REPUBLIC OF TÜRKİYE

AKDENİZ UNIVERSITY

DEVELOPING AN UNSUPERVISED METHOD FOR APPLIANCE-LEVEL ENERGY DISAGGREGATION

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INSTITUTE OF NATURAL AND APPLIED SCIENCES

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MASTER OF SCIENCE THESIS

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This thesis was accepted unanimously by the jury on 12/06/2025.

Prof. Dr. Melih GÜNAY (Supervisor)

Assoc. Prof. Dr. Hamza Feza CARLAK

Asst. Prof. Dr. Kamer ÖZGÜN

ÖZET

CİHAZ SEVİYESİNDE ENERJİ AYRIŞTIRMA İÇİN GÖZETİMSİZ YÖNTEMLERİN GELİŞTİRİLMESİ

Şirin AZAZİ DEVECİ

Yüksek Lisans Tezi, Bilgisayar Mühendisliği Anabilim Dalı
Danışman: Prof. Dr. Melih GÜNAY

Haziran 2025; 43 sayfa

Elektrik tüketimi hakkında detaylı geri bildirimler, kullanıcıları tasarrufa teşvik ederek enerji israfını, dolayısıyla karbon salımını azaltır. Elektrik iç tesisatına bağlı her cihazın tüketimini ayrı ayrı ölçmek yüksek maliyetli ve zordur. Günümüzde birçok elektrik sayacı haberleşme ve dakikada bir ya da daha sık ölçüm raporlama kabiliyetine sahiptir. Geniş bir ölçüm aralığını kapsayan elektrik ölçüm verilerini yük ayrıştırma amacıyla veri madenciliği teknikleriyle işleyip, tesisattaki cihazların ayrık tüketim serilerini tahmin etmek ve kullanıcılara daha zengin geri bildirimler sunmak mümkün olabilir.

Bu tez çalışması ile, düşük ölçüm raporlama sıklığına sahip sayaç verilerine de uygulanabilen, gözetimsiz, hızlı ve kolay anlaşılır bir yük ayrıştırma yöntemi geliştirilmesi amaçlanmıştır.

Yöntem; veri ön işleme, değişim noktası tespiti, özellik çıkarımı, kümeleme ve son işlem adımlarından oluşmaktadır. Bir konuttan üç aydan uzun bir süre boyunca toplanmış elektrik tüketim verileriyle yapılan uygulamada bazı cihazların tüketimleri başarıyla ayrıştırılmıştır. Bulgular, yöntemin kaynakları kısıtlı ortamlarda dahi uygulanabilir ve anlamlı sonuçlar üretebilir olduğunu göstermektedir.

ANAHTAR KELİMELER: Değişim Noktası Tespiti, Kümeleme, NILM, Segmentasyon, Yük Ayrıştırma, Zaman Serisi

JÜRİ: Prof.Dr. Melih GÜNAY
Doç. Dr. Hamza Feza CARLAK
Dr. Öğr. Üyesi Kamer ÖZGÜN

ABSTRACT

DEVELOPING UNSUPERVISED METHODS FOR APPLIANCE-LEVEL ENERGY DISAGGREGATION

Şirin AZAZİ DEVECİ

MSc Thesis in COMPUTER ENGINEERING
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Detailed feedback on electricity consumption encourages users to save energy, thereby reducing energy waste and consequently carbon emissions. However, measuring the individual consumption of each device connected to an internal electrical wiring system is costly and technically challenging. Today, many electricity meters have communication capabilities and can report measurements at least once per minute. By processing electricity meter data that covers a wide measurement range using data mining techniques, it may be possible to estimate the disaggregated consumption time series of individual devices and provide users with more insightful feedback.

This thesis aims to develop an unsupervised, fast, and easily interpretable load disaggregation method that can also be applied to meter data with low reporting frequency.

The method consists of several steps: data preprocessing, change point detection, feature extraction, clustering, and postprocessing. In a case study using electricity consumption data collected over more than three months from a single household, the consumption of certain devices was successfully disaggregated. The findings indicate that the proposed method can be applied even in resource-constrained environments and is capable of producing meaningful results.

KEYWORDS: Change Point Detection, Clustering, Energy Disaggregation, NILM, Segmentation, Time Series

COMMITTEE: Prof.Dr. Melih GÜNAY
Assoc. Prof. Dr. Hamza Feza CARLAK
Asst. Prof. Dr. Kamer ÖZGÜN

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I express my sincere gratitude to my advisor, Prof. Dr. Melih GÜNAY, for his guidance, support, and encouragement. I am deeply grateful for the opportunity to work under his mentorship.

I would also like to thank my family, especially my daughter Defne, for their support and constant encouragement throughout my education and professional life. Their presence has been a source of immense joy and strength to me.

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TEXT OF OATH

I declare that this study "Developing Unsupervised Methods For Appliance-Level Energy Disaggregation", which I present as master thesis, is in accordance with the academic rules and ethical conduct. I also declare that I cited and referenced all material and results that are not original to this work.

12/06/2025

Şirin AZAZİ DEVECİ

SYMBOLS AND ABBREVIATIONS

Abbreviations

AMI	: Advanced Metering Infrastructure
ANN	: Artificial Neural Network
CNN	: Convolutional Neural Network
DCT	: Discrete Cosine Transform
DFT	: Discrete Fourier Transform
DT	: Decision Tree
DTW	: Dynamic Time Warping
FFT	: Fast Fourier Transform
FHMM	: Factorial Hidden Markov Model
FSM	: Finite State Machine
HAN	: Home Area Network
HMM	: Hidden Markov Model
Hz	: Hertz
KNN	: K-Nearest Neighbors
LSTM	: Long Short-Term Memory
NALM, NIALM	: Non-Intrusive Appliance Load Monitoring
NILM	: Non-Intrusive Load Monitoring
PELT	: Linearly penalized segmentation
SAX	: Symbolic Aggregate Approximation
STFT	: Short-Time Fourier Transform
SVM	: Support Vector Machine
WT	: Wavelet Transform
W	: Watt

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1. INTRODUCTION

Energy disaggregation, also known as non-intrusive load monitoring (NILM) or non-intrusive appliance load monitoring (NALM, NIALM), refers to the process of estimating the electricity consumption of individual electrical appliances connected to the same wiring system, using measurements of total consumption typically obtained at the main breaker level. This method is used to determine when appliances are turned on and off, and how much electricity they have consumed during the operating period by distinguishing different consumption characteristics from total consumption time series without the need for installing separate measuring devices for each individual electrical appliance. Power consumption in a wiring system can be expressed as shown in (1.1), where $P(t)$ is a time series representing the total power consumption, which is the sum of the $P_n(t)$ series representing the individual consumption of M appliances and the error ϵ. Disaggregation aims to estimate the time-dependent consumption of devices connected to the wiring system, namely the $P_n(t)$ series, using the total consumption values expressed by the $P(t)$ series, as illustrated in Figure 1.1

$$P(t) = \sum_{n=1}^{M} P_n(t) + \epsilon \tag{1.1}$$

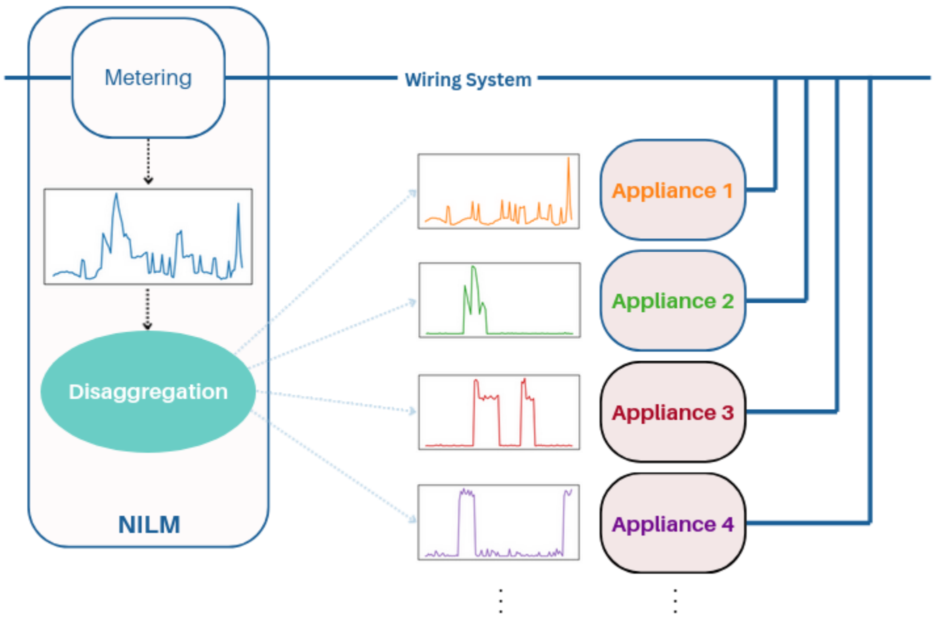


Figure 1.1. Simplified Illustration of NILM Systems

Due to high energy costs and climate concerns, energy efficiency remains a priority. While electrical energy usage in industrial environments is monitored for various purposes, high-resolution energy monitoring systems are not commonly found in residential and commercial settings. The cost of establishing and operating an infrastructure to measure the consumption of each electrical appliance individually can be prohibitively high. However, simply increasing consumer awareness by making electricity consumption visible can encourage more efficient energy use. While real-time premise level measurement data can provide 9.2% savings, this rate can go up to 12% with appliance-level feedback, and when augmented appliance-level feedback is presented to consumers together with associated services such as diagnostics, recommendations, channeling to programs, and marketing, it has the potential to exceed 12% (Armel et al. 2013). More cost-effective and widely applicable energy monitoring solutions can be developed for residential and commercial consumers by augmented appliance-level feedback through disaggregation.

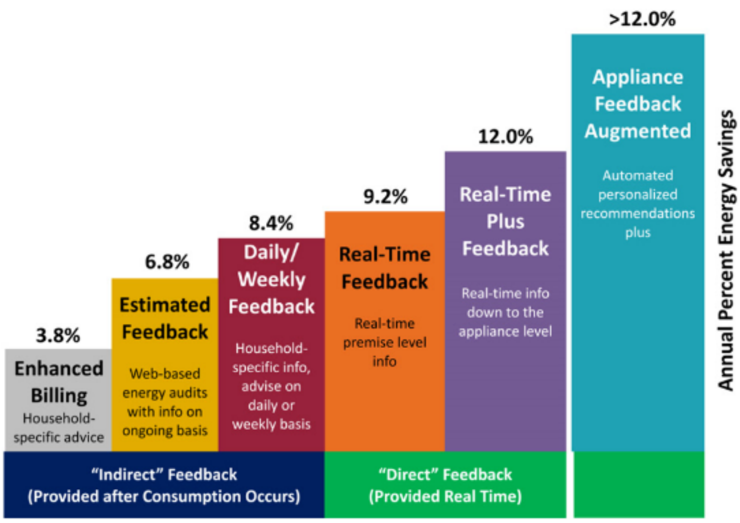


Figure 1.2. Residential savings due to energy consumption feedback (Armel et al. 2013)

There are several non-intrusive load monitoring solutions available in the USA, Europe, and Australia (Guidehuse Inc. 2025;Venture Radar 2025). These products often promise to reduce energy costs, lower carbon footprints, detect anomalies even when users are away from home, and provide personalized insights into electricity consumption for households. Some of these products are also favored by prosumers, who generate electricity by installing renewable energy sources such as solar panels on their properties and sell any surplus energy to electricity distribution companies. Granular energy monitoring and data-driven energy management are becoming increasingly important for consumers, even at the household level. With the growing deployment of connected electricity meters capable of high-resolution recording, utilities and meter manufacturers are also becoming key players in this ecosystem.

In addition to energy efficiency, utilities can also use consumption patterns for audit purposes. Well-recognized consumption data can be leveraged within demand-response mechanisms to enhance the efficiency of electricity production, transmission and distribution systems and contribute to sustainability (Zeifman and Roth 2011; Najafi, Moaveninejad, and Rinaldi 2018). Organizations with distributed branches can utilize this data to monitor human activity, detect anomalies, track savings, and identify potential malfunctions throughout their operations. Another potential use case is applying electricity consumption data for activity monitoring of elderly individuals living alone, especially as the population ages (Alcalá et al. 2017; Chalmers et al. 2020).

Although disaggregation can only be performed using only real power measurements, a more detailed analysis can be achieved by incorporating reactive power and harmonic measurements. Advances in information technology have made it easier to continuously record and monitor electricity consumption in any location. However, recording all electrical parameters of voltage and current with high sampling frequency is still an option that significantly increases costs. High frequency measurements will be needed to capture transitions or sudden changes and distinguish low power consuming appliances. Nevertheless, relatively low frequency data provided by affordable electricity meters can also be used to distinguish large loads (Froehlich et al. 2010). In NILM systems, raw measurements are usually processed in end devices (measurement equipments) and the electrical signal features to be used are transferred to a central information system or cloud, then disaggregation processes are carried out in the information system. However there are also systems where disaggregation processes are also carried out in end devices. Individual consumption characteristics are obtained by processing time series of electrical signal features with optimization, machine learning or deep learning techniques. Naturally, in addition to the benefits they provide, NILM systems can also lead to privacy concerns, especially for architectures where data is transferred to the cloud, as they can provide information about consumer activities and usage habits (Armoogum and Bassoo 2019).

This study aims to develop an unsupervised method for separating different appliance consumption patterns using household electricity consumption data through change point detection and clustering, and to provide a literature review on disaggregation studies and systems. The experiments were conducted using data collected from a household meter over an extended period. Preliminary studies on the subject were previously presented in Azazi Deveci and Günay (2024). The thesis includes a review of the relevant literature, followed by a detailed explanation of the method consisting of preprocessing, change point detection, segment feature extraction, clustering, and postprocessing steps. The results obtained from applying the method to the dataset are then evaluated.

2. LITERATURE REVIEW

2.1. General Framework

Each country has its own electrical installation regulations and the number of phases, wiring methods, and types of device connections used in residential buildings vary according to these (McEachern 2002). Therefore, infrastructure differences should be taken into account when evaluating electrical energy measurement data. In Türkiye, single-phase or three-phase electricity can be connected to residential buildings. However, almost all electrical appliances used in homes have single-phase connections. If a three-phase electrical supply is connected to a residence, the lines and loads are distributed to balance consumption over the phases. For example, the lines of washing machines, dishwashers and other sockets are connected to separate phases (EMO 2023). As another example, in US residences mostly a two-phase circuit is used with balanced or unbalanced ("power consumption is not the same on the two legs") loads which are connected to one or two phases according to the voltage level requirement of the appliance (Hart 1992). In studies using total power consumption, the importance of these differences will be eliminated, since the consumption in all phases will be added up.

Hart (1992) is considered a pioneer in disaggregation studies in which the method is named as "Nonintrusive Appliance Load Monitoring" (NALM) and defined as estimating individual loads and other relevant statistics such as time-of-day variations by analysis of the current and voltage waveforms of the total load and checking for certain signatures which provide information about the activity of the appliances. In the study, the usage cases of NALM are listed as follows, and it is evaluated that the information obtained may be a privacy issue:

- Energy audits of utilities, using the data collected for one week to one month
- Evaluation of the results of measures taken for energy saving
- Failure analysis for appliances
- Detection of movements in the house for security purposes
- Demand-side load management control

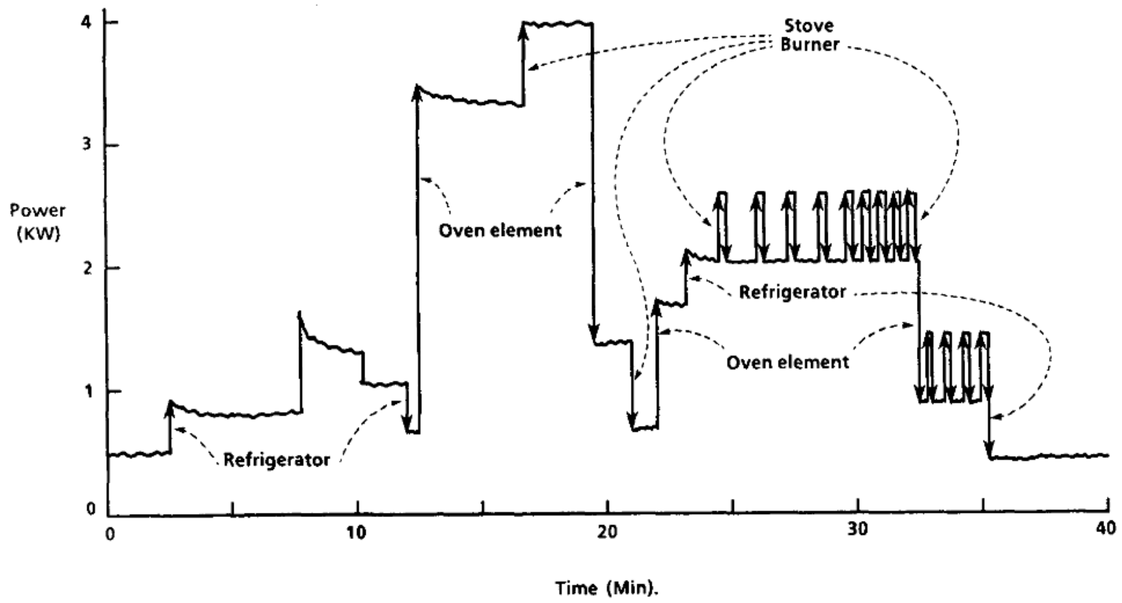


Figure 2.3. Signatures and Step Changes in Total Power Consumption (Hart 1992)

Hart (1992) uses a model-based approach for describing individual appliances and their combinations. While modelling the individual appliances and their combination to decompose the load, appliance models are classified as "ON/OFF", "Finite State Machine" (FSM) and "Continuously Variable". "ON/OFF" model appliances may be either off or a single type of on state such as a toaster or light bulb. During this classification, it is assumed that there is no power generation taking place in the load. To allow multiple discrete states, state transitions and operating power levels, FSM model is defined. Refrigerators with defrost states, three-way lamps, dishwasher or clothes dryer can be modelled as FSM. Continuously variable appliances generalizes the FSM model with an infinite number of states. These appliance models are illustrated as in Figure 2.4

Measurement data frequency of the measurement device is important for capturing signatures of the appliances and directly affects the number of appliances to be recognized during disaggregation (Gopinath et al. 2020). Armel et al. (2013) derived number of appliances identified according to the frequency of measurement data as in Table 2.1. As the sampling rate increases, the cost of the measurement hardware and the NILM system also increases exponentially (Kaselimi et al. 2022). Therefore, a selection should be made based on the number and characteristics of the appliances to be recognized and the aim of the disaggregation process. The home consumption data collected for this study was

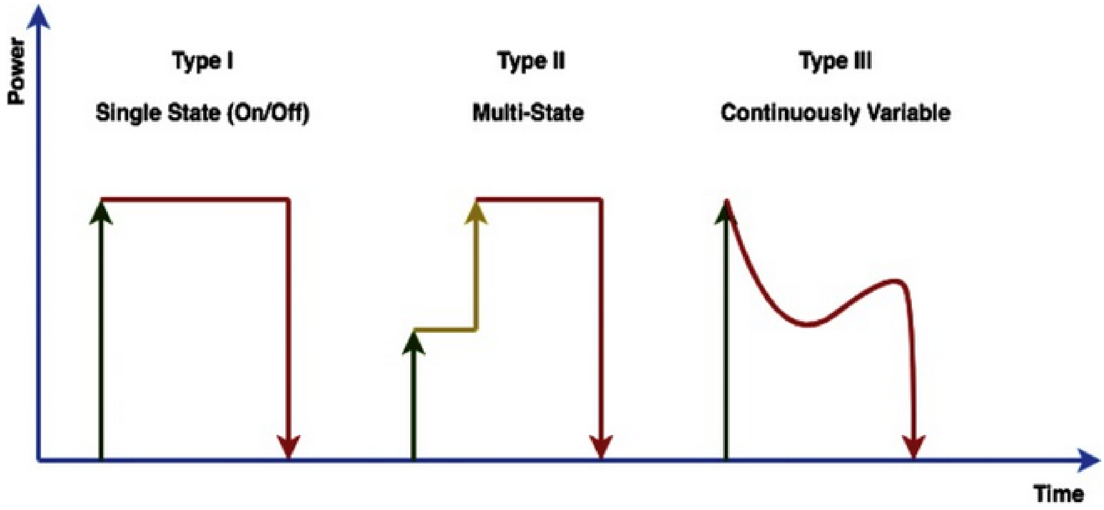


Figure 2.4. Appliance Operating States (Gopinath et al. 2020)

recorded with an electricity meter that can record data at most once a minute. Therefore, we could expect to detect 3-10 appliance consumption patterns, using the data collected.

Table 2.1. Measurement data frequency and appliances identified (Armel et al. 2013)

Data frequency analyzed	**Appliances identified**
1 h–15 min	3
1 min–1 s (1 Hz)	<10
1–60 Hz	10-20
60 Hz–2 kHz	Not known
10–40 kHz	20-40
>1 MHz	40-100

Another important issue besides measurement frequency is the selection of features to be used. Steady-state features, transient features or non-traditional features of the electric signal can be used to define appliance signatures (Hart 1992;Gopinath et al. 2020). Since the majority of commercial smart meters collect data up to 1 Hz (Kaselimi et al. 2022), the most commonly used features are active power, reactive power, current, power factor or statistical data related to them. Of course, meter data quality must also be taken into account and appropriate preliminary data processing must be carried out. Studies have shown that real power and power factor measurement devices that promise 3% accuracy can show large differences ranging from 10% to 20% (Zeifman and Roth 2011). As the sampling rate and spectrum analysis capabilities of the measuring device increase, it becomes possible to use different features obtained from harmonics, transient voltage-current or transformations such as FFT, STFT, WT. Since residential electricity consumption is also related to people's needs, movements and habits, other parameters such as the time of consumption, peak times or other measured environmental values such as temperature and humidity are also non-traditional features that can be evaluated for disaggregation.

2.2. Methods and Algorithms for NILM

Hart (1992) defines load estimation as a combinatorial optimization problem as in (2.2) where $\hat{a}(t)$ is the estimated state of the appliances at time t, which minimizes the error. However, using heuristic algorithms is also advised to have reasonable results, as it is an NP-complete weighted set problem and computationally intractable, and the complete set of $P_i(t)$ is never known or can change depending on user behavior or seasonal changes. The algorithm proposed as a result of the study consists of the following steps: Measuring 1-second power and voltage RMS values, normalizing real and reactive power, listing step changes in data by edge detection, clustering the listed step changes, building the On/Off or FSM appliance models, revealing on and off times of appliances based on the built models, tabulating statistics of energy usage and naming the appliances.

$$\hat{a}(t) = \arg\min_{a} \left| P(t) - \sum_{i=1}^{n} a_i P_i \right| \tag{2.2}$$

When the studies conducted in the following years are examined, approaches to disaggregation methods can be classified as "event-based" or "eventless". (Dash and Sahoo 2022). Event-based solutions performs event detection on various features as current, power, voltage, environmental variables, transient features, statistical features etc. Event detection can be performed using heuristic models, probabilistic models or a matched filters and the performance of disaggregation mostly depends on the event identification steps. This is followed by appliance identification implemented using a library matching, machine learning or an optimization based approach. Machine learning based identifiers like KNN, SVM, ANN, LSTM, CNN, DT, ensembled algorithms like bagging or boosting, fuzzy logic based classifiers etc. do not need maintenance of appliance signature and provide good accuracy, but usually need individual appliance consumption measurements as ground truth data. The eventless approach aims to perform disaggregation utilizing low-frequency data obtained from existing smart meters. Eventless disaggregation uses unsupervised learning algorithms like clustering or HMM, deep learning models like CNN, LSTM or Auto Encoders for blind-source separation and uses a multi-label classification. This approach can be used for all On/Off, FSM or continuously variable appliances and has good scalability and adaptability. On the other hand, this algorithms generally require massive data for training, and handling the data can be challenging for commercial products. As an example to eventless approach, Kelly and Knottenbelt (2015) has researched deep learning approaches for NILM technology by adapting neural network architectures to energy disaggregation using the UD-DALE dataset (Kelly and Knottenbelt 2015b), finding that both neural networks used in the study achieve better scores than combinatorial optimization or FHMM models. Additionally, the study emphasized that these deep neural network disaggregation architectures both generalize well to unseen examples, do not require ground truth data, and training is computationally expensive.

In residences, the load distribution among appliances is neither homogeneous nor balanced. While some appliances switch to the 'On' state multiple times a day, others may operate only a few times a week or even per month. An iterative clustering approach may assist in addressing this challenge. Schirmer and Mporas (2023) mentioned that, in one study, DTW-based iterative subsequence clustering was used to improve the estimates in FHMM, while in another study, an iterative method was employed in which the appliance with the highest consumption was identified at each step and subtracted from the total.

Disaggregation algorithms can be executed on a home area network (HAN) gateway device or cloud (sending the measurement data through the HAN to a computer, smart phone, in-home display, smart phone or directly cloud) , on the smart meter (storing and processing the measurement data, then sending the results to the utility or a HAN gateway) or at the utility's back office (sending the measurement data to utility via an AMI network and performing disaggregation on the utility servers or third parties) (Armel et al. 2013).

Since energy measurements are time series, various time series data mining techniques can be applied during disaggregation processes. Time series data mining techniques can be grouped under the main headings of clustering, segmentation, classification, pattern identification, anomaly detection, motif discovery, trend analysis, forecasting, and visualization (Esling and Agon 2012). Clustering is a mining technique used to find groups in a data set where the distances between group members are minimum and the distances between groups are maximum. Just as time series can be clustered as a whole using methods like Self-Organizing Maps (SOM), Hidden Markov Models (HMM) or Support Vector Machines after defining a distance function, the sequences or time points of the series can also be clustered (Aghabozorgi, Shirkhorshidi, and Wah 2015). Representation methods like DFT, DWT, SVD, DCT, SAX etc. transforms the time series to a lower-dimensional space and extracts the features of the raw signal. As the first step in measuring electrical energy consumption, sampling voltage and current signals, transforming the signal from the time domain to the frequency domain, and calculating RMS and harmonic values using methods like the Discrete Fourier Transform (DFT) on the meter for predefined intervals can serve as an example of this process. While the frequency of the data drops from kHz to Hz and its computational complexity decreases, the key characteristics of the signal are still retained and allowing us to process it effectively. For segmenting the time series data and performing subsequence clustering, change points in the time series data should be determined. Change points can be thought of as the moment that an event occurred, e.g. an appliance starts or stops working, changes steps in an energy measurement time series. Sliding windows approach (growing the segment until it exceeds an error bound), top-down approach (partitioning the time series recursively until stopping criteria met), bottom-up approach (merging the segments starting from a possibly fine approximation) are defined as approaches those can be used for segmentation in Keogh et al. (2004).

In this study, it is aimed to apply an event-based disaggregation approach, detecting change points in the measurement time series, partitioning the time series into segments between the change points, analyzing the changes in segment transitions, performing cluster processes using change point and segment features, and then to obtain disaggregated series using clustered segments and change points. Not all components of the NILM architecture is modeled, but using the measurement data that was recorded by an afford-

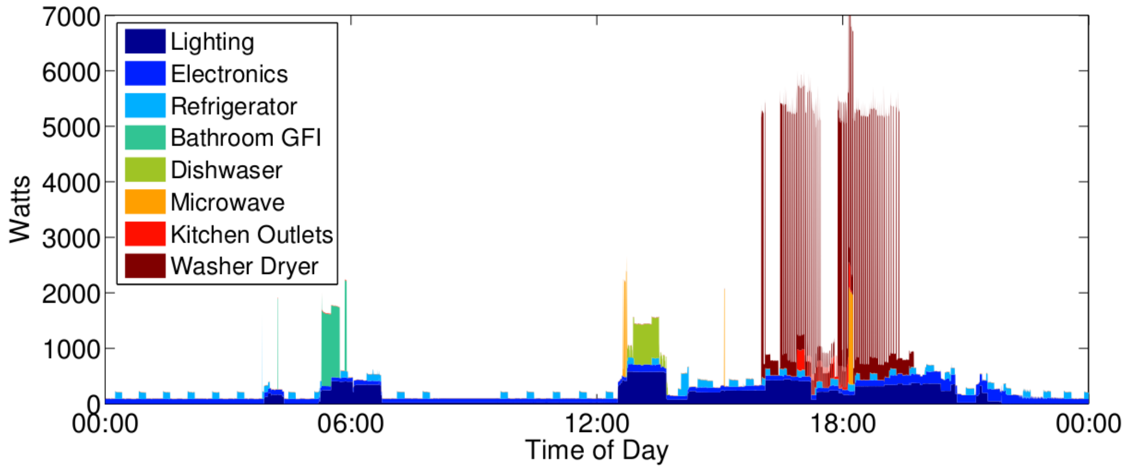


Figure 2.5. Daily consumption of appliances in REDD (Kolter and Johnson 2011)

able on-the-shelf electricity meter, a method is developed to disaggregate the obtained low-frequency measurement data and estimate the individual consumption series of the appliances.

2.3. Open Datasets

In order to conduct NILM research and sustain method development and testing activities, open data sets that include individual appliance consumption as well as total consumption are needed. The Reference Energy Disaggregation Data Set (REDD) is the first and one of the most widely used NILM datasets, containing whole-home and individual appliance consumption data from 24 houses (Kolter and Johnson 2011). In the following years, dozens of datasets —mostly containing residential energy consumption data with various electrical features— were published. Iqbal et al. (2021) examined 42 published datasets, most of which provide real residential consumption data including individual appliance consumption, and discussed the characteristics, strengths and weaknesses, areas of use and difficulties encountered in these datasets. The most important problems identified in the datasets were gaps, insufficient labeling of appliances and contradiction in available data.

2.4. Issues and Challenges

Although the increasing diversity of open datasets and applicable techniques will help to facilitate more NILM research, this area also has its own unique challenges. Some issues and challenges listed in Kaselimi et al. (2022) and (Dash and Sahoo (2022)) can be summarized as follows:

- Adaptability and Generalization Ability: There is a need for techniques that can be generalized to different homes and data sets. NILM techniques often fail to achieve sufficient generalization. Problems with data sets also make it difficult to develop reliable algorithms.

- Identifying less energy-consuming appliances: The variety of low energy consumption appliances and the similarity of some of their consumption characteristics make it difficult to separate their consumption.

- Incorporating User's Feedback: To increase the accuracy of NILM systems, systems must be developed that continuously integrate user feedback and recommendations.

- Providing Explainable Models: In order to increase user confidence, the internal workings and outputs of the models must be explainable and understandable.

- User Privacy Issues: Privacy is an important issue for NILM to address, as electricity consumption can provide data on users' movements and habits, and model development requires large amounts of data.

- Achieving Fairness: NILM systems should be developed taking into account different socio-economic and environmental factors.

3. MATERIAL AND METHOD

3.1. Material

In this study, the electricity consumption of an apartment was recorded at one-minute intervals at the circuit breaker level using a cost-effective electricity meter over a period of several months between October 2024 and January 2025 (Deveci 2025). Statistics of the meter data is given in Table 3.2 and approximate average power values of the appliances int he apartment are as in Table 3.3. Electricity consumption was recorded using an Entes ES3-80LSE electricity meter for approximately 3.5 months, and the recorded data were regularly transferred to a computer via the meter's Ethernet connection interface. ES3-80LSE is a 3-phase electricity meter that can measure active, reactive and apparent energy. The shortest interval at which it can record measurements is one minute. This is considered a very low measurement data frequency (Schirmer and Mporas 2023).

Table 3.2. Statistics of meter data used for disaggregation

	Number of Measurements	**Missing Values**	**Min.**	**Max.**	**Mean**	**Std. Dev.**
Active Power	149814	329	1.78	7032.81	228.276	446.559
Reactive Power	149814	329	-149.65	582.45	77.986	110.826

Individual consumption of electrical appliances was not recorded on a continuous basis. However, in order to provide information about the consumption characteristics of frequently used electrical appliances, short-term recordings were made using Tapo P110 smart plug. The smart plug data was collected using a Python script that utilizes the "python-kasa" library. Some measurements sampled at 1 Hz, as well as their 1-minute resampled versions (1/60 Hz) for a refrigerator, a dishwasher, and a washing machine, are visualized in the Figure 3.6, Figure 3.7 and Figure 3.8. These sample records did not include reactive energy measurements of the appliance consumptions. Resampling was performed to provide insight into the potential data losses and the characteristics of the data we may encounter when using meter readings with a 1-minute sampling interval. As illustrated in these figures, 1-minute resampling leads to the loss of some fine-grained

Table 3.3. Electrical appliances in the apartment and power ratings on their labels

No	Appliance	Power	Reactive Load
1	Refrigerator	100-150	Inductive
2	Dishwasher	2000-2400	Inductive
3	Washing machine	500-2300	Inductive
4	Hair Dryer	2200	Inductive
5	Oven	790-3300	-
6	Air conditioner	1090-1115	Inductive
7	Oil-filled radiator 1	2300-2730	-
8	Oil-filled radiator 2	2000	-
9	Water Heater	1950	-
10	Kettle	1800	-
11	Iron	3000	-
12	Vacuum Cleaner	750	Inductive
13	TV	193	Capacitive
14	Charge Adapter 1 (Laptop)	65	Capacitive
15	Charge Adapter 2 (Mobile Device)	10	Capacitive
16	Modem	35	Capacitive
17	Access Point	15-30	Capacitive
18	LED Lights	5-20	Capacitive
19	Incandescent bulb	150	-

information regarding the energy consumption of the appliances. For example, when the refrigerator starts operating, it draws nearly 1000 W of power instantaneously, however this consumption rapidly decreases and stabilizes at a steady-state level. In the 1-minute resampled measurements, although a spike is still observed at the activation point, it appears at a much lower level, reflecting a smoothed version of the actual consumption profile. A similar situation is observed for the dishwasher and washing machine consumptions, where certain step changes and spikes are lost due to resampling. While this smoothing effect may be considered a form of preprocessing in approaches based on average consumption, it results in a loss of information in scenarios where more detailed feature extraction from segments or finer-grained disaggregation is required.

In the first studies, a low resolution, preprocessed and partial versions of the REDD data set (Kolter and Johnson 2011, Inesylla 2025) and the ENERTALK (Shin et al. 2019) dataset were tried to be used for verification purposes. However, these datasets have a measurement data frequency above the measurement resolution targeted by the study. The original version of the REDD dataset is no longer accessible, and the accessible version does not include reactive consumption. The ENERTALK dataset sampled the measurement data at a frequency of 15 Hz, which is higher than the rate targeted by the study. There are not enough data on the data quality of the ENERTALK dataset, and the size of the data causes difficulties in processing it with the existing development and test equipment used in the study. Therefore, in the following phases, methods were developed and tested using the data collected within the scope of the study.

Throughout the study, a laptop that has an i7-1255U processor, 12 CPUs, and 16 GB of RAM was used for data processing, method development, and testing activities. The proposed method was implemented and tested using Knime, Python and Jupyter Notebook. The development process used the following libraries: Pandas for data manipulation, NumPy for numerical operations, Ruptures for change point detection, and Matplotlib for data visualization.

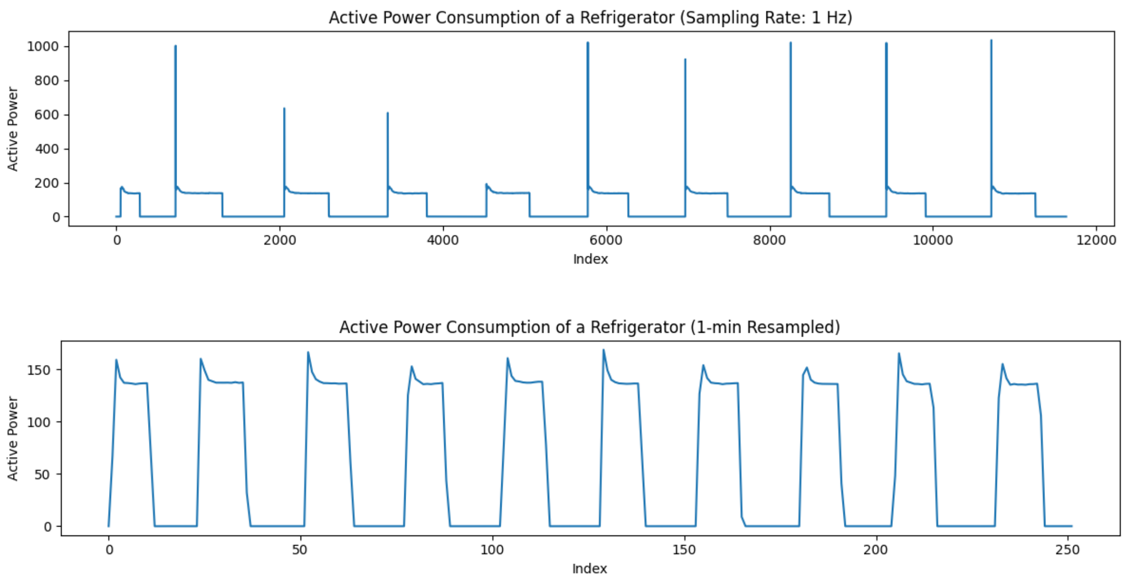


Figure 3.6. Active power consumption of a refrigerator

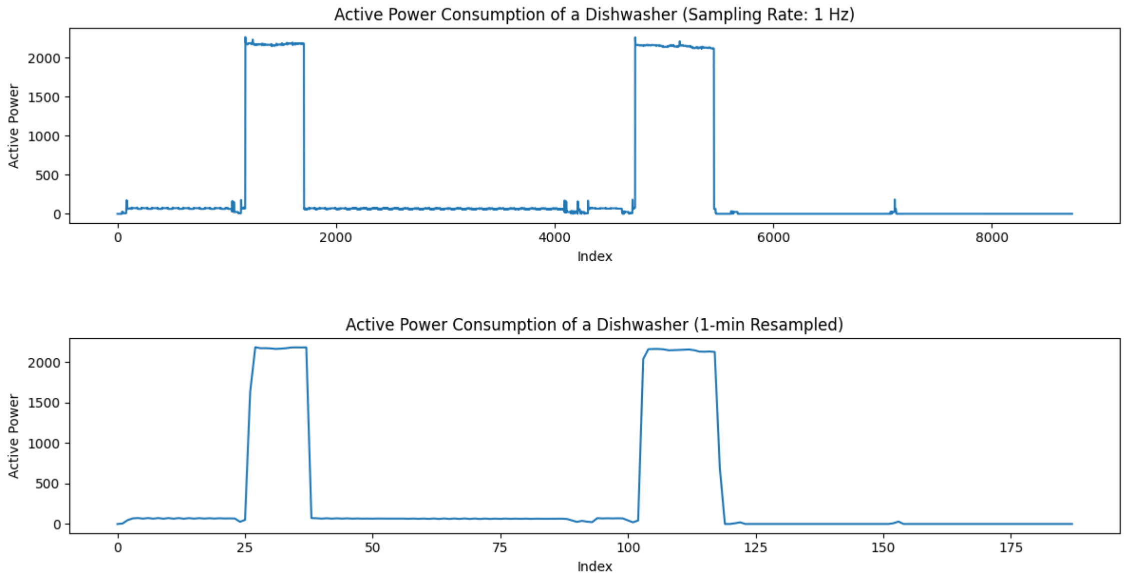


Figure 3.7. Active power consumption of a dishwasher

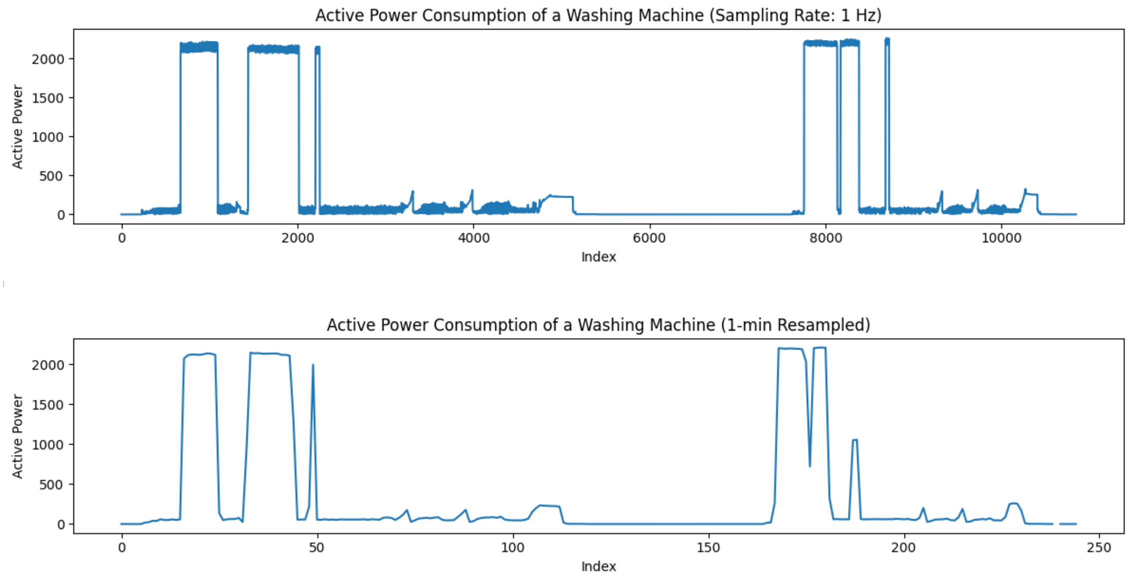


Figure 3.8. Active power consumption of a washing machine

3.2. Method

The collected measurement data, which has a measurement data frequency of 1/60 Hz (once a minute), was processed using a series of methods that can be grouped into five main categories, as summarized in in Figure 3.9.

The process steps and short descriptions used in the method are listed below:

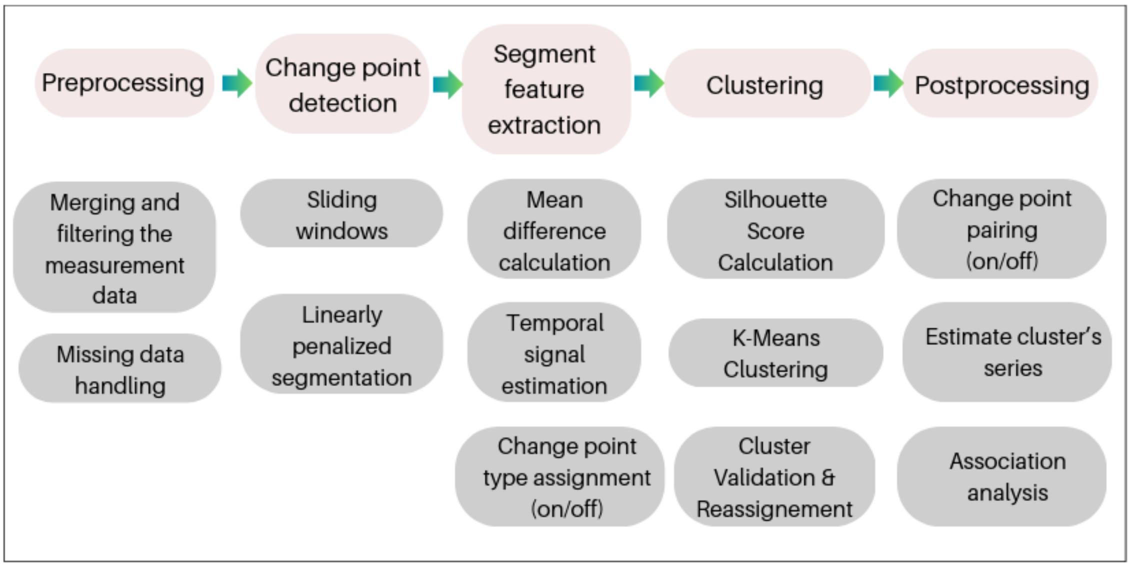


Figure 3.9. Segmentation and Clustering Method

- Preprocessing: Preprocessing includes merging the measurement files taken from the electricity meter, filtering the measurements to be used, missing data handling, removing duplicates, sorting etc.

- Change Point Detection: Performing change point detection by moving sliding windows across the data and using these change points to define segments.

- Segment Feature Extraction: For each segment, predicting the continuation of the signal from the previous segment, estimating the average active and reactive consumption values and their corresponding time series for the current segment, calculating the consumption change, and classifying the segment as On or Off based on this change.

- Clustering: Calculating the Silhouette Score and determining the most appropriate number of clusters for clustering, applying K-Means clustering, cluster validation and reassignment

- Postprocessing: Change point pairing, estimating clusters' series, association analysis, cluster activity analysis

Studies on the subject were started by generating synthetic signals with different heights, widths, off-time repetition frequencies, offsets and signal characteristics (square, saw, etc.), aggregating these signals and testing the method using aggregated signal data. This kind of start facilitated the initial coding of the method, the design of the data structures to be used throughout the process, and the preliminary testing of the method in its simplest form, free from data-related complications. Subsequently, development and testing proceeded with the preprocessed, partial (e.g. daily measurements of a house) (Kolter and Johnson 2011, Inesylla 2025) and the ENERTALK (Shin et al. 2019) datasets, and was later carried out using data collected from a residential environment.

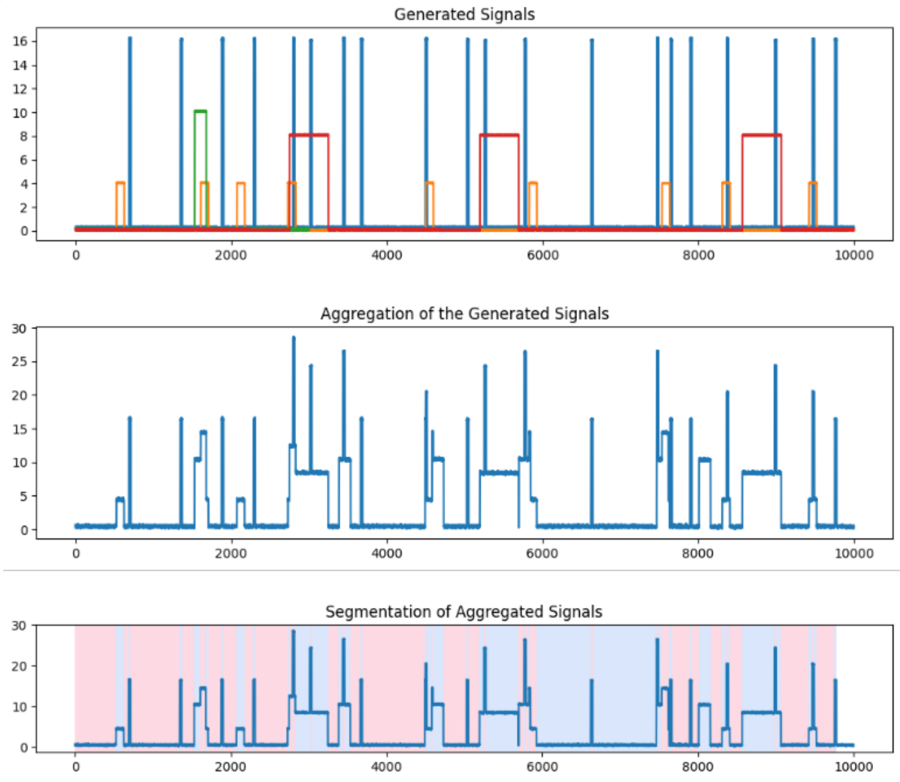


Figure 3.10. Early Studies on Generated Signals

During the implementation of the method, the "numpy" library was used for storing, processing and feature extraction of signal sequences, the "pandas" library was used for storing and processing segment features in a dataframe, the "matplotlib" and "seaborn" libraries were used for visualization.

3.2.1. Preprocessing

The electricity meter used provides the measurement data in spreadsheets files consisting of two seperate sheets. One of the sheets contains summary information, while the other contains measurement details. Voltage and two-way current, energy, power parameters are measured by the meter, and the average consumed power data is used in the study. As the amount of data recorded in the meter increases, the transfer time becomes excessively long, and sometimes a timeout error is received. For this reason, the data is periodically transferred to the computer at intervals of up to 1 week.

The Knime application was employed to merge active and reactive power data from the transferred files, remove duplicate records, analyze missing data, filter the dataset, and apply interpolation methods to fill in missing measurements for time intervals with incomplete data. This represents the preprocessing stage of the data collected from the apartment. The process steps are shown in Figure 3.11

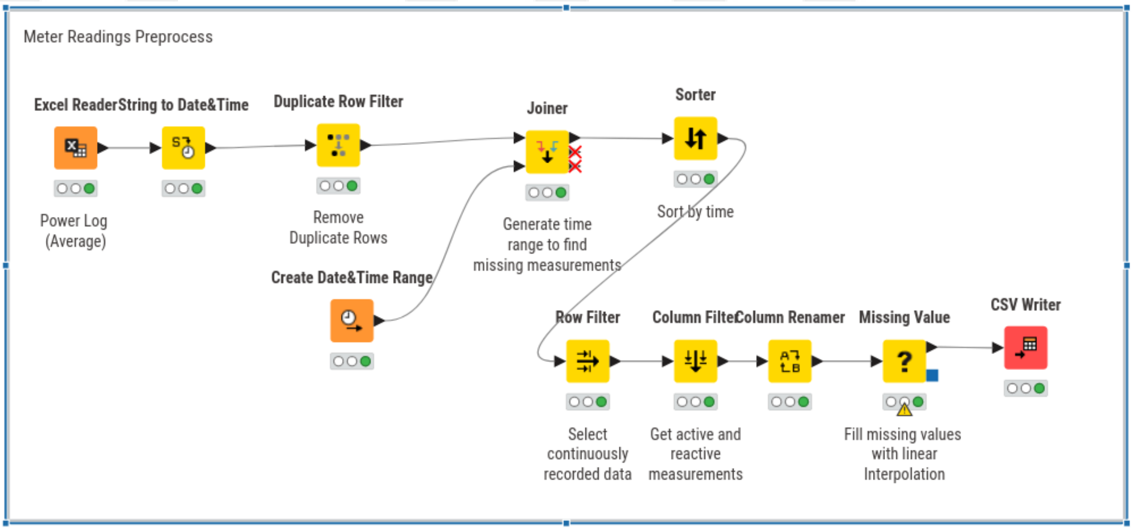


Figure 3.11. Preprocessing metering data using Knime

3.2.2. Change point Detection, Segmentation and Feature Extraction

In this study, an 'event-based' approach has been adopted. This approach involves identifying moments when an appliance is activated, deactivated, or undergoes a state change. Subsequently, the measurement data is segmented based on these events, and features are extracted for each of the resulting segments. Change point detection was done using the Python "ruptures" library, which is a Python library for off-line change point detection which provides methods for the analysis and segmentation of non-stationary signals (Truong, Oudre, and Vayatis 2020). It provides several search methods as dynamic programming, Pelt (Linearly penalized segmentation), kernel change detection, binary segmentation, bottom-up segmentation and window sliding segmentation. In this study, the Pelt search method was preferred for change point detection. The Pelt method computes the segmentation which minimizes the constrained sum of approximation errors for a given model and penalty level. This method can achieve high average of performance on the univariate time series (Van den Burg and Williams 2020). One of the important issues when using the Pelt method is choosing the appropriate penalty value. In measurements taken from a residence in which there are multiple appliances with different consumption levels, consumption characteristics, and operating times, different penalties may be needed to detect the change point and sub-segments. For this reason, in the study, change point detection was performed by using multiple penalty values, and then segments with same start-end times were singularized. Figure 3.12 shows the differences between change points detected using different penalty values (Color change indicates a detected change point).

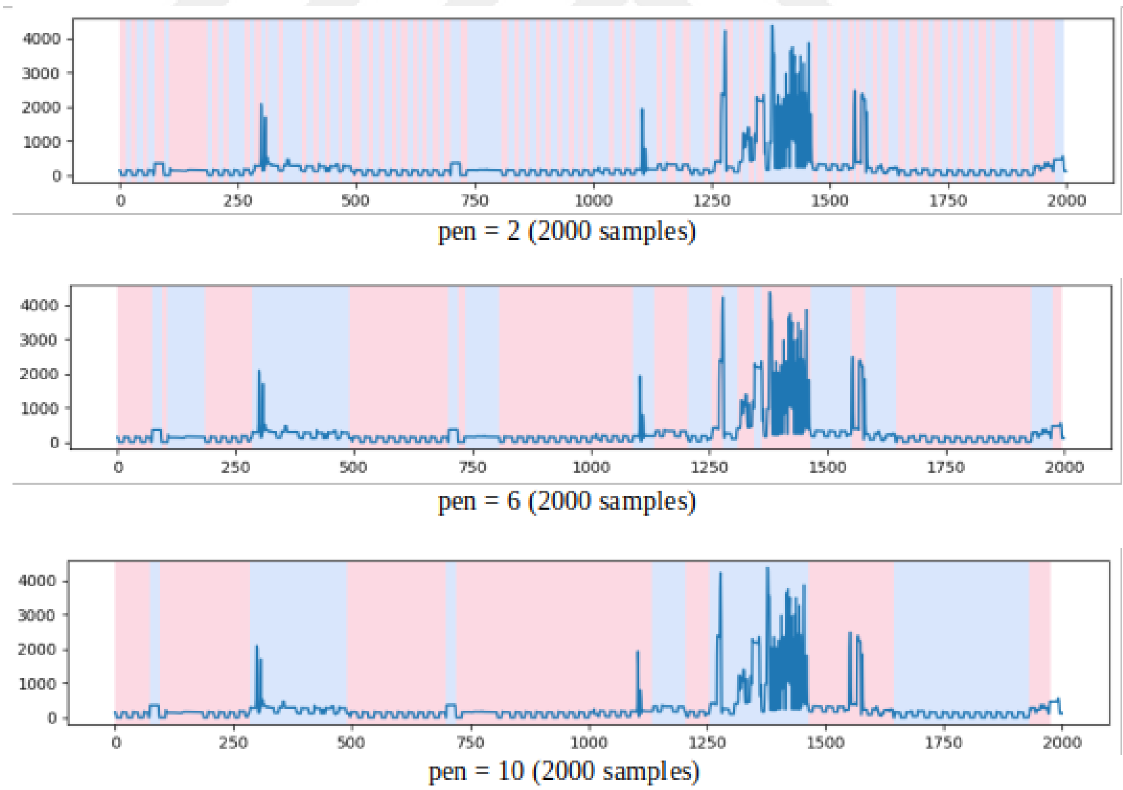


Figure 3.12. Change points detected using different penalty values

Due to insufficient computer resources to process the entire measurement time series at once and perform change point detection on all data, the series was divided into sliding windows, each window was analyzed separately and the results were combined. Feature extraction was performed immediately after the completion of change point detection for each window. The features extracted for each sub-segment are active and reactive mean differences, descriptive statistics and the width of the segment. At the same time, in order to construct the decomposed series after the clustering process is completed, estimated series free of mean consumption in the previous segment was defined for each segment. Since change point detection is performed with multiple penalty values, all duplicate segments with the same start and end time are deleted after the feature extraction phase is completed. In the last stage of feature extraction, the active power and reactive power differences between consecutive segments are calculated and the event type (On/Off) at the beginning of the segment is determined. In the last stage of feature extraction, the active power and reactive power differences between consecutive segments are calculated, the event type (On/Off) at the beginning of the segment is determined, and by thresholding using active power differences, segments containing noise or differences too small to be detected are not included in the clustering process.

3.2.3. Clustering

The purpose of using clustering in the study is to estimate how many different electrical appliances perform the segmented and feature-extracted electrical consumptions, On/Off events of these appliances and in which segments the consumptions are performed by the same appliances, thus creating insights into the individual consumptions of each electrical device. Hierarchical Clustering, Density Based Clustering (DBSCAN), Mean Shift Clustering, and K-Means Clustering was evaluated. In order to obtain the best results, it is necessary to optimize the parameters to be used when applying the clustering methods. Hierarchical Clustering involves selecting a linkage method, distance metric, and optionally the number of clusters or cut-off threshold, DBSCAN requires eps and minimum samples, mean Shift depends on the bandwidth, whereas the data set used does not have a homogeneous distribution in terms of the frequency of operation of the electrical appliances that cause consumption, their operating times, and their consumption characteristics, and making optimization tough. For example, while the refrigerator operates at regular intervals and many times a day, washing machines and dishwashers may operate several times a week and in different operating modes. As a more extreme example, the oven may operate once a week or once every few weeks. These characteristics of the data should be taken into account when determining the optimal number of clusters. Due to these characteristics of data, the traditional methods used to determine the optimal parameters do not always give good results. However K-Means clustering can take the number of clusters as input, and that can be compared to the average number of appliances in a residence. The properties of the centroids obtained with this method can also be compared to the known consumption levels of the appliances in the house. Therefore, it is easier to assess the optimal parameters determined. For this reason, it was decided to continue with K-Means Clustering in the later stages of the study.

Three features were used for clustering: Difference in average active power consumption between sequential segments, difference in average reactive power consumption between sequential segments, and the window size of the segment. Some additional features such as the maximum active consumption value within the segment, standard deviation and frequency domain features of the time series in the segment were also tried to be included in the data set, but it was found that they negatively affected the clustering. Standard scaling has been applied before starting the clustering process in the dataset. However, when we reduced the effect of window size, it was observed that the clustering performance improved, so its weight was reduced. For a segment to be included in the clustering process, the difference in average active energy consumption had to exceed a certain threshold. During the experiments, a threshold of around 5 W was generally used, which ensured that the change points resulting from noise or deviations in the measurement were not effective in clustering.

K-Means clustering is a simple, widely used clustering algorithm which partitions the data into K clusters, calculates the average of members for each cluster to determine the center of the cluster (centroid), and iteratively reassigns each point to the nearest centroid until convergence (Madhulatha 2012). K-Means clustering algorithm is preferred for its linear complexity and ease of implementation. In this study, the algorithm was run on the three-dimensional feature data.

K-Means clustering requires the determination of the number of clusters before the

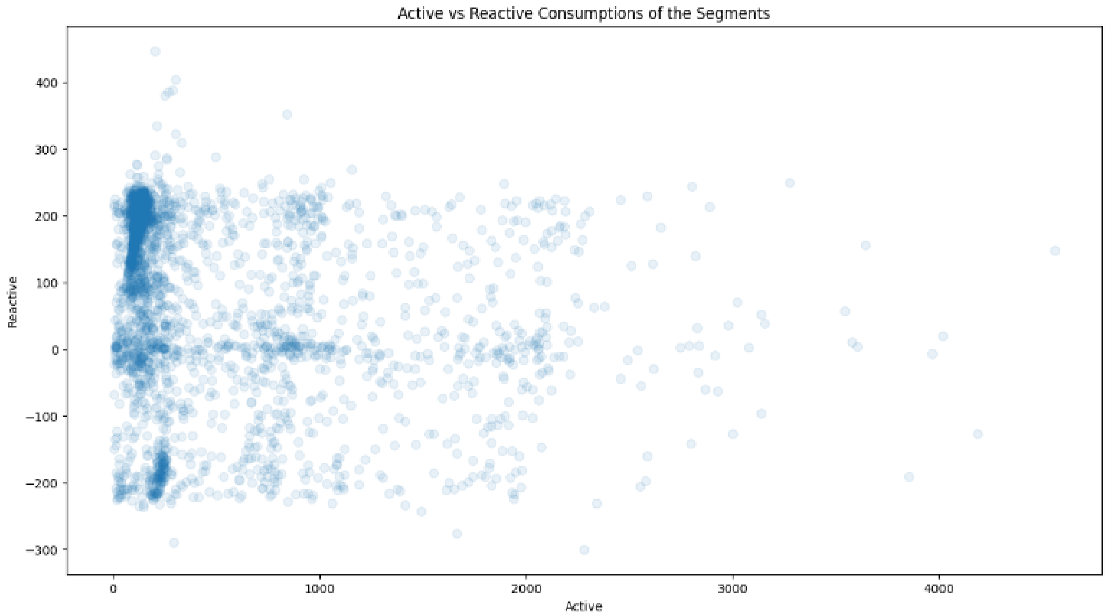


Figure 3.13. Active vs Reactive Consumptions of the Segments

execution of algorithm. In the study, the approximate number of electrical appliances in the residence that we record the measurements (number of the clusters) was known. However, due to the very low measurement data frequency, some of the low-consumption appliances can not be identified and a criterion should be defined to generalize the method.

Elbow criterion is one of the methods that can be used to determine number of the clusters for a data set (Madhulatha 2012). The elbow method generally suggested a cluster count of 5 to 7 in studies, which is well below the number of electrical appliances we expect to find in a residence. Figure 3.14 visualizes the result of an evaluation made with the Elbow method.

Silhouette method is another method used to determine number of clusters in data D. M. Saputra, D. Saputra, and Oswari 2020. It combines separation measure and cohesion measure. When the Silhouette scores of the data set used in the study are calculated with different cluster numbers and the K-Means method, a view like in Figure 3.15 emerges. When evaluating the Silhouette score, it is recommended to use the number of clusters corresponding to the highest Silhouette score. As can be seen in the graph, this value for the data set under study is between 2 and 5. However, like the number of clusters we obtained in the Elbow method, this is also well below the number of appliances we expect to find in a residence. Another thing to note in the graph is that the silhouette score

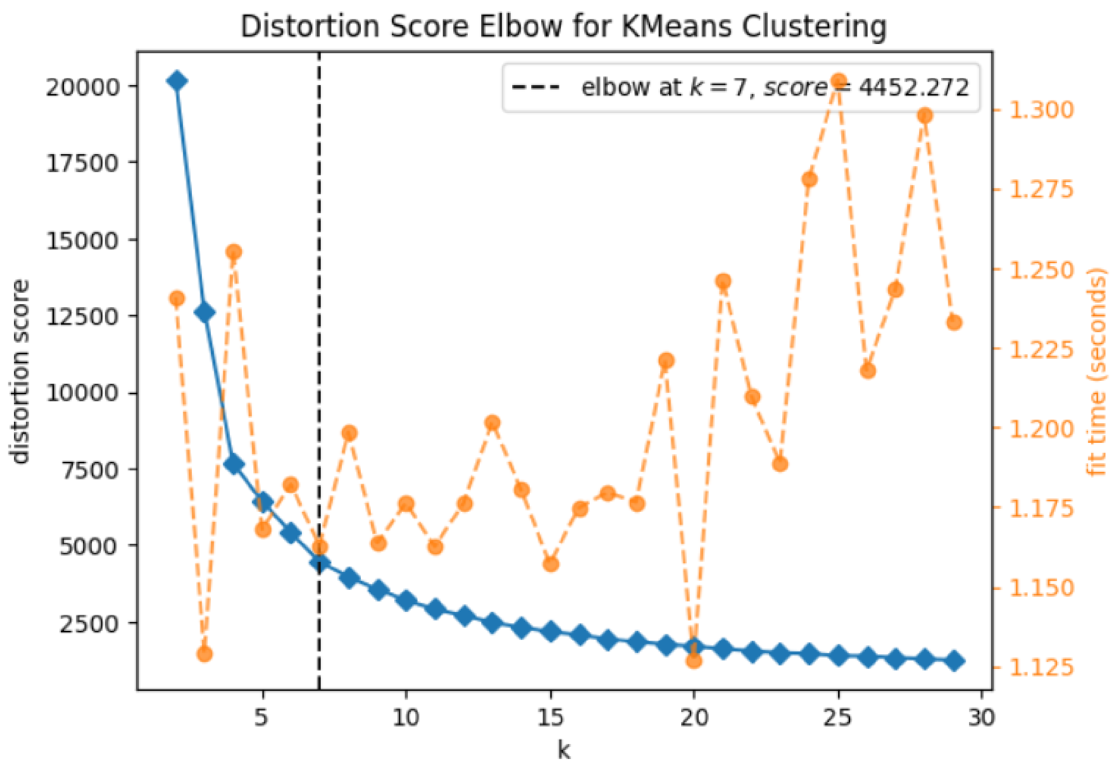


Figure 3.14. Elbow Method Results

drops rapidly after one cluster number. So, one option is to use the largest number of clusters with a reasonable score. For this, we can use the number of clusters just before the point where the biggest downward break occurs in the score graph, i.e. where clustering performance suddenly starts to deteriorate. This number is usually obtained around 10 in different iterations of the method.

After obtaining an optimal number of clusters, K-Means clustering was applied, centroids were determined and cluster numbers were assigned for each change point on the threshold detected in the energy consumption time series. However, it was found that in some iterations, some invalid clusters were obtained. Clustering was implemented for On and Off type changes together in order to make matching. Therefore, as a result of clustering, it was expected that the rate of consecutive transitions (On-Off or Off-On) will be high within the series of events. However, in some iterations which were rare, clusters containing only On or only Off type change points were detected. In order to prevent these errors, a regulation has been made to invalidate clusters which low transition rates, and to assign the data in this invalid clusters to the nearest valid cluster.

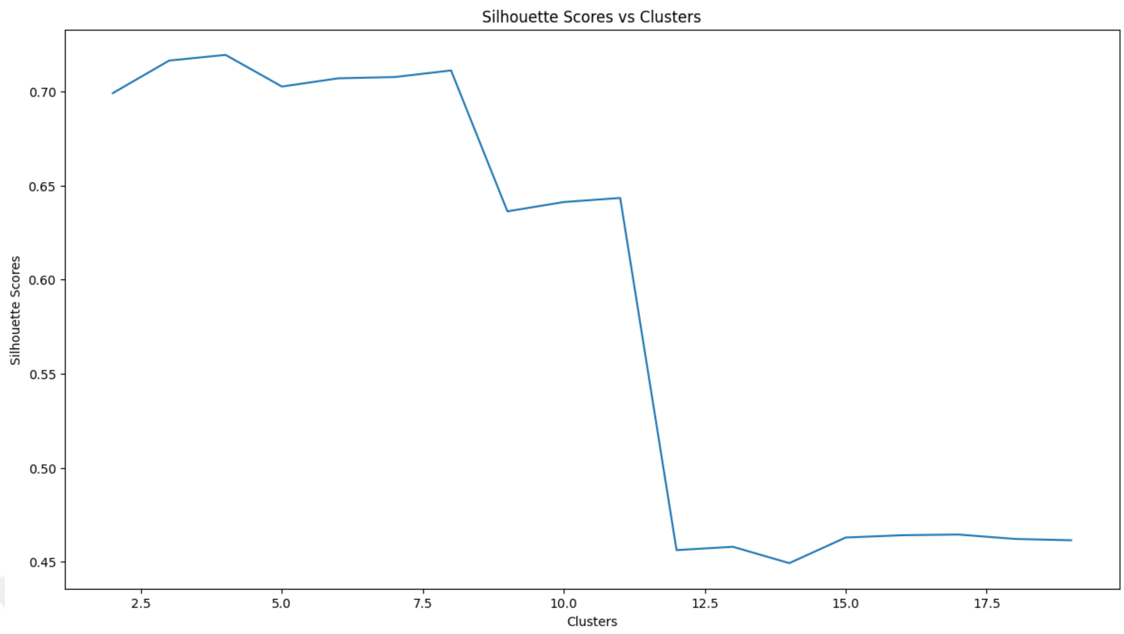


Figure 3.15. Silhouette Scores vs Clusters

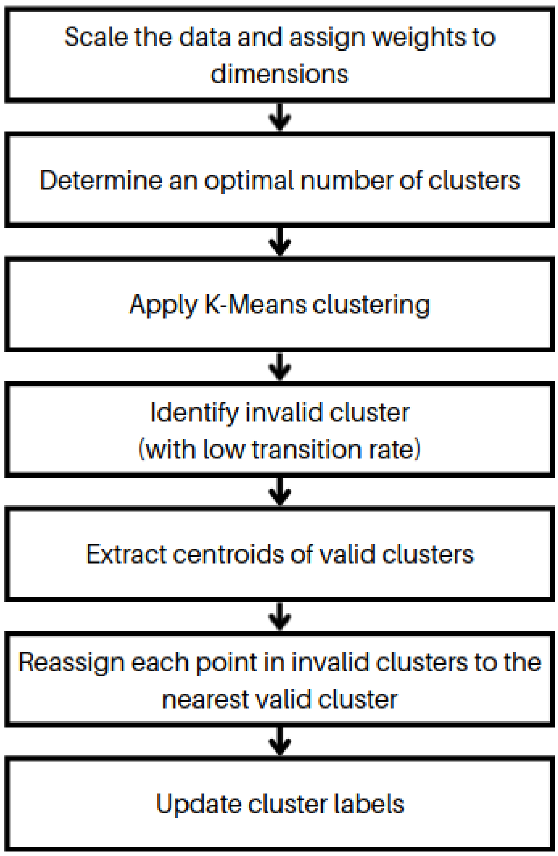


Figure 3.16. Stages of the clustering process

3.2.4. Disaggregated Signal Construction

After the clustering process is completed, the segments belonging to each cluster are sorted and the On and Off events belonging to the segment class are tried to be matched. The purpose here is to continue the signal as if this split never occurred, if after the On event of the cluster, events belonging to another cluster occur and the segment is split. Thus, the consumption of each cluster (i.e. appliance type) can be turned into a continuous time series, visualized and presented to users (Azazi Deveci and Günay 2024). However, while polynomial regression was previously used to adapt the signal to another segment of different length while preserving its properties, resampling was used in current studies, because it has been determined that high deviations can occur with polynomial regression. The "tslearn" library was used for resampling the segment according to the desired length.

Algorithm 1: Disaggregated Signal Construction

Require: Time-ordered list of segments $\mathbf{L}$ including assigned cluster number c, estimated signal array of the segment $\mathbf{S}$, start index of the segment i_s, end index of the segment i_e, type of the segment t, length of the signal array of the measurements l

Ensure: List of disaggregated signal arrays $\mathbf{D}$

```
Initialize an empty list D_i
for each element L_i in L do
    if t = "on" then
        i_r ← i_s of the next "off" type segment with the same c
    end if
    if i_r > i_e then
        Resample S to length of i_r − i_s
        Set D_i[i_s : i_e] = S
    end if
    Append D_i to D
end for
return D
```

3.2.5. Association Analysis

The consumption of multi-state appliances in different states can be perceived as separate devices. Association analysis was experimented to prevent such a situation from causing incorrect estimations and to be able to recognize the associations of different states of multi-state appliances. For this purpose, cluster numbers of segments starting with events of type "On" are listed, consecutive cluster id elements in different sized windows are prepared with sliding window method, encoding transformation is performed with transaction encoder that keeps the information of existence/absence for each element. Then, element groups with at least 0.7 support ratio were found with apriori algorithm and association rules with at least 1 lift ratio were detected. In the last stage, the number of clusters of frequent item sets obtained with association analysis was combined. In this section, it was checked whether the cluster centroids to be combined have the same reactive consumption characteristic in order to avoid incorrect matches. The Apriori algorithm is a popular association analysis algorithm that generates candidate item groups, performs support counting for the item groups, and finds item groups that meet the specified support and lift levels (Huang et al. 2000). Python's "mlxtend" library was used to implement the apriori algorithm and obtain frequent item sets.

3.2.6. Activity Analysis

The days and hours when electrical appliances are used intensively may vary depending on their purpose of use and the routine of those living in the house. For this reason, activity analysis was included in the study. This analysis was done by simply creating a heatmap for each cluster to visualize the results, showing consumption intensities by day and hour of the week.

4. RESULTS AND DISCUSSION

4.1. Results of Change point Detection, Segmentation and Feature Extraction

As a result of segmentation of the preprocessed data with the PELT method using three different penalty values, approximately 12,300 change points were detected in each iteration. Table 4.4 shows the change point counts for an iteration. At each change point detection, the features of the new segment are extracted by taking into account the signal levels and features of the previous segment and added to the dataframe that stores the segment features. Following segmentation including feature extraction, duplicate segments, if any, are deleted. After removing duplicate segments, the remaining number of segments is approximately 11,000. This means that an event is detected approximately every 13 minutes in average.

Table 4.4. Change Points Detected for Each Penalty Value

Penalty Value	Change Points Detected
2	9,869
6	1,496
10	954
Total	12,319

4.2. Results of Clustering and Disaggregated Series Construction

When all stages of clustering including scaling, scoring, clustering, validation and reassignment are completed, clusters ranging in number from eight to twelve are obtained in each iteration. Table 4.5 gives the centroid features of ten clusters obtained by K-Means clustering in one of the iterations. The relationship between the cluster distribution and active and reactive energy consumption is shown in can be seen in Figure 4.17. In this iteration, the transition rate of all clusters obtained is above the threshold, so no clusters needed to be dropped, and their members reassigned. After constructing the disaggregated series, a partial view for each constructed cluster is given in Figure 4.18 and Figure 4.19. In each graph in these figures, the total active power consumption measured and

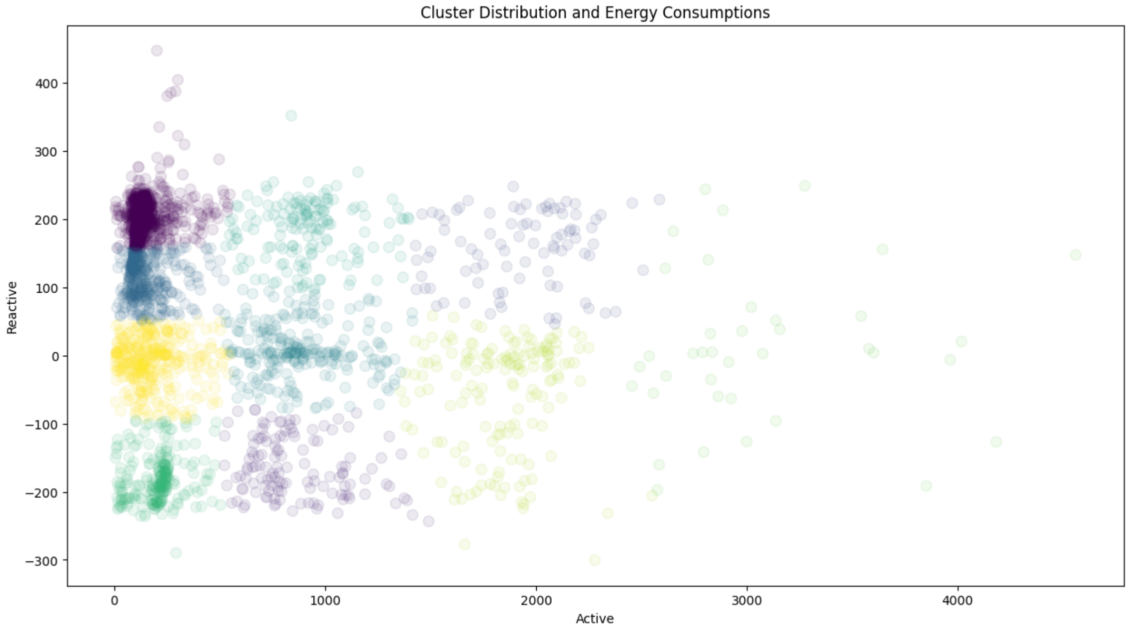
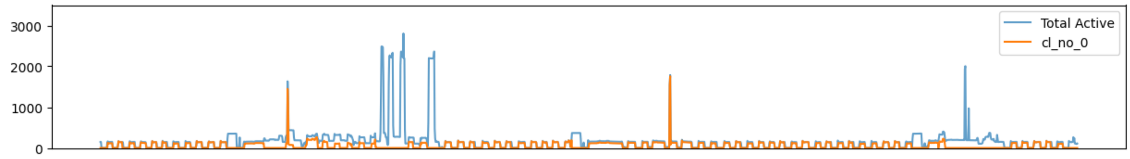


Figure 4.17. Cluster Distribution (Active vs Reactive Consumption)

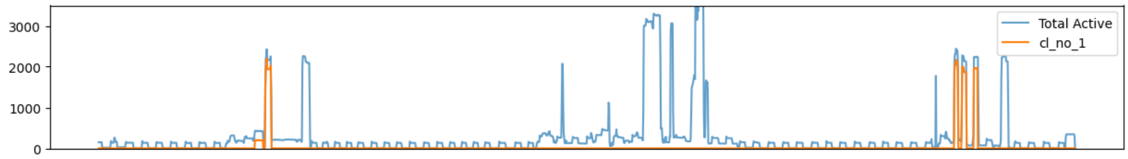
Table 4.5. Centroids Obtained with K-Means Clustering

Cluster No.	Active Consumption	Reactive Consumption	Window Size
0	136.35	204.97	13.74
1	852.87	-164.49	21.58
2	1935.22	158.20	18.74
3	149.00	111.36	53.90
4	878.50	5.98	48.81
5	927.98	182.04	16.82
6	197.67	-182.45	31.86
7	2965.15	13.80	28.06
8	1839.50	-60.67	25.40
9	203.98	-6.80	115.83

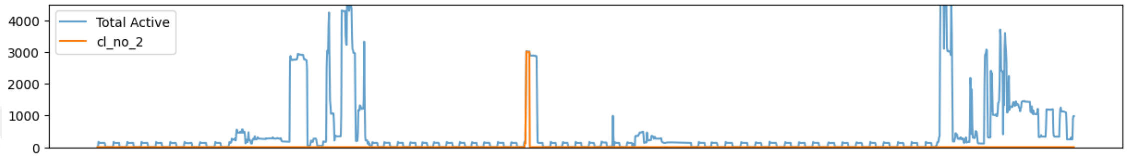
the disaggregated series constructed for an obtained cluster are shown together for a time interval of 2000 minutes (nearly 33 hours). Since the operating times of the appliances are different from each other, all the graphs listed may not belong to the same time interval.



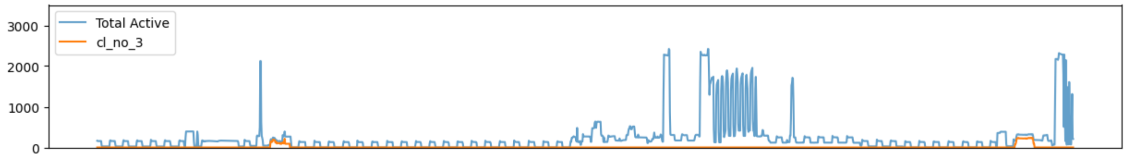
(a) Cluster 0



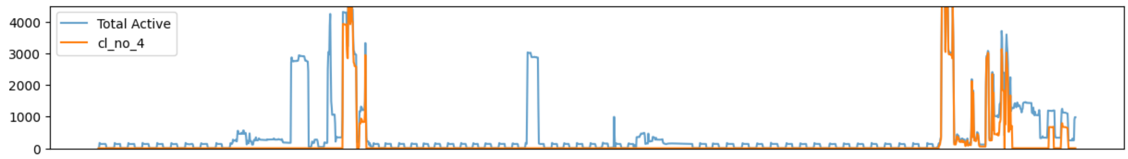
(b) Cluster 1



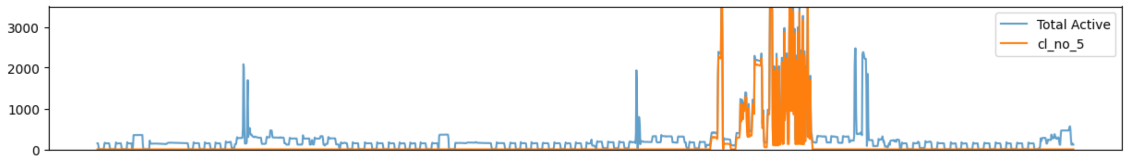
(c) Cluster 2



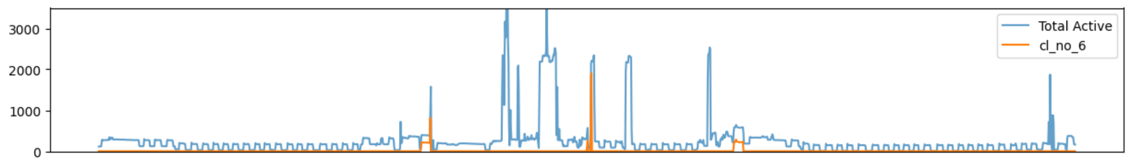
(d) Cluster 3



(e) Cluster 4

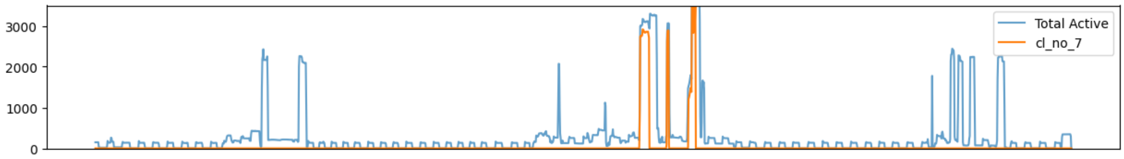


(f) Cluster 5

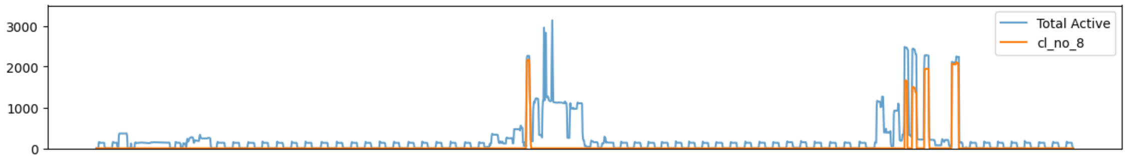


(g) Cluster 6

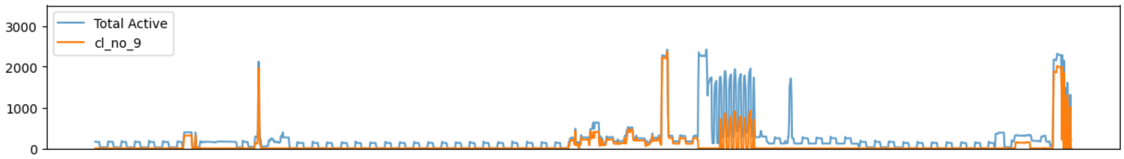
Figure 4.18. Disaggregated Signal Views (Part 1



(a) Cluster 7



(b) Cluster 8



(c) Cluster 9

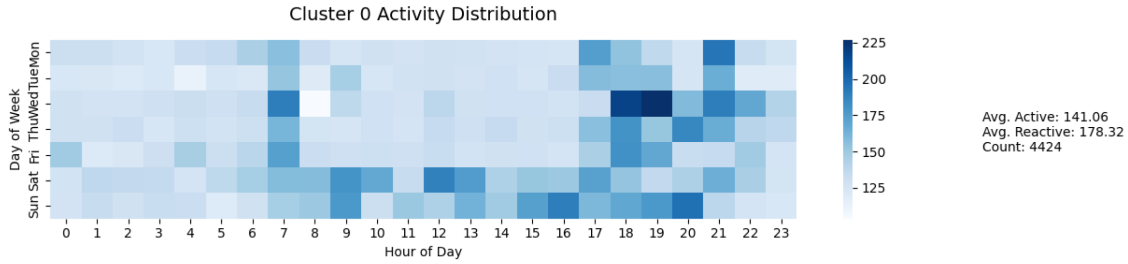
Figure 4.19. Disaggregated Signal Views (Part 2)

4.3. Results of Association Analysis

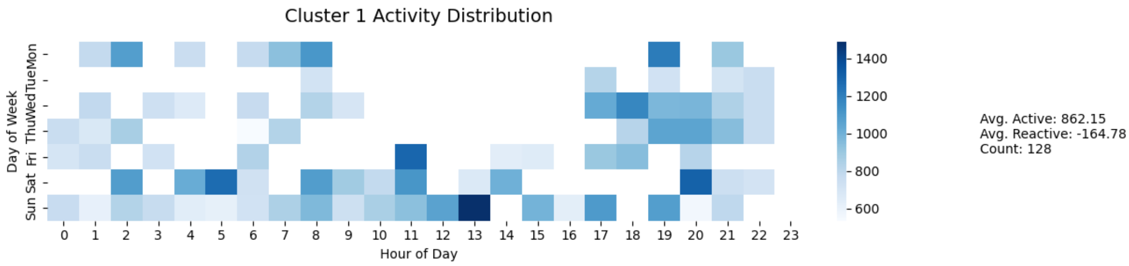
Association analysis was not as effective as expected in detecting multi-state appliances, but a small number of associations were detected. In the iteration whose results are listed, an association was detected between Cluster 0 and Cluster 3 and between Cluster 0 and Cluster 9 as a result of the association analysis performed with a minimum support ratio of 0.7 and a lift threshold of 1. Therefore, Cluster 3 and Cluster 9 series were relabeled as Cluster 0 and the resulting number of dissaggregated series decreased to eight.

4.4. Results of Activity Analysis

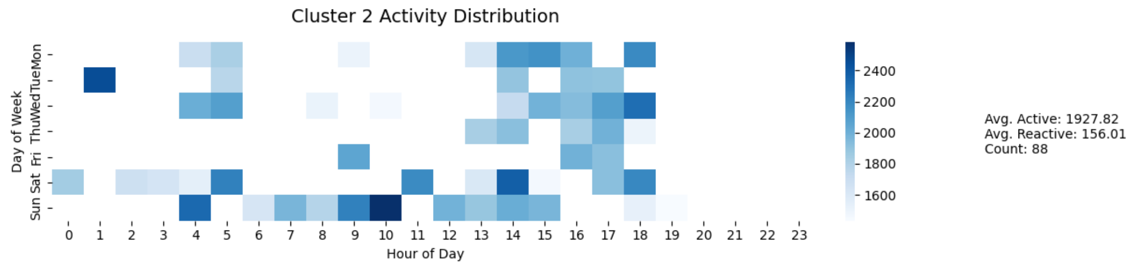
After cluster associations were detected and necessary merges were completed, activity analyzes for the resulting clusters were obtained as in Figure 4.20 and Figure 4.21. These analyses provide us with insights into both the operating characteristics of the appliances and the activity within the residence.



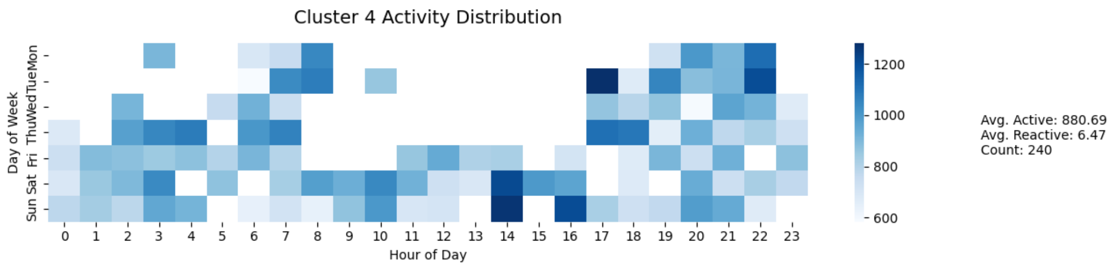
(a) Cluster 0



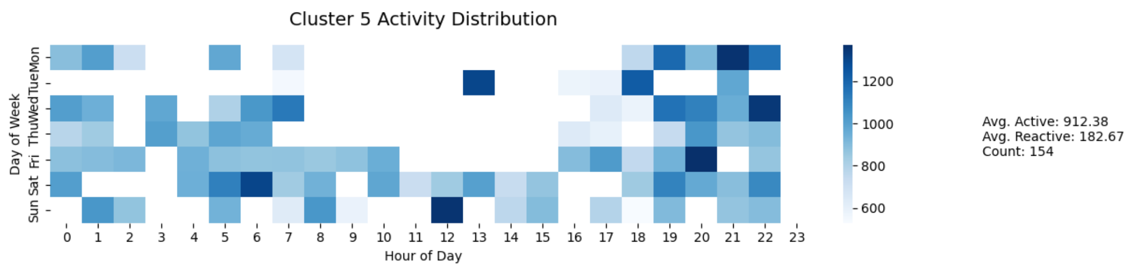
(b) Cluster 1



(c) Cluster 2

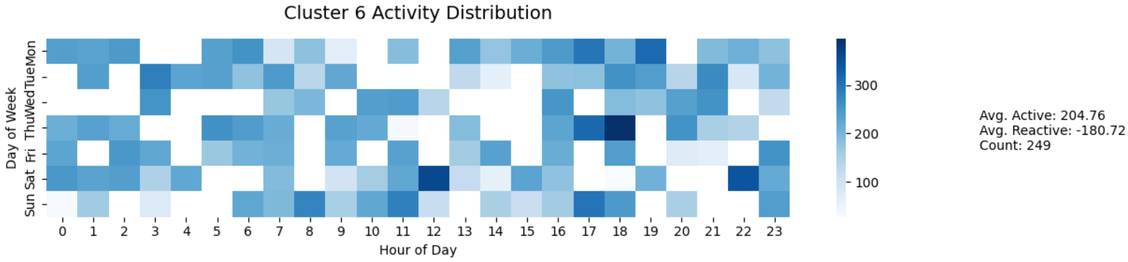


(d) Cluster 4

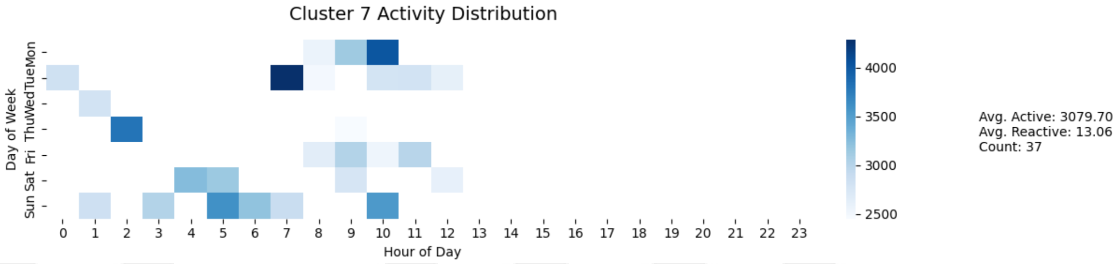


(e) Cluster 5

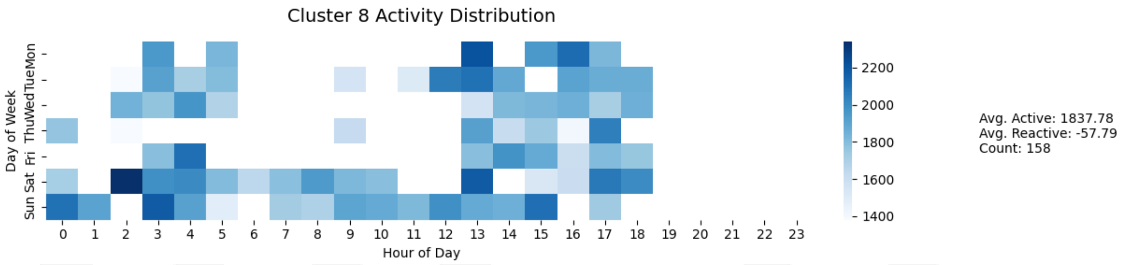
Figure 4.20. Activity Distribution of the Clusters (Part 1)



(a) Cluster 6



(b) Cluster 7



(c) Cluster 8

Figure 4.21. Activity Distribution of the Clusters (Part 2)

4.5. Discussion

In the mentioned iteration of the method, eight appliances' consumption is estimated. Considering the centroid values, average active consumption, reactive characteristics, estimated disaggregated series and activity analysis of the obtained clusters, it is possible to make an idea about what these appliances are.

For example, we can observe that appliance in Figure 4.18a (Cluster 0) consumes power periodically and always at similar levels throughout the day. If we also take into account that the active power value listed in Table 4.5 for the centroid of this cluster is 136 W, and it has an inductive load due to the positive reactive consumption, we can assume that the appliance in question is a refrigerator. The fact that we observe that it works every day of the week and every hour of the day in the activity analysis confirms this prediction. Again, according to the activity analysis, the consumption of this appliance increases for about an hour in the morning and for a few hours in the evening during the week, and it consumes electricity at similar and low levels during the other hours. This is also compatible with the activities of a family at home that is not at home during working hours on weekdays. Since the refrigerator is opened more during breakfast and dinner hours, it requires more electricity consumption for cooling. When we examine the weekend consumption of this appliance, we see an increase in consumption from morning to evening. To test the accuracy of this estimation, we can make a visual comparison between actual refrigerator consumption measurements and some samples from Cluster 0. Figure 4.22 presents the graphs of 250 minutes of real refrigerator consumption data alongside five 250-minute partial samples taken from Cluster 0. Upon examining the graphs, the similarities become noticeable. However, it can be observed that some On/Off state transitions, especially in samples 2 and 5, were not detected and thus were missed. These errors are likely undetected change points that occurred during periods of high consumption by other appliances, indicating a need for improvement in this area. Nevertheless, it can be said that the overall signal characteristics of Cluster 0 are consistent with the real measurements.

Cluster 1 appears to have a capacitive load, and usually residences do not have capacitive loads that consume this level of power. However, today, electrical appliances such as washing machines and air conditioners can contain brushless DC motors and switched-mode power supplies with these motors (Torres n.d.). Therefore, the capacitive reactive load we see here may be a combination of appliances that consume low power and can create capacitive loads, such as LED lights, televisions, charging adapters, modems and access points, when the refrigerator and no other motorized household appliances are working, or it may belong to one of the states of a washing machine. It may be possible to distinguish between these appliances with measurement data having a higher measurement data frequency.

Cluster 2 could be a dishwasher or washing machine due to its consumption level and inductive reactive load. However, it is not possible to make a clear distinction between these two appliances. When we compare the actual dishwasher and washing machine

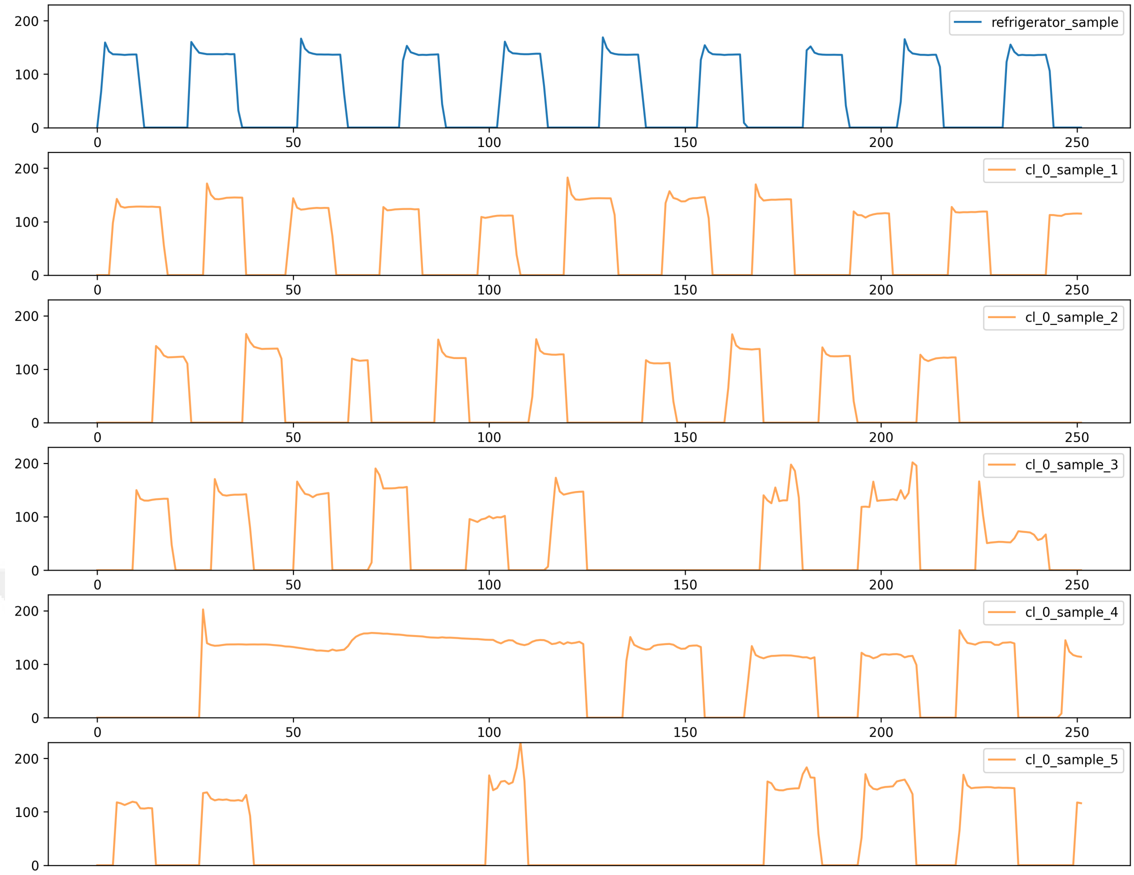


Figure 4.22. Visual Comparison of Actual Refrigerator Consumption with Cluster 0 Estimates

measurements obtained in the study with some partial samples taken from Cluster 2 as in Figure 4.23, we gain stronger evidence that this cluster contains measurements related to both appliances. While the patterns of some samples align well with dishwasher consumption, others appear more consistent with washing machine usage. There are also examples, such as Sample 8 and Sample 10, that differ somewhat from the typical real consumption patterns. It may be possible to explain these differences with studies that will collect more actual consumption data under different operating conditions of both the dishwasher and the washing machine.

Cluster 4 has a nearly pure resistive power consumption of 880 W. Based on this, we can say it is an appliance that functions as a heater. However, this heater device can be an oven, an oil-filled radiator or a water heater operated at medium level.

Cluster 5 is an appliance with an inductive load and an active power consumption

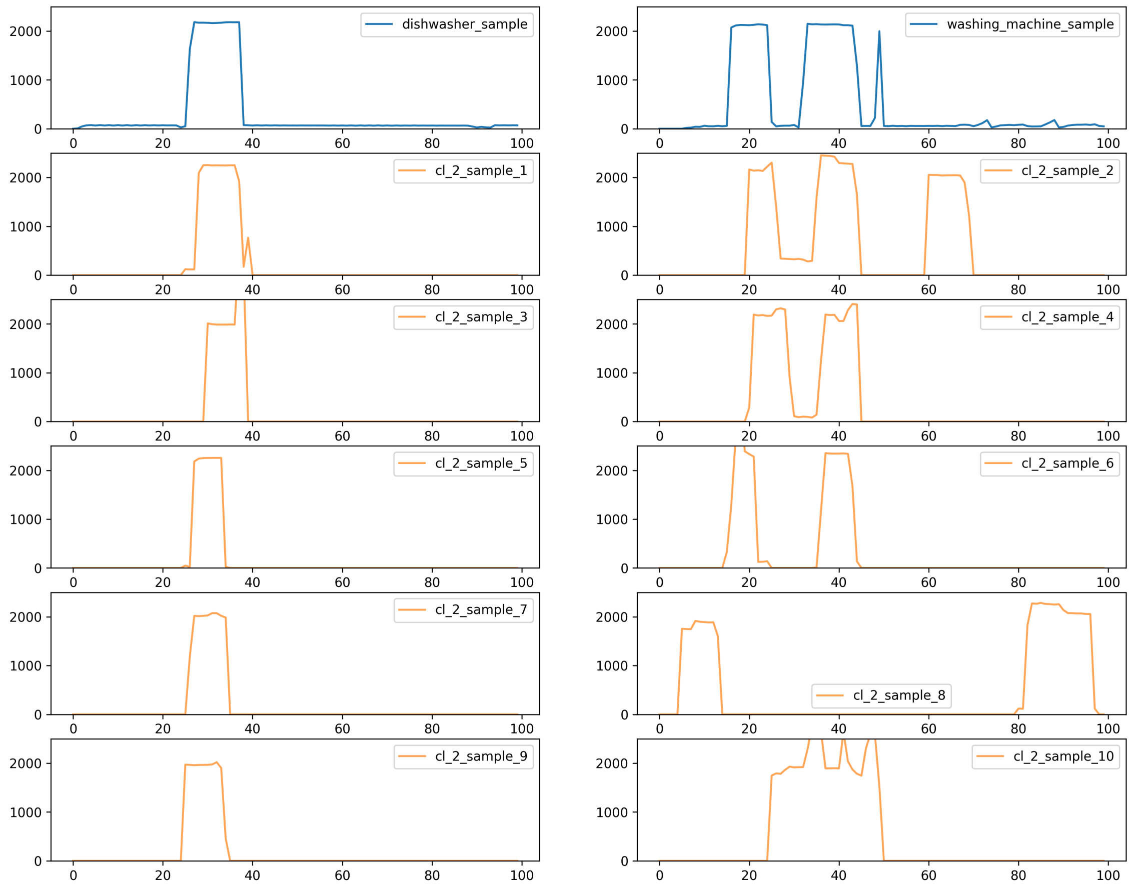


Figure 4.23. Visual Comparison of Actual Dishwasher and Washing Machine Consumption with Cluster 2 Estimates

of approximately 912 W. It is used intensively on weekday evenings and weekend afternoons, although there is also some consumption occurring after midnight according to the activity distribution. It is likely that this cluster includes energy usage patterns associated with a vacuum cleaners and an air conditioner.

Cluster 6 has a capacitive load profile and low energy consumption. Its consumption pattern is consistent with that of a television.

Cluster 7 has an almost purely resistive load with a power level of around 3000 W. It was found to have operated 37 times during the data collection period. Its usage is concentrated in the morning hours. This appliance very likely corresponds to the consumption of an iron.

Cluster 8 also exhibits a near-resistive consumption pattern. Its power consumption, around 1800 W, suggests that the appliance may be a kettle. However, considering that the data was recorded during the late autumn and winter, it is also possible that measurements from a high-power heater or radiator are partially included in this cluster.

As observed, the applied method led to the estimation of eight distinct appliance consumption patterns. While some of the identified clusters can be confidently associated with specific devices, others appear to include consumption from multiple appliances. Nevertheless, the number of identified devices is consistent with the number of appliances expected to be detected at measurement data frequencies ranging from 1 minute (1/60 Hz) to 1 second (1 Hz), as reported in Armel et al. (2013).

As shown in Table 4.6, the total of the estimated disaggregated power consumption accounts for 66% of the measured actual consumption. The difference may be due to both undetected appliance consumption and limitations of the disaggregated signal estimation approaches. Additional studies involving long-term recordings of the actual consumption of all appliances used in the household, along with total consumption, would help identify the reasons for this gap more clearly and yield results closer to the actual consumption.

Table 4.6. Comparison of Estimated Total Consumption with Actual Total Consumption

Category	**Sum Value (kW)**	**Percentage of Actual Total Active Sum (%)**
Sum of Cluster 0	6177.734601	18.08
Sum of Cluster 1	1752.962143	5.13
Sum of Cluster 2	1664.517278	4.87
Sum of Cluster 4	5446.185596	15.94
Sum of Cluster 5	1769.891658	5.18
Sum of Cluster 6	1414.810814	4.14
Sum of Cluster 7	1367.853377	4.00
Sum of Cluster 8	2965.103532	8.68
Overall Cluster Sum	22559.058999	66.03
Actual Total Active Sum	34165.059460	100.00

The overall execution time of the proposed method except the preprocessing was approximately 220 seconds.

5. CONCLUSION

Although examining electricity consumption at the appliance level and providing users with feedback about individual sub-consumer components can lead to energy savings, this benefit is often missed because measuring the consumption of each device separately is difficult and costly. To avoid these difficult and costly methods while still capturing the mentioned opportunities, it is possible to perform augmented appliance-level consumption detection (energy disaggregation) using various machine learning and data mining techniques.

In this study, a multi-step unsupervised method is proposed as a solution to this problem. The method consists of sequential stages including data preprocessing, change point detection, feature extraction, clustering, and postprocessing steps such as disaggregated signal construction and association analysis. The proposed method does not require training data, enables useful results even at very low measurement data frequencies, and has low resource requirements. For this purpose, measurement data frequency of one sample per minute were collected from a household where information about the appliances used and the residents' lifestyle habits was available, and the proposed method was applied.

In the preprocessing stage, the data collected in segments were merged, the features to be used (active and reactive consumptions) were selected, and missing data were handled. Subsequently, change point detection was applied, the measurement time series was segmented, and feature extraction was performed. K-Means clustering was then conducted using a three-dimensional feature set. The validity of the obtained clusters was evaluated, and reassignment was performed for invalid cluster members. Association analysis was conducted to identify the consumption patterns of multi-state appliances. Disaggregated series were constructed, and alongside these, the characteristics of cluster centers as well as the activity distributions of each cluster by days of the week and hours of the day were examined.

As a result of the method, consumption patterns of eight appliances were estimated. While some of the estimates yielded clear results, it was found that others included consumption from multiple devices. The method, implemented on a personal computer, enabled the analysis of approximately 3.5 months of measurements in about 3.5 minutes.

Given the duration of the observation and data collection phases, these results represents a highly efficient outcome. Moreover, experiments indicate that comparable performance can be achieved when the method is applied to shorter data windows. These results suggest that, due to its simplicity and speed, the method is well-suited for deployment on privacy-preserving, resource-constraint edge devices, where efficient execution is critical.

In future, further development of the method's cluster validation and association analysis steps is expected to enable high-accuracy results for more appliances even when using data from low-cost, widely deployed electricity meters that operate at very low measurement data frequencies, such as one measurement per minute. Applying the method to datasets that include real appliance data will enable the extraction of performance metrics, thereby improving its accuracy and reliability, and facilitating its generalization.

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CURRICULUM VITAE

Şirin AZAZİ DEVECİ

EDUCATION

Master of Science 2022-Present	Akdeniz University Institute of Natural and Applied Sciences Computer Engineering, Antalya
Bachelor of Science 1998-2003	Çukurova University Faculty of Engineering and Architecture Electrical and Electronics Engineering, Adana

WORK EXPERIENCE

Linarit, 2019-Present	Business Developer, Project Manager, Engineer
Akdeniz EDAŞ, 2016-2018	Information Technologies Manager
Enerjisa, 2013-2016	Network Team Lead
AYEDAŞ, 2010-2013	Deputy Manager of Information Technologies
TEDAŞ, 2005-2010	Network Engineer
MEES, 2004-2005	Sales Engineer

PUBLICATIONS

Şirin Azazi Deveci and Melih Günay (2024). "Unsupervised Pattern Extraction of Time Series Data for Energy Disaggregation". In: *2024 9th International Conference on Computer Science and Engineering (UBMK)*, pp. 1–6. DOI: 10.1109/UBMK63289.2024.10773561

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