim$ 30 minutes [36]), which means that the estimated energy consumption is non-real-time. In addition, the existing solution on the market cannot provide the details to distinguish individual electricity usage of different users in the same region, e.g., a home or an office. The main reason is that multiple people share these appliances. Thus, making a one-to-one match between the power consumption and the device user is difficult.

In this project, we aim to disaggregate the power consumption of each appliance connected to the smart plug and break down each user's energy consumption and usage patterns. It is different from the existing solutions focusing on energy disaggregation for major appliances or power analysis for the whole household. There are two concrete goals of this project: 1)Algorithm performance improvement for real-time energy disaggregation; 2)New method/perspective for energy data and user behaviour analysis. i.e., one-to-one-mapping energy disaggregation in device-sharing environments by multi-users.

The impact of this study on relevant areas also includes:

- Learn how each different appliance contributes to the electricity consumption of the whole house and how that varies through time.
- Estimate the electricity consumption of each appliance at a given time/or near real-time.
- Understand the behavior patterns of residents.
- Labelling the dataset using predicted events.

4 Methodology

4.1 An Overview of Energy Disaggregation

Energy disaggregation is a challenging blind source separation problem that infer energy consumption of electrical appliances on each branch circuit in a building through total power consumption [23], aiming to separate the energy consumption of individual appliances from the total consumption readings of multiple appliances (i.e., the aggregated data from the smart meter) [20] [24]. Fig. 1 is presented to illustrate the overall concept of energy disaggregation of individual appliances. In the figure, the end-user individual appliances data are sent to a local aggregator which is later sent to the edge or cloud for energy management including operation and retail billing.
In a traditional smart home concept, the smart meters are responsible to capture the aggregated information and communicate with the operators. However, in an edge/IoT connected today's energy disaggregation paradigm, end-users will have more autonomy by receiving actionable insights by knowing the individual appliance behaviors and patterns resulting from the data-driven disaggregation mechanism. To explain the modeling of energy disaggregation, consider the following example with the aggregate data of energy appliances such as kettle, electric heater, laptop and projector. Suppose there is a sequence of readings from a house-level meter denoted as $X = (x_1, x_2, ..., x_t)$, where t is the length of the sequence. The problem of energy disaggregation is to disaggregate X into the energy consumption sequence of individual appliances:

$$Y^i = (y_1^i, y_2^i, ..., y_t^i), y_t^i \in R^+, \ i = 1, \ldots, I, \tag{1}$$

where $R^+ = [0, \infty)$, I is the number of known appliances, and $t \in 1, 2, ..., T$ is the index of samples. At any time, t, x_t is assumed to be the summation of the readings from all the known appliances and unknown appliances with background noise, denoted by u_t, i.e.,

$$X_t = \sum_{i=1}^{I} {y_t}^i + u_t. \tag{2}$$

Then, the energy disaggregation is to find the following inverse functions so that the energy consumption of individual appliances from the total power consumption can be obtained:

$$f^i : X \to Y^i, \; i = 1, \dots, I. \tag{3}$$

Since the energy disaggregation can identify and classify the energy consumption of individual appliances, it thus greatly facilitates energy control. Disaggregated data provides valuable information to facilitate power system planning, load forecasting, new types of billing procedures, and better service to customers (e.g., providing energy consumption details and pinpointing the origins of certain customer complaints). For policymakers, knowing the amount of energy each category of appliances consumes is critical to developing and evaluating energy use policies. There are many applications of energy disaggregation, such as accurate energy billing, occupancy monitoring, appliance classification, faulty appliance detection, building efficiency, and demand-side management [38].

To put it bluntly, energy management is monitoring the use of all electrical devices in the house, including operating states and instantaneous power. There are two types of methods for energy disaggregation: Non-intrusive Load Monitoring and Intrusive Load Monitoring.

- Non-intrusive Load Monitoring.

'Non-intrusive' load monitoring (NILM) consists of measuring energy consumption using a smart meter, which is usually placed at the meter panel and works based on the aggregated data where the disaggregation algorithms attempt to approximate the individual appliance characteristics. In other words, the method relies only on a single device that can measure aggregated data and an energy disaggregation algorithm to enable energy management without installing additional sensors.

- Intrusive Load Monitoring.

On the contrary, 'Intrusive' load monitoring utilizes a low-end metering device for the measurement of the electricity consumption of one or more appliances residing within the end-user dwelling as indicated by the name [43].

While traditionally research has focused on the non-intrusive energy disaggregation, recent advancement on the ML/artificial intelligence (AI), IoT/edge computing with the proliferation of accurate and affordable smart plugs have highlighted the need for research and development of the intrusive load monitoring.

4.2 Algorithms for Real-Time Energy Disaggregation

Accurate real-time energy disaggregation is the key to realising smart energy management. This section details the algorithm development for real-time energy disaggregation, considering the model structure, learning paradigm and the data format for energy consumption.

4.2.1 Recurrent Neural Networks

Neural networks have been proven to be a promising approach to the energy disaggregation problem, as NNs can extract latent features of the appliance from the power consumption data. We apply Recurrent Neural Networks (RNN) as the target model, which has an excellent performance in processing sequential data (e.g., the power consumption data with time series) [26] [35] [41].

4.2.2 Learning Paradigms

Given a sequence of total power consumption readings from the whole house, $X = (x_1, x_2, ..., x_t)$, where t is the length of the sequence, the power consumption sequence of the i^{th} appliance is expressed as $Y^i = (y_1^i, y_2^i, ..., y_t^i)$. According to the different output structures of disaggregation models, there are mainly two different learning paradigms, as following:

- Sequence-to-Sequence (Seq2Seq), it is designed to predict a set of disaggregated power consumption sequences for a single appliance.
- Sequence-to-Point (Seq2Point), it is designed to predict a disaggregated power consumption value of the appliance at a certain point.

Since the midpoint of the Seq2Seq model has the minimum prediction error, Zhang et al. [44] proposed a sequence-to-point paradigm to pursue better performance. The comparison experiments showed the effectiveness of the Seq2Point model, which outperformed the Seq2Seq model and is faster due to lower computational cost. Based on the previous discussion, we adopt the RNN model with Seq2point learning algorithms for real-time energy disaggregation. That is, a window of past aggregate data, $[t - w, t]$, as the input to infer the consumption at a single point t. The appregate data at t is given as the input to predict the power value of one of the appliance at time t [31]. Then, the disaggregated appliance data is labeled by event detection for the data analysis.

4.3 Energy Data Analysis and User Behavior Analysis

4.3.1 Events Detection

According to the literature review in Section 3, the operating status of the appliance is related to the output power consumption, and the on-power threshold is the critical parameter. In previous studies [27] [44], an appliance is considered working when the output power consumption exceeds an on-power threshold. In our work, the above principle is adopted to detect the device's state. Given $W(i)$ is the on-power threshold of the appliance i, p_t^i is the aggregated power of the appliance i at time t. $p_t^i \geqslant W(i)$ indicates that the appliance i is being "ON" state at time t. In other words, events will not be detected if $p_t^i < W(i)$. Note that, both single-state appliances and multi-state appliances can perform event detection with this method. Then, the energy usage patterns of different users can be obtained by analyzing the energy consumption behavior of individual users.

4.3.2 Analyzing the power consumption for different appliances

To understand how the energy consumption of a whole house changes along with that of the individual appliances, more detailed energy data analysis is essential. In this section, we analyze the power consumption of different appliances in different time windows. As shown in Fig. 2, the individual power consumption of each appliance can be obtained after energy disaggregation, and then the energy consumption data can be split into several small time windows to observe its energy consumption changes in different time slots (see Fig. 3). The energy consumption of appliances in each time window can be calculated separately to form the total energy consumption in units of the given time window.

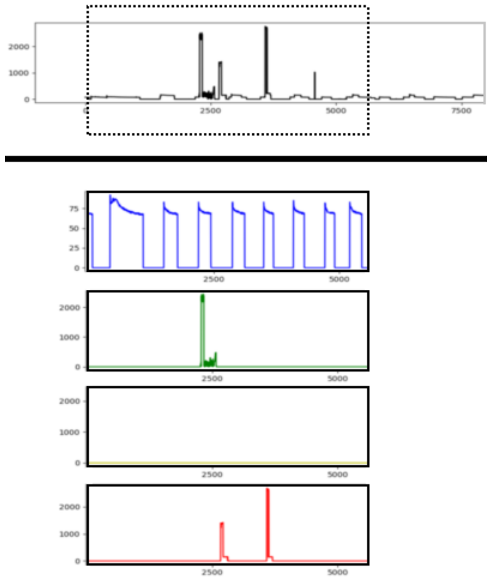


Figure 2: Energy Disaggregation for Different Appliances.

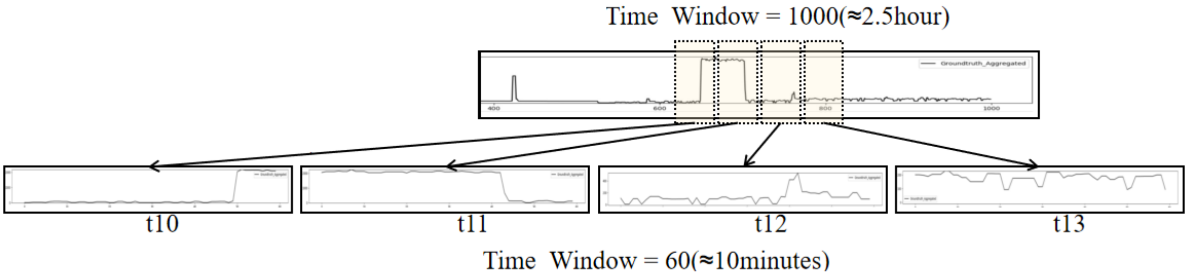


Figure 3: Analyzing the power consumption in different time windows.

5 Datasets

5.1 Public Datasets of Power Consumption

There are some existing studies for energy disaggregation, which adopt supervised Machine Learning methods [13] to pursue high accuracy. That is, they rely on the labelled dataset with device signatures for training the model, and then the trained model can be used for energy disaggragation of the unlabelled data. Some studies are focusing on collecting dataset for energy monitoring [29] [5] [7] [33] [8] [40] [27] [10] [23] [28]. These datasets are compared in Table 3, and some public datasets are available for researchers to develop new algorithms or as a test benchmark.

The release of these datasets, especially some large-scale labelled datasets, accelerate the development of many ML algorithms for energy disaggregation and power consumption analysis, e.g., supervised machine learning and deep learning. For example, Neural Networks and Deep Learning have been proven to outperform the previous algorithms (e.g., HMM) [24]. These datasets with detailed labels can be used as training datasets, testing datasets and benchmarks to train ML models, evaluate model's performance, and compare energy-disaggregation algorithms.

5.2 Data Format for Energy Disaggregation

Generally, there are two types of sample data.
(1) One is high-frequency sampling data, which is usually the collected current and voltage current waveforms. These raw data can be converted to the power metrics using Short-time Fourier Transform (STFT) [23], i.e., real and reactive power with a time series. See the equations below:

$$P_k(t) = |I_k(t)| \cdot \sin(\theta(t)) \cdot |V_1(t)|$$
$$Q_k(t) = |I_k(t)| \cdot \cos(\theta(t)) \cdot |V_1(t)|$$

in which P_k is the real power, Q_k is the reactive power, I_k is the k^{th} harmonic component of the transformed current waveform, and V_1 is the first harmonic component of the transformed current waveform. Note that the current and voltage sampling rates are usually 12kHz, while the processed power metrics are 60Hz.
(2) Another is low-frequency sampling data, collected from individual smart plugs,

Table 3: Comparison of several disaggregation datasets [23]

Dataset	Location	No.of units	Duration	Aggregate Rate	Appliance Rate	Labeled	Year
REDD [29] http://redd.csail.mit.edu	USA	6	3-19 days	1Hz&15kHz	1/3 Hz	No	2011
BLUED [5] http://portoalegre.andrew.cmu.edu:88/BLUED	USA	1	8 days	12kHz	-	Yes	2012
Smart* [7] http://traces.cs.umass.edu/index.php/Smart/Smart	USA	3	3 months	1Hz	1Hz	No	2012
AMPds [33] http://ampds.org/	Canada	1	1 year	1/60 Hz	1/60 Hz	No	2013
iAWE [8] http://iawe.github.io/	India	1	73 Days	1Hz	1Hz	No	2013
SustData [40] https://osf.io/2ac8q/	Portugal	50	4-17 months	50 Hz	2s/3s	No	2014
UK-DALE [27] https://data.ukedc.rl.ac.uk	UK	4	3-17 months	16 kHz	1/6 Hz	Yes	2015
SmartSim [10] https://github.com/klemenjak/smartsim	-	1	7 Days	-	1 Hz	-	2016
REFIT [37] https://www.refitsmarthomes.org/datasets/	UK	20	2 years	-	8-10s	Yes	2017
EMBED [23] http://embed-dataset.org/	USA	3	14-27 Days	12 kHz	1 Hz	Yes	2018
SynD [28] https://github.com/klemenjak/synd/	-	1	180 days	-	5 Hz	-	2020

smart meters, ambient sensors (e.g., light intensity sensors [3]), or WiFi modules. The plug load sampling rate is usually 1∼2 Hz.

Datasets with event labels would be very beneficial for energy disaggregation, as they can serve as a benchmark for model evaluation. However, collecting labelled datasets is not easy because the labelling process is often very costly, which requires a lot of human resources, resources, and time, including the need for pre-installing sensors or electricity meters to collect raw data, recording events to mark the state changes of the appliance on the electricity consumption time series, taking a long time to record enough events for analysis. In [3], researchers have to manually label the detected event according to occupants' written diaries, which record daily activities and related electrical devices with timestamps. It can be said that collecting labelled data used to be one of the biggest challenges for energy management. Therefore, some researchers are dedicated to collecting, labelling and publishing datasets for energy disaggregation - today, we have some public datasets available for direct use [5].

REDD [29] is a freely available dataset, collected from 10 families with a total of 119 days. It records the electricity consumption of the whole house at a high frequency (15kHz), in which there are up to 24 individual circuits in a home. Each circuit device operates at 0.5 Hz. The data and code is publicly available on the web: http://redd.csail.mit.edu.

UK-DALE [27] is also an open-access dataset, which collects whole-house energy consumption (16 kHz) and appliance-by-appliance energy consumption (1/6 Hz) from five UK homes. In this dataset, house 1 is recorded for up to 655 days, which is the longest duration of all available public datasets so far. Besides, the switching status of the device is fully recorded. Thus, the datasets can be used to further analyze user behavior. The dataset is available from https://jack-kelly.com/data/.

EMBED [23] is a public dataset for Energy Monitoring released in 2018. The data is collected from three apartments in Los Angeles, California, with fully labels of power measurements (i.e., aggregate power data and plug load data). In particular, appliance events are distinguished and labeled via different power sockets, which guarantees the fairly high accuracy of this dataset. In contrast to the previous datasets, EMBED's contributions include containing fully labeled appliance events and plug consumptions for appliances that could be connected to power sockets. Some follow-up studies, such as self-configuring event detector for building electricity monitoring [2] are performed based on this dataset. The dataset is available for download at http://embed-dataset.

org/. More other datasets are listed in Table 3.

5.3 The Testbed and Data Acquisition

One outcome of the project is to build a small-scale IoT-based network for power consumption data collection at the home/office, which has been done in collaboration between Deakin University and Unico Enterprise Services Pty Ltd (UNICO) company, which is an Australian technology consultant and systems integrator, focusing on technology innovation through IT solutions. The testbed consists of three Smart plugs with ZigBee connectivity, one gateway, and an AWS-based cloud server, as shown in the Fig. 4. Specifically, three smart plugs are matched to the gateway and establish communication connections through the ZigBee connectivity. The energy raw data (e.g., instantaneous power and energy consumption data) is collected at a sampling frequency of 15 minutes and uploaded to the cloud server, as shown in the Fig. 10. This testbed consists of a low-cost and flexible wireless architecture based on smart plugs that can collect energy consumption data in small-scale IoT networks (e.g., officies).

(a) Smart Plug (b) Smart Plug (c) Gateway

(d) Testbed

Figure 4: Data Acquisition Equipment.

6 Results & Discussion

6.1 Use Case Scenarios and Experiment Settings

Since the project time is limited and the data acquisition is a time-consuming task, We design a use case scenario (i.e., device-sharing environment by multi-users) to generate simulated data and use it for a proof-of-concept. We assume that there are three users ($User1$, $User2$, $User3$) and four shared appliances ($A1$, $A2$, $A3$, $A4$) in the room (see Fig. 5). Given several periods, $T1, T2, T3, T4$, the correspondence between the user and the device usage is as follows: $User1 \rightarrow A2\&A4$, $User3 \rightarrow A4$, $User1 \rightarrow A2\&A4$, $User2 \rightarrow A3$. We selected four representative appliances based on one of the public datasets, REFIT, collected in a real-world setting, to simulate the energy consumption data. Then, supervised Machine Learning methods were adopted [13] to pursue high accuracy. The simulated datasets include the aggregated energy consumption on the total circuit and individual power consumption for different appliances on the branch circuit as the ground truth. Specifically, all four appliances have different power usage patterns, such as the freezer with periodic output energy consumption (i.e., $A1$), the dishwasher triggered by an activity (i.e., $A3$), the microwave with multi-modes (i.e., $A4$), and washing machines with multi-state operations (i.e., $A2$). Fig 6 visually shows an example of the simulated data.

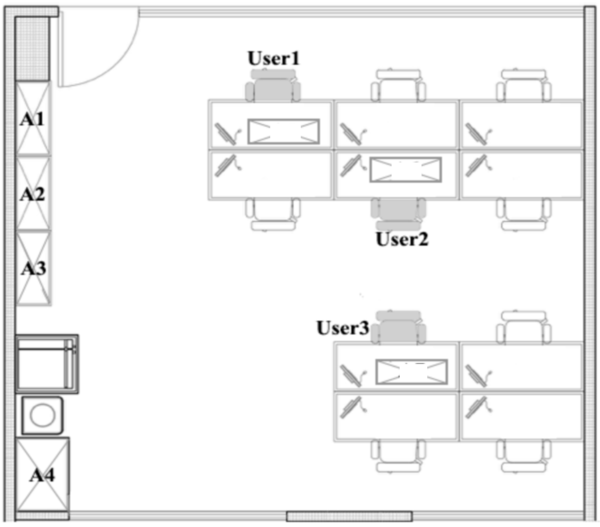
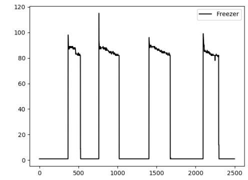
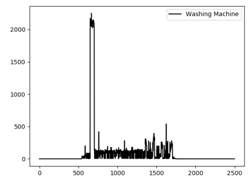


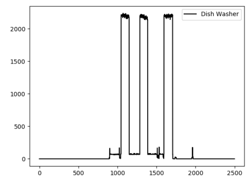
Figure 5: A Use-case Scenario for Device Sharing environment by Multi-users.



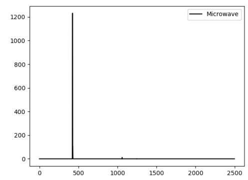
(a) Freezer



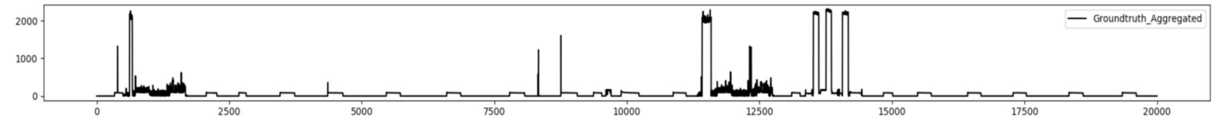
(b) Washing Machine



(c) Dish Washer



(d) Microwave



(e) Aggregated Data

Figure 6: An example of the simulated data.

The experiment uses simulated datasets. All experiments are performed on the same dataset and evaluation metrics for comparison purposes. For the Seq2Point learning paradigm [44], the Mean and standard deviation of each appliance need to be calculated from the overall dataset for normalization, and the transformed data is used as input for training different machine learning models. The parameters used are listed in Table 4. In the original Seq2Point method, an input window of 1 hour to infer a single point. In this experiment, the length of the input vector is set to 60 samples, corresponding to a 10-minutes time window. All the experiments are based on Python and Matlab implementation. Although different input sizes may affect the performance of the different appliance models, the experiment used the same settings (shown in Table 5) to compare the results of different algorithms.

Table 4: Parameters for Normalization and Event Detection

Appliances	Mean	Standard Deviation	On-Power-Threshold
Fridge	34	45	10
Dish Washer	48	312	200
Microwave	3	60	200
Washing Machine	20	185	20

Table 5: Parameters for modeling

Train Datasets	Test Datasets	Time Window	Batch Size	Sample Rate	epochs
400,000	200,000	60	1000	10s	20

6.2 Evaluations Matrics

There are two evaluation ways for this project, which correspond real-time energy disaggregation and usage pattern analysis. In particular, the loss is measured by Mean Absolute Error (MAE) and Normalised Signal Aggregate Error (SAE), and events (i.e., on/off) detection is evaluated by Precision, Recall and F1-Score. Moreover, the effectiveness of the energy data analysis is verified by the benchmark. These metrics are as follows:

$$MAE = \frac{1}{T} \sum \left| y_t^{'} - y_t \right|$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

where T means the length of the test timeseries; y_t means the real power consumption at time t; $y_t^{'}$ means the estimated power consumption at time t; TP means the number of true on detection; FP means the number of false on detection; FN means the number of false off detection.

6.3 Performance and Discussion

6.3.1 Result 1: real-time energy disaggregation

The results show that the proposed method, RNN(Seq2point), outperforms other methods in the comprehensive performance, shown in Table. 6. The partial result is visualized in Fig. 7.

Table 6: MAE of Power Consumption Value Prediction.

Methods	Freezer	Washing Machine	Dish Washer	Microwave
Ours	6.2	11.16	10.0	2.3
RNN(Seq2Seq)	38.4	18.4	23.8	14.5
WaveNet [24]	20.9	3.1	10.3	3.7
CNN [44]	24.5	5.0	21.0	4.0

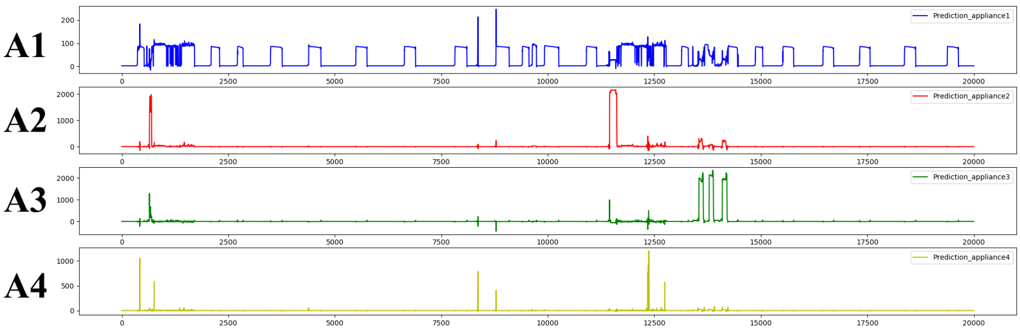


Figure 7: Real-time Energy Disaggregation for Different Appliances.

6.3.2 Result 2: Event Detection and Energy Usage Pattern Analysis

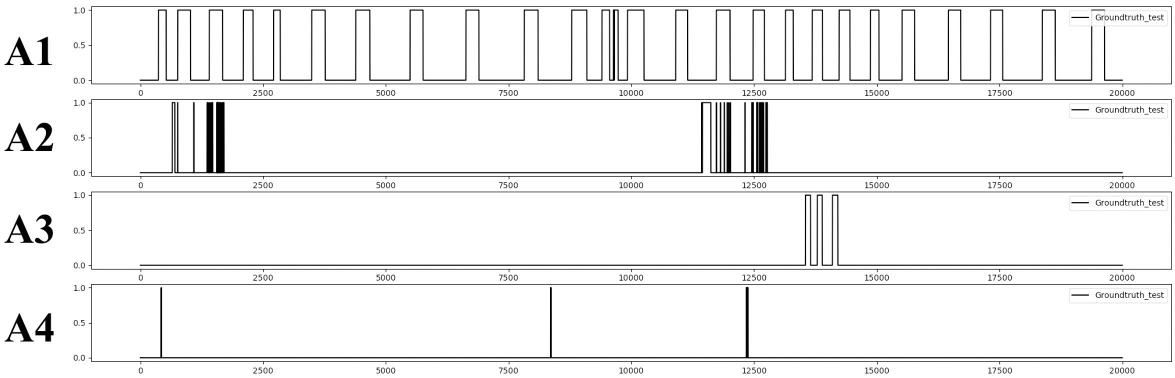
The comparison experiment is performed between the proposed method and the most related one, shown in Table 7. The proposed method outperforms the counterpart in terms of precision, recall and F1-Score. The results is visualized in Fig. 8.

Table 7: Events Prediction Performance.

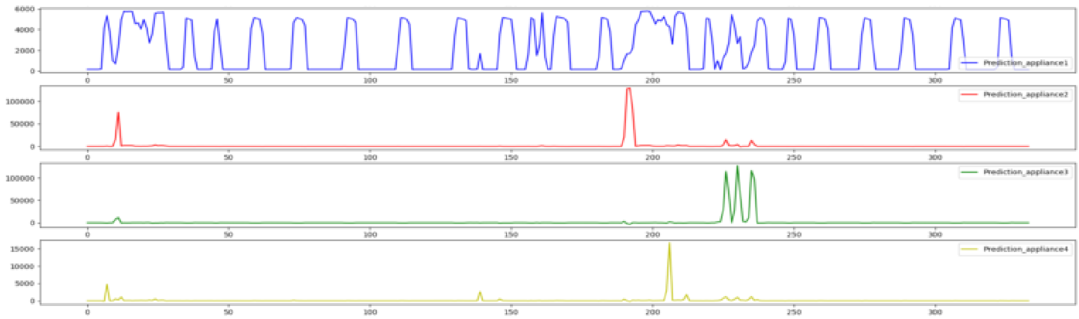
Metrics	Learning Paradigms	Freezer	Washing Machine	Dish Washer	Microwave
Precision	Ours	95%	53%	74%	89%
	Seq2Seq	85%	25%	73%	54%
Recall	Ours	98%	82%	100%	89%
	Seq2Seq	98%	73%	87%	83%
F1-Score	Ours	0.96	0.64	0.85	0.89
	Seq2Seq	0.88	0.38	0.79	0.66

6.3.3 Result 3: Analyzing power consumption patterns for users.

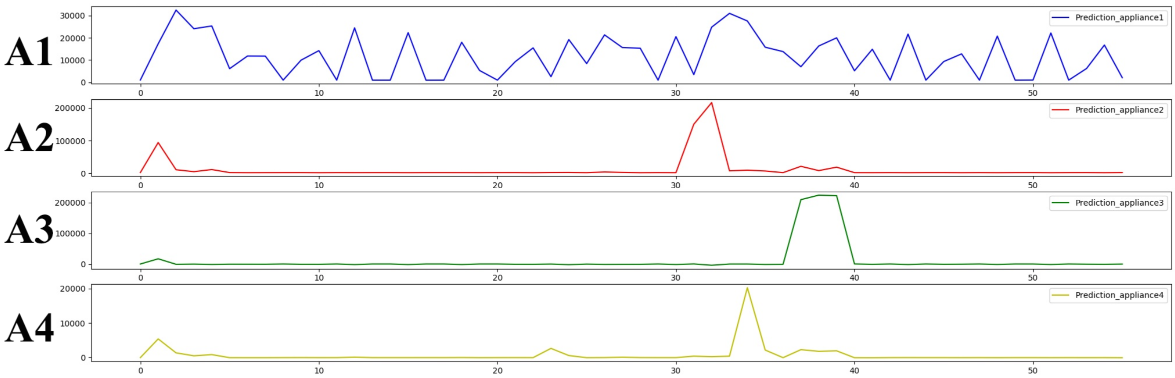
The results show the proposed method can accurately disaggregate the power consumption for different users by analyzing the individual behavior. The partial result is visualized in Fig. 9.



(a) Event Detection and Labels.



(b) Energy Usage Pattern when Time Window = 10minutes.



(c) Energy Usage Pattern when Time Window = 1hour.

Figure 8: Event Detection and Energy Usage Pattern Analysis.

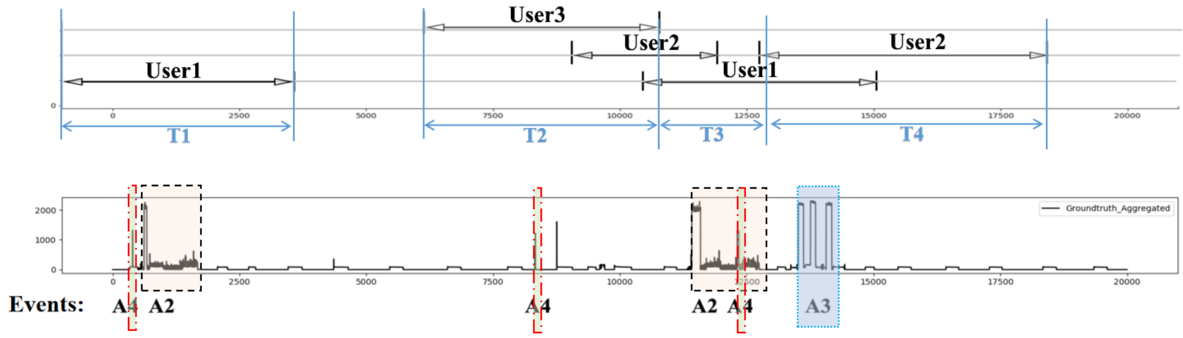


Figure 9: Analyzing Power Consumption Patterns for Different Users.

The corresponding between the users and the appliances at different time segments is consistent with the ground truth.

T1: $User1 \rightarrow A2\&A4$

T2: $User3 \rightarrow A4$

T3: $User1 \rightarrow A2\&A4$

T4: $User2 \rightarrow A3$

7 Conclusion & Future Work

7.1 Key Findings

7.1.1 Project Outcome

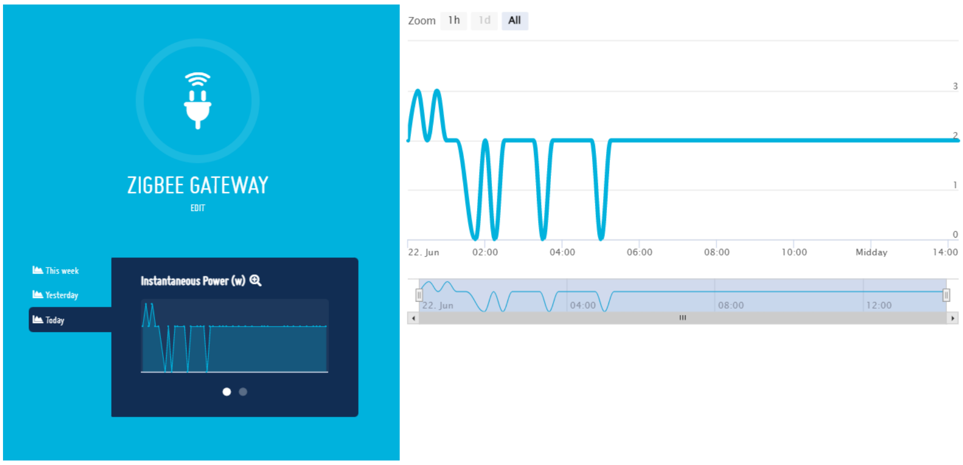
1. Building a low-cost, flexible wireless architecture: a scalable wireless architecture IoT network with a varying number of smart plugs is built to allow real-time data analytic. The testbed is based on UNICO/CarbonTrack Gateway, and Smart plugs with ZigBee connectivity. the data collection from the cloud server includes total energy consumption data collection and individual power data monitoring. See Fig. 10

2. Energy data analytics with unlabelled smart plug data: local ML models are developed to label the data based on simulations, including training ML models using labels for energy disaggregation and analysing the power consumption of different appliances in different time windows. See Section 6.

3. Framework for smart energy consumption based on the analysis of each individual and the energy usage pattern, which can support informed real-time to guide smart energy project proposal consumption. See Fig. 11.

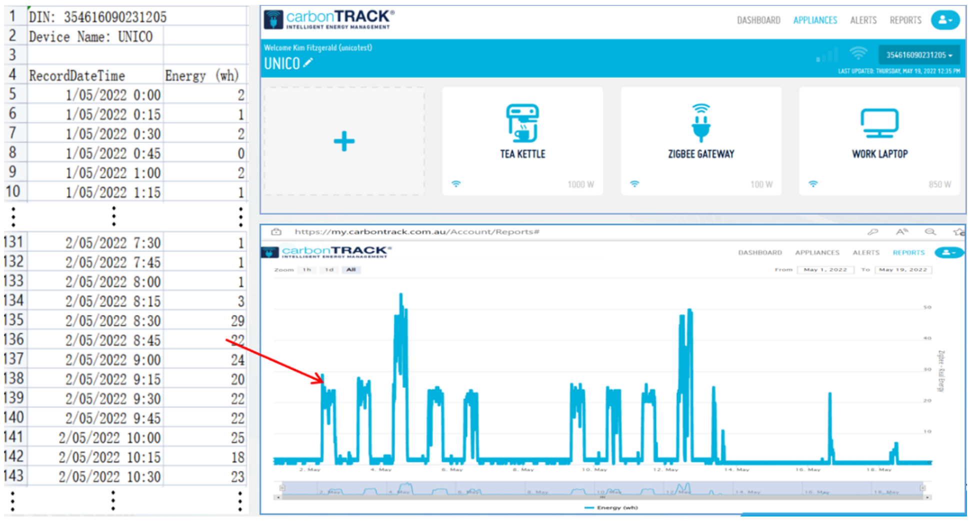
7.1.2 Other Research Findings

To solve the problem of poor accuracy in predicting energy disaggregation values, the key is to develop new algorithms to improve the performance (e.g., accuracy or efficiency). The ability to extract features in deep learning algorithms (e.g., RNN) is helpful to screen data features, especially since RNN has a higher accuracy when processing power parameters with time series. Seq2point learning is more efficient than seq2seq learning for extracting output features and with a smaller amount of calculation. Some preliminary information can be helpful for labeling data and



(a) Individual Instantaneous power data monitoring.

(b) Individual Energy Consumption Data monitoring.



(c) Total Energy Consumption Data collection.

Figure 10: Data Collection from the cloud server.

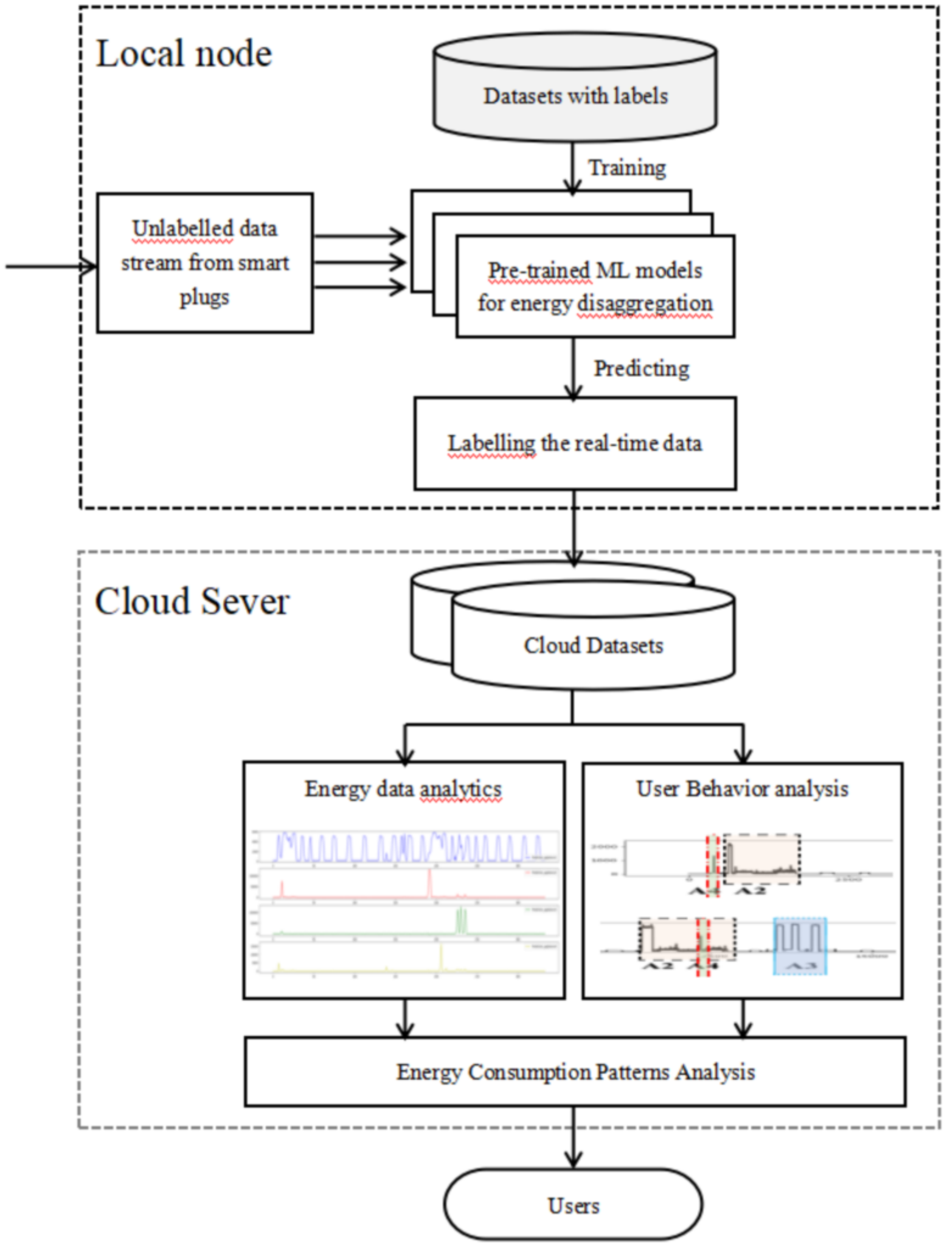


Figure 11: A framework for small-scale home/office energy management.

improving the estimation accuracy, e.g., the number of users, types of appliances, etc. [36]. The algorithm designed is expected to enable accurate energy disaggregation in real-time by power consumption datasets collected by low-cost IoT networks.
To identify the load, appliance signatures can be considered as the main feature of distinguishing different devices.

7.2 Future Work

7.2.1 Edge Computing for Energy Prediction Systems

In this project, we have focused on a local (home) energy management server that performs energy disaggregation and user behaviour analysis locally using models trained by local datasets. However, if a network of local servers can be formed, each local server can be seen as an edge computing device. In this case, a lot of novel tasks can be carried out with a wide range of datasets that can be collected from connected local servers. For example, suppose that the energy price can be dynamically adjusted according to the demand. Then, it is important to predict the amount of energy consumption locally and globally. To this end, there are a few issues to be considered as follows.

- Each local energy management server can be seen as a device or machine and be connected through wireless channels, e.g., cellular systems. In this case, massive machine-type communication (MTC) technology can be used to support their connectivity [1] [9].
- For dynamic pricing [22], it is necessary for each local energy management server to send its predicted energy consumption. While it is possible to use a local model for predicting energy consumption, it would be more beneficial to consider a global model that can be trained with more data sets of other local energy management servers. To this end, we can consider federated learning [30] [32], which does not require to exchange data sets for privacy issues, but parameter vectors. When MTC protocols in cellular systems, e.g., 5th generation (5G) systems, are used, federated learning can be efficiently implemented by taking into account the norm of the gradient vector in random access [12].

- In addition, as in [17], each local model at a local energy management server can be trained with local datasets as well as those in other local energy management servers for a better energy disaggregation performance. In addition, a global model for dynamic pricing can be considered with all the data sets stored at local local energy management servers.

7.2.2 Appliance Signature Analysis for Identification Systems

According to the literature review in Section 3, the early NILM technology focused on computing the energy consumption of individual appliances based on estimating the operating state of major appliances in the total load [19]. That is, the characteristics of the appliance (e.g., the real and reactive power) are used as unique “signatures” for each appliance, and devices can be discerned from the aggregated data [45]. The appliance signature can be used for the appliance identification system. Since the appliance signature describes the output power characteristics of different appliances, it can play more roles in the smart grid system, such as:

- Appliance classification:
  One of the most common use-cases of energy disaggregation is appliance classification. Future research aims to extend the capabilities to accurately identify different models of each appliance categories, their possible energy ratings, and other properties.

- Faulty device diagnosis:
  Disaggregated energy profiling of appliances can help early identification of faulty devices. If one or more functionalities of any device is not working properly (e.g., device is not going in hibernation or sleeping mode), it will be captured by its individual consumption profile. Remedies taken from such action can help to diagnose the technical problem and long time cost savings.

7.2.3 Other Potential Use Case Scenarios

- Occupancy Monitoring:
  Disaggregated energy patterns will help to monitor the occupancy probability remotely. This use-case related to occupancy monitoring by activity recognition can be of great use for critical applications in age-care and medical facilities,

children monitoring or remote occupancy identification in conference/meeting rooms, etc.

- User psychology and cognitive behavior analysis:
  Energy usages patterns tell a lot about the habits and behavior of an individual. Authors in [4] employs the energy disaggregation algorithms to detect the abnormal user activities within aging population.

- Context-aware smart systems:
  Energy profiling can help in providing additional context information for smart systems that can react and respond to changing situations in the home or office.

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